Advancing the Theory and Methods for Understanding Employment Effects of Environmental Regulation: Workshop Agenda

Chair: Kerry Smith (Arizona State University)

8:00-8:20	Coffee and pastry
8:20-8:35	**Kerry Smith** (Arizona State University) – Introduction
8:35-8:45	**Al McGartland** (Environmental Protection Agency (EPA) – EPA Context
8:45-9:15	**Anna Belova** (Abt Associates), **Wayne Gray** (Clark University), **Joshua Linn** (Resources for the Future), & **Richard Morgenstern** (Resources for the Future)–BGLM: **"Environmental Regulations and Industry Employment: A Reassessment"**
9:15-9:30	**Discussant: Reed Walker** (University of California, Berkeley)
9:30-9:50	**Discussant addressing BGLM paper and related policy issues: Michael Greenstone** (Massachusetts Institute of Technology/Brookings Institution)
9:50-10:15	Open discussion
10:15-10:30	Break
10:30-11:00	**Timothy J. Bartik** (W.E. Upjohn Institute for Employment Research): **"The Social Cost of Potential Job Losses Due to Environmental Regulations: How Job Losses' Social Costs Compare to Lost Earnings and Overall Social Costs of Regulations"**
11:00-11:30	**Discussant:Arik Levinson** (Georgetown University) (15 minute talk followed by open discussion)
11:30-12:00	**Nicolai Kuminoff** (Arizona State University), **Todd Schoellman** (Arizona State University), & **Christopher Timmins** (Duke University)–KST: **"Can Sorting Models Help Us Evaluate the Employment Effects of Environmental Regulations?"**
12:00-12:30	**Discussant: Daniel J. Phaneuf** (University of Wisconsin) (15 minute talk followed by open discussion)

12:30-1:30	Lunch
1:30-2:00	**Discussant addressing Bartik and KST papers: R. Scott Farrow** (UMBC) (20 minute talk followed by open discussion)
2:00-2:30	**Richard Rogerson** (Princeton University): **"Assessing the Economic Effects of Environmental Regulations: A General Equilibrium Approach"**
2:30-3:00	**Discussant: Timothy J. Kehoe** (University of Minnesota) (15 minute talk followed by open discussion)
3:00-3:30	Break
3:30-4:00	**Robert Shimer** (University of Chicago): **"A Framework for Valuing the Employment Consequences of Environmental Regulation"**
4:00-4:30	**Discussant: Carolyn Fischer** (Resources for the Future) (15 minute talk followed by open discussion)
4:30-5:00	**Discussant addressing Rogerson and Shimer papers: Charles Brown** (University of Michigan) (20 minute talk followed by open discussion)
5:00-5:30	**Kerry Smith** – Discussion and wrap-up.

Advancing the Theory and Methods for Understanding Employment Effects of Environmental Regulation: Participant Bios

Timothy J. Bartik is a senior economist at the W.E. Upjohn Institute for Employment Research. His research focuses on state and local economic development and local labor markets. Bartik's 1991 book, *Who Benefits from State and Local Economic Development Policies?*, is an influential review of how local policies affect economic development. Bartik is co-editor of *Economic Development Quarterly*, the only journal focused on local economic development in the United States. He has also published extensively in the academic literature on: hedonic price models, business location decisions and how they are affected by state business taxes, environmental regulations, and other public policies; evaluating the benefits of local development policies. Bartik's 2001 book, *Jobs for the Poor: Can Labor Demand Policies Help?*, proposed public service jobs and wage subsidies. Bartik's work was extensively cited in the debate during 2009 and 2010 over job creation policies. Bartik's new book was published in January, 2011: *Investing in Kids: Early Childhood Programs and Local Economic Development*. According to Nobel prize-winning economist James Heckman, "Tim Bartik has written a thoughtful book on the value of a local approach to financing and creating early interventions to foster child development." More recently, he has examined the relative benefits of preschool programs for different economic groups. Bartik received his PhD in economics from the University of Wisconsin–Madison in 1982. He earned a BA from Yale University in political philosophy in 1975. Prior to joining the Upjohn Institute in 1989, he was an assistant professor of economics at Vanderbilt University.

Anna Belova, Abt Associates Inc., serves as an analyst for research projects supporting various US government agencies and other institutions. She specializes in cross-disciplinary applied policy analysis and quantitative modeling. Her portfolio includes a diverse set of studies on human health and enterprise impacts of environmental regulations. In addition to employment effects of environmental regulations, currently pursued research areas are: health inequality (focusing on biomarkers); valuing costs of chronic illness; regulation-induced technological change. Anna Belova holds a Ph.D. in economics from Clark University.

Charles Brown is Professor of Economics at the University of Michigan and Research Professor at the Survey Research Center, where he is director of the Panel Study of Income Dynamics and a co-investigator with the Health and Retirement Study. He is an empirically-oriented labor economist. His past research has focused on topics such as compensating differentials for undesirable working conditions, effects of minimum wage laws and of EEO policies, the determinants of enlistment and re-enlistment in the military, and the relationship between the size and "age" of employer and labor market outcomes. Current work focuses on measurement error in survey data, consequences of the relatively equal opportunity in the military for children of black soldiers, post-retirement benefit adjustment in pension benefits, and labor supply decisions of older salaried workers.

Scott Farrow is a Professor of Economics at UMBC, a part of the University System of Maryland. Previously he was the Chief Economist of the US Government Accountability Office (GAO) and has been on the faculty at Carnegie Mellon University and the Pennsylvania State University. Dr. Farrow received his Ph.D. and M.A. in Economics from Washington State University and his B.A. from Whitman College. His work focuses on the economic and risk based evaluation of government programs with emphasis on the environment, natural resources, and issues in benefit-cost analysis. He is the founding editor of the Journal of Benefit-Cost Analysis.

Carolyn Fischer is a Senior Fellow at Resources for the Future and Associate Director of its Center for Climate and Electricity Policy. Her research addresses policy mechanisms and modeling tools that cut across a variety of environmental issues. In the areas of climate change and energy policy, she has published articles on designing cap-and-trade programs, fuel economy standards, renewable portfolio standards, energy efficiency programs, technology policies, the Clean Development Mechanism, and the evaluation of international climate policy commitments. A current focus of her research is the interplay between international trade and climate policy, options for avoiding carbon leakage, and the implications for energy-intensive, trade-exposed sectors.

Fischer holds a Ph.D. in Economics from the University of Michigan. With RFF since 1997, she is also a fellow of the CESifo Research Network and a Visiting Professor at the University of Gothenburg. She has served on the Board of

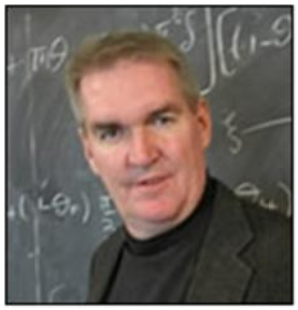
Directors of the Association of Environmental and Resource Economists, was a staff economist for the Council of Economic Advisors, and serves on the Editorial Board of *Resource and Energy Economics*.

Wayne Gray holds the John T. Croteau Chair in Economics at Clark University, where he's taught since 1984, when he received his Ph.D. in economics from Harvard University. Dr Gray is also a Research Associate at the National Bureau of Economic Research, the Director of the Boston Census Research Data Center, and a member of the EPA's Environmental Economics Advisory Committee. Dr. Gray's research focuses on the effectiveness and economic impact of government regulation of environmental and workplace hazards, including studies on productivity, investment, and plant location, working with plant-level data for steel mills, oil refineries and pulp and paper mills.

Michael Greenstone is the 3M Professor of Environmental Economics in the Department of Economics at the Massachusetts Institute of Technology, and the Director of the Hamilton Project. He is on the MIT Energy Initiative's Energy Council and on MIT's Environmental Research Council. In addition, he is a Senior Fellow at the Brookings Institution and a Research Associate at the National Bureau of Economic Research. He served as the Chief Economist for President Obama's Council of Economic Advisors in the first year of his Administration. His research has been funded by the NSF, NIH, and EPA, as well as private foundations. Greenstone received a Ph.D. in economics from Princeton University and a BA in economics with High Honors from Swarthmore College.

His research is focused on estimating the costs and benefits of environmental quality. He has worked extensively on the Clean Air Act and examined its impacts on air quality, manufacturing activity, housing prices, and infant mortality to assess its costs and benefits. He is currently engaged in a large scale project to estimate the economic costs of climate change. Other current projects include examinations of: the benefits of the Superfund program; the economic and health impacts of indoor air pollution in Orissa, India; individual's revealed value of a statistical life; the impact of air pollution on life expectancies in China; the efficacy of environmental regulations in India; and the costs and benefits of an emissions trading market in India.

Greenstone is also interested in the consequences of government regulation, more generally. He is conducting or has conducted research on: the effects of federal antidiscrimination laws on black infant mortality rates; the impacts of mandated disclosure laws on equity markets; and the welfare consequences of state and local subsidies given to businesses that locate within their jurisdictions.



Timothy J. Kehoe is originally from Newport, Rhode Island. He received his B.A. in Economics and Mathematics from Providence College in 1975 and his Ph.D. in Economics from Yale University in 1979. He has held teaching positions at Wesleyan University, the Massachusetts Institute of Technology, and the University of Cambridge in England.

Tim has been a professor in the Department of Economics at the University of Minnesota since 1987, where he is currently Distinguished McKnight University Professor. In addition, he is an adviser to the Federal Reserve Bank of Minneapolis. His research and teaching center on the theory and application of general equilibrium models.

Tim advised the Spanish government on the impact of joining the European Community in 1986 and the Mexican government on the impact of joining the North American Free Trade Area in 1994. In 1997, working with a team from the Mexican consulting firm SAI Derecho y Economía, he designed a foreign trade and investment reform program for Panama. The Panamanian government enacted this program in 1998.

Tim has held visiting professorships at many universities, including CEMFI (Centro de Estudios Monetarios y Financieros), the Universidad de Alicante, the Universitat Autònoma de Barcelona, the Universitat de Barcelona, the University of California-Los Angeles, the Universidad Carlos III de Madrid, the Instituto Tecnológico Autónomo de México, the University of Maryland, El Colegio de México, the Norwegian School of Economics, the Universitat Pompeu Fabra, the Stockholm School of Economics, and Victoria University of Wellington. He has written over 100 books and scholarly articles and has supervised or co-supervised more than 60 Ph.D. theses in Economics. He has received numerous research grants and awards, including 9 grants from the National Science Foundation.

Tim was named a Fellow of the Econometric Society in 1991, he was made Doctor Honoris Causa by the Universidade de Vigo in Spain in 2008, and he was made Miembro de Honor of the Asociación Española de Economía in 2010. His community outreach work includes a position on the Board of Economists of the Minneapolis Star Tribune and a stint as a columnist for the St. Paul Pioneer Press.

Nicolai Kuminoff is an assistant professor of economics at Arizona State University. His research on sorting behavior (and the hedonic equilibria that arise from sorting processes) considers how the logic of revealed preferences extends from individual choices to market and non-market processes. Much of Nick's research aims to improve our understanding of what can be learned about the benefits and costs of prospective environmental regulations from the tradeoffs we observe people making between their consumption of market goods and non-market goods.

Arik Levinson is a Professor in the Economics Department of Georgetown University and a Research Associate at the NBER. His current projects study explanations for the reductions in pollution from U.S. manufacturing, direct measurements of the technological improvements leading to those improvements, environmental Engel curves for the U.S. consumers from 1978 to the present, and explanations for California's steep reductions in energy use relative to other U.S. states.

Joshua Linn's research centers on the effect of environmental regulation and market incentives on technology, with particular focus on the electricity sector and markets for new vehicles. His work on the electricity sector has compared the effectiveness of cap and trade and alternative policy instruments in promoting new technology, including renewable electricity technologies.

Several of his studies on new vehicles markets investigate the effect of CAFE standards on new vehicle characteristics and the effect of gasoline prices on new vehicle fuel economy. Past research on the manufacturing and pharmaceuticals sectors has explored the effect on new technology of price and consumer demand incentives. He has published in leading general interest and field journals in environmental, energy, and health economics.

Linn, who joined RFF in March 2010, was an assistant professor in the economics department at the University of Illinois at Chicago and a research scientist at MIT. At MIT, he served as executive director of the MIT Study of the Future of Solar Energy.

Richard D. Morgenstern is a senior fellow at the Resources for the Future (RFF) in Washington, D.C. Before joining RFF in the year 2000, he had built a career as an academic and a policy maker. He was a tenured economics professor at Queens College of the City University of New York in the 1970s and has also he taught at American University, Yeshiva University, the University of Pennsylvania and Oberlin College. Morgenstern first joined the federal government as an analyst at the Congressional Budget Office before being named Deputy Assistant Administrator of Energy, Natural Resources and the Environment. Subsequently, he served at the U.S. Environmental Protection Agency, where he held various positions, including Director of the Office of Policy Analysis. He served (briefly) as the Agency's Acting Deputy Administrator in 1993.

At RFF, Morgenstern's research focuses on the economic analysis of environmental issues with an emphasis on the costs, benefits, evaluation, and design of environmental policies, especially economic incentive measures. His analysis also focuses on climate change, including the design of cost-effective policies to reduce emissions in the United States and abroad.

Morgenstern received his A.B. degree in economics at Oberlin College and his Ph.D. in economics at the University of Michigan. He has published dozens of articles on environmental economics and policy and he has authored/edited of several books, including New Approaches on Energy and the Environment: Policy Advices for the President (with Paul R. Portney) and Reality Check: "The Nature and the Performance of Voluntary Environmental Programs in the United States, Europe, and Japan" (with William A. Pizer).

Daniel J. Phaneuf is an Associate Professor in the Department of Agricultural and Applied Economics at the University of Wisconsin, Madison. Prior to joining the faculty at Wisconsin this year, he was on the faculty at North Carolina State University for thirteen years. He received his Ph.D. from Iowa State University and a BS from Saint John's University in Minnesota. Currently he is the managing editor of the Journal of Environmental Economics and Management. Dr. Phaneuf's research interests are associated with nonmarket valuation and applied econometrics. He prepared the overview chapter on the economic modeling of recreation demand for North Holland's Handbook in Environmental Economics. His research has appeared in specialty field journal for environmental and resource economics as well as in the *Review of Economics and Statistics*, the *Journal of Econometrics*, the *Journal of Business* *and Economic Statistics* and the *Journal of Economic Perspectives*. He spends summers visiting at the University of Kiel so he can complete a PhD level text in Environmental economics with his co-author, Till Requate, for Cambridge University Press.

Richard Rogerson joined the faculty of Princeton University in spring of 2011, where he is a Professor of Economics and Public Affairs. He obtained his Ph.D. in Economics from the University of Minnesota in 1984 and has previously held faculty positions at the University of Rochester, New York University, Stanford University, the University of Minnesota, the University of Pennsylvania, and Arizona State University. Dr. Rogerson's teaching and research interests are in the fields of Macroeconomics and Labor Economics. His published work includes papers on labor supply and taxes, business cycle fluctuations, the effects of labor market regulations, financing of public education, and development. He currently serves as Associate Editor of the Review of Economic Dynamics and Co-Editor of the American Economic Journal: Macroeconomics, and has previously served as Co-Editor of the American Economic Review and Associate Editor of the Journal of Monetary Economics, the Journal of Economic Dynamics and Control and the International Economic Review. He is a Visiting Scholar at the American Enterprise Institute, a Research Associate at the National Bureau of Economic Research, and a fellow of the Econometric Society.

Todd Schoellman is Assistant Professor of Economics at Arizona State University. He obtained his PhD from Stanford in 2007 and has previously been on the faculty at Clemson University. His research interests lie at the intersection of macroeconomics, growth, and labor economics, with a special emphasis on human capital. His recent publications have been in the *Review of Economic Studies and Quantitative Economics*.

Robert Shimer is the Alvin H. Baum Professor in Economics and the College at the University of Chicago. He is a research associate at the National Bureau of Economic Research, a research fellow at the Institute for the Study of Labor (IZA), and a consultant to the Federal Reserve Banks of Atlanta, Chicago, and Minneapolis. He is a fellow of the Econometric Society and the Society of Labor Economists, an elected member of the American Academy of Arts and Sciences, and the recipient of the Sherwin Rosen Prize for Outstanding Contributions in the Field of Labor Economics. He is the author of one book and numerous refereed papers published in top academic journals, including the *American*

Economic Review, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. He is also a past editor of the *Journal of Political Economy*.

V. Kerry Smith is a Regents Professor and W. P. Carey Professor of Economics at Arizona State University. He is a University Fellow at Resources for the Future, and a Research Associate with the National Bureau of Economic Research. He came to ASU from North Carolina State University where he was the University Distinguished Professor and was Director of the Center for Environmental and Resource Economic Policy. Prior to North Carolina State, he held positions as the Arts and Sciences Professor of Environmental Economics at Duke and the Centennial Professor of Economics at Vanderbilt.

Christopher Timmins is a Professor in the Department of Economics at Duke University, with a secondary appointment in Duke's Nicholas School of the Environment. He holds a BSFS degree from Georgetown University and a PhD in Economics from Stanford University. Professor Timmins was an Assistant Professor in the Yale Department of Economics before joining the faculty at Duke in 2004. His professional activities include teaching, research, and editorial responsibilities. Professor Timmins specializes in natural resource and environmental economics, but he also has interests in industrial organization, development, public and regional economics. He works on developing new methods for non-market valuation of local public goods and amenities, with a particular focus on hedonic techniques and models of residential sorting. His recent research has focused on measuring the costs associated with exposure to poor air quality, the benefits associated with remediating brownfields and toxic waste under the Superfund program, the valuation of non-marginal changes in disamenities, and the causes and consequences of "environmental injustice". He has also recently begun a new research project on the social costs of hydraulic fracturing for the extraction of natural gas.

Professor Timmins is a research associate in the Environmental and Energy Economics group at the National Bureau of Economic Research, and has served as a reviewer for numerous environmental, urban, and applied microeconomics journals. He currently serves on the editorial board of the American Economic Review and is a co-editor of the *Journal of Environmental Economics and Management*.

Reed Walker is a Robert Wood Johnson Scholar in Health Policy Research at the University of California - Berkeley. He received a Ph.D. in economics from Columbia University in 2012. His research consists primarily of themes pertaining to the fields of public and labor economics in the context of environmental and health policy. In his research, he explores the social costs of environmental disamenities such as air pollution and how regulations to limit these pollutants interact with firm and worker behavior. Ongoing work explores the interactions between environmental policy, health policy, and social policy in the United States. After completing the Robert Wood Johnson program, he will take a position as an assistance professor at the University of California-Berkeley's Haas School of Business.

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A Framework for Valuing the Employment Consequences of Environmental Regulation

Robert Shimer*

February 10, 2013

Abstract

I develop a two sector model in which one sector produces a good that generates pollution, a negative externality. I show that even if it takes time for workers to switch sectors, the optimal tax on the dirty good depends only on the marginal rate of substitution between private consumption of the dirty good and pollution. The time it takes workers to switch sectors and the number of workers near the margin for switching affects the employment response to the optimal tax but not the tax itself.

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*University of Chicago, Department of Economics, 1126 East 59th Street, Chicago, IL, 60637 (e-mail: robert.shimer@gmail.com). This research was supported by a grant from the Environmental Protection Agency. The paper was prepared for a conference on the "Employment Effects of Environmental Regulation" on October 26, 2012. I am grateful to Ivan Werning and conference participants for comments. The views expressed in this paper reflect that of the author and not necessarily of the Environmental Protection Agency.

1 Introduction

The goal of this paper is to develop a framework for evaluating the welfare consequences of environmental regulation, with an explicit focus on the possibility that these regulations may temporarily boost the unemployment rate. This approach draws on the modern theory of unemployment pioneered by Lucas and Prescott (1974). I consider an economy with two sectors. One produces a clean good, while the other produces a dirty good that generates a negative externality, "pollution." Everyone in the economy would like to consume both goods but suffers from the pollution caused by other people's consumption of the dirty good. I explore how a tax on the consumption of the dirty good and subsidy to the consumption of the clean good shifts individuals' consumption behavior and hence the production of the two goods.

I am particularly interested in situations in which a worker's human capital is specific to the production of one of the goods. It is possible for the worker to produce the other good, but doing so entails undergoing an unemployment spell with a consequent loss of income. In this environment, a tax on a subset of the goods in the economy hurts the workers with a comparative advantage in producing those goods because it reduces the pre-tax price of the good and hence the value of those workers' human capital. Conversely, a subsidy to a good improves the welfare of the producers of that good. Therefore any effort to tax goods that create negative externalities will have distributional consequences, which makes a welfare analysis of such policies tricky.

There are also some interesting dynamic aspects to the tax policy. Over time, a pollution tax will cause some workers who produce the dirty good to leave that sector and move to the clean sector of the economy, enduring a spell of unemployment. This gradually shifts the number of workers able to produce each of the goods, again with potential consequences for the optimal tax.

I show that despite these considerations, the optimal tax on the dirty good depends only on individuals' preferences, their marginal rate of substitution between the private consumption of the dirty good and pollution. In particular, it is independent of how costly is an unemployment spell and how specific is human capital.

I first consider a static model in which the dirty sector is already in decline so that some workers would be leaving it for the clean sector even without any tax. In this case, an increase in the tax on the dirty good does not affect workers' relative income, although it does induce more workers to exit the dirty sector. Under the assumption that the willingness to reduce private consumption in return for a reduction in pollution does not depend on an individual's wealth, I find that everyone agrees on the optimal tax rate. Moreover, that tax rate can be expressed as a function of the marginal rate of substitution between private consumption of the dirty good and pollution. In particular, it does not depend directly on how much unemployment workers experience as a result of the tax policy change.

I then develop a dynamic model in which workers are continuously moving back and forth between the two sectors of the economy because of idiosyncratic shocks to their human capital, or more precisely to their ability to produce each of the goods. In this case a tax on one of the goods must change workers' relative income and so has real distributional consequences. I abstract from these distributional issues by looking at an economy with complete financial markets. Alternatively, one could allow taxes on the winners (workers with a strong comparative advantage at producing the clean good) and subsidies to the losers (workers with a strong comparative advantage at producing the dirty good). I therefore focus on the optimal policy from the perspective of an individual with the mean level of income. Such an individual's preferred tax on the dirty good is again a simple function of the marginal rate of substitution between his private consumption of the dirty good and pollution. Once again, this does not depend on how time-consuming it is for workers to switch sectors of the economy, nor does it depend on how strong is the comparative advantage that some workers have for working in one sector of the economy.

These results may seem surprising, so it is worth emphasizing that they do not imply that the optimal size of the two sectors is independent of the strength of comparative advantage or the duration of unemployment. To be concrete, suppose that there are many workers with a strong comparative advantage at producing the dirty good or who would face a long unemployment spell before finding a job producing the clean good. Although this fact would not affect the optimal tax, it would imply that workers are unresponsive to the optimal tax. As a result, if workers are strongly attached to the dirty sector, then it is optimal for more workers to continue producing the dirty good. Nevertheless, a policy maker who can tax the production of the dirty good does not need to understand the strength of comparative advantage or the unemployment consequences of his policy in order to compute the optimal tax. In contrast, a policy maker choosing an optimal quantity restriction would need to know this information.

I focus throughout this paper on a scenario in which there are two goods, one clean and one dirty, and no technology for abating the pollution generated by the dirty technology. Other scenarios are certainly empirically relevant. For example, it may be possible to reduce pollution by expanding the labor devoted to producing a third good, say an abatement technology. One could model unemployment of workers moving into this sector as well using similar tools to the ones I develop here. I would expect that optimal policy does not directly depend on how hard it is to train a worker to use the abatement technology, but instead could be expressed in terms of simple formulae that do not explicitly acknowledge the existence of unemployment.

The paper proceeds by first developing a static model in which workers are initially allocated to one sector of the economy and must decide whether to move to the other sector at the cost of foregoing some of their income. In Section 3 then develop a dynamic model in which workers continually move across sectors in response to idiosyncratic productivity shocks, experiencing unemployment when they move. In both models, the decentralized equilibrium would be Pareto optimal in the absence of any pollution. The externality creates a role for taxes and in both models I focus on developing simple expressions for the optimal tax rate. Section 4 discusses the robustness of my main findings and concludes.

2 Static Model

2.1 Environment

This section develops a simple static general equilibrium model with unemployment. I consider an economy which uses labor to produce two goods, a clean good and a dirty good. The economy is inhabited by a large number of individuals $i \in [0, 1]$. The assumption that there is a continuum of individuals formalizes the notion that each individual acts as if his own actions affect neither the level of pollution nor the prices in the economy.

Each individual supplies a unit of labor inelastically, consumes the two goods, and also cares about how much of the dirty good is produced. In particular, for a particular individual i, let c_i denote his consumption of the clean good, d_i denote his consumption of the dirty good, and D denote the total production (and hence consumption) of the dirty good, $D \equiv \int_0^1 d_i di$. I assume the individual's preferences are ordered by the utility function $V(u(c_i, d_i), D)$ where V is increasing in its first argument and weakly decreasing in its second. In addition, I assume that the subutility function u is positive-valued, increasing, concave, and has constant returns to scale.[1] This implies that the marginal rate of substitution between the two private goods, $u_c(c_i, d_i)/u_d(c_i, d_i)$, is a decreasing function of the ratio c_i/d_i. I also assume u satisfies Inada conditions, so this ratio approaches infinity when $c_i/d_i = 0$ and it approaches 0 at the opposite extreme. This ensures that both goods are always consumed in equilibrium.

[1] The assumption of constant returns to scale is equivalent to assuming u is homothetic, since V is an arbitrary increasing function.

Each individual maximizes utility subject to a budget constraint $p_c c_i + p_d d_i = y_i$, where y_i is his income, discussed further below, and p_c and p_d are the price of the two goods in terms of an arbitrary numeraire. When choosing his consumption, the individual takes as given the price of the two goods as well as the total production of the dirty good D. It follows that he sets the marginal rate of substitution u_c/u_d equal to the ratio of prices $p_c/p_d \equiv q$. Equivalently, homotheticity of the utility function u implies that each individual chooses $d_i = c_i f(q)$, where f is an increasing function. The budget constraint then implies

$$p_c c_i = \frac{q y_i}{q + f(q)} \text{ and } p_d d_i = \frac{f(q) y_i}{q + f(q)}$$

Now let $C \equiv \int_0^1 c_i di$ denote total consumption and production of the clean good. Integrating the previous expressions across individuals implies that the ratio of total consumption of the dirty good to total consumption of the clean good is also an increasing function of the relative price q:

$$\frac{D}{C} = f(q). \tag{1}$$

For example, if $u(c, d) = c^a d^{1-a}$ for some $a \in (0, 1)$, $f(q) = (1 - a)q/a$ and so the expenditure share on good C, $p_c C/(p_c C + p_d D)$, is a constant a. This is the case where the marginal rate of substitution between the two goods is 1. If the goods are poorer substitutes, then an increase in the relative price of the clean goods raises the expenditure share on clean goods.

I next turn to the worker's income. This is the product of his wage, which depends on the sector he works in, and the amount of time he works, which depends on whether he switches sectors. More precisely, the wage per unit of labor input for a worker producing the clean good is w_c and the wage per unit of labor input for a worker producing the dirty good is w_d. Now assume that prior to the single time period, a fraction n_c^0 of the workers were engaged in producing the clean good and the remaining $n_d^0 = 1 - n_c^0$ were engaged in producing the dirty good. If a worker continues to produce the same good, he can supply one unit of labor. If he switches industry, he spends a fraction $1-\phi$ of the period unemployed before he finds a job, and so can only supply ϕ units of labor.[2] Each worker will stay in his original sector if moving reduces his income and move if it raises his income. Let n_c denote the number of workers who actually work in the clean sector and $n_d = 1 - n_c$ denote the number of workers who actually work in the dirty sector. Then assuming some workers produce in each sector, workers' mobility decisions imply

$$n_c \gtreqless n_c^0 \Rightarrow \begin{cases} w_d = \phi w_c \\ \phi^{-1} w_c \geq w_d \geq \phi w_c \\ w_d = \phi^{-1} w_c. \end{cases}$$

That is, if workers move between sectors, $n_c \neq n_c^0$, then it must be the case that movers are indifferent about doing so, earning the same labor income in either sector, while workers in the growing sector strictly prefer to stay in that sector.[3] If wage gaps are not large enough to cover the cost of unemployment,

[2] I assume that the individual does not enjoy any additional leisure while he is unemployed, but it is straightforward to modify this assumption.

[3] This indifference condition holds in equilibrium and uses the fact that both goods are always consumed. Otherwise it would be possible to drive all workers into one sector while

then workers remain in their old sector.

A worker in sector $s \in \{c, d\}$ produces one unit of good s if he works full time and ϕ units of that good if he is moving into the sector and so spends some time unemployed. It follows that production of the two goods is

$$C = (1-\phi)\min\{n_c, n_c^0\} + \phi n_c \text{ and } D = 1 - (1-\phi)\max\{n_c, n_c^0\} - \phi n_c \quad (2)$$

For example, if workers do not switch sectors, $n_c = n_c^0$ and so $C = n_c^0$ and $D = 1 - n_c^0$. If workers move into the clean sector, $n_c > n_c^0$ and output of the clean good is boosted for a fraction ϕ of the period by the $n_c - n_c^0$ who move into the sector, while output of the dirty good is reduced by $n_c - n_c^0$ throughout the period.

I assume that the market for the two goods is competitive, but the government levies a tax at rate τ_c on the sale of the clean good and τ_d on the sale of the dirty good. As a result, the price of the two goods is equal to the after-tax cost of producing them, $p_c = (1 + \tau_c)w_c$ and $p_d = (1 + \tau_d)w_d$. The government runs a balanced budget, which requires $\tau_c w_c C + \tau_d w_d D = 0$, so one of the taxes is negative. These two tax instruments are complex enough to allow the government to obtain the first best allocation, but I consider other equivalent tax systems below.

To complete the characterization of equilibrium, I now look at two cases. In the first, there is no reallocation of workers across sectors, $n_c = n_c^0$, and all workers prefer to stay in the original sector rather than enduring an unemployment spell but possibly higher wages in the other sector. In the second,

still keeping a sufficiently large wage gap to encourage workers to move.

some workers switch sectors and all workers in the shrinking sector are indifferent about moving. The equilibrium always takes one of these two forms. I show that the impact of tax changes depends on which configuration the equilibrium has. In the first case, a marginal change in taxes has distributional consequences but no impact on pollution. In the second, a marginal change in taxes has no distributional consequences and instead gives rise to a simple formula for the optimal pollution tax.

2.2 Equilibrium when there is no reallocation

I start my analysis with the case in which there is no reallocation in equilibrium, so $n_c = n_c^0$. In that case, consumption of the two goods is simply given by the initial allocation of labor, $C = n_c^0$ and $D = 1 - n_c^0$. Then equation (1) pins down the relative price of the two goods q as a function of the initial labor share n_c^0:

$$f(q) = \frac{1 - n_c^0}{n_c^0}.$$

For this to be an equilibrium, it must be the case that workers do not want to move,

$$\frac{q}{\phi} \geq \frac{1 + \tau_c}{1 + \tau_d} \geq \phi q,$$

which may or may not hold. In particular, a large enough tax on the dirty good and subsidy to the clean good will always lead to a violation of the second inequality and induce some workers to move to the clean sector, the alternative configuration that I turn to next.

In the case with no equilibrium reallocation, a change in the taxes τ_c and

τ_d does not change the relative price of the two goods because it does not change the production of the two goods and relative prices must clear the goods market. In particular, such a tax also does nothing to abate pollution. It does, however, have distributional consequences. Combine the government budget constraint $\tau_c w_c C + \tau_d w_d D = 0$ with the expression for the relative wage $w_c/w_d = q(1+\tau_d)/(1+\tau_c)$ to get

$$\tau_c = -\frac{D/C\tau_d}{q + \tau_d(D/C + q)},$$

decreasing in the tax on dirty goods τ_d since q, C, and D are all independent of the tax rate. It follows then that the relative wage satisfies

$$\frac{w_c}{w_d} = q + \tau_d(q + D/C).$$

Since aggregate output is unchanged and workers producing the clean good are relatively wealthier, they are made better off by an increase in the tax on dirty goods. Conversely, workers producing the dirty good are made worse off. The bottom line is that when there is no reallocation in equilibrium, labor is supplied inelastically and so pollution taxes have distributional affects but do not affect pollution. An increase in the tax on the dirty good helps the workers producing the clean good at the expense of the workers producing the dirty good.

2.3 Equilibrium when there is reallocation

I turn next to the configuration in which some workers are moving between sectors. To be concrete, suppose that they are moving from the dirty sector to the clean sector, $n_c > n_c^0$. For these workers to be willing to move and others to be willing to stay in the dirty sector, it follows that $w_d = \phi w_c$. Since prices satisfy $p_c = (1 + \tau_c)w_c$ and $p_d = (1 + \tau_d)w_d$, the relative price $q = p_c/p_d = \frac{1+\tau_c}{(1+\tau_d)\phi}$. Then equation (1) pins down the ratio of the production of dirty and clean goods, $D = Cf(q)$, while the production function (2) pins down D and C as functions of n_c. Solving for n_c gives

$$n_c = \frac{1 - (1 - \phi)n_c^0 f\left(\frac{1+\tau_c}{(1+\tau_d)\phi}\right)}{1 + \phi f\left(\frac{1+\tau_c}{(1+\tau_d)\phi}\right)}$$

For this to be an equilibrium, it is necessary and sufficient that $n_c > n_c^0$ or equivalently $\frac{C}{C+D} > n_c^0$. It is straightforward to verify that this is true if and only if the tax on dirty goods is too large for the first type of equilibrium to obtain.

In an equilibrium with mobility, an increase in the tax on dirty goods and commensurate decrease in the tax on clean goods lowers the relative price of the clean good, $q = \frac{1+\tau_c}{(1+\tau_d)\phi}$, thereby reducing the demand for the dirty good and inducing more workers to migrate out of the industry. To understand the welfare consequences of this, it is useful to first think about a case in which there is no pollution externality, $V(u, D) = u$. Take a typical individual i with income y_i, either w_c or $w_d = \phi w_c$. Since average income is $Y = w_c n_c^0 + w_d(1 - n_c^0)$ and preferences are homothetic, it is easy to verify that she consumes

$c_i = (y_i/Y)((1-\phi)n_c^0 + \phi n_c)$ and $d_i = (y_i/Y)(1-n_c)$, i.e. her share of the production of the two goods.

Now by varying the taxes τ_c and τ_d, the government can change n_c and hence the equilibrium level of consumption of the two goods; however, as long as there is some mobility, it cannot change anyone's relative income y_i/Y. This is $\frac{1}{n_c^0+\phi(1-n_c^0)}$ for the n_c^0 individuals who start in the clean sector and $\frac{\phi}{n_c^0+\phi(1-n_c^0)}$ for the $1-n_c^0$ individuals who start in the dirty sector. Therefore, individual i would like the government to set taxes so that n_c maximizes $u(c_i, d_i) = (y_i/Y)u((1-\phi)n_c^0 + \phi n_c, 1-n_c)$. The solution to this problem sets the marginal rate of substitution equal to the relative productivity of the marginal worker in the two sectors, $u_c(c,d)/u_d(c,d) = 1/\phi$, or equivalently $d/c = f(1/\phi)$. To achieve this objective, each individual prefers that the government not levy a distortionary tax, that is it should set $\tau_c = \tau_d = 0$. This result is not particularly surprising. Absent any externality, there is no role for distortionary taxes.

I now reintroduce the assumption that the dirty good causes a negative externality, $V_D(u, D) < 0$. This creates an obvious role for a Pigouvian tax to reduce the production of the dirty good. Yet whether all workers will agree that a such a tax is beneficial is unclear since differences in wealth may induce individuals to value the negative externality differently. That is, the marginal rate of substitution between their private consumption of dirty goods and their external consumption of pollution,

$$\sigma^{d,D} \equiv \frac{\partial V(u(c,d),D)/\partial d}{\partial V(u(c,d),D)/\partial D},$$

may differ across individuals. While this is potentially a real issue, it is not central to this paper. To circumvent this problem, I make a particular assumption on preferences which ensures individuals have a common interest about taxes. I assume that preferences over private consumption and pollution take the form

$$V(u, D) = \Psi(u/v(D)) \tag{3}$$

for some increasing functions Ψ and v.[4] In this case, the marginal rate of substitution between dirty goods and pollution for an individual consuming the average amount (C, D) is

$$\sigma^{d,D} = \frac{v'(D)/v(D)}{u_d(C, D)/u(C, D)}.$$

Under this restriction, every individual prefers the same tax rate.

To prove this, first note that each individual recognizes that his relative income is unaffected by small changes in the tax rate: an individual who is initially working in the dirty sector earns ϕ times as much as an individual who is initially working in the clean sector as long as there is some mobility from the dirty sector to the clean sector. As a result, an individual's income relative to average income, y_i/Y, is still either $\frac{\phi}{n_c^0+\phi(1-n_c^0)}$ or $\frac{1}{n_c^0+\phi(1-n_c^0)}$, depending on his initial sector. Now homothetic preferences imply that all individuals allocate the same share of their income to dirty consumption, $d_i/c_i = f(q)$. It follows that the ratio of dirty consumption d_i to pollution D for any individual i is

[4] I also assume that v satisfies appropriate conditions which ensure that the social optimum has an interior level of production of the dirty good. Convexity is sufficient but not necessary.

simply equal to their income relative to average income y_i/Y. That is, a pollution tax changes supply of clean and dirty goods without any distributional impact.

Now consider the optimal level of the tax. A marginal increase in the tax that induces one worker to move out of the dirty sector reduces production of the dirty good and of pollution by 1 and raises production of the clean good by ϕ. Thus an individual whose relative income is y_i/Y wants employment in the dirty sector to solve

$$\begin{aligned} \max_{n_c,c,d,D} \; & \Psi(u(c,d)/v(D)) \\ \text{s.t. } c &= \frac{y_i}{Y}((1-\phi)n_c^0 + \phi n_c), \\ d &= \frac{y_i}{Y}(1-n_c), \\ \text{and } D &= 1-n_c. \end{aligned}$$

The first constraint recognizes that his consumption of the clean good is a fraction y_i/Y of aggregate production of that good, the second constraint recognizes the same property for the dirty good, and the third constraint equates production of the dirty good to pollution. Eliminating c, d, and D using the constraints and the homogeneity of u, I get that an individual with relative income y_i/Y chooses n_c to solve

$$\max_{n_c} \Psi\left(\frac{y_i}{Y} u\big((1-\phi)n_c^0 + \phi n_c, 1-n_c\big)/v(1-n_c)\right).$$

The choice of n_c is obviously independent of y_i/Y, as I asserted earlier. Optimal production of the two goods then satisfies the first order condition

$$\frac{v'(D)}{v(D)} = \frac{u_d(C,D) - \phi u_c(C,D)}{u(C,D)}.$$

Equivalently, since the marginal rate of substitution between clean and dirty goods, u_c/u_d, is equal to the relative price q, which in turn equals $\frac{1+\tau_c}{(1+\tau_d)\phi}$, I get

$$\frac{\tau_d - \tau_c}{1+\tau_d} = \sigma^{d,D}. \tag{4}$$

That is, the optimal pollution tax is simply a function of the marginal rate of substitution between dirty goods and pollution for a hypothetical individual with the average level of income. If such an individual would be unwilling to give up any of his dirty goods in return for a reduction in pollution, then the optimal tax is zero. As he becomes more willing to make this substitution, the optimal tax wedge is larger. This is the key result from the static model.

A curious aspect of the optimal tax formula (4) is that unemployment does not directly appear in it. That is, the optimal tax wedge $\frac{\tau_d-\tau_c}{1+\tau_d}$ is independent of the amount of time it takes workers to switch from the dirty industry to the clean one, $1-\phi$, and how many workers need to switch industries, $n_c - n_c^0$. Indeed, the tax wedge would be unchanged if there were no unemployment in the model, $\phi = 1$. Intuitively, it is simply necessary to tax the dirty good by enough to equate the private cost of purchasing the good to the social cost of consuming it.

This analysis is a bit misleading for two reasons. First, for general preferences the marginal rate of substitution between dirty goods and pollution,

$\sigma^{d,D}$, is not a constant but depends on the production of both the clean and dirty goods, and hence on the easy of mobility ϕ. Put differently, to know the optimal level of pollution, it is necessary to understand the tradeoff between the dirty good and pollution not only at the current level of production but at the purported optimal level. While in practice it may be difficult to learn this key parameter, this issue is not made any more difficult by the presence of unemployment.

The second reason the analysis is misleading is that the government budget constraint links the two tax rates. To see this, combine the government budget constraint $\tau_c w_c C = \tau_d w_d D$ with the wage ratio $w_d = \phi w_c$ to get $\tau_c = -\frac{\tau_d D}{\phi C}$. Then using $q = \frac{1+\tau_c}{(1+\tau_d)\phi}$ and the optimal tax formula (4), I get $q = \frac{1-\sigma^{d,D}}{\phi}$ at the optimum. Finally, the consumer problem implies $D/C = f(q)$ and so

$$\frac{D}{C} = f\left(\frac{1-\sigma^{d,D}}{\phi}\right). \tag{5}$$

Assuming that $\sigma^{d,D}$ is constant, this is decreasing in the fraction of time that a worker who switches sectors is employed ϕ. It follows that if ϕ is small, it is optimal to allow more production of the dirty good. Despite this, the initial condition n_c^0 still does not enter into the optimal tax calculation. This is because, once workers are moving across sectors, the marginal cost of reallocation is constant.[5]

The last few paragraphs may appear to be contradictory, so it is worth emphasizing why they are not. Equation (4) states that the optimal tax wedge

[5]The entire analysis in this subsection is of course predicated on the assumption that $n_c > n_c^0$. If equation (5) implies $D/C > (1-n_c^0)/n_c^0$, then there is no reallocation.

depends only the marginal of substitution between dirty goods and pollution. To compute it, it is not necessary to know the severity of the consequent unemployment problem. Equation (5) states that the desired ratio of dirty to clean consumption depends on how severe the unemployment problem is. The reconciliation is simple. A given tax schedule (τ_c, τ_d) will induce more workers to reallocate, and hence a smaller ratio D/C, if ϕ is larger, so mobility is less costly.

There is a formal equivalence between tax and quantity regulation in this environment. Nevertheless, if the government does not understand the unemployment consequences of sectoral reallocation, taxes offer a clear advantage. The optimal tax formula depends only on preferences, while the optimal quantity restriction requires understanding both preferences and technology.

Equation (4) pins down the optimal tax wedge between consumption of the dirty and clean goods. I then pinned down the level of the two taxes with the government budget constraint. It is worth noting that the government can accomplish the same objective with other tax instruments. For example, suppose the government taxes the consumption of the dirty good at $\tau_d = \sigma^{d,D}/(1-\sigma^{d,D})$ and rebates the proceeds lump-sum to households. It is easy to verify that the equilibrium allocation is unchanged. Alternatively, the government can use the proceeds to compensate the workers who were initially employed in the dirty sector, lessening the redistributive consequences of the optimal policy.

The bottom line is that when workers are moving from the dirty sector to the clean sector, an increase in the tax on the dirty good induces more workers to move and raises their consumption. Under particular assumptions, it is possible to abstract from the distributional consequences of this policy and focus on the tax rate that all workers find optimal. Curiously, the formula for the optimal tax can be expressed in terms of preferences, without reference to how much unemployment the optimal pollution tax causes. Nevertheless, if it is harder for workers to reallocate across sectors, a given tax induces fewer workers to reallocate and so it optimal to allow for more pollution.

2.4 Discussion

The simple model is useful for illustrating some principles and organizing thoughts but is too stylized to be taken seriously. One assumption that seems particularly problematic is that all workers in a given sector either strictly prefer to stay in their sector or are indifferent about moving out of the sector. This gave rise to two distinct cases, one with no reallocation where taxes were purely redistributive (Section 2.2) and one with reallocation where taxes abated pollution but did not affect the wealth distribution (Section 2.3). Moreover, the model predicts that if some workers are moving from the dirty sector to the clean sector, there are no workers moving in the opposite direction.

In reality, there are always workers moving in both directions between any two sectors of the economy. Moreover, it seems likely that even if some workers find it optimal to exit a sector, there are other workers who would find leaving to be very painful. An important next step is therefore to develop a model that has the features of both cases. One way to do this is to introduce idiosyncratic shocks that affect the costs and benefits of switching sectors for each worker. Depending on how many workers are near the margin of indifference, such a model will give rise to results that look more like one or the other of the two cases I have analyzed so far. In particular, if the distribution of idiosyncratic shocks is not too disperse and most workers are initially quite happy to stay in their sector, a small increase in pollution taxes will primarily redistribute wealth from workers in the dirty sector to those in the clean sector, while a larger increase will reduce pollution with little additional distributional consequences. With a more disperse shock distribution, any change in taxes will have both effects, hurting workers who are far from the indifference margin while also inducing workers who are at the margin to pay the cost of moving to the clean sector.

A model with worker heterogeneity will also predict that the initial distribution of employment will matter for the optimal tax because the marginal cost of reallocating workers across sectors will naturally be increasing in the amount of reallocation. That is, the first few workers to exit a dirty industry might have been on the margin of exiting in any case and so will find the cost of exiting to be relatively small. But a larger tax will induce a larger contraction in demand for the dirty good and hence in employment, which will cause more workers to exit. The cost for these inframarginal workers will naturally be larger. A correct tax formula will therefore have to account for the initial distribution of employment as well.

A second weakness of this simple model is that it lacks any real dynamics. It takes time for a displaced worker to find a new job. As some workers leave a sector, wages increase and the remaining workers find it more attractive to stay. It is conceptually straightforward to extend the model to allow for switching sectors to take a real amount of time and thus to explore the dynamic employment consequences of environmental regulation. In particular, as some workers exit an industry, the remaining workers will be selected to be those who are more attached to the industry, making further reductions in employment more costly. To understand the importance of these forces, I turn to a dynamic model with idiosyncratic shocks.

3 Dynamic Model

3.1 Environment

I consider a discrete time environment. Let $t = 0, 1, \ldots$ denotes the time period. The economy is again inhabited by a unit measure of individuals $i \in [0, 1]$. Each individual is infinitely-lived, discounts the future with factor $\beta \in (0, 1)$, and has preferences over consumption of the clean good, $c_{i,t}$, consumption of the dirty good, $d_{i,t}$, and pollution D_t given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_{i,t}, d_{i,t}, D_t).$$

I assume u is increasing in its first two arguments, decreasing in its third argument, and strictly concave. Each individual is uncertain about his own future private consumption $(c_{i,t}, d_{i,t})$ because he does not know whether he will be employed and how much he will earn in the future. The expectations operator $\mathbb{E}_0$ captures this by assuming individuals seek to maximize their expected lifetime utility.

An individual's productivity depends on where he works and evolves stochastically over time. At any point in time t, assume that individual i can potentially produce either $\ell_{c,i,t}$ units of the clean good or $\ell_{d,i,t}$ of the dirty good. There are two reasons a worker cannot achieve this productivity. First, individual i can only work in one sector. Second, if an individual attempts to switch sectors, there is a chance he will fail and instead be unemployed.

More precisely, if a worker was last employed in sector $s \in \{c, d\}$, he is free to work in that sector in the current period. In that case, his labor income is $w_{s,t}\ell_{s,i,t}$, the product of his wage and his productivity. If he instead attempts to switch to sector s', he obtains a job with probability ϕ, in which case he earns $w_{s',t}\ell_{s',i,t}$. Otherwise he is unemployed during period t.

Thus at the start of a period t, worker i observes $(\ell_{c,i,t}, \ell_{d,i,t})$ and the sector where he was last employed, $s_{i,t-1} \in \{c, d\}$. He then decides whether to work in sector $s_{i,t-1}$. If he does, $s_{i,t} = s_{i,t-1}$ and he earns $w_{s_{i,t},t}\ell_{s_{i,t},i,t}$. If he attempts to switch to sector s', he succeeds with probability ϕ, in which case $s_{i,t} = s'$ and he earns $w_{s_{i,t},t}\ell_{s_{i,t},i,t}$. Otherwise he fails, is unemployed, earns nothing, and remains attached to his old sector, $s_{i,t} = s$. Finally, let $n_{s,i,t} = 1$ if a worker i succeeds in working in sector s in period t.

Potential productivity follows a first order Markov process conditional on current employment. More precisely, denote current potential productivity by $\ell \equiv (\ell_c, \ell_d)$ and current employment status by $s \in \{c, d, \varnothing\}$, where $s = c$ represents a worker employed in the clean sector, $s = d$ represents a worker employed in the dirty sector, and $s = \varnothing$ denotes an unemployed worker. Then potential productivity next period takes value $\ell' = (\ell'_c, \ell'_d)$ with probability

$\pi(\ell'|\ell, s)$. This notation is quite general. It recognizes that productivity may be persistent, that employment may enhance productivity, and that the enhancement may be sector specific, so a worker employed in sector s becomes more productive only in sector s. I assume the realization of the idiosyncratic productivity shock is independent across individuals and over time. This means that there are no aggregate shocks in the model.

Each worker employed in sector s produces one unit of good s per unit of potential productivity. Thus the aggregate output of the clean and dirty goods are

$$C_t = \int_0^1 \ell_{c,i,t} n_{c,i,t} di \text{ and } D_t = \int_0^1 \ell_{d,i,t} n_{d,i,t} di. \tag{6}$$

As in the static model, the two goods are sold in competitive markets and so the wage per unit of productivity in the two sectors is related to the output prices via

$$p_{c,t} = (1 + \tau_{c,t}) w_{c,t} \text{ and } p_{d,t} = (1 + \tau_{d,t}) w_{d,t}. \tag{7}$$

The government rebates the proceeds from any tax receipts lump-sum, with T_t denoting the lump-sum transfer.

I turn next to a description of financial markets. Individuals are risk-averse and face an uncertain income stream due both to unemployment risk and human capital risk. For reasons that I discuss below, I abstract from this idiosyncratic uncertainty by assuming financial markets are complete. Formally, each individual belongs to a household that seeks to maximize the average member's utility. The household observes each individual's potential productivity and tells him where to seek work in each period. It then pools the income and uses the proceeds to provide each member with a common level of consumption of the clean good, c_t, and dirty good d_t. Critically, I assume that although the household is large enough to pool risk, it is still small relative to the size of the economy and so treats the aggregate production of the dirty good, D_t, as fixed.

It follows that the household seeks to maximize

$$\sum_{t=0}^{\infty} \beta^t u(c_t, d_t, D_t),$$

subject to the budget constraint

$$\sum_{t=0}^{\infty} \left(p_{c,t}c_t + p_{d,t}d_t\right) = \sum_{t=0}^{\infty} \left(w_{c,t} \int_0^1 \ell_{c,i,t} n_{c,i,t} di + w_{d,t} \int_0^1 \ell_{d,i,t} n_{d,i,t} di + T_t\right), \quad (8)$$

where the integrals reflect the fact that the household has many members, with individual i producing $\ell_{j,i,t}$ units of good j if he works in that sector. In addition, the household faces the laws of motion for the potential productivity of each member i, $\pi(\ell'|\ell, s)$, conditional on her search strategy s. Note that I have dropped the expectations operator, since the large family does not face any uncertainty.

The assumption that large households insure individuals against all idiosyncratic risk is extreme. I make it for two reasons. First, without complete markets, tax policy would have a redistributive effect, as in the static model without sectoral reallocation in Section 2.2. Workers with a comparative advantage in producing the clean good would like to tax the dirty good both because of the pollution externality and because it moves relative prices in favor of the good they produce. Workers with a comparative advantage in producing the dirty good conversely may prefer to subsidize production of that good despite the pollution externality. In an environment with complete markets, I can abstract from this tension and focus on the average worker's preferences.

Second, without the large household assumption or some other assumption that ensures markets are complete, characterizing individual behavior is much more complicated.[6] Individuals will wish to save when their productivity is temporarily high and borrow when it is low or when they are unemployed. While this consumption-savings problem is interesting, I view it as detracting from the main message of the paper. For example, incomplete markets would potentially be relevant even in an environment without unemployment ($\phi = 1$), if individuals cannot insure themselves against idiosyncratic fluctuations in their productivity.

Finally, I assume that the government must run a balanced budget in each period,

$$\tau_{c,t} w_{c,t} C_t + \tau_{d,t} w_{d,t} D_t = T_t.$$

Together with the goods market clearing conditions in equation (6) and the relationship between prices and labor costs in equation (7), this implies

$$p_{c,t} C_t + p_{d,t} D_t = w_{c,t} \int_0^1 \ell_{c,i,t} n_{c,i,t} di + w_{d,t} \int_0^1 \ell_{d,i,t} n_{d,i,t} di + T_t,$$

[6] An exception is the case when $u(\lambda c, \lambda d, D) = \lambda u(c, d, D)$. In this case, individuals have an infinite intertermporal elasticity of substitution in consumption and the consumption-savings problem is trivial to solve. My general formulation allows for a finite intertemporal elasticity of substitution but at the cost of having to assume markets are complete.

so the household budget constraint (8) must hold in every period.

In equilibrium, households optimally choose where each individual should attempt to work and how much of each good to consume, taking as given taxes, prices, and wages. In addition, the government and private budget constraints hold at each date. The equilibrium depends on the initial conditions, including the joint distribution of potential productivity and initial sector, $(\ell_{c,i,0}, \ell_{d,i,0}, s_{i,-1})$. It also depends on the tax and transfer policy $(\tau_{c,t}, \tau_{d,t}, T_t)$.

I proceed in three steps. First, I describe an alternative formulation of the household's problem. Second, I use that problem to describe individuals' decisions about where to work. Finally, I compare these outcomes to that of a hypothetical social planner who wishes to maximize the utility of the representative household and use this to compute the optimal tax policy.

3.2 Alternative Formulation

A typical household produces $\int_0^1 \ell_{c,i,t} n_{c,i,t} di$ units of the clean good and $\int_0^1 \ell_{d,i,t} n_{d,i,t} di$ units of the dirty good in period. Because of taxes, it can only afford to consume $\int_0^1 \ell_{c,i,t} n_{c,i,t} di/(1+\tau_{c,t})$ units of the clean good and $\int_0^1 \ell_{d,i,t} n_{d,i,t} di/(1+\tau_{d,t})$ units of the dirty good. The government collects the remaining output and rebates it lump-sum to households.

Of course, in equilibrium all households behave the same and so their consumption is equal to their production. Nevertheless, the tax distortion affects their behavior because each household imagines that it can consume a different amount than it produces. That is, in equilibrium each household attempts to maximize

$$\sum_{t=0}^{\infty} \beta^t u(c_t, d_t, D_t),$$

subject to the production constraints

$$c_t = \frac{\int_0^1 \ell_{c,i,t} n_{c,i,t} di + C_t \tau_{c,t}}{1 + \tau_{c,t}}$$

and

$$d_t = \frac{\int_0^1 \ell_{d,i,t} n_{d,i,t} di + D_t \tau_{d,t}}{1 + \tau_{d,t}}.$$

The households treat C_t and D_t as fixed. They understand that the evolution of potential productivity ℓ depends on how a worker is allocated between the two sectors. They also recognize that mobility frictions limit the possibility of reallocation. They then choose how to allocate their workers in order to maximize utility. In equilibrium, those choices imply $c_t = C_t$ and $d_t = D_t$, so all households behave identically.

This formulation simplifies the household's problem by avoiding the need to discuss the determination of wages and prices. Of course, it is possible to find the wages and prices that decentralize the equilibrium; however, since I am mainly concerned with equilibrium allocations, it is not necessary to compute these prices.

3.3 Mobility

I focus instead on the key mobility decision. A typical individual starts period t with levels of potential productivity $\ell = (\ell_c, \ell_d)$ and a connection to sector s.

Denote his expected lifetime contribution to the household's utility by $J_t(\ell, s)$. To analyze mobility, it is easiest to express this recursively. I start with the value to the household of a worker who previously worked in the clean sector:

$$J_t(\ell, c) = \max \Bigg\{ \frac{\ell_c u_c(C_t, D_t, D_t)}{1+\tau_{c,t}} + \beta \sum_{\ell'} \pi(\ell'|\ell, c) J_{t+1}(\ell', c) \ , \\ \phi \left(\frac{\ell_d u_d(C_t, D_t, D_t)}{1+\tau_{d,t}} + \beta \sum_{\ell'} \pi(\ell'|\ell, d) J_{t+1}(\ell', d) \right) \\ + (1-\phi)\beta \sum_{\ell'} \pi(\ell'|\ell, \varnothing) J_{t+1}(\ell', c) \Bigg\} . \quad (9)$$

The first term in the maximization shows her contribution to household utility if she remains in the clean sector. She produces ℓ_c units of the clean good. The government takes a fraction $\tau_{c,t}/(1+\tau_{c,t})$ of that, while the remainder increments household utility by the marginal utility of consumption of the clean good, $u_c(C_t, D_t, D_t)$. Her continuation value depends on the new productivity draw, which in turn depends on the fact that she worked in the clean sector.

The second term in the maximization shows her expected contribution to utility if she attempts to switch sectors. She succeeds with probability ϕ, in which case she produce ℓ_d units of the dirty good. The household keeps a fraction $1/(1+\tau_{d,t})$ of that, incrementing marginal utility by $u_d(C_t, D_t, D_t)$ per unit of consumption. Finally, the worker has a continuation value that reflects the fact that she has switched sectors. If the worker fails to find a job, she is unemployed, contributes nothing to current utility, and has a continuation value that reflects her status as an unemployed worker with attachment to the clean sector.

The value of a worker who previously worked in the dirty sector is symmetric:

$$
\begin{aligned}
J_t(\ell, d) = \max \Bigg\{ & \frac{\ell_d u_d(C_t, D_t, D_t)}{1+\tau_{d,t}} + \beta \sum_{\ell'} \pi(\ell'|\ell, d) J_{t+1}(\ell', d) \; , \\
& \phi \left(\frac{\ell_c u_c(C_t, D_t, D_t)}{1+\tau_{c,t}} + \beta \sum_{\ell'} \pi(\ell'|\ell, c) J_{t+1}(\ell', c) \right) \\
& \qquad + (1-\phi)\beta \sum_{\ell'} \pi(\ell'|\ell, \varnothing) J_{t+1}(\ell', d) \Bigg\} . \qquad (10)
\end{aligned}
$$

The interpretation of each term is unchanged.

Given a path of taxes and transfers (or aggregate production), it is conceptually straightforward to solve for the individual's mobility decision by iterating the value function. Given mobility decisions, it is possible to compute the supply of the two goods using equation (6) and hence verify that this is consistent with the conjectured level of production. If so, we have an equilibrium. Otherwise it is necessary to update the guess about aggregate production.

3.4 Optimal Allocation

Rather than solve the household's problem directly, I seek to find the tax rate that maximizes the utility of a hypothetical individual who consumes the average amount of output produced,

$$\sum_{t=0}^{\infty} \beta^t u(C_t, D_t, D_t).$$

I answer this by examining a social planner's problem, where the social planner recognizes that production of the two goods satisfies

$$C_t = \int_0^1 \ell_{c,i,t} n_{c,i,t} di \text{ and } D_t = \int_0^1 \ell_{d,i,t} n_{d,i,t} di$$

The social planner internalizes the impact of production of the dirty good. He also understands that the evolution of potential productivity ℓ depends on how workers are allocated between the two sectors in the current period, while mobility frictions limit the possibilty of reallocation.

At the start of each period, every worker is described by her potential productivity $\ell = (\ell_c, \ell_d)$ and by the sector she last worked in $s \in \{c, d\}$. The worker can then either produce ℓ_s units of good s or attempt to produce $\ell_{s'}$ units of the other good $s' \neq s$, succeeding with probability ϕ. Let $H_t(\ell, s)$ denote the marginal value to the average individual's utility of a worker (ℓ, s) at the start of period t. For a worker with past employment in the clean sector, this solves

$$\begin{aligned} H_t(\ell, c) = \max \Bigg\{ & u_c(C_t, D_t, D_t)\ell_c + \beta \sum_{\ell'} \pi(\ell'|\ell, c) H_{t+1}(\ell', c), \\ & + \phi \left(\big(u_d(C_t, D_t, D_t) + u_D(C_t, D_t, D_t)\big)\ell_d + \beta \sum_{\ell'} \pi(\ell'|\ell, d) H_{t+1}(\ell', d) \right) \\ & + (1-\phi)\beta \sum_{\ell'} \pi(\ell'|\ell, \varnothing) H_{t+1}(\ell', c) \Bigg\}. \end{aligned} \quad (11)$$

If the worker is assigned to the clean sector, she works for sure and produces ℓ_c units of the clean good, valued at the marginal utility of the clean good.

If the worker is assigned to the dirty sector, she only works with probability ϕ, producing ℓ_d units of the dirty good, valued at its marginal utility which incorporates both the consumption benefit u_d and the pollution cost u_D. Otherwise, the worker does not produce any output and remains attached to the clean sector. Likewise, for a worker with past employment in the dirty sector, the social value of the worker solves

$$\begin{aligned} H_t(\ell, d) = \max \Bigg\{ & \big(u_d(C_t, D_t, D_t) + u_D(C_t, D_t, D_t)\big)\ell_d + \beta \sum_{\ell'} \pi(\ell'|\ell, d) H_{t+1}(\ell', d), \\ & + \phi \left(u_c(C_t, D_t, D_t)\ell_c + \beta \sum_{\ell'} \pi(\ell'|\ell, c) H_{t+1}(\ell', c) \right) \\ & + (1-\phi)\beta \sum_{\ell'} \pi(\ell'|\ell, \varnothing) H_{t+1}(\ell', d) \Bigg\}. \end{aligned} \tag{12}$$

Optimal mobility decisions solve these two equations.

Rather than solve the planner's problem directly, I find the tax and transfer system that decentralizes the allocation chosen by the planner. Once again, let

$$\sigma_t^{d,D} \equiv \frac{-u_D(C_t, D_t, D_t)}{u_d(C_t, D_t, D_t)}$$

denote the marginal rate of substitution between the dirty good and pollution at time t. Set

$$\tau_{c,t} = 0 \text{ and } \tau_{d,t} = \frac{\sigma_t^{d,D}}{1 - \sigma_t^{d,D}}. \tag{13}$$

That is, a household consumes its production of the clean good but only consumes a fraction $1 - \sigma_t^{d,D}$ of its production of the dirty good. The rest is taxed and rebated lump-sum back to all households Then it is easy to verify that equations (9) and (10) from the decentralized equilibrium are equivalent to equations (11) and (12) from the social optimum. That is, if the time path of production of the two goods is socially optimal and taxes satisfy equation (13), then all individuals attempt to produce the good that the social planner would like them to produce.

Equation (13) implies

$$\frac{\tau_{d,t} - \tau_{c,t}}{1 + \tau_{d,t}} = \sigma_t^{d,D}, \tag{14}$$

equivalent to the static optimal tax formula. In the static economy, it was unimportant how the pollution tax revenue was rebated to households. I showed it could be done either by subsidizing the consumption of the clean good or by providing a lump-sum transfer. This was because there were only two goods and hence one relative price that needed to be corrected through taxes. In the dynamic model, there are two goods at each date. It is necessary to get the right relative price of the two goods at each date and the right relative price of the clean good at two different dates. The former is accomplished by any tax satisfying the static equation (14). The latter requires that the tax on the clean good is constant at different dates, which I accomplish by setting it equal to zero. Any time-varying tax on the consumption of the clean good distorts intertemporal decisions about when to produce and when to switch sectors. It will therefore be inefficient. Since in general the revenue from taxing the dirty good is time-varying, it is necessary to have time-varying lump-sum transfer in order to ensure efficiency.

3.5 Wages and Prices

If so desired, we could also back out the equilibrium prices and wage rates. Since all households are identical, there is no room for trade, so this is simply a question of finding the prices and wages that ensure there is no desire to trade. One can verify that for households to be satisfied with their static consumption of the two goods, we require that

$$\frac{u_c(C_t, D_t, D_t)}{p_{c,t}} = \frac{u_d(C_t, D_t, D_t)}{p_{d,t}}.$$

This states that the marginal rate of substitution between the two goods is equal to the price ratio.

In addition, for the households to be satisfied with the timing of their consumption, we require that

$$\frac{u_c(C_t, D_t, D_t)}{p_{c,t}} = \beta \frac{u_c(C_{t+1}, D_{t+1}, D_{t+1})}{p_{c,t+1}}.$$

This states that the intertemporal marginal rate of substitution between the clean good in consecutive periods is again equal to the price ratio.

Finally, competition among firms ensures $p_{c,t} = (1 + \tau_{c,t})w_{c,t}$ and $p_{d,t} = (1 + \tau_{d,t})w_{d,t}$. Using these equations and fixing a numeraire, e.g. consumption of the clean good in period 0, it is straightforward to solve for the entire time path of wages and prices in any equilibrium.

4 Discussion and Conclusion

The models I have developed in this paper are deliberately stylized but capture an essential feature of many recent theories of unemployment: unemployment is a necessary consequence of the reallocation of workers across sectors of the economy. If the economy did not reallocate workers, it would be unable to take advantage of new technologies. Thus, while unemployment is a costly outcome for an individual worker, enduring some unemployment is still optimal for the economy as a whole. Indeed, the models in this paper share a common feature that, in the absence of pollution, the decentralized equilibrium without taxes would be socially optimal. This is a useful benchmark because it allows me to explore how policy optimally deals with a pollution problem alone.

Nevertheless, it is worth stressing that there are other recent theories of unemployment in which the equilibrium without pollution or taxes is still inefficient. Many of the papers build on the Mortensen and Pissarides (1994) model of unemployment and examine the role of wage rigidities (Shimer, 2005; Hall, 2005; Shimer, 2010). These papers focus on the behavior of wages over the business cycle, but wage rigidities can arise in the cross-section as well. In particular, an increase in the tax on dirty goods should reduce the wage for workers producing those goods and so should induce some workers to move out of the sector. Suppose that for some reason the wage does not fall and instead workers are rationed in their ability to supply labor to the dirty sector. Workers who fail to find a job are unemployed but be induced to stay attached to the dirty sector in the hope of eventually finding a job.

Although working out that model goes beyond the scope of this paper, I would not expect the that key formula in this paper is stil applicable in this rigid wage environment. Instead, taxes would optimally address the labor market friction and perhaps rise less than would otherwise be expected. While this is potentially a real issue, it does not seem that environment policy is well suited to dealing with problems that originate in the labor market. That is, rigid wages would cause in an inefficient allocation of labor across sectors even absent any pollution problem. While there may be a role for the government to address this inefficiency, its connection with environmental regulation is tenuous.

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Assessing the Economic Effects of Environmental Regulations: A General Equilibrium Approach

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Abstract

I describe standard macroeconomic methods for assessing the effects of policy on allocations and welfare. I then embed a version of a benchmark industry equilibrium model into an otherwise standard version of the one sector growth model and describe how this setting provides a useful structure for the analysis of environmental regulations that impact on one particular sector but which might reasonably have important aggregate effects.

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1. Introduction

Evaluating the effects of policy or regulation on allocations and welfare is a key goal of applied economic analysis. The methods that are used to evaluate these effects differ across studies and areas. One approach emphasizes the use of explicit economic models in which the primitives–preferences, technologies and endowments–are rigorously specified and equilibrium allocations are derived from these primitives. The analysis of specific policies or regulations then requires the analyst to specify the details of the policy or regulation, and solve for the new equilibrium that would emerge in the presence of the policy or regulation. Because the structure includes an explicit description of preferences, one can evaluate the welfare effects in an internally consistent way. I will refer to this as the structural approach to policy evaluation.

This paper discusses the application of the structural approach in the context of studies that seek to evaluate the economic consequences of policies or regulations that are motivated by environmental concerns. I begin the paper by describing two distinct benchmark models that are commonly used for structural policy analysis. The first of these is the one sector neoclassical growth model, and the second is an industry equilibrium model. The simple one sector growth model and its many variants are routinely used to evaluate policy questions in both the macroeconomic and public finance literatures. The one sector neoclassical growth model is particularly well suited to the assessment of policies which are aggregate in nature (that is, policies that apply to all firms, or all households). This is routinely the case in the analysis of either macroeconomic policies or tax policies.

Another important property of this model in the context of these types of analyses is that it is explicitly general equilibrium, so that one can trace out the full extent of the impact of these policies on the overall economy.

If most environmental policies shared this property of being "aggregate" in nature, then the one sector growth model would be a suitable framework for implementing the structural approach. However, many environmental regulations are targeted at specific industries rather than the whole economy. The second model that I describe is a partial equilibrium model of a specific industry. In contrast to the one sector growth model which focuses on aggregate economic outcomes, this model emphasizes establishment level dynamics in investment and labor decisions and how they influence establishment level growth dynamics, including the process of entry and exit. By offering a rich description of heterogeneity at the establishment level and the choices made by establishments, this class of models seems well suited to studying the effects of very specific regulations that interact with these various decisions and the heterogeneity that exists among establishments. However, while offering a rich partial equilibrium setting, this framework does not allow one to assess the aggregate effects on the economy, or put somewhat differently, does not allow one to address the extent to which the impacts on the directly affected industry are propagated to the rest of the economy through general equilibrium effects.

Having described each of these two approaches and illustrated how simple versions of them can be used to carry out structural evaluations of policy in the context of environmental regulations, I then describe a hybrid model that combines the two approaches into a tractable framework. Specifically, it allows one to build a rich model of the particular industry while at the same time embedding it into the structure of the one sector growth model. Connecting this hybrid model to the data is effectively the same as connecting the two benchmark models to the data, and I show that solving for steady state equilibria in the hybrid model can be done in a particularly simple fashion. While I carry out my discussion in the context of some very simple prototype models in order to maximize transparency, I discuss how these models can be enriched along many dimensions. The key output is a framework that can simultaneously be used to connect to a large set of industry specific details in the affected industry and trace out potential general equilibrium effects and permit a consistent evaluation of welfare effects.

An outline of the paper follows. In Section 2 I describe the simple one sector growth model and describe how it could be used to evaluate an environmental regulation that was applicable to the entire production sector. In particular, I describe one method for calibrating the model and then quantitatively evaluate how a stylized environmental regulation affects both allocations and welfare, both in the long run (across steady states) and including short run transition effects. I emphasize that the same method can be applied independently of whether the regulation affects labor market outcomes, that is, one does not need to make any special adjustments to the welfare calculations depending on what happens in the labor market. Section 3 describes a benchmark industry equilibrium model, discusses how one might calibrate it to specific industry data, and then quantitatively evaluates three different types of regulations in the context of a numerical example that captures some generic features of establishment dynamics. Although I do this in the context of a very simple benchmark model, a key message is that evaluating many components of environmental regulations will typically require that the model being used incorporates a rich set of features. Finally, Section 4 develops the hybrid model that combines the two benchmark models. A key feature of the model is that it allows for a flexible specification in terms of how the directly affected industry interacts with the rest of the economy, both in terms of its relative size and the degree to which its output is either complementary or substitutable with economic activity in the rest of the economy. After developing the model I describe how steady state equilibrium can be easily calculated in the model and evaluate one prototype policy to illustrate some features of the model and emphasize a few basic messages. Section 5 concludes.

2. Benchmark I: Aggregate (One Sector) Analysis

In this section I illustrate how a benchmark aggregate model–the one sector neoclassical growth model–is commonly used for policy analysis, and in particular how macroeconomists use it to evaluate the welfare cost of policies. Of particular interest is that the analysis allows for policies to affect aggregate labor market outcomes and as a result the welfare analysis takes labor market effects into account.

2.1. Model

Here I describe a simple version of the representative agent one sector neoclassical growth model that serves as the benchmark model for modern macroeconomic analysis. I emphasize that what I am describing here is the simplest version of this model. One can extend the model along any number of dimensions to yield a much richer model. But this simplest version will serve as the best way to illustrate the general method that I describe, since this method is easily transferred to richer specifications of the model. Also, for now I abstract from any considerations that might serve to provide a welfare improving role for environmental regulations. I will add such considerations later on in this section when we consider the effects of a specific regulation.

There is a representative household that is infinitely lived, with preferences given by:

$$\sum_{t=0}^{\infty} \beta^t u(c_t, 1 - h_t)$$

where c_t is consumption in period t, h_t is the fraction of the time endowment that is devoted to market work, $0 < \beta < 1$ is a discount factor and U is the period utility function. There is an aggregate production function that uses capital (k_t) and labor (h_t) services to produce output (y_t) according to a constant returns to scale production function $F(k_t, h_t)$:

$$y_t = F(k_t, h_t).$$

Output can be used for either consumption or investment (i_t):

$$c_t + i_t = y_t$$

and the economy's capital stock evolves according to:

$$k_{t+1} = (1 - \delta)k_t + i_t$$

where $0 < \delta < 1$ is the depreciation rate. The economy begins period 0 with some initial capital stock, denoted by $\hat{k}_0$. In the subsequent analysis I will assume standard regularity conditions on utility and production functions.[1]

2.2. Equilibrium

If one is going to ask how policy affects outcomes in the economy one has to adopt some notion of how outcomes are determined, i.e., one has to adopt some notion of equilibrium. As is standard in the macroeconomic literature, we will study a competitive equilibrium, though one can certainly consider alternatives.[2] I will say a little bit about one alternative later on in which wages are set at a level that is "too high" relative to the competitive equilibrium.

[1] Note that I abstract from both population growth and technological progress in this specification. As is well known, one could inlcude this in the original specification, but then assuming that the specification is consistent with balanced growth, a change of variables effectively removes the growth associated with these forces, effectively reducing the model to the specification that I study.

[2] It is easy to extend the model to allow for a continuum of intermediate goods producers who produce differentiated products and behave as monopolisitic competitors. Such a specification is common in the macroeconomics literature that emphasizes price or wage stickiness. See, for example, Christiano, Eichenbaum and Evans (2005).

I note that one can formulate the equilibrium with households owning capital and renting it to firms, or alternatively with firms accumulating capital that they use in production, and households owning the capital stock indirectly through their ownership of the firm. The two formulations are equivalent in terms of equilibrium allocations, so it does not matter for substantive analysis. I will focus on the formulation in which households own capital and rent it to firms each period. I will also consider what is referred to as a sequence of markets equilibrium, in which we envision the economy evolving through time with a small set of markets opening each period. In particular, in each period there will be a market for current output, in addition to factor markets for both capital and labor services. The price of output can be normalized to one in each period, with the prices for labor and capital services denoted by w_t and r_t respectively. The one period ahead interest rate is implicitly given by $r_{t+1} - \delta$.

With this formulation an equilibrium is defined as a list of sequences $\{c_t^*\}$ $\{h_t^*\}$ $\{k_t^*\}$ $\{i_t^*\}$ $\{y_t^*\}$ $\{w_t^*\}$ and $\{r_t^*\}$ such that the quantities solve the household's lifetime utility maximization problem taking prices as given, production choices maximize profits taking prices as given and markets clear.

For future purposes it will be useful to have expressions that characterize equilibrium allocations. For the economy as currently described the competitive equilibrium will necessarily be Pareto efficient and so one can obtain expressions for the equilibrium allocations by solving an appropriate Social Planner's problem. But since we will also be interested in solving for the equilibrium in the presence of distortions, it is useful to have a method that works even when the equilibrium allocation is not Pareto efficient. Here I sketch this method.

The household problem can be written as:

$$\max \sum_{t=0}^{\infty} \beta^t u(c_t, 1-h_t)$$

$$\text{s.t. } c_t + k_{t+1} - (1-\delta)k_t = w_t h_t + r_t k_t,\ c_t \geq 0,\ k_t \geq 0,\ 0 \leq h_t \leq 1,\ k_0 \text{ given}$$

With standard regularity conditions it is sufficient to consider interior solutions for c_t, k_t and h_t. Letting λ_t be the Lagrange multiplier for the period t budget equation, the first order conditions for c_t, h_t and k_t are:

$$\beta^t u_1(c_t, 1-h_t) = \lambda_t \tag{2.1}$$

$$\beta^t u_2(c_t, 1-h_t) = \lambda_t w_t \tag{2.2}$$

$$\lambda_{t-1} = \lambda_t(r_t + 1 - \delta) \tag{2.3}$$

Taking the ratio of equation (2.1) at time t and $t+1$ and using equation (2.3) gives:

$$\frac{u_1(c_t, 1-h_t)}{\beta u_1(c_{t+1}, 1-h_{t+1})} = r_t + (1-\delta) \tag{2.4a}$$

And taking the ratio of equations (2.1) and (2.3) gives:

$$\frac{u_2(c_t, 1-h_t)}{u_1(c_t, 1-h_t)} = w_t \tag{2.5}$$

The profit maximization problem of the firm gives the standard first order conditions:

$$F_1(k_t, h_t) = r_t$$
$$F_2(k_t, h_t) = w_t$$

Substituting from the firm's first order conditions into equations (2.4a) and (2.5) and using the market clearing condition, we have that an equilibrium allocation must satisfy:

$$\frac{u_1(c_t, 1-h_t)}{\beta u_1(c_{t+1}, 1-h_{t+1})} = F_1(k_{t+1}, h_{t+1}) + (1-\delta) \tag{2.6}$$

$$\frac{u_2(c_t, 1-h_t)}{u_1(c_t, 1-h_t)} = F_2(k_t, h_t) \tag{2.7a}$$

$$c_t + k_{t+1} = F(k_t, h_t) + (1-\delta)k_t \tag{2.8}$$

in addition to the initial condition plus a transversality condition. Equilibrium prices can be inferred once knows equilibrium quantities directly from the firm's first order conditions.

We will also be interested in a steady state equilibrium for this economy. In the steady state all prices and quantities are constant over time, so we simply look for solutions to equations (2.6)-(2.8) that are constant (and so do not necessarily satisfy the initial condition). That is, we look for values k^*, h^*, and c^* that solve:

$$\frac{1}{\beta} = F_1(k^*, h^*) + (1-\delta)$$

$$\frac{U_2(c^*, 1-h^*)}{U_1(c^*, 1-h^*)} = F_2(k^*, h^*)$$

$$c^* = F(k^*, h^*) - \delta k^*$$

As is well known, starting from an arbitrary positive initial condition, the equilibrium allocations will converge to their steady state values, so if one is considering an economy that has been operating for some amount of time, it is natural to focus on the steady state allocation as a starting point for how the economy will respond to changes moving forward in time.

2.3. Policy and Welfare Analysis

This model (and its various extensions) are routinely used in the macroeconomics literature to assess the effects of various fiscal policies on allocations and welfare.[3] Given the motivation for this paper, I describe the general method of analysis in this literature for the case of a policy which although highly stylized, has an interpretation that is relevant in the context of environmental policy. Specifically, consider a policy that is unexpectedly enacted and adopted in a particular period, that we will for convenience think of as period 0. The policy requires that each unit of capital must be augmented with an additional piece of equipment to lessen the extent of a certain kind of emission that is released during the production process. This additional capital has zero marginal product from the perspective of producing output. In particular, I assume that in order to satisfy the regulation,

[3] There are far too many examples to cite, but two examples are Lucas (1990), who analyzes capital taxation, and Prescott (2004) who analyzes labor taxation. While I study a version of the growth model with infinitely lived agents, the same methods can be used to study models with overlapping generations. See, for example, Auerbach and Kotlikoff (1987).

a firm that uses k_t units of capital services will only have $(1-\lambda)k_t$ units of capital from the perspective of capital services used in production. That is, in terms of producing output, a fraction λ of a firm's capital stock is not productive. Note that from the perspective of analyzing the aggregate effects of regulation, with a particular focus on how labor market implications enter into the analysis, an interesting feature of this policy is that it indirectly increases the demand for labor in the sense that the economy needs to produce the additional (but unproductive) capital.

As I noted earlier, when I originally described the model I abstracted from any elements that might give rise to a welfare role for environmental regulation. A simple way to extend the analysis to give a role for such policy is to posit a period utility function of the form:

$$u(c_t, 1-h_t) - d(P_t)$$

where P_t is a measure of the aggregate amount of pollutants in the environment in period t and d is a function that captures the disutility associated with these pollutants. There would be another set of relations that describe the relationship between the current stock of pollutants and current and past production decisions, including both the volume of production and the nature of how the production took place. The fact that production decisions influence the aggregate level of pollutants implies the presence of an externality that gives rise to possible welfare benefits from various sorts of regulatory policies.

Several clarifying remarks are in order. First, note that I have assumed that the externality enters into the utility function in a separable fashion. I have assumed this not because it is necessarily warranted, but rather in order to justify the type of "partial" analysis that I will focus on. I use the word "partial" to refer to a separation between the costs and benefits of environmental regulation. To be sure, if one is interested in analyzing optimal environmental policy then one must necessarily consider both the costs and the benefits simultaneously even if the economic and environmental elements enter into utility functions in a separable fashion. However, my goal is to examine a method that can be used to evaluate the economic costs of specific regulations without presuming the ability to measure the benefits that would also result. If the environmental effects did not enter preferences in a separable fashion then one cannot assess the economic costs without knowing exactly how the environmental impacts enter, as changes in pollutants would then influence the economic decisions and these interactions could affect the assessments of these costs. All of this is simply to say that I will adopt a narrow focus of assessing the economic costs of particular regulations, and the above assumptions are simply one way to rationalize such a narrow focus. But to the extent that one is prepared to take a stand on how the environmental factors actually enter into preferences, the methods that I describe can certainly be applied. That is, I could alternatively assume that the period utility function is of the form:

$$u(c_t, 1 - h_t, P_t)$$

and specify some explicit relationship between past and present production decisions and current pollution. Having specified these relationships I could carry out the exact same exercise that I describe below for the separable case. One could also allow for an effect of the level of pollutants on health, which could show up as an increase in the amount of discretionary time that individuals have, allowing for both more leisure time and more time devoted to work.

In assessing the effects of this policy on allocations and welfare it is natural to assume that the economy is initially in the steady state equilibrium that corresponds to the situation in which there is no environmental regulation, at which time the regulation is introduced without any prior anticipation. Assessing the consequences of the introduction of this policy requires solving for the new equilibrium that will result, starting from the initial condition that the economy starts in the no-regulation steady state.

Some notation will be useful. I will use c_U^* to denote steady state consumption in the economy prior to the enactment of the regulation, and will use c_R^* to denote the steady state level of consumption that results after the regulation has been enacted, and similarly for other variables. By assuming that the economy starts in the unregulated steady state at time 0 when the regulation is announced and enacted, we are assuming that the initial capital stock, k_0 is equal to k_U^*. In the absence of the adoption of the regulation, the economy would have continued to be in the unregulated steady state, so that this allocation would have persisted each period moving forward. But given that the regulation was adopted, the economy will have a new equilibrium that we denote by sequences $\{c_t^R\}\{h_t^R\}\{k_t^R\}\{i_t^R\}\{y_t^R\}\{w_t^R\}\{r_t^R\}$.

We can follow the same procedure that we previously used to derive conditions to characterize the equilibrium allocations in the absence of the regulation to derive expressions that characterize the equilibrium in the presence of the new regulation. In fact, nothing changes from the first order conditions that we derived from the household optimization problem. There is, however a change in the firm's conditions for profit maximization. Specifically, on account of the new regulation, a firm that rents k_t units of capital will only have $(1-\lambda)k_t$ units of capital that are used to produce output, with the remaining units used to reduce emission of pollutants. As a result, the firm's first order conditions now become:

$$\begin{aligned} (1-\lambda)F_1((1-\lambda)k_t, h_t) &= r_t \\ F_2((1-\lambda)k_t, h_t) &= w_t \end{aligned}$$

Following the same procedure as above and substituting these conditions into the expressions that we derived from the household's first order conditions gives: equilibrium will satisfy:

$$\frac{u_1(c_t^R, 1-h_t^R)}{\beta u_1(c_{t+1}^R, 1-h_{t+1}^R)} = (1-\lambda)F_1((1-\lambda)k_{t+1}^R, h_{t+1}^R) + (1-\delta)$$

$$\frac{u_2(c_t^R, 1-h_t^R)}{u_1(c_t^R, 1-h_t^R)} = F_2((1-\lambda)k_t^R, h_t^R)$$

$$c_t^R + k_{t+1}^R - (1-\delta)k_t^R = F((1-\lambda)k_t^R, h_t^R)$$

Note that in the last equation only a fraction $(1-\lambda)$ of the capital stock is useful in producing output, but that investment includes both the productive capital and the capital that is used to reduce emissions.

The new steady state equilibrium allocations will be values k^*, h^*, and c^* that solve:

$$\frac{1}{\beta} = (1-\lambda)F_1((1-\lambda)k_R^*, h_R^*) + (1-\delta)$$

$$\frac{u_2(c_R^*, 1-h_R^*)}{u_1(c_R^*, 1-h_R^*)} = F_2((1-\lambda)k_R^*, h_R^*)$$

$$c_R^* = F((1-\lambda)k_R^*, h^*) - \delta k_R^*$$

Solving for the equilibrium allocations following the adoption of the regulation serves to address the issue of how the regulation will affect allocations. But what about the welfare effects, or, more specifically given my narrow focus, what about the welfare effects net of environmental benefits? The literature often distinguishes between two different notions. One notion is to compare the original steady state outcome that existed prior to the policy change with the new steady that emerges after the policy change. Loosely speaking, if we wanted to compare how the policy affects an individual who is born into the original steady state with someone who is born into the future steady state, then this comparison is relevant. But if we want to assess how the adoption of the policy will affect the welfare of those who are around at the time of the policy change then it is important to study not just the long run consequences but also the transition to the new steady state. The second notion of welfare change will take into account not only the new steady state allocation that is achieved but also the nature of the transition path to the new steady state.

In each case the welfare criterion is conceptually the same, with the only difference being that one of them includes the period of transition. In words, our measure of welfare is the fractional change in per period consumption in the original steady state that would make the representative household indifferent between staying in the original steady state and moving to the new equilibrium. In the case of steady state welfare comparisons we only compare the two steady state allocations. In the other case we evaluate the utility after the regulation using the entire time series in the post-adoption period. More formally, if we let Δ^S be the change in welfare associated with comparing only the two steady state outcomes then it is defined by:

$$u((1+\Delta^S)c_U^*, 1-h_u^*) = u(c_R^*, 1-h_R^*).$$

And if we let Δ^T be the change in welfare taking into account the transition path to the new steady state, it is defined by:

$$\frac{1}{1-\beta}u((1+\Delta^T)c_U^*, 1-h_u^*) = \sum_{t=0}^{\infty}\beta^t u(c_t^R, 1-h_t^R).$$

By way of interpretation, note that if one of these measures of welfare change is equal to .01, it means that individuals would be willing to give up 1% of their consumption forever in order to stay in the original steady state.

This measure of welfare change has three appealing properties. First, it is firmly connected to the utility functions of the individuals in the economy. Second, it offers a value that is easy to interpret quantitatively. And third, it does not require any auxiliary assumptions to implement. For example, although the setting that I have described above has the property that the initial steady state allocation is Pareto efficient and as a result the steady state equilibrium prices do reflect certain marginal valuations, exactly the same welfare criterion can be applied if we had instead assumed that the original economy had some other distortion so that the original allocation was not efficient. At the same time it is important to note that there is nothing unique about this particular welfare measure. One could have instead scaled up the allocation of both consumption and leisure to produce a different but conceptually similar measure.

Given an economy with heterogeneous consumers, one can apply the same concept at the aggregate level given any weighting scheme for individual utilities, and one can also apply it at the level of each individual in the economy to study the distribution of welfare gains and losses.

2.4. Calibrating the Model

In order to illustrate the methods discussed in the previous subsection it will be useful to consider a quantitative example. This requires choosing function forms and parameter values. Here I describe a standard procedure in the macroeconomics literature for making these choices. I note that the methods that I describe later on do not depend in any way on how one chooses to calibrate the model; for present purposes this should just be seen as one set of choices.

I begin with functional forms. We need to choose functional forms for the production function and the period utility function. It is standard in the macroeconomics literature to assume that the aggregate production function is Cobb-

Douglas:

$$y_t = k_t^{\theta} h_t^{1-\theta},$$

though more general specifications are sometimes used.

A commonly imposed requirement that influences the set of possible period utility functions is that the preferences be consistent with balanced growth in the presence of technological progress. Assuming that we also want to require strict concavity of the utility function, this imposes that the period utility function be either of the form:

$$\log c_t + v(1 - h_t)$$

if preferences are separable between consumption and leisure, or of the form:

$$\frac{1}{1-\sigma}[c_t v(1 - h_t)]^{1-\sigma}$$

where v is a strictly positive, strictly increasing, strictly concave function and the parameter σ is strictly positive. This still permits quite a range of functions, but for purposes of illustration I will use as my benchmark the commonly used specification of:

$$u(c_t, 1 - h_t) = \alpha \log c_t + (1 - \alpha) \log(1 - h_t).$$

However, to illustrate more generally how labor market effects operate I will also consider a slightly more general period utility function that does not necessarily lie in the set of balanced growth preferences:

$$u(c_t, 1 - h_t) = \alpha \frac{c_t^{1-\sigma} - 1}{1 - \sigma} + (1 - \alpha) \log(1 - h_t)$$

Having specified functional forms, we now have to choose parameter values. Given the functional form choices, there are 4 parameter values to assign in the benchmark setting (in the more general case considered we also need to assign a value to σ): θ, δ, α, and β. While there are a few variations on how to choose these parameters, the ultimate values are quite similar, so I just describe one procedure. The value of θ is chosen to match the observed time series average for the share of income going to capital, which is around .30. In steady state, the value of the real interest rate, which is also the real return to capital, is given by $(1/\beta) - 1$. Studies typically target an annual value of 4%, which is in between the observed real returns on a safe asset like treasury bonds and the average real return on risky assets such as equity. The value of δ is chosen so that the ratio of investment to output in the steady state is equal to its time series average, typically taken to be around .20. Finally, the value of α is set so that the fraction of available discretionary time that the representative household devotes to market work matches the average of this value in the population of individuals who are 16 and older, or sometimes between the ages of 16 and 65. A typical value is .33.

Given the above targets and interpreting a period to be one year, standard values for parameters would be $\theta = .30$, $\beta = .96$, $\delta = .08$ and $\alpha = .3644$. Note that in calibrating the model to these targets I have abstracted away from taxes. One can easily incorporate these and apply the same calibration procedure, though the values of some parameters will be affected. In the case of the slightly more general class of preferences that do not force utility from consumption to be logarithmic, one must set a value for the preference parameter σ, but conditional on that choice one can adopt the same procedure as above to set values for the other values. The only parameter value that is affected is α.

2.5. An Example

In this section I present some quantitative results to illustrate the method just discussed in the context of the regulatory policy that I described earlier. I will consider five different values of the parameter λ that serves to parameterize the extent of the regulation. I begin by presenting the results for steady state effects and then consider the transition effects as well.

2.5.1. Steady State Effects on Allocations

Using the calibrated values from the previous subsection and having utility from consumption be logarithmic (i.e., $\sigma = 1$), Table 1 shows how regulations characterized by different values of λ affect the relative steady state values for each of several values, in addition to the implied steady state welfare change.

Table 1

Steady State Effects of Regulation: $\sigma = 1$

	$\lambda = 0$	$\lambda = .01$	$\lambda = .02$	$\lambda = .03$	$\lambda = .04$	$\lambda = .05$
k_R^*/k_U^*	1.00	.996	.991	.987	.983	.978
h_R^*/h_U^*	1.00	1.00	1.00	1.00	1.00	1.00
y_R^*/y_U^*	1.00	.996	.991	.987	.983	.978
c_R^*/c_U^*	1.00	.996	.991	.987	.983	.978
w_R^*/w_U^*	1.00	.996	.991	.987	.983	.978
h_R^*/h^*	0.00	.002	.004	.006	.008	.010
Δ^S	0.00	$-.004$	$-.009$	$-.013$	$-.017$	$-.022$

Readers who are familiar with real business cycle models will probably note that the regulation that I am considering is equivalent to making capital services less efficient, and that since with a Cobb-Douglas technology all technological change is equivalent to neutral technological change, the results in Table One are identical to those that one would get if we instead considered a permanent decrease in aggregate TFP by the fraction $1-(1-\lambda)^\theta$. In particular, this regulation serves to lower total accumulation of capital, and capital, output, consumption and wages all decrease by the same percentage relative to the original steady state. Steady state hours do not change, since the defining feature of preferences that are consistent with balanced growth is that hours of work do not respond to permanent changes in TFP.

The reader may at first find it curious that output and total capital decrease by the same amount, given that productive capital decreases by even more than total capital. This is reconciled by noting that although the percent drop in effective capital is larger than the percent drop in total capital, capital's share in output is less than one, so that output does decrease by less than the percent change in productive capital.

The second row from the bottom in the table reports the fraction of total labor that is used to produce the equipment that is used to reduce emissions rather than produce output. Even though there is no change in total hours worked across the two steady states, there is a change in how labor is allocated. Moreover, note that although there is no change in the amount of total hours worked, there is a decrease in wages across the two steady states. An important message is that when considering labor market effects it is not sufficient to focus on total hours of work or total employment. Had it not been for the change in wages, the implied welfare losses would have been much smaller.

Because hours do not change across the two steady states it is easy to infer the implied welfare change, since it is simply the percent change in consumption. The welfare losses are roughly linear in the size of the regulation over the region that is studied in the table. To the extent that any effects that have a welfare loss of 1% or greater are viewed as quite large in the macro literature, the table shows that this type of aggregate regulation can generate quite sizable losses in welfare net of environmental factors. Although the regulation I consider is a very stylized one and the model is a simple benchmark, it serves to illustrate that regulations that impact firm level capital stocks on the order of one percent or more, if sufficiently broad in scope so as to affect most of the economy, can have sizeable aggregate effects.

In the case just studied, there was no change in aggregate hours worked. This was due to the utility function that was used. Given a specific interest in incorporating labor market changes into the welfare analysis of regulatory changes it is perhaps of interest to consider an alternative specification in which there are also steady state effects on aggregate labor. Table 2 repeats the analysis of Table One except that in the calibration it is assumed that the utility from consumption takes the form of $c^{.5}$, i.e.,, that $\sigma = .5$.

Table 2

Steady State Effects of Regulation: $\sigma = .5$

	$\lambda = 0$	$\lambda = .01$	$\lambda = .02$	$\lambda = .03$	$\lambda = .04$	$\lambda = .05$
k_R^*/k_U^*	1.00	.994	.987	.981	.974	.967
h_R^*/h_U^*	1.00	.998	.996	.993	.991	.989
y_R^*/y_U^*	1.00	.994	.987	.981	.974	.967
c_R^*/c_U^*	1.00	.994	.987	.981	.974	.967
w_R^*/w_U^*	1.00	.996	.991	.987	.983	.978
h_R^*/h^*	0.00	.002	.004	.006	.008	.010
Δ^S	0.00	$-.005$	$-.009$	$-.014$	$-.018$	$-.023$

As in the previous case, the steady state features proportional declines in capital, output, and consumption, though these declines are now slightly larger than in the previous case. The reason for this is that there is now a decrease in hours worked across the two steady states, with the extent of the decrease an increasing function of λ. Note that the change in wages is the same as in the previous case. Also note that to first order, the welfare effects are the same. In the previous case there was no change in hours of work and a decrease in consumption relative to the initial steady state, whereas in this case the drop in consumption is larger but there is now an increase in leisure. The key point here is that one does not need to do anything special in applying this method depending upon whether the policy affects steady state hours of work. A very simple message that this example illustrates is that one should not identify changes in labor with changes in welfare; as just noted, the welfare effects in the two cases are basically the same even though the effects on labor are quite different.

2.5.2. Effects Including Transitions

As noted earlier, if one wants to understand how the change in regulation will affect those individuals who are currently living in the economy, abstracting from effects along the transition path could lead to a misleading picture of the nature of the changes. As a practical matter it is typically more demanding to carry out analyses of transition paths than it is to simply compute steady states. Beyond this, I would argue that transition paths are much less robust than steady state effects, to the extent that there are many details that could affect the nature of transitions without affecting the final steady state that is reached. For example, if there are any anticipation effects associated with the introduction of a regulation, this could affect the transition, but assuming the regulation is permanent and individuals come to realize that it is, then anticipation effects at the time of adoption will not influence the final steady state. Also, model features such as adjustment costs can affect transitions without affecting steady states. With these types of considerations in mind it is quite useful to know how important the transition effects might be. If they tend to be very close to the steady state effects then perhaps these additional complications can be dispensed with. Of course, there is no reason to think that the answer will not be context dependent. But in this section I examine this issue in the context of the adoption of the regulation that we studied in steady state in the previous section.

Solving for transition dynamics in the one-sector growth model is relatively straightforward. I do it using a shooting algorithm. Because the regulation that I am considering as an example is equivalent to a permanent reduction in TFP, there are theoretical results that tell us that the paths for capital and consumption starting from an arbitrary initial condition will be monotone and converge to the new steady state. In Figures one through three I show the transition paths for capital, consumption and hours over the first 25 years of the transition for the case in which $\lambda = .05$ and $\sigma = 1$, i.e., utility that is logarithmic in consumption.

A few properties are worth noting. First, convergence happens quite rapidly. Although the capital stock is initially more than 2% higher than its eventual steady state value, after only five years it is less than 1% away. Consumption is effectively never more than 1% higher than its steady state value, and after five years it is less than one half of one percent from its steady state value. And hours are never more than one half of one percent from their new steady state value. While consumption and capital decrease monotonically to their new steady state values, hours is increasing. The reason for the latter is that the relatively high initial value

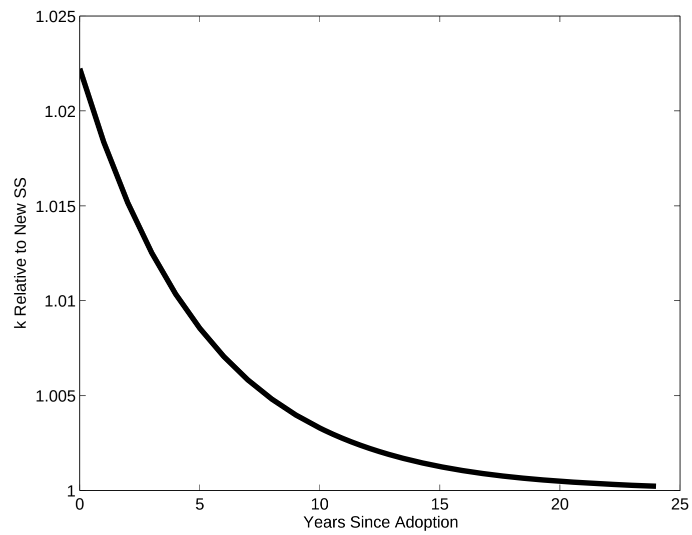

Figure 1: Transition Path for Capital

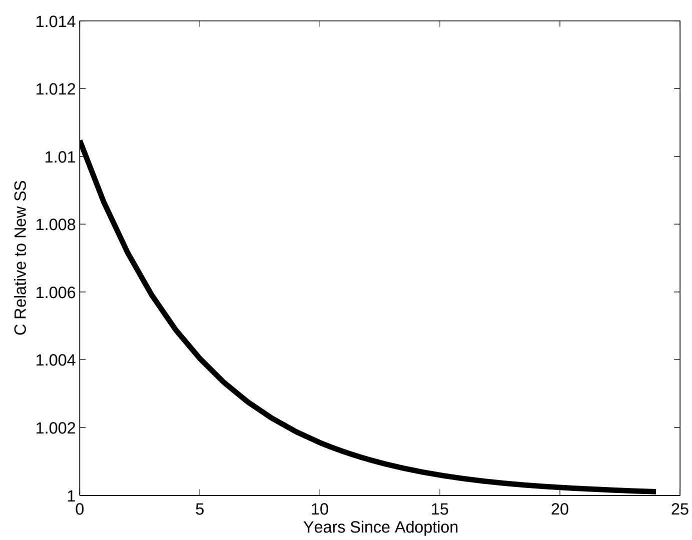

Figure 2: Transition Path for Consumption

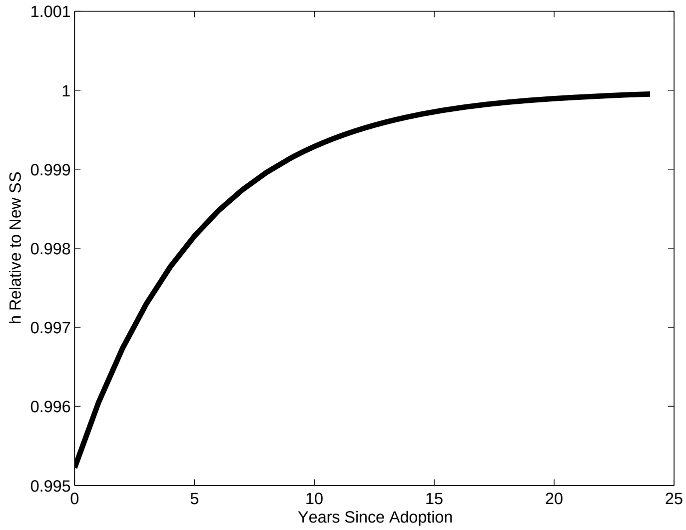

Figure 3: Transition Path for Hours

of capital implies that there is less desire to work due to intertemporal substitution effects. As capital decreases towards its new steady state value the interest rate increases to its steady state level and so do hours. While these transition dynamics are well known to economists who work with the one-sector growth model, it is worth pointing out that the initial decrease in hours immediately following the adoption of the regulation does not reflect any sort of "disequilibrium" in the labor market, that is, this decrease is part of an efficient response in the economy. As I briefly discuss later, one could introduce additional features into the analysis, such as wage rigidities and various sorts of adjustment costs that reflect the lack of skill transferability or search frictions, some of which may serve to amplify the initial decrease in hours worked. But the mere presence of a decline in hours worked is not by itself evidence of these additional features.

From a welfare perspective, note that during the transition there is higher consumption and leisure relative to the eventual steady state allocation, so that steady state welfare losses will exaggerate the extent of the losses that include the transition period. In fact, the welfare change that includes the transition path turns out to be $-.019$ as opposed to the value of $-.022$ when only considering the steady state. I conclude that the transition is not of first order importance in assessing welfare effects in this context. Table 3 reports the two different welfare changes for the case of $\sigma = 1$ and the five different values of λ.

Table 3

Welfare Effects: Steady State and Transition

	$\lambda = .01$	$\lambda = .02$	$\lambda = .03$	$\lambda = .04$	$\lambda = .05$
Δ^S	$-.004$	$-.009$	$-.013$	$-.017$	$-.022$
Δ^T	$-.0037$	$-.0075$	$-.011$	$-.015$	$-.019$

The main message from the table is that the effects of including the transition in this case is relatively small. This reflects the fact that the economy is never that far from its new steady state, and that after five years the allocations are all quite close to their new steady state values.

2.6. Discussion and Extensions

The goal of this section has been to lay out a benchmark macroeconomic model, describe how it is typically used to evaluate the welfare effects of policy, and then illustrate this in the context of one example of a highly stylized environmental regulation that affects the entire economy. I have tried to emphasize that the example studied here was purposefully simplified in order to best illustrate the general method. However, I think it is worth noting just a few of the many ways of interest in which the analysis could be extended.

In the spirit of the growth model I have assumed a putty-putty technology, in the sense that in the initial period of the regulation, some of the preexisting capital stock will actually be converted from being used to produce output to being used to reduce emissions. One could reasonably argue that a putty-clay formulation would be more natural, so that the equipment used to reduce emissions needs to be produced rather than converted. One might also consider the possibility that there are some sorts of adjustment costs associated with trying to increase the scale of production of this equipment too rapidly. And in view of these issues, it might be of interest to consider some sort of a gradual adoption process for the regulation, or even a grandfather clause for preexisting capital. All of these types of features can be incorporated somewhat readily and do not require any conceptual changes in the basic methodology. While these types of considerations might not have much impact of the steady state outcomes, they could matter for the effects during the transition period.

One could also consider situations in which the initial equilibrium has very different features. In particular, one could assume that wage setting practices in the labor market result in a level of the real wage that is higher than the competitive equilibrium level, so that hours worked in equilibrium do not correspond to the efficient level. One could then repeat the analysis in this setting, though one would need to make some assumption about how the regulation would influence wages, if wages are not determined by demand and supply. But again, the method outlined above can be equally well applied in this case as well. Related to this, one could assume that there is some sort of rigidity in wages that influence the transition dynamics from one steady state to another. As a result the transition might involve a reduction in hours if wages do not fall sufficiently fast.[4] This would increase the size of the welfare losses associated with the transition dynamics.

Lastly, consistent with the earlier discussion, one could potentially incorporate effects of lower pollution in a non-separable fashion if there were sufficient information available to guide such a specification. For example, if lower pollution promotes health and thereby enhances the enjoyment of leisure time or makes workers more productive at work by reducing the incidence of sickness, then such effects can be incorporated.

3. Benchmark II: Industry Analysis

In this section I lay out a partial equilibrium model that serves as a useful starting point. The model I describe here is a simple version of the industry equilibrium model of Hopenhayn (1992).[5] Melitz (2003) developed a variant of this model which has become the workhorse model used in international trade for thinking about the effects of trade policy. Ryan (2012) uses a version of this model to

[4] See the recent paper by Shimer (2013) for an analysis of how extreme wage rigidity can affect the transition dynamics.

[5] This type of analysis is also closely related to the span of control model analyzed in Lucas (1979).

study the effects of regulation on the cement industry. The model will give rise to a stationary (or steady state) equilibrium in which the aggregate behavior of the industry is constant over time, at the same time that the industry exhibits a rich set of dynamics at the establishment level, with establishments growing, shrinking, exiting and entering. As a result the model is both sufficiently rich to connect with key facts about establishment dynamics at the micro level while also permitting one to focus on industry aggregates. The model that I describe below should be viewed as the simplest prototype within a broad class of models. That is, it is possible to extend the model that I describe below to allow for a much richer set of features. I note some of these extensions later in this section, but from the perspective of exposition, I feel it is best to work with the simplest model within this class.

3.1. Model

I consider an industry consisting of many individual establishments that produce a homogeneous product. (The analysis can easily be modified to the case of firms that produce differentiated products.) The industry faces a time invariant inverse demand curve for its output given by $P(Y_t)$, where Y_t is the amount of output produced by the industry in period t.[6]

The unit of production in the industry is a plant. Each plant i has a production function:

$$y_{it} = z_{it} f(k_{it}, h_{it})$$

[6] We could easily allow for trend growth in demand but since it will not play any role in the analysis that follows I have abstracted from this feature.

where f is a strictly increasing and strictly concave function, k_{it} is input of capital services, h_{it} is input of labor services, and z_{it} is idiosyncratic plant level productivity. The fact that the function f is strictly concave implies that there is an efficient scale at the plant level and is critical in this framework to generate a non-degenerate distribution of plant sizes.[7] The idiosyncratic plant level productivity term z_{it} is assumed to be stochastic. This will allow the model to capture the large volume of job reallocation that occurs across establishments within an industry. (See, for example Davis. Haltiwanger and Schuh (1996)). In the differentiated product version of this model one could achieve this type of reallocation through either changes in relative productivity or changes in the relative demand for the differentiated products coming from changes on the consumer side. For our purposes there is no loss in generality by having all of these changes induced by changes in productivity. I will assume that the cdf for next period's shock z_{it+1} given today's realization z_{it} is given by a cdf $\Phi(z_{it+1}; z_{it})$. We will assume that the cdf has a mass point at 0 and that 0 is an absorbing state. Thus, receiving a draw of zero will be identified with exit. In many applications one might suspect that endogenous exit is an important channel of response to changes in regulations, and in a later subsection I describe how to endogenize exit by allowing for a fixed per period operating cost. But for present purposes the analysis is much more transparent with exit modeled as an exogenous process. Labor and capital services

[7] If we instead considered the model with differentiated products then we could have constant returns to scale in the production technology at the plant level, and the curvature needed to produce a non-degenerate plant-size distribution could instead by achieved by having curvature in preferences via imperfect substitutability of the differentiated products. Melitz (2003) adopted this type of specification in his analysis.

can be rented in competitive factor markets with time invariant prices w and r respectively. Because the analysis in this section is explicitly partial equilibrium, the maintained assumption is that changes within this industry have no effect on the factor prices that firms in this industry face.

We also allow for entry into the industry. The entry process works as follows. Each period there is an unlimited number of potential entrants. In order to enter in period t a potential entrant must pay a nominal cost c_e. After paying this cost, the entrant will receive an initial draw for its idiosyncratic productivity that is a draw from a distribution with cdf $\Upsilon(z)$. These draws are assumed to be iid across entrants, so that the expected quality of new entrants is independent of the amount of entry. If a potential entrant pays the entry cost in period t it begins operation in that same period with productivity given by its draw from the distribution described by $\Upsilon(z)$. Beyond the initial period, the idiosyncratic productivity of a new entrant will evolve according to the same stochastic process described previously.

We assume that firms discount future profits using the interest rate R.

3.2. Steady State Industry Equilibrium

I focus on the steady state equilibrium in this industry. The key feature of a steady state equilibrium is that industry output and hence the price will be constant over time. As noted above, although aggregates will be the same from one period to the next in a steady state equilibrium, there will be a lot of change at the microeconomic level, consistent with what we see in the actual data.

Let P^* denote the steady state equilibrium price in this industry. Because our analysis is partial equilibrium, this is the only endogenous price in the model. So finding a steady state equilibrium for this model requires that we find the value P^*. Consider the profit maximization problem faced by an individual establishment in the steady state equilibrium that has current productivity z. This plant could be either a plant that produced last period and has received its new shock for the current period, or a plant that was created last period, with z being its initial draw from the distribution. Its current period profit maximizing behavior is static: it is optimal to choose quantities of labor and capital today so as to maximize current period profit net of factor costs, since choices made today have no impact on future profits. The resulting profits will be a function of $P^*$and z, which we define by:

$$\pi(P^*, z) = \max_{k,h} \ \{P^* z f(k, h) - wh - rk\}$$

Let $V(z, P^*)$ be the value function for an establishment with current productivity z in steady state equilibrium when the output price is P^*.The Bellman equation for this value function is:

$$V(z, P^*) = \pi(p^*, z) + \frac{1}{1+R} \int V(z', P^*) d\Phi(z', z) dz'$$

Since $\pi(P^*, z)$ is increasing in P^*, it is easy to show that $V(z, P^*)$ is also increasing in P^*.

Now consider the entry decision. The expected return to entry net of entry costs is given by:

$$-c_e + \int V(z, P^*) d\Upsilon(z)$$

Since $V(z, P^*)$ is increasing in P^* it follows that the expected return to entry is also increasing in P^*. Given our assumption of an unlimited number of potential entrants, in equilibrium it must be that the net return from entering is not positive. Additionally, if there is entry in the steady state equilibrium, then the net return from entering must equal zero. It follows that if there is entry (and hence exit) in the steady state equilibrium, then P^* must be such that:

$$-c_e + \frac{1}{1+R} \int v(z, P^*) d\Upsilon(z) = 0$$

Because entry and exit are robust features in the data, we will focus on parameterizations such that there is entry and exit in the steady state equilibrium. Having determined P^* we now also know the level of output in the steady state equilibrium. Note that we pinned down P^* by requiring that the net return to entry is zero. This implies that all potential entrants are indifferent about entering. In steady state there is a constant flow of entrants. The steady state size of the industry will be increasing in this volume given that we are fixing P^* and that the exit rate is exogenous. We will determine the volume of entry by requiring that the amount of entry be such that the steady state size of the industry generate the right amount of output given that the price must be P^*. We next describe how to compute this level of entry. To do this it is useful to introduce one additional piece of notation. Assume that there is a mass of incumbents with distribution over z

values described by a measure $\mu(z)$. If we follow this group for one period, they will get new draws for z next period, and some of them will receive draws of zero and exit. The resulting measure of these establishments one period later will be denoted by $T\mu$. An important property of this operator is that it is homogeneous of degree one, i.e., if we double the mass of incumbents today, we will have double the mass of remaining firms tomorrow.

Suppose that there was a unit mass of entry in each time period. Then in the resulting steady state distribution the mass of firms of exactly age 0 will be given by the unity and because of the law of large numbers they will be distributed according to the cdf $\Upsilon(z)$. Denote the resulting measure by $\mu_0(z)$. In steady state, we can also determine the measure of establishments that are exactly one year old–since these would be the establishments who began one year earlier and did not exit after one year. This measure, which we denote by μ_1 will simply be equal to $\mu_1 = T\mu_0$.Continuing in this fashion we can trace out the measure of z's for each cohort in the steady state, and they are given by repeated applications of T to the distribution μ_0. Given that we know the measure of establishments over z's for each cohort in the steady state, we can also compute the amount of output produced by each cohort in the steady state. In particular, letting $Y_j(1)$ denote the amount of output produced by the cohort of age j in the steady state when there is a unit mass of entry in each period, we have that:

$$Y_j(1) = \int y(z, P^*)\mu_j(dz)$$

where $y(z, P^*)$ is the optimal output level for an individual establishment that has current productivity z if the steady state price in equal to P^*. Total output is then given by

$$\sum_{j=0}^{\infty} Y_j(1)$$

This is an infinite sum. It will be finite if establishments are exiting fast enough, so that the mass of establishments of older ages goes to zero sufficiently rapidly. If this does not happen, then there does not exist a steady state equilibrium for the economy. We will assume that exit happens sufficiently fast that a steady state equilibrium does exist, so that the sum is finite. Denote the value of this sum by $Y(1)$. It follows that this is the amount of output that would be produced in the steady state equilibrium if the output price were $P^*$and there was a unit mass of entry in each period. While we know that the steady state price must equal P^* assuming that there is entry in the steady state, we know that the steady state output consistent with this price is given by $Y^* = D^{-1}(P^*)$. As we noted before, the operator T is homogeneous of degree one. It follows that if we had entry of mass 2 in each period, steady state output would be $2Y(1)$. It follows that the amount of entry that occurs in the steady state equilibrium is given by $Y^*/Y(1)$. This completes the algorithm for finding the steady state equilibrium.

3.3. Policy Analysis and Welfare Effects

There are various types of regulations that we might consider in the context of this model. For example, if a regulation requires that plants buy more expensive capital equipment in order to cut down on some pollutant, this could be captured as an increase in the per unit cost of capital services, or as a need to use capital services beyond what is required to simply produce a given amount of output. A regulation which requires more documentation and studies prior to authorizing new start-ups can be modeled as an increase in the entry cost c_e. A third policy is one that requires a fixed per-period cost of compliance, perhaps associated with additional monitoring. While each of these cases operates through slightly different channels, they have a great deal in common in terms of the nature of their effects.

To provide continuity with the analysis in the previous section, I begin by considering a regulation that requires firms to purchase additional capital to reduce the amount of emissions that they produce. In particular, assume that the policy implies that if an establishment hires k_{it} units of capital that a fraction λ of this capital will be used to reduce emissions with only a fraction $(1-\lambda)$ being actively used for production.

It follows that the value of $\pi(z, P^*)$ will decrease for any given values of its arguments. This implies that at the old equilibrium price, the net expected return to entering will be negative, so that the equilibrium price must be higher. This in turn implies that output must be lower. The higher value of P^* will change the optimal size of an establishment conditional on its value of z. If this effect is positive, and since exits are exogenous, the only way that output can be lower in the steady state is if the mass of entry in the steady state is lower. If the effect on establishment level output is negative, then the effect on entry is ambiguous.

Alternatively, consider a regulation that makes entry more costly, perhaps by requiring additional documentation or impact studies up front. Although this has no direct effect on $\pi(z, P^*)$ for given values of its arguments, this policy will also lead to an increase in P^* via the free entry condition, since the cost c_e has increased. This increase in P^* will necessarily increase optimal establishment size in this case, since there is no impact on the production function. It follows that entry must decrease. Similarly, if there is an increase in a per period compliance cost, this also reduces profits at the original equilibrium price, implying that the price must increase and that entry must decrease. One of the key messages that this simple qualitative analysis serves to communicate is the importance of the entry margin in bringing about adjustment to the new equilibrium.

Next we consider the issue of assessing the welfare cost associated with these types of policies. Unlike the analysis in the previous section, there is no utility function that is specified as part of this industry equilibrium analysis. Standard practice for computing welfare in this framework would be to take the area under the demand curve as a measure of the value of the industry's output, plus any profits accruing to firms, less the cost of any inputs that are used to produce output. That would include the resource costs associated with entry. Changes in this measure across steady states would give us the appropriate steady state change in welfare. Implicitly, this method assumes that if total employment changes in this industry, there is no direct cost or benefit associated with this change. In this sense, partial equilibrium analyses do not provide an internally consistent method for assessing the welfare costs that might be associated with changes in labor input to the industry being studied.

3.4. Calibration

If one wants to use this model to carry out quantitative evaluations of policy changes then it is necessary to choose functional forms and assign parameter values. Whereas there is widespread agreement on what constitutes a reasonable calibration of the one sector growth model, this is somewhat less true for the industry equilibrium considered in this section. In part this reflects the fact that it is an industry model and different industries can display different patterns of establishment dynamics. Additionally, there are more variants of this model in use, with less agreement as to what constitutes the natural benchmark. Having noted this qualification, here I describe one calibration procedure.

In what follows I will assume that f takes the following form:

$$f(k,h) = k^{\alpha} h^{\theta}$$

where α and θ are both positive and $\alpha + \theta < 1$.

I begin with the stochastic process for idiosyncratic shocks. There are two aspects to this process, one describing the exogenous exit dynamics and the other describing the productivity dynamics conditional on remaining in the industry. I restrict attention to a specification in which z takes values in a finite set with N elements, ordered so as to be increasing. In the examples below, N is 11 and the values are equally spaced on the interval $[1, 4]$. For each value of z I will assume that there is a decreasing function $\phi(z)$ that gives the probability of exit (i.e., a zero productivity draw for next period). In the examples computed below, I assume that the exit rate is decreasing in the value of z, and ranges from .05 to .15, varying linearly in z. With probability $1 - \phi(z)$ the evolution will follow a given stochastic process. Given the simple structure of the benchmark model, i.e., that the profit maximizing choice of inputs is static, it follows that stochastic processes for both factors and output will closely mimic the stochastic process for the idiosyncratic shocks. An AR(1) process in logs is the most common choice for this process:

$$\log z_{it+1} = \rho_z \log z_{it} + \varepsilon_{it+1}.$$

This results in a process for establishment size that exhibits mean reversion. The distribution of the innovations in this process will have a significant impact on the nature of the steady state distribution of establishment sizes. A common choice is to assume that these innovations are distributed according to a normal distribution, implying that the steady state establishment size distribution will resemble a log normal distribution. It is well known that this distribution does not have as much mass in the upper tail as is found in the data, and choosing the innovations to come from a Pareto distribution would help with this issue, though normal is the more common choice in the literature. In the calculations that I carry out I assume a very simple process that captures the spirit of the above process. For any interior value of z, I assume that with probability .95, productivity will be the same next period as this period. And with probability .025, the productivity will move up or down one position. A the two boundaries I assume that the entire .05 probability reflects the probability of a one step move into the interior of the set.[8]

The second stochastic process concerns the distribution that new entrants draw their initial productivity from. A key observation from the data is that new establishments tend to be small. A richer model might have additional features, such as learning, that influence the size of new entrants, but in this simple model, the average size of new entrants is dictated entirely by their average productivity draw, subject to them choosing to operate. This implies that the mean productivity draw of new entrants must be sufficiently low relative to the steady state distribution of productivity shocks. Subject to meeting this criterion, the distribution does not seem to matter that much. In the calculations that I carry out below I will assume that the distribution is uniform on the three lowest points in the set of idiosyncratic shocks.

The other functional form to specify is the industry inverse demand function. I assume that this relationship exhibits a constant elasticity:

$$P_t = AQ_t^{-\eta}$$

Having specified a particular process on the idiosyncratic shocks, the remaining parameters are the prices r, R and w, the demand parameters η and A, the two technology parameters α, θ, and the cost of entry parameter c_e. Several values can be normalized to reflect a choice of units. The values of A and w can both

[8] See, for example, Hopenhayn and Rogerson (1993) for a calibration procedure that posits an AR(1) process with normal innovations and discusses how to calibrate it using data on job creation and destruction. See also Khan and Thomas (2007) for a model with many additional features and a richer calibration strategy.

be normalized to one with no loss of generality. I will also impose that the steady state price of output, P^* will be equal to one, again as a normalization. As we will see later, this amounts to fixing the units in which the fixed costs are measured. For the results shown below I assume that $\eta = 1$.

If we set a period equal to one year, and make use of the relationship between the interest rate and the depreciation rate and the value of r in a standard growth model (the interest rate is r less the depreciation rate in these models), then setting $R = .04$ would suggest that $r = .12$ as a reasonable choice.

The values for α and θ can be chosen by targeting values for capital's share, labor's share and the residual. There is no definitive estimates of the latter value, though typical calibrations assign a 15% share to this category. Using a $1/3 - 2/3$ split between capital and labor of the remaining 85% yields $\alpha = .255$ and $\theta = .595$. The value of the entry cost is then pinned down by the requirement that the free entry condition is satisfied given all of the other parameter assignments.

Although I have considered a very simple stochastic process for idiosyncratic shocks, the steady state distribution of establishment sizes does match some key features found in the data. For example, the steady state distribution of establishments is heavily skewed towards smaller establishments, at the same time that the majority of employment is accounted for by larger establishments. In the steady state the labor input at the largest establishment is roughly $10,000$ times the labor input at the smallest establishment. If we interpret the smallest establishments as those with one worker, then the three lowest productivity levels would correspond to establishments with less than 20 workers. Roughly 93% of establishments then have less than 25 employees, but these establishments account for less than half of total labor input that is hired by the industry.

Now I consider a few specific policies. Results are shown in Table 4.

Table 4

Effects of Regulation in the Industry Equilibrium Model

	$\%\Delta p$	$\%\Delta E$	$\%\Delta H$	$\%\Delta avg\ h$	$\%\Delta welfare$
capital requirements	2.79	$-.46$	0.00	.47	-2.72
per period compliance cost	1.89	-11.3	0	13.3	-2.20
increased entry cost	1.44	-9.1	0	10.0	-1.43

The first row considers the case of a regulation that requires hiring of additional capital services. Suppose that the policy is such that establishments need to hire an additional 10% of capital to sufficiently lower emissions. The new steady state price turns out to be 2.79% higher, so that output is also 2.79% lower. The change in welfare relative to the initial expenditure in the industry turns out to be -2.72%. Entry, denoted by E, falls by .46%, so that in the new steady state the number of firms falls by the same amount. Average firm size is actually higher by .47% which implies that the effect of the higher price dominates the direct effect of the regulation. This policy produces proportional changes in size across the size distribution, given the nature of the production function. There is no change in aggregate employment due to this policy. I note that there is nothing general about this particular outcome, as it results from the assumption of a unitary elasticity of demand.

The second row considers a policy that introduces a fixed compliance cost for all active establishments. The size of the cost is set at 10% of the average profit level in the original steady state equilibrium. The effects are qualitatively similar to those of the first row, except that the effects on entry and average establishment size are much larger, though offsetting. To gauge the magnitude of the two different regulations, note that in the original equilibrium, capital's share of output is roughly 25% so that a 10% increase in capital costs holding behavior constant would amount to a 2.5% increase in costs. Profits represent 15% of output in the original steady state, so 10% of this represents 1.5% of output. Note that output decreases even though nothing happens to total labor input. This occurs because the increase in average firm size is suboptimal and leads to a decrease in average labor productivity.

The third row considers a 10% increase in entry costs. The qualitative effects are again similar. Note that in the initial steady state, entry costs represent roughly 8.5% of total output, so a 10% increase amounts to roughly a .85% increase in costs.

Since I have not calibrated to a particular industry and a specific regulation, the above values are simply illustrative. But having said this, I think it is fair to say that moderate sized changes in regulations can have sizeable effects on welfare.

3.5. Discussion and Extensions

To facilitate exposition I have focused on the simplest version of an industry equilibrium model that incorporates establishment level dynamics and allows for entry and exit of establishments. However, it is straightforward to extend the model in a number of directions. I note a few of these here. First, it is straightforward to endogenize the exit decision. To do this, assume that in addition to the variable costs associated with hiring labor and capital services there is a fixed cost of operation that any plant incurs, denoted by c_f. An establishment can avoid incurring this fixed cost in period t by exiting, which means ceasing to exist. In particular, a plant is not allowed to avoid the fixed cost by not producing output this period and waiting to see if a better shock is realized next period. The period t value of idiosyncratic productivity is assumed to be observed before a plant makes its decision about whether to continue in operation. One could still maintain some amount of exogenous exit as was the case in the simpler model.

I assumed that the only dimension of heterogeneity was the establishment level TFP shock. One could allow for additional sources of heterogeneity, in terms of fixed costs, technology share parameters etc... One could also enrich the specification of technology in various ways, perhaps allowing for vintage effects that would lead to heterogeneity in technology and perhaps heterogeneity in the extent to which different establishment cause pollution. The literature on establishment dynamics has considered a variety of factors that may be quantitatively important in influencing dynamics, such as different types of adjustment costs, learning effects about technology, learning effects about demand etc... These kinds of effects can easily be incorporated.

While I have listed a number of generic extensions that might be of interest, it is undoubtedly the case that for an applied study of a given industry there are likely to be features of that specific industry which will motivate the inclusion of particular features.

In the above analysis I have focused on steady state effects. One can also consider transition dynamics. In the simple model studied here, the key source of dynamics is the adjustment in the entry process, since this is the only dynamic element in the benchmark model that I studied. In a model with an endogenous exit decision there would also be dynamics in the exit process. There are two basic forms that the adjustment dynamics may take in the examples considered above, all of which served to decrease the profitability of entry and lead to a higher price. One possibility is that the price increases immediately to the new steady state level and there is entry throughout the adjustment process. The other possibility is that the price increases to the new steady state only after some periods. In this case there will be no entry during the period in which the price is below the new steady state price, since entry is only profitable at the new steady state price. As establishments exit the price will increase, eventually reaching the new steady state level and making entry profitable again. While these two types of adjustment seem intuitive, one cannot rule out price paths in which the price oscillates around the new steady state price. Unlike the case of the one sector growth model where transition paths are well understood and have been thoroughly characterized, this is not the case for partial equilibrium industry equilibrium models.

4. A Hybrid Model: Industry Equilibrium Analysis Within An Aggregate Model

In this section I develop a tractable framework that allows one to consider a rich description of the industry (or industries) affected by a specific regulation while simultaneously allowing for an analysis of the potential aggregate or general equilibrium effects that are associated with the regulation. Moreover, the framework lends itself to welfare calculations that are tightly connected to individual preferences and can be applied in a wide range of circumstances.

The essence of the model is to retain the basic structure of the one sector growth model but to allow for multiple intermediate goods sectors. Each intermediate goods sector combines labor and capital to produce its output. The intermediate goods are then combined through another production function into the single final good. The single final good can then be used as either consumption or investment. This type of production structure is popular in macroeconomics in the study of wage and price rigidities, as it retains the tractability of the one-sector growth model while allowing for monopolistic competition among intermediate goods producers, thereby providing a coherent framework for thinking about wage and price rigidities. In the macro literature these models assume that each intermediate good is produced by a single firm. In contrast, the prototype model that I develop here will assume that there are two intermediate goods sectors. One of these will represent the industry which is the prime focus of study given the regulation being considered. The second intermediate goods sector will be the aggregate of all other sectors. While we could treat these two sectors symmetrically in terms of modeling, my benchmark model will impose an asymmetry, with the idea being that the industrial structure is most important in the context of the directly affected industry. So while I will explicitly consider the industrial organization of this sector, and model it in the fashion of the industry equilibrium model from the previous section, the other sector will be captured by an sectoral aggregate production function. While one could also introduce the details of firm level dynamics into the non-regulated sector, it is not clear that this is of first order importance and increases the tractability of the model. The details follow.

4.1. Model

There is a single final good in the economy, and there is a representative household that is infinitely lived, with preferences given by:

$$\sum_{t=0}^{\infty} \beta^t u(C_t, 1 - H_t)$$

where all of the objects are as defined in an earlier section. There are two intermediate goods. The final goods sector combines the two intermediate goods into the final good using a constant returns to scale production function:

$$Y_t = G(Q_{1t}, Q_{2t})$$

where Q_{it} is the input of intermediate i in period t. We will assume that intermediate good 2 is the sector that is directly affected by the regulation that is being considered. A natural choice for the production function G is a constant elasticity of substitution function:

$$G(Q_1, Q_2) = [aQ_1^\gamma + (1-a)Q_2^\gamma]^{1/\gamma}$$

With this choice the parameter a can be used to capture the relative importance of the sector being considered in terms of it share of aggregate value added, and the parameter γ captures the extent to which this intermediate is substitutable with goods or services produced elsewhere in the economy.

As in the one sector growth model, aggregate output can be used for either consumption or investment, but we also assume that this final good is the good that is used in the entry process:

$$C_t + I_t + E_t c_e = Y_t$$

where E_t is the amount of entry in period t and c_e is the cost of entry. The aggregate capital stock evolves as before:

$$K_{t+1} = (1-\delta)K_t + I_t.$$

In the model I develop here I will assume that capital is freely mobile between sectors, so that:

$$K_t = K_{1t} + K_{2t},$$

though it may well be of interest to consider the case in which each sector has its own capital stock and there is no mobility of capital across sectors.

The technology in sector 1 is standard, in that it is represented by a constant returns to scale aggregate sectoral production function:

$$Q_{1t} = F(K_{1t}, H_{1t})$$

where K_{1t} and H_{1t} are inputs of capital and labor in sector 1, respectively.

In contrast, in sector 2 we model production by specifying plant level technologies and allowing for establishment level dynamics driven by idiosyncratic shocks, in addition to entry and exit. The details are the same as those in the previous section, namely a plant level production function $z_{it}f(k_{it}, h_{it})$, idiosyncratic shock process denoted by $\Phi(z_{it+1}, z_{it})$, and entry cost of c_e, which will be measured in units of the final good. New entrants draw their initial productivity shock from a distribution with cdf $\Upsilon(z)$.

As in any general equilibrium model, all firms are owned by the household sector. For the final goods firm and the firm in sector 1 there will be zero profits in equilibrium on account of the constant returns to scale assumption, so there are no effects associated with ownership. For sector 2, given that there are decreasing returns to scale at the plant level, and entry costs, profits will typically be non-zero. Although there is a zero profit condition for entry, this does not imply that the aggregate of cross-sectional profits are zero if the interest rate is positive.

4.2. Equilibrium

Although one can certainly solve for transitional dynamics in this model, as in the last section, my analysis here will focus on steady state equilibria. I will normalize the steady state price of the final good to be equal to unity. A steady state equilibrium will then be characterized by four prices: two factor prices (w and r for labor and capital respectively) and two intermediate goods prices (p_1 and p_2 for intermediate goods 1 and 2 respectively). The relevant quantities in a steady state equilibrium are aggregate consumption and hours worked for the household (C and H), aggregate production quantities in sector 1 (Q_1, H_1, and K_1), aggregate quantities in sector 2 (Q_2, H_2, and K_2) and the volume of per period entry in sector 2 (E). All of the establishment level variables can be computed given these values.

I next show how to solve for this steady state equilibrium. The procedure will draw on the various first order conditions that have been derived previously, so rather than re-derive these conditions I will simply refer to past derivations as needed. To begin, note that the household problem in this model looks exactly like the household problem in the one sector neoclassical growth model, so that it remains true that in a steady state competitive equilibrium we must have:

$$r = \frac{1}{\beta} - (1 - \delta)$$

Profit maximization in the final goods sector and in intermediate sector 1 imply that following standard conditions:

$$\begin{aligned}
p_1 F_1(K_1, H_1) &= r \\
p_1 F_2(K_1, H_1) &= w \\
G_1(Q_1, Q_2) &= p_1 \\
G_2(Q_1, Q_2) &= p_2
\end{aligned}$$

where it should be noted that we have used the fact that the price of the final good is normalized to one. Suppose we knew the value of p_2. Because G displays constant returns to scale, marginal products of G depend only on relative factor inputs, so that knowing the value of p_2 implies that we can then infer the value of p_1. Similarly, knowing r/p_1 allows us to infer w/p_1. It follows that we know the values of all prices once we know the value of p_2. However, from our analysis of industry equilibrium in the previous section, we know that the free entry condition imposes a specific relation between r, w, and p_2. In fact, the above procedure implies that w is a decreasing function of p_2. It follows that expected profits net of entry costs are strictly monotone in the conjectured value of p_2, so that checking the free entry condition will allow us to determine all of the steady state equilibrium prices.

Having determined all of the prices, we know determine the allocation of factors across sectors. Given prices that are consistent with free entry, we can determine the steady state outcome within intermediate sector 2 given a unit mass of entry in steady state. This will produce a particular volume of output. As we noted above, the first order condition of the final good firm tells us the value of Q_1 consistent with any value of Q_2. In fact, since the ratio is pinned down, this condition will scale the values of these two outputs proportionally. Knowing this we can infer the amount of aggregate labor and capital being used, and hence also the steady state level of consumption, since we know that investment is exactly equal to depreciation in steady state. Since changing the mass of entry simply scales al quantities up and down, it follows that C and H are being scaled up as we vary E. To determine the equilibrium value of E we simply check the households condition for optimal labor supply. The wage rate is given and as we vary the amount of entry we increase consumption and decrease leisure, so at some scale of operation the marginal rate of substitution between consumption and leisure will be equal to the wage rate.

4.3. Calibration, Policy Analysis and Welfare

Calibrating this model is basically a matter of combining the two calibration procedures documented earlier. Specifically, the details of intermediate sector 2 can be calibrated to capture the key features of establishment dynamics in this sector. And while I have specified a very simple model, all of the extensions which were discussed in the previous section can also be implemented here in order to capture whatever features seem central in the context of the specific industry being studied and the particular policy or regulation being considered. The technology for combining the two intermediate goods is purposefully allowed to be flexible in order to capture the potentially different role of various sectors that one might want sector 2 to represent. Having specified this, sector one will be calibrated to match standard aggregates given the rest of the production structure.

To illustrate the method I adopt the following calibration. For sector 1, we assume a Cobb-Douglas production function with capital share equal to .30. And as in the earlier exercises, we again set the depreciation rate on capital equal to .08. For the production function that combines outputs of the two sectors we assume a constant elasticity of substitution production function:

$$G(Q_1, Q_2) = [aQ_1^\rho + (1-a)Q_2^\rho]^{1/\rho}$$

and will consider a few different settings for both a and ρ to illustrate their role. As earlier, we assume that the period utility function is of the form:

$$\alpha \log c + (1-\alpha)\log(1-h).$$

For the same reason as before, I set $\beta = .96$ in order to generate an annual steady state interest rate of 4%.

For sector 2, I adopt the same specification for functional forms and parameter values as in the previous section. Specifically, I let $f(k,h)$ take the form $f(k,h) = k^{\alpha_2}h^{\theta_2}$, and set $\alpha_2 = .85 * .3$ and $\theta_2 = .85 * .7$ so that capital and labor shares in this sector will be proportional to the capital and labor shares in sector 1, with the difference between that the sum of the exponents is unity in sector 1, and .85 in sector 2.

For the first set of results I will consider the case in which ρ tends to zero so that the production function that aggregates the outputs of the two sectors is Cobb-Douglas. There are three parameters that still need to be set: α, a, and c_e. These are determined by requiring that the steady state match three targets. First, I require that steady state hours worked represent one third of the households time endowment. Second, as a normalization of units for the two different sectoral outputs I require that in the steady state equilibrium the ratio of the two prices is unity. Third, to fix the relative importance of sector 2 in the overall economy I assume that the value of sector 2's output is 10% of the value of sector 1's output. Given that the relative price of the two goods in steady state is unity, this amounts to the condition that steady state output of sector 2 is 10% of the steady state output of sector 1.

Here I briefly sketch the procedure that one can follow to implement the last steps of this calibration. Given a value for ρ, profit maximization in the final good sector implies:

$$\frac{p_2}{p_1} = \frac{(1-a)}{a}(\frac{Q_2}{Q_1})^{\rho-1}$$

This condition can be used to determine the value of the parameter a. Given a value of a, one can then use the individual first order conditions for Q_1 and Q_2 to determine the level of both p_1 and p_2. As is standard in the growth model, and as we derived earlier, the steady state rental rate on capital is connected to the discount factor and the depreciation rate via:

$$r = \frac{1}{\beta} - (1-\delta).$$

Given values for r and p_1, the first order condition for capital in the profit maximization problem for the representative firm in sector 1 pins down the capital to labor ratio in sector 1:

$$p_1\theta(\frac{k_1}{h_1})^{\theta-1} = r$$

And knowing the capital to labor ratio implies that the value of the wage can be inferred from the analogous first order condition for labor in sector 1:

$$p_1(1-\theta)(\frac{k_1}{h_1})^{\theta} = w$$

At this point, all of the prices have been determined. As in the previous section, given values for all of the prices, one can calculate the expected return to entry in sector 2, as was done in the previous section. Given that the net return to entry must equal zero in equilibrium, this condition is used to pin down the value of the entry cost c_e.

It remains to determine the value of the preference parameter α. This is determined by requiring that total time devoted to work equals to chosen target. Specifically, the previous steps ensured that the net return to entry in sector 2 is zero. It follows that any level of (constant) entry is consistent with this condition. But, higher levels of entry in sector 2 lead to higher levels of steady state output in sector 2, and also in sector 1, since sector 1 output is necessarily ten times the output of sector 2 given the calibration. The values for r and w determined above imply that capital to labor ratios are determined in both sectors. It follows that higher levels of entry will simply increase the total amount of labor. Hence, the amount of entry can be determined by requiring that total labor equals the target. Given the amount of entry, and the volume of labor supplied, one can use the previous information to compute the level of steady state consumption. Given values for steady state consumption, steady state labor, and the wage rate, we can infer the value of α that is consistent with the household's first order condition for labor supply.

Given a calibrated version of the model, we could now introduce various policies as earlier in the paper and compute the effect of these policies on both steady state allocations and welfare.[9] To facilitate comparison with the earlier results in the one sector model I will focus on policies that are interpreted as raising the amount of capital that needs to be hired in sector 2 in order to generate the same level of services from capital. As discussed earlier, one interpretation of such a policy is that firms need to use a more expensive form of capital in order to reduce emissions, and I will parameterize it in the same way as previously, with λ parameterizing the policy.

Table 5 presents results for how this type of policy affects a variety of steady state outcomes both in the benchmark calibration and in three other settings.

[9] One can also compute transition paths from one steady state to another in this type of model, though this is a bit more intensive in terms of computation and is not dealt with in this paper. However, Veracierto (2001) is an early example of a paper that solved for transition dynamics in a model with heterogeneous firms and endogenous entry.

Table 5

Policy Effects in the Two Sector Model Relative to Initial SS

	Benchmark		$Q_2/Q_1 = .20$	$\rho = .25$	$\rho = -.25$
% change in:	$\lambda = .05$	$\lambda = .15$	$\lambda = .85$	$\lambda = .85$	$\lambda = .85$
Y	$-.16$	$-.52$	$-.96$	$-.53$	$-.51$
C	$-.13$	$-.41$	$-.78$	$-.41$	$-.41$
K	$-.26$	$-.81$	-1.46	$-.80$	$-.82$
H	$-.09$	$-.27$	$-.46$	$-.26$	$-.27$
Q_1	$-.04$	$-.13$	$-.25$	$-.02$	$-.21$
Q_2	-1.4	-4.3	-4.44	-5.47	-3.51
h_1	$+.01$	$+.03$	$+.05$	$+.14$	$-.04$
h_2	-1.20	-3.76	-3.47	-4.95	-2.98
p_2/p_1	$+1.30$	$+4.29$	$+4.34$	$+4.29$	$+4.29$
Welfare	$-.11$	$-.36$	$-.61$	$-.33$	$-.38$

The first two columns consider two levels of the policy in the benchmark calibration, one in which the effective capital services in sector two are reduced by 5% and a second policy in which the reduction is 15%. To first approximation, the effects of the larger policy are just a proportionately scaled version of the effects in the smaller policy setting, and so I focus my discussion on the second column. All of the effects are intuitive in terms of their direction. That is, we see that this policy has a negative effect on total output, total consumption, total labor supply and the total capital stock. Turning next to the sectoral effects, we see that output of both sectors decreases, though the decrease in sector 2 is more than an order of magnitude larger. Because the policy directly effects sector 2, making it more costly to produce output in that sector, it is intuitive that sector 2 will experience a greater impact. Loosely speaking, holding factor prices as given, the decrease in efficiency in sector 2 leads to an increase in the relative price in sector 2 from the free entry condition, and this increase in price reduces the demand for sector 2 output, leading to less demand for labor and capital in sector 2. In the partial equilibrium model of the previous section, this is the whole story. But in the general equilibrium model considered here, this excess supply of factors of production creates general equilibrium effects. These general equilibrium effects involve changes in factor prices and factor supplies. These in turn influence the demand for sector 2 output, thereby feeding back into the steady state change in the price of sector 2. The net effect of these is that labor in sector 1 increases by a very small amount, while output of sector 1 decreases. That is, the decrease in overall capital accumulation dominates the effect of there being additional labor allocated to sector 1. Consistent with the effects just described, the price of output in sector 2 increases relative to the price of output from sector 1. Note that in steady state, the rental rate on capital is necessarily determined by the discount factor and the depreciation rate, so all of the adjustment in the capital market occurs on the quantity side.

The final row of the table reports the steady state welfare loss relative to the initial steady state equilibrium. Although the policy has a large effect on inputs and output in sector 2, since this sector is a relatively small part of the overall economy, the overall welfare effect of these changes is much less. While not exactly true, the overall welfare effects are similar in magnitude to the percentage change in output in sector 2 times the share of sector 2 in total output. As we will see shortly, the extent to which this calculation provides an accurate estimate of the overall welfare costs is very much influenced by the extent of substitutability between sector 1 and sector 2 in the production of the final good.

The third column of Table repeats the exercise from the second column except that the model is calibrated so that sector 2 is large relative to sector 1. Specifically, in the benchmark calibration it was assumed that sector 2 was only one tenth as large as sector 1, whereas in the third column it is assumed that sector 2 is one fifth as large as sector 2 in the original steady state equilibrium. Note that this implies that sector 2 is roughly 9% of total output in the benchmark calibration and roughly 17% in the alternative calibration. Perhaps not surprisingly, the third column indicates that the aggregate effects are increased roughly proportionately to the importance of sector 2 in overall economic activity. Interestingly, however, the change in output and labor in sector 2 is not much effected. The reason for this is that the direct effect on sector 2 is independent of the size of sector 2; it is only the general equilibrium effects that are influenced by the size of sector 2.

The final two columns consider values for the elasticity of substitution between the two sectoral outputs on either side of unity. The basic message is that the greater the extent to which sector 1 output can be substituted for sector 2 output, the larger is the reallocation of production away from sector 2 and toward sector 1. However, the effect on aggregates is relatively minor, and the welfare cost is slightly larger if there is less substitutability. An important implication is that the size of the effects on sector 2 is not necessarily a good indication of the overall welfare loss. Specifically, comparing the effects on hours worked in sector 2 between the cases of $\rho = +.25$ and $\rho = -.25$, we see that the decrease is more than one and half times larger when $\rho = +.25$, but that the welfare losses are really quite similar.

4.4. Extensions

Consistent with the earlier analysis, one can consider any number of extensions to the simple prototype that I have described. To the extent that one is concerned about the labor market consequences of dislocation, there are a couple of different features that could be incorporated. One simple feature is to assume that there are labor adjustment costs in the technology, i.e., in addition to the possibility of utility costs associated with moving labor input across sectors. A second, and related possibility is that one could assume that there is sector specific human capital. One could model human capital accumulation in different ways, but one way would be to assume that there is human capital accumulated via a learning by doing technology. One might also want to consider the possibility of sector specific physical capital, as noted earlier. These features might be particularly relevant for understanding transition dynamics. While transition dynamics in this model will be a little bit more complicated than in the simple one sector growth model and I have not explicitly discussed them, it is certainly feasible to compute transition dynamics in this model.

5. Conclusion

The goal of this paper has been to summarize a method that can be used to evaluate the aggregate effects of environmental regulations for both allocations and welfare, with a particular emphasis on contexts which are dynamic and in which labor market effects are present. The approach described here is structural, in the sense that it specifies a given structural model and uses the model to predict how a given change in regulation will affect the equilibrium outcomes in the economy. I have developed a simple hybrid model which amounts to embedding industry equilibrium analysis into an otherwise standard version of the one sector growth model. I argue that this is likely to be a useful framework for assessing environmental regulations that are largely focused on a particular industry, but which at the same time are thought to potentially have important aggregate consequences. The structure I described allows for a rich description of establishment dynamics in the industry of interest, and allows for a fairly flexible yet tractable assessment of the general equilibrium effects.

The focus in this paper has been on describing a general method, rather than in producing a particular assessment of a given policy or regulation. For purposes of transparency in exposition, I have focused on the simplest possible specifications, and considered some fairly generic types of regulations to illustrate the method. But I have also tried to emphasize that the methods described here can be used in much more complex versions of the models that I described. For specific applications this is likely to be important.

An issue that I have not addressed here is the extent to which the methods I have described can offer reliable assessments of the effects of policies. While it is useful to know that the method can accommodate a wide range of specifications, the method will only be useful if one can establish that particular specifications do give reliable answers to questions of interest. This is an issue at the forefront of applied research in macroeconomics and applied economics more generally, and will require that we confront the predictions of specific versions of the model with observed outcomes that result from specific changes in regulation. Developing these models and assessing their reliability is a key issue for future research.

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Can Sorting Models Help Us Evaluate the Employment Effects of Environmental Regulations?

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Can models of worker and household sorting be used to consistently evaluate environmental regulations that affect the demand for labor? We take the first steps toward building unemployment into a model of sorting across the housing and labor markets. To demonstrate how the model could, in principle, be used to assess a prospective regulation, we build a "layoff simulator" for Northern California. Our simulator replicates stylized facts about earnings losses from mass layoffs. Moreover, the simulator suggests that earnings losses may be a poor proxy for welfare if unemployment increases the probability of migration. Finally, we find that the state of the business cycle (recession vs. expansion) is important for predicting changes in earnings and welfare.

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How important are the employment effects of federal regulations? Some regulatory evaluations include estimates for the number of jobs that are expected to be created or destroyed, but there is no widely accepted framework for monetizing these effects. Five consecutive years of high unemployment have motivated policymakers to look for ways to integrate employment effects into benefit-cost analyses (OMB 2012). Most of the discussion to date has focused on ideas for adjusting measures of lost earnings to anticipate the duration of unemployment (Mansur and Posner 2012). In this paper, we extend the literature to begin to consider spatial aspects of the problem.

The majority of job searches are inherently spatial.[1] A worker's job location limits where he can live, and his house location limits where he can work. These constraints link the housing and labor markets in ways that influence the spatial mobility of the labor force. For example, according to the American Housing Survey, "new job or job transfer" is the second most frequently cited reason for moving out of a former dwelling.[2] Likewise, "convenient to job" is the most frequently cited reason for selecting a new neighborhood. These statistics reinforce the need to consider the implications of layoffs for spatial mobility. If an unemployed worker's best job offer is far from his house, then he may decide to move. If he perceives the quality of life in his new neighborhood to be lower (higher) than his old neighborhood, then he may experience a significant welfare loss (gain) in addition to any change in earnings.

Equilibrium models of Tiebout sorting are often used to predict the welfare effects of policies that influence the quality of life by altering the spatial distribution of public goods. Most applications assume the policy has no effect on wages or employment (Kuminoff, Smith, and Timmins 2013). However, a few recent studies have adapted the canonical Tiebout framework to model links between work-

[1] Approximately 75% of U.S. workers report that they spend no time telecommuting (Noonan and Glass, 2012).

[2] The most frequently cited reason is "to establish own household". See appendix tables A1 and A2 for a historical summary of key findings from the Census Bureau's American Housing Survey from 1999 through 2009.

ers' participation in the housing and labor markets (e.g. Kuminoff 2010, Bishop 2011, Mangum 2012). In this paper, we extend Kuminoff's model to develop a framework for evaluating the welfare effects of a prospective regulation that would improve environmental quality while simultaneously generating layoffs. In order to assess the potential importance of labor market migration for the welfare effects of layoffs, we build a "layoff simulator" for Northern California.

I. Overview of Methods and Results

Our analysis is based on a model of how people decide where to live and work. Households are assumed to differ in their job skills and in their preferences for local public goods, housing, and a composite private good. Different job locations offer different (wage, commuting) options. House locations differ in the public goods they provide, and in the price of housing. Each household is assumed to weigh its options before choosing the job-house combination that maximizes its utility. Kuminoff (2010) develops an empirical model of this choice process and calibrates it to data from Northern California.

In this paper, we extend Kuminoff's model to introduce unemployment. When a worker in our model loses his job, he experiences a temporary unemployment spell. Its duration may vary with the worker's skills and with the state of the broader economy (e.g. recession versus expansion). At the end of the unemployment spell, the worker finds a new job. We force the worker to move to his best available job in a different metro area, holding the worker's occupation fixed but allowing him to change industries. Thus, unemployment is treated as a constraint on the worker's labor market mobility. Forcing unemployed workers to migrate allows us to evaluate the *potential* for labor market migration to influence the welfare effects of layoffs. A key feature of our model is its ability to capture the richness of commuting options in a major urban area. Northern California is comprised of eight contiguous metropolitan areas, making it possible to commute between some of them (e.g. live in Oakland, work in San Jose).

Table 1: Wage and Welfare Effects of Layoffs, by Original Job Location

	(1)	(2)	(3)	(4)	(5)	(6)
			Share experiencing an increase in:			
Job Location in 2000	Expected change in real wages	Δ in wages / Δ in welfare	housing price	air quality	school quality	commute time
Northern California	-5,547	76%	0.27	0.42	0.55	0.59
Oakland MSA	-5,452	81%	0.22	0.31	0.59	0.57
Sacramento MSA	-2,604	35%	0.68	0.83	0.28	0.78
San Francisco MSA	-6,603	86%	0.12	0.20	0.63	0.47
San Jose MSA	-7,237	89%	0.13	0.46	0.58	0.52
Santa Cruz MSA	-6,703	119%	0.16	0.61	0.80	0.78
Santa Rosa MSA	-5,621	97%	0.26	0.30	0.68	0.73
Vallejo MSA	-3,347	58%	0.34	0.31	0.48	0.79
Yolo MSA	-3,125	52%	0.55	0.72	0.58	0.79

Note: Column 1 reports the expected change in real wages. It equals the change in annual wages from moving to a new job plus an annualized measure of the wages lost during a spell of temporary unemployment. Column 2 reports the change in wages as a share of equivalent variation (EV). EV reflects the changes in wages, housing prices, local public goods, and commute times experienced by households who lose their jobs. Columns 3 through 6 report the shares of households experiencing increases in housing prices, air quality, school quality, and commute times at their new locations. The underlying calculations and assumptions are explained in the main text.

Table 1 summarizes our main results. The model predicts that the average Northern California worker's wage would decline by $5,547 if he were to lose his job and relocate to a different metro area (column 1). Approximately 70% of this reduction is due to a loss of job-specific human capital. The other 30% comes from wages lost during his unemployment spell. Our layoff simulator predicts that earnings losses account for only 76% of the change in welfare (column 2). The remaining welfare losses come from a novel margin: even after workers find new jobs, they often face a tradeoff between moving to a less desirable community with, for example, lower air quality (column 4) or remaining in their current community and driving a longer commute (column 6).

Our model also predicts that the wedge between the earnings effect and the welfare effect will differ greatly across workers according to their age, experience, education, occupation, job skill, preferences, and geographic location. For example, workers who lose their jobs in the Sacramento metro area experience relatively small reductions in wages when they move to new jobs (row 3). However, most of them end up in more expensive communities with lower quality schools. The reduction in their quality of life accounts for 65% of the welfare effect from losing their job. In contrast, the reduction in earnings experienced by the average worker in Santa Cruz exceeds their reduction in welfare. This is because people who move out of Santa Cruz often end up in communities where they pay less for housing and have access to better performing public schools.

The results in table 1 are based on a "normal" state of the business cycle in which workers who lose their jobs are unemployed for an average of 6 months. We also consider "recession" and "expansion" scenarios, adapting the methodology from Shimer (2005, 2012) to model the distribution of unemployment spells in each scenario. Not surprisingly, we find that the state of the business cycle matters for the welfare effects of layoffs.

Overall, our findings suggest that spatial migration has the potential to be of first order importance for evaluating the welfare effects of layoffs. This conclusion is general. We do not evaluate any specific regulation. In principle, our simulator could be adapted to predict the welfare effects of a specific regulation targeting air pollution or school quality that would also affect the demand for labor. The simulator can also be easily modified to embed any assumption about the share of unemployed workers who will find new jobs in the same metro area.

Of course, we abstract from reality in several ways. We do not estimate the effects of regulations on firm profits or on the deadweight loss from unemployment insurance programs. Moreover, our analysis has a static partial equilibrium perspective. We do not model moving costs, dynamics, or general equilibrium adjustments to housing prices, wages, and endogenous local public goods. For example, high unemployment could cause housing prices to fall. This might benefit renters, while reducing homeowners' assets and increasing their probability of foreclosure. These are important considerations for future research.

The remainder of the paper is organized as follows. Section II outlines the conceptual sorting model from Kuminoff (2010) and then extends it to consider layoffs. Section III explains how we calibrate the model and use it to build our layoff simulator. Section IV presents results, Section V discusses caveats, and Section VI identifies important directions for future research. Finally, section VII provides some concluding remarks.

II. An Intra-Urban Sorting Model with Unemployment

A. The spatial landscape

Consider an urban area containing $k = 1, \dots, K$ labor markets and $j = 1, \dots, J$ housing communities. Each (j,k) pair represents a unique house-job combination, and each combination requires a commute time, $t_{j,k}$. Communities differ in the annualized after tax price of housing, p_j, and in a vector of local public goods, g_j. Public goods are defined here to include services produced from tax revenue, such as public school quality, as well as environmental amenities such as air quality.

Households differ in terms of their exogenous nonwage income (*nw*), their relative preferences for different public goods (γ), and their overall preferences for public goods relative to private goods (α). Let $q_j(\gamma)$ represent the composite provision of public goods in community j as perceived by a household with γ-type preferences. Since households differ in their preferences over public goods, they may differ in the way they rank communities by overall public goods provision. Households also differ in their disutility of commuting to work (ϕ).

Workers are assumed to face spatially differentiated job opportunities. Let

$w_k(\theta)$ represent the wage schedule in labor market k. It defines the wages paid to workers as a function of their job skill, θ. One can think of $w_k(\theta)$ as a hedonic wage function. The k subscript on the wage function recognizes that, conditional on skill, a worker may be compensated differently in different labor markets due to spatial variation in regulation, tax rates, agglomeration effects, local cost-of-living adjustments, unionization, and other factors that affect labor demand.

Working households are assumed to be price-takers and to have perfect information about the spatial landscape.[3] They evaluate their feasible job-house locations and select the combination that maximizes their utility from consumption of housing (*h*), a numeraire good (*b*), public goods, and commute time,

$$(1) \qquad \max_{j,k,h} U\left[q_j(\gamma_i), h_j, b, t_{j,k}, \alpha_i\right] \quad subject\ to\ \ y_{i,k} = p_j h_j + b.$$

Their interrelated choices in both markets will determine their income ($y_{i,k}$) and their annual expenditures on housing ($p_j h_j$). Assuming households are free to choose continuous quantities of housing in each community, the utility maximization problem can be rewritten in indirect terms: $V\left[q_j(\gamma_i), t_{j,k}, \alpha_i, y_{i,k}\right]$.

B. Indirect Utility

Equation (2) provides a parametric expression for the indirect utility obtained by household *i* in community-job *j,k*.[4] The first term in the CES function represents utility from public goods, and the second represents utility from the private good component of housing and the disutility from commuting.

[3] While the model allows some households to be retired, they do not play a direct role in our analysis. Retired households are assumed to ignore the labor market. They select a community, which determines their housing expenditures and their consumption of public goods.

[4] For additional background on the properties of this specification for utility see Epple and Sieg (1999), Sieg et al. (2004), and Kuminoff (2010).

(2) $$V_{i,j,k} = \left\{ \alpha_i \left(q_{i,j}\right)^{\rho} + \left[\exp\left(\frac{y_{i,k}{}^{1-\nu} - 1}{1-\nu} - \phi_i t_{j,k} \right) \exp\left(-\frac{\beta P_j^{\eta+1} - 1}{1+\eta} \right) \right]^{\rho} \right\}^{\frac{1}{\rho}},$$

$$\text{where} \quad q_{i,j} = \gamma_{i,1} g_{1,j} + \ldots + \gamma_{i,N-1} g_{N-1,j} + \gamma_{i,N} \xi_j \,.$$

All households are assumed to share the same elasticity of substitution between public and private goods (ρ) as well as the same housing demand parameters: price elasticity (η), income elasticity (ν), and demand intercept (β). Applying Roy's Identity yields a Cobb-Douglas demand curve for housing,

(3) $$h_i = \beta p_j^{\eta} y_i^{\nu} \,.$$

While households are assumed to share a common set of demand parameters, individual demand varies with income.

Households also differ in their preferences over a linear index of public goods provided by each community, $q_{i,j}$. Of the N public goods in the index, *N-1* are observable. The N^{th} public good ($g_{N,j} = \xi_j$) is not observed by the econometrician.[5] Households differ in the weights they place on each public good in the index $\left(\gamma_{i,1},\ldots,\gamma_{i,N}\right)$ and in their overall preferences for public goods relative to private goods $\left(\alpha_i\right)$. The weights are assumed to sum to 1, allowing α_i to be defined separately as a scaling parameter on the strength of preferences.

The primary earner of each household is assumed to possess skills that determine the wages they would earn in each job location. Job skill is divided into observed and unobserved components: $\theta = [x, \varepsilon]$. The worker's age, education, and occupation (e.g. biomedical engineer, locksmith, lawyer) are among the ob-

[5] ξ_j can be interpreted as a composite index of all the *unobserved* public goods under the restriction that they are vertical characteristics; i.e. the weights in the index of unobserved public goods are all constants. This is an example of the "pure characteristics" approach to modeling the utility from a differentiated product (Berry and Pakes 2007).

servable dimensions of skill represented by x. Unobserved features of skill, such as the quality of the worker's education and their "ability", are represented by ε.

Each household's total income is observed at their chosen location $\left(y_{i,k^*}\right)$ along with the primary earner's hourly wage $\left(w_{i,k^*}\right)$ and hours worked $\left(h_{i,k^*}\right)$. Nonwage income (nw_i) is defined as the difference between wage income and total income: $y_{i,k^*} = nw_i + h_{i,k^*} \cdot w_{i,k^*}$. These objects are combined with the observable attributes of job skill to define household income at every possible location:

(4.a) $\quad y_{i,k} = y_{i,k^*}$ $\qquad$ at the observed job location, k^*.

(4.b) $\quad y_{i,k} = nw_i + h_{i,k^*} \cdot \left[\overline{w}_k(x_i) \cdot \varepsilon_{i,k}\right]$ $\qquad$ at any other job location: $k \neq k^*$.

A household's total income is observed at their chosen location (4.a). Equation (4.b) defines the counterfactual income a working household would receive if its primary earner were to move to a different job. Nonwage income (including the wages of any secondary earners) and hours worked are assumed to remain the same. However, the wage that the primary earner would earn in their new job depends on the local demand for their skills. $\overline{w}_k(x_i)$ represents the average wage paid to observationally equivalent workers in labor market *k*. If $\varepsilon_{i,k}$ is greater (less) than 1, worker *i* would earn more (less) than the average wage. Notice that the *k* subscript on $\varepsilon_{i,k}$ allows for spatial heterogeneity in the market value of a worker's idiosyncratic skills. For example, a lawyer who is highly skilled in agricultural law may have $\varepsilon_{i,k} > 1$ in a job location dominated by farming and $\varepsilon_{i,k} < 1$ in a job location dominated by manufacturing.

The job location decision can present working households with a long-run tradeoff between leisure time and the consumption of private goods. Holding his house location fixed, a worker may be able to increase his wage by commuting to a more distant labor market. His willingness to make this commute depends, in part, on $\phi_i t_{j,k}$, where ϕ_i is a parameter describing his disutility from commuting and $t_{j,k}$ is the commute time between *j* and *k*. For a worker with $\phi_i = 0$, there is no disutility from commuting. As ϕ_i increases, so does the threshold wage needed to induce the worker to lengthen their commute. By influencing a worker's job location, ϕ_i can affect the amount of income his household has to spend on housing and other private goods.

The specification for utility in (2)-(4) generalizes the Epple-Sieg (1999) model of neighborhood sorting that has been used to estimate preferences for air quality in the Los Angeles metro area (Sieg et al. 2004) and to evaluate the welfare implications of the Clean Air Act Amendments (Smith et al. 2004). Specifically, equation (2) reduces to their specification for utility in the special case where wage income is exogenous to location choice, households have vertically differentiated preferences (i.e. $\gamma_i = \gamma$ for all *i*), and the joint distribution of preferences and income is lognormal. We now proceed to extend the model in (2)-(4) to depict job transitions for workers who unexpectedly lose their jobs.

C. Job Transitions

If a worker is laid off, the transition to a new job may take some time. The unemployed worker must prepare a resume, search for vacancies, and go through an interview process. If a prospective job is located far away, the worker may choose to search for housing simultaneously. We denote by ω_{rst} the probability that a worker who loses their job in industry *r* at time *t* will find a job within *s* weeks. We propose to construct ω_{rst} using the actual job-finding experiences of workers who experience unemployment in the data. In practice we consider three temporal scenarios for the incidence of job loss: losing a job during a boom, when jobs are relatively easy to find; losing a job during an "average" period; and losing a job during a severe recession, when jobs are difficult to find. By allowing for temporal variation we can address the question of whether aggregate business cycle conditions are relevant for cost-benefit analyses of environmental regulations that induce layoffs.

Finally, during the interim when a worker is looking for a new job we assume the worker collects unemployment insurance, ui_i. In this case, household income can be rewritten as

$$(5) \qquad y_{i,k} = nw_i + ui_i,$$

where $ui_i = h_{i,k^*} \cdot w_{i,k^*} \cdot \tau$. Unemployment insurance payments are expressed as a constant fraction (τ) of the worker's wage at the job they lost, consistent with current U.S. policy.

D. Welfare Implications of a Regulation with Employment Effects

Consider a policy that reduces pollution, while creating layoffs (or new job vacancies) in the targeted sector. If these changes are small relative to baseline pollution and employment, there may be little or no adjustment to market prices.[6] Equation (6) defines a partial equilibrium measure of annualized equivalent variation for a household that is unaffected by the layoffs or job vacancies.

$$(6) \qquad V\left[q_j^1(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k}\right] = V\left[q_j^0(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k} + EV\right].$$

EV is the amount of money one would have to give household *i* in year 0 (before the regulation) to make them as well off as they are in year 1 (after the regulation), given the change in environmental quality experienced by the household.

[6] In the case of a regulation that produces a "large" shock to the housing and labor markets, a sorting model such as this one can be used to simulate ex post equilibria, taking into account changes in housing prices, wage rates, and commuting patterns. However, fairly strong restrictions on preferences are required to guarantee the equilibrium is unique. Current research is focused on evaluating the external validity of these models. See Kuminoff (2011) and Kuminoff, Smith, and Timmins (2012) for a discussion.

Similar to the welfare measures reported in most empirical applications of sorting models, equation (6) holds job location and income fixed.

Welfare calculation is more complicated for the workers who move to new jobs following the regulation. These workers may have unemployment spells, adjustments to their wages, and adjustments to their job and / or house locations. These factors are reflected in the following, more general, measure of EV,

$$(7) \qquad V\left[q_l^1(\gamma_i), p_l, t_{l,m}, \alpha_i, \phi_i, y_{i,m}^1\right] = V\left[q_j^0(\gamma_i), p_j, t_{j,k}, \alpha_i, \phi_i, y_{i,k}^0 + EV\right].$$

The *l*,*m* subscripts on locations to the left of the equality recognize that when a temporarily unemployed worker moves to a new job, that job may be located in a different metropolitan area; i.e., the worker moves from k to m. This relocation may also induce the worker to move to a new housing community; i.e., from *j* to *l*. Alternatively, the household may choose to adjust one location, while keeping the other fixed: $(j = l, k \neq m)$ or $(j \neq l, k = m)$. For example, a worker who loses his job and finds a lower-paying one in the same metro area may decide to move to a similar house in a less expensive community with fewer public goods.

Because the model is inherently static, it assumes that each worker's next job is their second-best choice, without accounting for any intervening or temporary jobs. Likewise, it assumes that they earn their long-run salary immediately, without accounting for any initial period of lower salary or higher salary growth. The lack of dynamics also complicates the treatment of unemployment spells. As a matter of convenience, we convert the wages lost during the worker's unemployment spell into an annuity, using the worker's expected lifespan and an interest rate set to match the cost of a borrowing on a 30-year fixed rate mortgage. Intuitively, we are assuming the household finances its consumption during the unemployment spell by borrowing against their house, spreading the temporary wage shock across the worker's expected lifespan.

Equation (8) decomposes ex post annual real income into three components.

$$(8) \qquad y_{i,m}^{1} = h_{i,k^*} \cdot \left[\overline{w}_m(x_i) \cdot \varepsilon_{i,m}\right] + nw_i - A_i \ .$$

The first component is the wage at the worker's new job: $h_{i,k^*} \cdot \left[\overline{w}_m(x_i) \cdot \varepsilon_{i,m}\right]$. The worker is assumed to work the same number of hours as he did at his old job, h_{i,k^*}.[7] His hourly wage depends on the quality of his match to his new job, determined by the market specific skill parameter ($\varepsilon_{i,m}$). The second component is the household's nonwage income, which is also assumed to be fixed. The final component is our annualized measure of the total wages lost during the worker's period of temporary unemployment:

$$(9) \qquad A_i = \left[\frac{d_i}{12} \cdot \left(h_{i,k^*} \cdot w_{i,k^*}\right) \cdot (1-\tau)\right] \left(\frac{e^{\pi}-1}{1-e^{-\pi N}}\right),$$

where d_i indicates the number of months the worker is unemployed and $1-\tau$ measures the share of monthly income lost after the worker collects unemployment insurance. Thus, $\left[\frac{d_i}{12} \cdot \left(h_{i,k^*} \cdot w_{i,k^*}\right) \cdot (1-\tau)\right]$ is the total wage income lost during the period the worker is unemployed. It is annualized over the number of years the worker can expect to live, *N*, using an interest rate of π.[8]

Equation (9) is consistent with the idea that some workers who find new jobs may be underemployed. Underemployment is modeled here at the extensive margin. That is, the worker's occupation and hours worked are assumed to be fixed, but his second-best job option may be in an industry that does not allow him to fully utilize his occupational skills. The loss of industry-specific or job-specific human capital may cause the worker's wage to decline.

[7] To relax this assumption, one would need to extend the sorting model to include a labor supply decision at the intensive margin.

[8] If a new regulation creates jobs, the additional vacancies will mechanically reduce the average duration of unemployment. The opposite will be true if the regulation produces layoffs. However, these changes will be small as long as aggregate layoffs from the regulation are small relative to current unemployment.

Together, equations (7)-(9) illustrate how the spatial and temporal dimensions of unemployment affect welfare measures generated by a static sorting model. These equations also illustrate why household mobility should prevent us from interpreting observed changes in earnings as measures of the welfare effects from layoffs or newly created jobs. Specifically, equation (9) illustrates how changes in earnings fail to account for the welfare implications of: (i) changes in commute time for households moving from j,k to l,m; (ii) changes in housing expenditures for households moving from j to l; and (iii) changes in the public goods consumed by households moving from j to l.

As an extreme case, consider a worker who, prior to the regulation, chose to work at a low paying job in order to live in a desirable community. If the worker loses his job because of the regulation, his next best alternative may be to move to a less desirable community near a higher paying job. If the worker's unemployment spell is brief, his annualized income could actually increase despite the fact that he is worse off from the move. Our point is simply that changes in earnings may understate or overstate welfare effects. The direction of the bias depends on whether the displaced workers move to neighborhoods with housing options, commuting options, and amenity bundles that they perceive to be more or less desirable.

E. Differences from a Conventional General Equilibrium Model

Compared to a conventional general equilibrium (GE) model of the economy, our sorting framework puts more emphasis on understanding the distribution of wage effects and welfare effects experienced by workers, and less emphasis on placing these effects within the context of social welfare. This allows us to approach the problem at a high level of resolution. For example, we can investigate the extent to which wage effects and welfare effects vary across working households according to demographic characteristics we can observe (e.g. income, occupation, industry) and according to estimated parameters representing unobserved features of their human capital and preferences for public goods. The sorting model also allows us to consider the role of space, recognizing that adjustments to earnings and public goods may be conveyed to households through spatial adjustment. In contrast, most GE models lack a spatial dimension. Finally, unlike most applied GE models, our sorting framework allows utility to be nonseparable in public goods.[9] This is important because it enables us to invoke the logic of revealed preferences to infer households' willingness-to-pay for environmental quality from observed tradeoffs between a complementary private good (housing) and the numeraire.[10] Thus, we can use the sorting model together with the logic of revealed preferences to consistently evaluate policies that improve environmental quality and simultaneously shock the demand for labor.

The flexibility allowed by our sorting model also comes at a cost. While it depicts interrelated behavior in multiple markets, it is a partial equilibrium framework. Unlike most GE models, the price of the numeraire good is assumed to be unaffected by shocks to the housing and labor markets. Furthermore, the lack of an explicit model of the firm or government means that we cannot construct measures of producer surplus, social welfare, or the deadweight loss from unemployment insurance schemes. Finally, unlike the broad class of dynamic stochastic GE models used in macroeconomics, our sorting framework does not allow us to predict the adjustment path to a new equilibrium.

III. Using the Model to Simulate Wage and Welfare Effects of Job Losses

In order to demonstrate how the sorting model could help us evaluate a regulation that is expected to induce layoffs, we use it to construct a "layoff simulator"

[9] The computable general equilibrium model developed by Carbone and Smith (2012) is a notable exception. See their paper for a discussion of the issues involved with building nonseparable preferences into general equilibrium models.
[10] More precisely, nonseparability recognizes that changes in environmental quality may affect marginal rates of substitution between different private goods. Assuming a parametric form for utility that satisfies Mäler's weak complementarity restriction then allows us to infer Hicksian welfare measures from observed behavior.

for Northern California. We begin by summarizing how Kuminoff (2010) calibrated the location choice model in (2)-(4) to data from Northern California. Readers are referred to his paper for econometric details. Then we explain how we adapt the calibrated model to predict the wage effects and welfare effects of layoffs. This involves three steps: (i) a mechanism to mimic job loss; (ii) a mechanism to predict where an unemployed worker will find a new job and how this will affect their choice of house location; and (iii) a mechanism to predict the duration of unemployment.

A. Calibration to Northern California

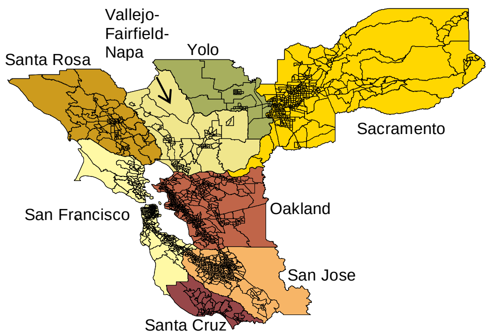
The model is calibrated to Northern California's two main population centers—the San Francisco and Sacramento consolidated metropolitan statistical areas.[11] Housing communities are defined by dividing the region into 122 unified school districts; job locations are defined by the region's 8 primary metropolitan statistical areas (PMSA), shown in figure 1.[12] The population is concentrated around the San Francisco Bay and the city of Sacramento, as seen by the density of census tracts in the map on the left. The set of possible location choices is defined by 268 community-PMSA combinations that, together, account for 99% of the working population.[13]

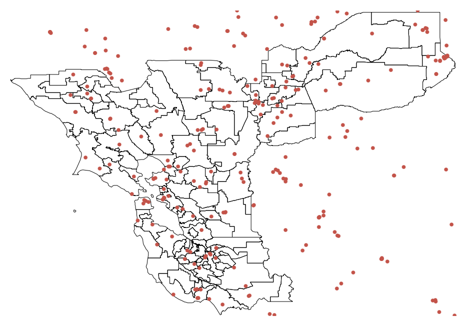
Housing prices were calculated from micro data on approximately half a million housing sales recorded by county assessors between 1995 and 2005. These data were used to calculate an index of community-specific housing prices using the hedonic procedure described in Seig et al. (2002). The index ranges from 1.00 to 6.51. Its distribution is consistent with the conventional wisdom that housing is particularly expensive in the Bay Area. All but one of the 25 most expensive

[11] This region contains approximately 9 million people, or 3% of the U.S. population.
[12] These definitions are standard ones in the empirical literatures on Tiebout sorting and Rosen-Roback sorting.
[13] The criterion used to select locations is that they must account for at least 500 working households (0.02% of the working population). This effectively excluded multiple-hour commutes between distant locations.

communities are located in the San Francisco and San Jose PMSAs.

Figure 1: San Francisco and Sacramento Consolidated Metro Areas





Notes: The map on the left illustrates census tracts overlaid on the eight primary metro areas in the study region. The map on the right illustrates the locations of air quality monitoring stations overlaid on public school districts.

Air quality is measured using concentrations of ground level ozone, one of the main components of urban smog. Northern California has some of the most spatially detailed information on ozone in the United States. The right-side map in figure 1 shows the locations of 210 monitoring stations in school districts. It is not uncommon for a district to have multiple monitoring stations. The exact ozone measure used is the average of the top 30 1-hour daily maximum readings recorded at each monitoring station during the course of a year. Households are assumed to be concerned with air quality near their house, not their job. Under this assumption, community-specific measures were constructed by first assigning to each house the ozone measure recorded at the nearest monitoring station, and then taking an average over all the houses in the community. Then, to control for annual fluctuation in ozone levels, the process was repeated for 1999, 2000, and 2001, and the results averaged. The final measure ranges from 0.031 (parts per million) in the highest air quality community to 0.106 in the lowest.

School quality is defined using California's Academic Performance Index (API), a composite index of standardized test scores, weighted across all subjects and grade levels. For each community, a three-year average API was constructed by weighting the score of each school in the community by its number of students from 1999-2001. The resulting measure ranges from 528 to 941. A set of community-specific fixed effects ($\xi_1,...,\xi_J$) is used to capture the composite effect of all other localized amenities on household location choices.

Finally, micro data on households and their location choices were drawn from the 5% micro data sample of the 2000 Census of Population and Housing. Key variables include house location, household income, and the primary earner's job location, occupation, industry, wage income, commute time, gender, age, race, and years of education.[14] If a worker were to move to a different job-house location, his counterfactual commute time is assumed to be the average commute time observed for that location.

Kuminoff (2010) uses these data to estimate the parameters of (2) for a 1-in-10 sample of Northern California households, randomly drawn using the Census PUMS household weights. Table 2 reports the estimated housing demand parameters used in our simulation. The price and income elasticities ($\eta = -0.39, \nu = 0.65$) are typical for empirical sorting models based on Epple and Sieg (1999). Given the signs of these parameters, the negative sign on ρ implies a downward sloping demand curve for public goods.

Table 2: Housing Demand Parameters Used to Calibrate the Model

β	η	ν	ρ
15.39	-0.39	0.65	-0.13

[14] Occupation is defined using the Standard Occupational Classification system. Industry is defined using the North American Industrial Classification System. Job and house locations are defined in the Census data as public use microdata areas (PUMA). In most cases, there is an exact mapping from PUMAs to PMSAs and unified school districts. In cases where PUMA boundaries overlap school district boundaries, we assigned households to communities based on the assumption that people are uniformly distributed across PUMAs.

Kuminoff partially identifies the heterogeneous parameters representing households' preferences and skills, adapting the logic of Manski (2007) and building on the econometric techniques of Bajari and Benkard (2005). This involves using a system of revealed preference inequalities to recover a separate set of values for $(\alpha_i, \gamma_i, \phi_i, \varepsilon_i)$ that is consistent with the observed behavior of each household. We use these preference sets to calculate measures of expected equivalent variation under the assumption that preferences are uniformly distributed within each set.

B. Mimicking Job Loss

We mimic the experience of losing a job by removing the primary earner's current job location from his choice set. The worker is forced to move to a new job in one of the seven remaining PMSAs. Thus, unemployment is treated as a constraint on the worker's labor market mobility. Forcing unemployed workers to migrate allows us to evaluate the *potential* for spatial migration in the labor market to influence the welfare effects of layoffs.

C. Predicting the Spatial Location of a New Job

After removing a worker's current job location from his choice set, we can determine which of the remaining PMSAs would maximize his utility, conditional on a draw for the heterogeneous parameters. This process works by assigning each worker to a job in his second-best spatial location. When a worker moves to a new PMSA he may find work in a different industry, but his occupation is assumed to be unchanged. We define occupations using 5-digit codes from the Standard Occupational Classification system. This allows us to match each worker to the range of wages paid to other workers with similar training.[15] Whether a

[15] For example, the 5-digit SOC codes distinguish between five types of social scientists: economists, market and survey researchers, psychologists, sociologists, and urban and regional planners.

worker's wage rises or falls at his new job depends on his idiosyncratic skills (ε_{ik}).[16] After moving to a new job location, the worker may choose to remain in the same housing community. If, however, the necessary commute time induces the worker to move to a different community, then his change in utility will also depend on his household's idiosyncratic tastes for amenities ($\alpha_i, \gamma_i, \phi_i$) in relation to the amenities provided by the new community. Thus, a household may prefer the amenities provided by the new community and the household's income may rise at the primary earner's new job, but both cannot occur simultaneously. Utility must decline when the household's preferred location is removed from their choice set.

There are three caveats to our predictions. First, recall that our model focuses exclusively on the primary earner's contribution to household income. Non-wage income is assumed to be fixed. Thus, we are ignoring any changes in commuting or wages that would be experienced by secondary earners in a household. In order to consistently predict how the incomes of secondary earners would adjust, the sorting model would need to be extended to depict bargaining within the household.[17] Second, we do not allow unemployed workers to move to lower-pay lower-skill jobs in the same metropolitan area (e.g. a machinist working as a cashier).[18] Again, the estimator does not identify skill parameters that would enable us to consistently model this possibility. Finally, since the heterogeneous preferences parameters are set identified, rather than point identified, we must address our uncertainty about the model's predictions for a particular household's ex post utility. We do this by integrating over the preference set recovered for each

[16] Recall that these parameters are recovered during the estimation.
[17] We return to this idea in section IV as a potential area for future research.
[18] The welfare effects of this outcome would lie within the range reported in the last two rows of table 3. We plan to model localized underemployment in future research.

household, assuming a uniform distribution, and then use the result to calculate a measure of expected equivalent variation.[19]

D. Predicting the Duration of Unemployment

Earnings losses and welfare effects will also depend on the duration of unemployment, as shown in (6)-(9). We address this by calibrating our layoff simulator to reflect the duration of unemployment spells observed in the Current Population Survey (CPS) at different stages of the business cycle.

The primary goal of the CPS is to provide monthly data on the labor market status of a sample of approximately 60,000 Americans. We construct from these files the subsample of unemployed workers age 16 or older between January 2002 and February 2012. We focus on this time period because the industry classifications were consistent over time, enabling us to construct industry-specific job finding rates. The CPS asks each unemployed worker how long they have been unemployed. Given the total number of workers unemployed at date t, u_t, and the number unemployed for more than s weeks at date $t+s$, u_{t+s}^s, we can construct an approximation to the job finding rate at various durations as:

$$(10) \qquad \omega_{s,t} = 1 - u_{t+s}^s / u_t \ .$$

The job finding rate ($\omega_{s,t}$) provides a measure for the share of workers who were unemployed at date t but found work within s weeks of that date. This technique follows Shimer (2005, 2012).

Since the CPS provides a wealth of information about unemployed workers, we can in principle calculate $\omega_{s,t}$ by industry of prior employment, geographic region, date of initial unemployment, and so on. In practice we calculate $\omega_{s,t}$ by

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[19] This is analogous to the standard practice of reporting measures of expected compensating variation calculated from random utility models that assume the presence of idiosyncratic preference shocks distributed according to a Type I extreme value distribution. Unlike a standard RUM, our model is partially identified. This makes it feasible to systematically evaluate the robustness of our results to the uniform distribution assumption. See Kuminoff (2010) for details.

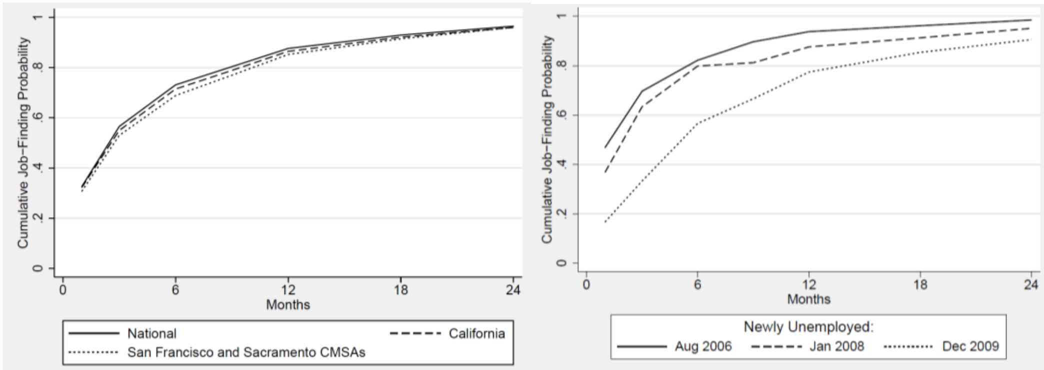
industry nationwide for a few key time periods. That is, we do not exploit the geographic information in the CPS to try to compute job finding rates specific to the San Francisco-Sacramento area. This choice is a conscious decision to focus on the margins of interest (differences in job-finding rates by industry and over the business cycle) in view of limitations on the available sample size.[20]

We abstract from geographic variation because our analysis indicates that job-finding rates for unemployed workers in the San Francisco-Sacramento area are similar to those for the nation as a whole. On the other hand, there are modestly larger differences by industry. Both of these differences are, however, dominated by the variation over the course of the business cycle. The right side graph in figure 2 shows the job-finding rates for workers who became initially unemployed in August 2006, January 2008, and December 2009. These months had the highest, median, and lowest job-finding rates in the first month in our CPS sample. By comparing this with the left side graph of figure 2, and with figure 3, one can see immediately that the differences in job-finding rates over the business cycle are much larger than those for geographic region or industry, and that they persist strongly for at least two years.[21] Our findings are consistent with the prior work of Hall (2006) and Shimer (2012), who document that variation in the job-finding rate over the business cycle explains most of unemployment fluctuations; and with the work of Şahin, Song, Topa, and Violante (2012), who document that cross-sectional mismatch explains little of aggregate unemployment, where mismatch is defined as variation in the vacancy-unemployment rate (e.g., tightness of labor markets) across geographic regions or industries/occupations.

[20] The primary problem is that the CPS is not a very large dataset. The calculation in (10) compares the number of unemployed workers at time t with the number of workers unemployed for at least k weeks during week $t + k$ (with the probability of finding a job during k weeks implicitly computed using the difference). This calculation provides useful results as long as the sizes of these cells are sufficiently large. In practice, cell sizes make it difficult to calculate job-finding rates for cross-tabulations. For example, we can reliably estimate job-finding rates for men or Californians or manufacturing workers, but not male manufacturing workers in California.

[21] Although the CPS documentation indicates that workers should be able to report almost arbitrarily long unemployment spells, we find that almost no workers report spells longer than two years, and that the maximum duration is 124 weeks. We truncate unemployment duration at two years.

Figure 2: Spatiotemporal Variation in the Cumulative Job Finding Probability



Note: The graph on the left displays the job finding probability for (i) the United States; (ii) California; and (iii) our study region. The graph on the right displays the job finding probability for workers who were newly unemployed in (i) August 2006; (ii) January 2008; and (iii) December 2009, our "expansion", "normal" and "recession" scenarios, respectively.

Figure 3: Cumulative Job Finding Probability, by Industry and Business Cycle

Note: These graphs display national cumulative job finding probabilities, by NAICS industry, for workers who were newly unemployed during expansion (Aug 2006), recession (Dec 2009), and normal (Jan 2008) periods. Job finding probabilities were estimated from data on unemployed workers in monthly CPS. In 1.6% of industry/month combinations, the estimated marginal job finding probability is negative due to sampling error. In these cases we use linear interpolation to restrict the job finding probability to be positive. Some 2-digit industries were aggregated to reduce sampling error. Specifically, Agriculture and Natural Resources = 11, 21; Manufacturing = 31-33; Wholesale/Retail Trade = 42, 44, 45; Transportation and Utilities = 22, 48, 49; FIRE = Finance and Insurance (52) and Real Estate and Rental and Leasing (53); Business Services = 54-56; Education and Health = 61-62; Entertainment and Food = 71-72; and Other Services = 51, 81, 92.

Since variation over the business cycle and industry of prior employment seem to be the most important channels, we focus on these. We perform three sets of welfare calculations. In each we assign to unemployed workers the job-finding rates that prevail in the data for workers from their industry at the national level. The calculations differ only in the assumed business cycle conditions. In particular, we feed in the actual job-finding probabilities that prevailed in August 2006, January 2008, and December 2009, which replicate “expansion”, “normal”, and “severe recession” labor markets. Doing so allows us to address whether aggregate economic conditions are important for the implied welfare costs of job loss from environment regulations.

IV. Results from the Northern California Model

Table 3 presents our aggregate results. All figures in the table are based on iterating over a random 1-in-10 sample of Northern California households, drawn using the Census Bureau’s household weights. Panel A summarizes the wages lost due to temporary unemployment. Wages lost per worker during the unemployment spell ranges from an average of $15,224 in our expansion scenario to an average of $30,821 in our recession scenario. Following (9), we convert these figures to annuities:

$$A_i = lost\ wages * \left(\frac{e^{.07}-1}{1-e^{-.07N}}\right),$$

where N is the number of life years remaining for the worker, based on Center for Disease Control life tables for the year 2000, and the interest rate is set to 0.07 to match the 1995-2005 average interest rate on a fixed rate 30-year home loan. The annualized wage loss from temporary unemployment ranges from $1,231 to $2,493.

Table 3: Annual Wage and Welfare Effects of Simulated Layoffs, per Household

A. TEMPORARY UNEMPLOYMENT

	expansion	normal	recession
Mean unemployment duration (months)	4.60	6.14	9.41
Net wages lost during unemployment period (mean per worker)	-15,224	-19,978	-30,821
Annualized net wage loss (mean per worker)	-1,231	-1,618	-2,493

B. CHANGE IN ANNUAL SALARY

Assumption about New Job	expansion	normal	recession
Rehired at identical job in original location	0	0	0
Move to 2nd best (job, house) location	-3,929	-3,929	-3,929

C. EXPECTED EQUIVALENT VARIATION

Assumption about New Job	expansion	normal	recession
Rehired at identical job in original location	-1,231	-1,618	-2,493
Move to 2nd best (job, house) location	-6,986	-7,287	-7,936

Notes: The first row of panel A summarizes the mean unemployment duration for the three scenarios shown in figure 3. The second row reports the wages foregone during the unemployment period for the average worker, net of unemployment insurance. Workers are assumed to collect unemployment insurance at 36% of the old wages. Row 3 converts the total loss to an annuity, using the worker's expected life years remaining and an interest rate of 7%. Row 2 of Panel B reports the mean change in wage from moving to the worker's second best job. Panel C reports the expected equivalent variation, taking into account the unemployment spell along with changes in wage and job-house location.

Panel B reports the average difference in annual salary between workers' new utility maximizing jobs and their old jobs. We consider two scenarios for how layoffs affect employment opportunities. In the first row, we depict the best outcome for workers, in which being fired does not diminish their job opportunities. At the end of a worker's unemployment spell, he is simply rehired at his old job (or hired at an identical job in the same location). Thus, there is no change in the worker's salary. The second row reports the change in wages when all workers are forced to move to their second-best job locations. Annual wages decrease by nearly four thousand dollars in this case.

Finally, Panel C reports the expected equivalent variation. Expected EV is calculated by integrating equation (7) over the distribution of unemployment spells for each business cycle scenario. In the normal scenario, for example, the range of predictions for expected EV per household per year ranges from -\$1,618 under the scenario where the worker is rehired at an identical job to -\$7,287 in the scenario where the worker has to move to their second best job location. In the first case, the state of the business cycle is very important for welfare measurement, with a 100% difference in EV between the recession and expansion scenarios. In contrast, the state of the business cycle is relatively less important when workers have to relocate. In that case, our measures of EV are driven by changes in salary at workers' new jobs and by changes in utility from moving to different housing communities and different commuting options.

Table 4 disaggregates the results by demographic group. For brevity, we just report results for "normal" business cycle conditions. Our qualitative predictions for the changes in earnings are consistent with the stylized facts about demographic variation in the income effects of layoffs. For example, consistent with Mansur and Posner's (2012) summary of the evidence from ex post models of the earnings effects of layoffs, we observe that earnings losses tend to be (i) larger for men relative to women, (ii) increasing in experience, and (iii) increasing in age.[22] Since our intra-urban sorting model is not constrained to reproduce any of these results, the fact that it does provides some preliminary support for the model's validity. The model also predicts that earnings losses will tend to increase in the level of education and will tend to be larger for homeowners relative to renters.

These trends in earnings losses are driven, in part, by differences in ex ante wages. By construction, the demographic groups with higher ex ante wages will experience larger annualized earnings losses due to temporary unemployment (column 1). However, the sorting model predicts the same pattern of relative magnitudes in the component of earnings losses from moving to a different job (column 2). In this case, our predictions for the differences across demographic

[22] Also consistent with Mansur and Posner (2012), we see that the earnings effects vary across space. See table 5.

groups reflect our estimates for the joint distribution of preferences and skills, in addition to ex ante wages.

Table 4: Wage and Welfare Effects of Layoffs, by Demographic Group

	(1) Annual adjustment for temporary unemployment	(2) Change in annual salary	(3) Expected change in real wages	(4) Expected equivalent variation
Population	-1,618	-3,929	-5,547	-7,287
Gender				
women	-1,288	-2,418	-3,706	-5,570
men	-1,815	-4,833	-6,649	-8,313
Age				
under 40	-1,309	-2,828	-4,137	-5,956
40-60	-1,846	-4,892	-6,739	-8,401
over 60	-2,089	-4,431	-6,521	-8,278
Education				
less than 13 years	-980	-2,295	-3,275	-4,609
13-16 years	-1,306	-2,757	-4,063	-5,705
more than 16 years	-2,161	-5,594	-7,755	-9,764
Experience				
less than 10 years	-1,110	-1,698	-2,808	-4,863
10-20 years	-1,610	-4,165	-5,775	-7,489
more than 20 years	-1,795	-4,554	-6,349	-7,995
Homeownership				
renters	-1,167	-1,979	-3,147	-5,023
owners	-1,910	-5,192	-7,102	-8,752

Note: Column 1 reports the wage loss from temporary unemployment, converted to an annuity using each worker's age and life-year tables for the year 2000 from the Center for Disease Control. The annualized loss reflects an expectation over the distribution of unemployment durations corresponding to the job finding probability distribution during "normal" labor market conditions. Column 2 reports the mean change in annual salary when workers move to their second best job locations. Column 3 is the sum of columns 1 and 2. Finally, Column 4 reports the expected equivalent variation.

Comparing columns 3 and 4 reveals that, in general, our measures of expected equivalent variation exceed the total reduction in earnings. This is because the workers' new job locations tend to induce them to consume (housing price, public good, commuting) bundles that they perceive to be inferior to the bundles they originally chose. The magnitude of this effect is substantial. On average, the expected welfare change for a worker who relocates his job to a different PMSA is 31% larger than the expected change in his wages. Variation in the percentage difference across demographic groups arises from differences in their ex ante locations, preferences, skills, and job opportunities.

Table 5 begins to illustrate the mechanisms that underlie the variation in the wedge between earnings losses and EV by reporting both measures broken out by the worker's original job location, along with information on the experiences of movers. For seven of the eight PMSAs, expected EV exceeds the wage loss. The size of the wedge between them depends on the changes in housing prices, commute times, and amenities experienced by households. The average differential is largest for the workers who lose their jobs in Sacramento (186%) because Sacramento households have the lowest ex ante wages, housing prices, and consumption of many amenities. When Sacramento workers move to jobs in different PMSAs, the physical distance between their old and new jobs induces 91% of them to move to housing communities closer to their new jobs. While their earnings reductions are relatively low, they typically have to pay much more for housing in their new communities. Housing prices are higher, in part, because their new communities tend to have less air pollution and greater provision of the unobserved public goods captured by the ξ index. Yet, these amenity improvements are insufficient to compensate the average Sacramento household for the increase in housing prices. The worker's original choice to live in Sacramento revealed that his household has strong preferences for private goods relative to public goods. This specific example illustrates a more general implication of the sorting model. The workers who chose to live in "dirty" areas based on relatively weak preferences for environmental quality may experience disproportionate welfare losses if they are effectively forced by a regulation to move to "clean" areas where housing prices and amenities are both higher. This is especially important for policies establishing minimum standards on environmental quality, since these policies effectively target the dirtiest areas.

Table 5: Wage and Welfare Effects of Layoffs, by Original Job Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Share experiencing an increase in:				
Job Location in 2000	Expected change in real wages	Expected equivalent variation	Share moving to different community	housing price	air quality	school quality	ξ	commute time
Oakland	-5,452	-6,728	0.94	0.22	0.31	0.59	0.24	0.57
Sacramento	-2,604	-7,443	0.91	0.68	0.83	0.28	0.66	0.78
San Francisco	-6,603	-7,659	0.94	0.12	0.20	0.63	0.15	0.47
San Jose	-7,237	-8,117	0.96	0.13	0.46	0.58	0.08	0.52
Santa Cruz	-6,703	-5,624	1.00	0.16	0.61	0.80	0.11	0.78
Santa Rosa	-5,621	-5,781	1.00	0.26	0.30	0.68	0.27	0.73
Vallejo	-3,347	-5,770	0.93	0.34	0.31	0.48	0.37	0.79
Yolo	-3,125	-5,983	0.90	0.55	0.72	0.58	0.44	0.79

Note: Columns 1 and 2 report the same measures of the expected changes in real wages and EV as in table 4. Column 3 reports the share of workers who are predicted to move to a different housing community after finding a new job in a different PMSA. Columns 4 through 8 report the share of households experiencing increases in housing prices, air quality, school quality, unobserved public goods, and commute times after moving to their new locations.

In contrast, workers in the high wage areas of San Jose and San Francisco tend to experience large earnings losses when they move to new jobs, along with reductions in air quality and ξ when they move to new houses. However, the differences between their earnings losses and EV are relatively small (12% to 16% on average) because most of them pay less for housing in their new communities and many of them experience reductions in commute times.

Finally, it is worth noting that our layoff simulator can be used to investigate the implications of job losses for any subgroup of the population that can be identified on the basis of worker and/or household characteristics reported in the Census PUMS data. For example, potential subgroups of interest might include the worker's specific industry and occupation, the household's income, house location, and the presence of children in the household. Table 6 provides an example of this by summarizing the expected EV for households where the primary earner works in the manufacturing sector, by the worker's age and original work location.[23] In future evaluations of specific regulations, our simulator could be used to focus on a small subset of workers in the particular industries, occupations, and metro areas that are targeted by those regulations.

Table 6: Wage and Welfare Effects of Layoffs in the Manufacturing Sector

		Expected change in real wages	Expected equivalent variation	Share of manufacturing workers
All Manufacturing		-7,674	-8,800	1.00
Job Location in 2000	Age			
Oakland	under 40	-4,882	-6,082	0.09
	over 40	-7,900	-8,915	0.12
Sacramento	under 40	-3,075	-8,451	0.05
	over 40	-5,741	-11,761	0.05
San Francisco	under 40	-5,005	-6,653	0.06
	over 40	-7,899	-8,791	0.06
San Jose	under 40	-6,981	-7,947	0.21
	over 40	-11,676	-11,337	0.25
Santa Cruz	under 40	-7,368	-5,994	0.01
	over 40	-7,689	-6,157	0.01
Santa Rosa	under 40	-4,081	-4,326	0.02
	over 40	-8,031	-7,981	0.02
Vallejo	under 40	-2,727	-4,617	0.01
	over 40	-7,184	-8,623	0.02
Yolo	under 40	-1,618	-4,401	0.01
	over 40	-4,996	-8,145	0.01

Note: The table reports expected changes in real wages and equivalent variation for workers in the manufacturing sector (NAICS 31-33) broken out by the worker's age and original job location. See the text and notes to tables 3-5 for definitions of the variables in each column.

[23] Appendix table A3 provides a second example: the average changes in real wages and EV by industry.

V. Discussion

Previous studies have used models of neighborhood sorting in a major metropolitan region to evaluate spatial variation in the prospective and retrospective benefits of regulations targeting environmental quality and other public goods (Sieg et al. 2004, Smith et al. 2004, Walsh 2007, Tra 2010, Klaiber and Phaneuf 2010, and Kuminoff 2011). Our simulations demonstrate that there is potential to extend the existing models to adjust welfare measures for the reductions in earnings and utility experienced by workers who lose their jobs (or face new job opportunities) as a result of the regulation. It would be straightforward to extend our calibrated partial equilibrium analysis to simulate the welfare effects of a specific regulation targeting air pollution, commute times, or public school test scores, given that the regulation is expected to induce layoffs (or new job opportunities) in specific industries and metro areas in Northern California.

Our results suggest that the net reduction in earnings experienced by a worker who loses his job may significantly understate the reduction in welfare experienced by that worker's household. In our simulations, the workers who remain in the same houses after losing their jobs tend to experience longer commutes after they relocate to new jobs. Moreover, the workers who move to new housing communities, closer to their new jobs, tend to consume (housing, amenity) bundles that they perceive to be inferior to the bundles at their original locations.

The sorting model also predicted that workers who move to new jobs in different metro areas will tend to be paid less due to a loss of job-specific or industry-specific human capital. This prediction is consistent with evidence from ex post studies of mass layoffs in general (Couch and Placzek 2010) and ex post studies of layoffs caused by environmental regulation in particular (Walker 2012). However, we did not allow workers to adjust the number of hours they work, or to look for jobs outside of their SOC 5-digit broad occupation (e.g. education administrator, detective and criminal investigator, cook). Because we ignore these potential dimensions of underemployment, our predictions for earnings losses and welfare losses may be attenuated.

As with all revealed preference models of housing and labor market outcomes, our specific predictions for the welfare costs of job losses depend on assumptions about unobserved sources of heterogeneity in preferences and skills among workers and households. There are, of course, several other limitations of our analysis that serve as caveats to our results and define potential avenues for future research. First, we have ignored moving costs, forward looking behavior, and dynamics. While focusing on a small geographic area at least mitigates the potential bias from ignoring moving costs, emerging research suggests that these issues are likely to be collectively important for welfare measurement in the sorting literature (e.g. Bishop 2011; Bayer et al. 2011).

Second, we did not attempt to simulate general equilibrium effects. If a particular regulation were to induce enough people to move, their migration patterns could lead to adjustments in housing prices, wage rates, commute times, and the provision of local public goods which, in turn, would feed back into welfare measures. While it is possible to solve for a new equilibrium that embeds these adjustments, relatively little is known about the uniqueness of equilibria in such general environments (e.g. Sieg et al. 2004, Timmins 2007, Kuminoff 2011). This is an area where more research is needed.

Third, our Northern California model is obviously limited in its geographic scope, covering only 3% of the U.S. population. Unfortunately, the model does not provide an easy way to predict immigration or emigration outside the study region. Moreover, the basic idea of spatial sorting suggests that unobserved heterogeneity in preferences and skills presents a fundamental problem for "function transfer" or "value transfer" approaches to transferring estimated welfare measures outside the geographic region of an existing study.[24]

Fourth, our focus has been limited to considering the welfare effects experienced by working households. We have not attempted to model the costs borne by employers. Nor have we attempted to model the deadweight loss of unemployment insurance programs. Thus, our model does not allow us to comment on the implications of a regulation for social welfare.

Finally, the basic idea of using a sorting model to simulate the welfare effects of layoffs presupposes that the analyst begins with a range of values in mind for the potential layoffs that could result from a prospective regulation. That is, the current generation of sorting models does not allow us to endogenously predict how a prospective regulation will affect the demand for labor. To do this, one would need to model the demand for heterogeneous labor on the part of differentiated firms. This would be an interesting and challenging direction for future research.

VI. Areas for Future Research

The residential sorting literature is an active area of research that is being pushed forward on many dimensions. In a review of the literature, Kuminoff, Smith, and Timmins (2013) summarize emerging research on: (i) modeling dynamics and forward looking agents; (ii) modeling housing supply, and (iii) model validation. Further advances in these areas will have implications for the way sorting models can be used to model unemployment in a spatial context.

Moving forward, one approach to using sorting models to systematically assess the effects of prospective regulations would be to develop more refined "regulation simulators" for several major metropolitan regions, similar to our Northern California model. Potential refinements could include tailoring the mecha-

[24] Spatial sorting violates one of the necessary conditions for valid benefit transfers (see Boyle et al. 2009).

nisms used to describe job loss, job match, and unemployment duration to the relevant study area and time period. A second approach would be to pursue the development of a national sorting model that integrates unemployment, moving costs (physical, financial, and psychological), dynamics, imperfect information, and heterogeneous skills and preferences for amenities, extending the recent work of Bayer, Kahn, and Timmins (2011), Bayer, McMillan, Murphy, and Timmins (2011), Bieri, Kuminoff, and Pope (2012), Bishop (2011), Kennan and Walker (2011), and Mangum (2012). In the remainder of this section, we discuss a few additional research areas that may be worth consideration.

A. Unitary v. Collective Household

Gemici (2008) models forward looking agents in a sorting framework that ignores housing market equilibrium. However, she recognizes that households may consist of two adults with frequently diverging economic motivations, and that this can lead to intra-household bargaining and conflict. The implications of joint location constraints on migration decisions, labor market outcomes, and divorce rates are therefore included. Gemici finds that family ties deter mobility, limiting the ability of spouses to simultaneously pursue labor market opportunities. In this context she endogenizes divorce, making it more likely when spouses have better career opportunities in different locations. With her estimated model, Gemici can simulate behavior under counterfactuals. Given the possibility for job separation to result in the breakup of marriage and the social costs that may accompany that breakup, this is an important complication to consider in future applications of residential sorting to unemployment.

B. (Dis)equilibrium

An important feature of sorting frameworks is that they describe long run equilibria. As we introduce the idea of unemployment into our model, the question arises of whether it is appropriate to model the world as being in long run equilibrium. If the world is not in long run equilibrium, then the challenge is to model the constraints that prevent instantaneous adjustment (e.g. moving costs, job search costs, information acquisition). Some models have sought to explain short term migration flows as functions of the differences in the net present value of future earnings and differences in amenities (i.e., the gravity model framework) – see Greenwood et al. (1991).

Disequilibrium models raise a practical problem. While we considered only small policies (i.e., that only displaced a single worker at a time), many real-world policies are large. For large policy changes, disequilibrium models are not able to predict what the world would have looked like in the absence of the policy. Without that counterfactual they are unable to generate welfare measures. In general, the concept of long run equilibrium is useful in constructing a theoretically consistent measure of welfare, but raises a number of important questions. How do we know if we are in long run equilibrium? Most applications simply assume it. In the context that we consider (i.e., movements after a disruptive regulation), the world may very well be in an adjustment phase. In our analysis, we focus on "small" policies that avoid this problem to some extent.

C. Spatial Unobservables

There are many factors that drive sorting across labor and housing markets, many of which are not observed by the researcher. How best to control for these? Gyourko and Tracy (1991) propose a random effects model. Bayer, Keohane and Timmins (2009) use panel variation in the index of local amenities derived from a horizontal sorting model based on repeated waves of census data. Other studies have suggested various approaches to developing instruments for endogenous variables (see Kuminoff, Smith, and Timmins 2013 for a review).

Given the current level of concern about omitted variable bias in empirical microeconomics, it would be useful to conduct research on defining a set of "best practices" for handling spatial unobservables in sorting models. Evidence from the extensive literature on reduced form program evaluation models is unlikely to translate directly to the sorting literature because of differences in econometric methods (e.g. partially identified nonlinear models in the sorting literature vs. point identified linear models in the program evaluation literature) and differences in the objects of interest (e.g. well defined welfare measures in the sorting literature vs. "effects" in the program evaluation literature). Explicit tests of the external validity of sorting models could also provide useful feedback (e.g. see Galiani, Murphy, and Pantano 2012).

D. Tracking Migration in Response to Regulatory Shocks

Finally, developing some direct evidence on the migration patterns of workers who lose their jobs could help to inform the most productive direction for future research. While aggregate migration data are widely available, it is not clear whether migration patterns are systematically different for workers who lose their jobs. Walker (2012) provides some initial evidence by tracking the *job locations* of workers who relocated within four states, reporting that more than 40% of job separators moved to new jobs in different counties. However, it is not clear how many of these job migrants moved to new houses. Likewise, Mangum's (2012) work on developing an "islands" model of metropolitan areas with unemployment begs the question of whether unemployed workers move to new metro areas *before* or *after* finding a specific job there. More generally, if the share of unemployed workers who move to new housing communities and labor markets is small, then a Roy-type model of labor market sorting might be more useful than a dual-market model of sorting across the housing and labor markets. If the share is larger but most movers stay within the same metro area, then a regional model of both markets—similar to the one is this paper—may be the most appropriate one to pursue. Lastly, if the share of workers who move cross-country is large, then advancing a national sorting model may be the most productive direction for research.

VII. Conclusion

Over the past decade, full-employment equilibrium models of housing market sorting have increasingly been used to evaluate the benefits of prospective environmental regulations. We demonstrated that the literature can potentially be extended to consider unemployment and some dimensions of underemployment. In a demonstration of the model where workers who lose their jobs were assumed to receive no benefits of improved environmental quality, we observed that the average worker's change in earnings was substantially smaller (in absolute magnitude) than their household's expected equivalent variation. This wedge arises because workers who move to new jobs often move to new housing communities as well. Their new communities often provide bundles of housing, commuting options, and local public goods that the movers perceive to be less desirable. These preferences were revealed by the movers' original location decisions. This non-wage effect on utility dominated welfare measures for workers in some metro areas and was a relatively minor component of welfare in other metro areas. Our analysis also suggests that the state of the business cycle, as reflected through the duration of unemployment spells, has the potential to be of first order importance in assessing the costs and benefits of environmental regulations from the perspective of working households.

Overall, the results from our preliminary analysis and from other recent papers in the literature cause us to be optimistic about the potential for using sorting models to evaluate the benefits and costs of environmental regulations that may result in layoffs. However, the current models should be refined and vetted before using them for “prime time policy analysis”. We made several specific suggestions for further research along these lines.

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SUPPLEMENTAL APPENDIX

Part A.I summarizes data on movers from the American Housing Survey. Part A.II reports additional results from the layoff simulator, by industry.

A.I. Reasons for Moving

Tables A1 and A2 summarize results from the "reasons for moving" tables in the biennial American Housing Surveys for 1999, 2001, 2003, 2005, and 2009. In table A1, "new job or job transfer" is consistently the second most frequently cited "main reason for leaving one's previous housing unit". In table A2, "convenient to job" is consistently the most frequently cited "main reson for choice of present neighborhood."

Table A1: Main Reason for Leaving Previous Unit

Main Reason	1999	2001	2003	2005	2007	2009
To establish own household	12%	12%	12%	11%	11%	11%
New job or job transfer	11%	11%	10%	10%	9%	9%
Needed larger house or apartment	10%	11%	10%	10%	9%	9%
To be closer to work/school/other	9%	9%	8%	9%	9%	9%
Other, family/personal related	8%	8%	8%	8%	8%	8%
wanted better home	8%	8%	8%	8%	8%	7%
Married, widowed, divorced, or separated	6%	5%	6%	6%	5%	5%
change from owner to renter or renter to ow	5%	5%	5%	5%	3%	5%
other housing related reasons	5%	4%	5%	5%	5%	4%
wanted lower rent or maintenance	4%	4%	5%	4%	4%	5%
Other, financial/employment related	3%	3%	3%	3%	3%	4%
Private displacement	1%	1%	1%	1%	1%	1%
Disaster loss (fire, flood, etc)	1%	0%	1%	0%	1%	1%
government displacement	0%	0%	0%	0%	0%	0%
Evicted from residence	0%	0%	0%	0%	0%	1%
All reported reasons equal	2%	2%	1%	1%	4%	4%
other	11%	12%	12%	14%	11%	12%
not reported	5%	4%	5%	4%	9%	6%
Number of observations	17,824	17,644	17,866	19,382	18,459	17,464

Table A2: Main Reason for Choice of Present Neighborhood

Main Reason	1999	2001	2003	2005	2007	2009
convenient to job	18%	21%	19%	19%	20%	20%
convenient to friends or relatives	13%	14%	16%	15%	14%	14%
house was most important consideration	14%	15%	15%	15%	10%	10%
looks/design of neighborhood	15%	14%	14%	15%	10%	10%
good schools	6%	7%	6%	7%	6%	6%
Convenient to leisure activities	2%	2%	2%	2%	2%	2%
Convenient to public transportation	1%	1%	1%	1%	1%	2%
other public services	1%	1%	1%	1%	1%	1%
All reported reasons equal	4%	3%	2%	2%	14%	11%
other	16%	18%	20%	21%	15%	19%
not reported	11%	3%	4%	2%	7%	4%
Number of observations	17,826	17,642	17,867	19,384	18,459	17,463

A.II. Additional Results from the Layoff Simulator

Table A3 reports the expected change in real wages and expected equivalent variation, by NAICS industry.

Table A3: Wage and Welfare Effects of Layoffs, by Industry

Industry	Expected change in real wages	Expected equivalent variation
Population	-5,547	-7,287
Industry		
Agriculture, forestry, fishing and hunting (11)	-5,418	-6,279
Mining (21)	-4,915	-7,032
Utilities (22)	-5,413	-7,237
Construction (23)	-4,463	-6,052
Manufacturing (31-33)	-7,674	-8,800
Wholesale Trade (42)	-4,841	-7,028
Retail Trade (44-45)	-4,090	-5,988
Transportation and Warehousing (48-49)	-4,278	-5,619
Information (51)	-6,284	-8,147
Finance and Insurance (52)	-8,684	-9,902
Real Estate and Rental and Leasing (53)	-7,956	-9,810
Professional, Scientific, and Technical Services (54)	-7,238	-9,368
Management of Companies and Enterprises (55)	-5,743	-8,006
Administrative and Support and Waste Management and Remediation Services (56)	-4,109	-5,536
Education Services (61)	-3,511	-5,729
Health Care and Social Assistance (62)	-4,621	-6,806
Arts, Entertainment, and Recreation (71)	-4,805	-6,307
Accomodation and Food Services (72)	-2,536	-3,906
Other Services, except Public Adminstration (81)	-4,277	-5,789
Public Adminstration (92)	-4,012	-6,297

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Social Costs of Jobs Lost Due to Environmental Regulations

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Social Costs of Jobs Lost Due to Environmental Regulations

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ABSTRACT

This paper estimates the social costs of job loss due to environmental regulation. Per job lost, potential social costs of job loss are high, plausibly over $100,000 in present value costs (2012 dollars) per permanently lost job. However, these social costs will typically be far less than the earnings associated with lost jobs, because labor markets and workers adjust, increased leisure has some value, and employers benefit from wage reductions. A plausible range for social costs is 8–32 percent of the associated earnings of the lost jobs. Social costs will be higher for older workers, high-wage jobs, and in high unemployment conditions. Under plausible estimates of job loss for most environmental regulations, the social costs of job loss will typically be less than 10 percent of other measured social costs of regulations. Therefore, adding in job loss is unlikely to tip many regulatory benefit-cost analyses.

JEL Codes: D61; Q52; J68

Key Words: Benefit cost analysis, worker displacement, environmental regulation, social cost of labor

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INTRODUCTION

The loss of jobs due to environmental regulation often looms large in political debate. Jobs are important to voters, but benefit-cost analysis of environmental regulations has not reached a consensus on the social costs of job loss.

This paper estimates a plausible range of dollar values for the social costs of job losses. I also estimate percentage effects of job losses on overall social costs of regulations.

I conclude that social costs are large per job lost. Per lost job, social costs probably exceed, in present value terms, over $80,000. However, social costs of job losses are much less than these lost jobs' earnings. I estimate that social costs of job loss are at most 32 percent of the associated earnings loss. Furthermore, a fairly wide range of social costs per job lost are plausible: from 8 to 32 percent of the associated earnings loss. Finally, social costs of job loss may be greater for older workers and higher-wage jobs, or in higher unemployment conditions.

Despite the large social costs of job loss, the effect of job loss on overall costs of regulations is rarely a large percentage. For most regulations, even if regulatory-induced job loss is permanent, social costs of job loss are less than 10 percent of overall social costs. More realistically, regulatory-induced job loss will lead to some offsetting job creation, due to shifts in demand and capital. Because this offsetting job creation provides benefits, net social costs of these jobs shifts will be further reduced.

Regulation's effect on jobs is a hot political issue, especially in an era of high unemployment. For example, in arguing in December of 2010 against increased regulation of industrial boiler emission of hazardous air pollutants, the American Forest and Paper Association claimed that the regulation might cost 40,000–60,000 jobs. Losing that many jobs is a strong argument when the unemployment rate is 9.4 percent, as it was when AFPA made its press release. Job loss is likely to be a strong argument for some time. The U.S. economy is currently 11 million jobs short of restoring the employment to population ratio prior to the Great Recession (Greenstone and Looney 2012). Environmental regulations will be considered in a high unemployment political situation for many years to come.

Job loss has been used to argue against increased regulation. Representative Fred Upton, chairman of the House Energy and Commerce Committee, has argued that “at a time of near double-digit unemployment, the Environmental Protection Agency (EPA) should stand down altogether from any action that will further hamstring our fragile economy” (Institute for Policy Integrity 2012).

The importance of job loss to the public naturally leads to the demand that job effects be incorporated in benefit-cost analyses of regulations. In the past, this normally has not been done. As pointed out by Masur and Posner (2012, p. 581), “agencies have long reported the predicted unemployment effects of regulations and have in some cases declined to choose certain regulatory options because the unemployment effects were too high. But they do not incorporate the unemployment costs into cost-benefit analysis, which is the standard basis for evaluating regulations, so it is not clear what role unemployment plays in their evaluation of proposed regulations.”

One rationale for not incorporating jobs in benefit-cost analysis is to assume that the economy is at “full employment.” The full employment assumption leads to the following argument for benefit-cost analysis to exclude costs of job loss: “In an economy or region experiencing full employment, economists typically assume that the opportunity cost of a worker’s labor is equal to the wages he or she earns. The rationale is that the wages earned are approximately equal to the value of the worker's output at an alternative job" (EPA 2011a, p. 15). That is, at full employment, any worker has the option of instantly moving to an equally productive job, or enjoying leisure of the same monetary value. Therefore, any "job loss" that occurs in the short run due to regulation merely moves us from one full employment equilibrium to another full employment equilibrium, where everyone can get a job at the prevailing wage. The adjustment to the job loss is costless.

A more realistic model recognizes that the economy often has considerable involuntary unemployment, but even so, a pragmatic defense for excluding job effects from benefit-cost analysis is that the social costs of job loss are uncertain. I argue in a previous paper that "involuntary unemployment makes benefit-cost analysis more difficult" (Bartik 2012). Economists have not reached a clear consensus on how to estimate the job effects of policies in labor markets with involuntary unemployment, and how to measure the social value of such job effects (Bartik 2012). The economic research literature offers diverse approaches to measuring and valuing job effects that are difficult to carry out and rely on arbitrary assumptions.

Although incorporating job effects may not be standard in benefit-cost analysis, this exclusion makes no sense to the public. As economist Paul Courant at the University of Michigan has pointed out, the public does not view jobs the way that most economists do. "Economists view labor as a cost . . . Mayors, undergraduates, presidents, union officials, and (other?) folks in bars *say* that they view labor (or, at least, jobs) as benefits" (Courant 1994, p. 875). As Courant muses, there does seem to be "something special about jobs" to the public.

How to respond to public concerns about job loss? One argument is that environmental regulations may also create jobs. As research by Morgenstern, Pizer, and Shih (2002) has pointed out, regulation may cause added jobs in pollution control, either in regulated firms or their suppliers. In addition, general equilibrium adjustments, macroeconomic adjustments, or policy may cause lost jobs in the regulated sector to be offset by job gains elsewhere in the national economy. I will briefly consider possible offsets in the present paper. However, this topic will be explored in more detail in other research for this project by Richard Morgenstern and his colleagues, and by Robert Shimer and Richard Rogerson. This new research is unlikely to change the following reality: accurately estimating the job effects of regulation is challenging.

But suppose we know the job effects of regulation. There remains the issue of what social value to put on these job effects. The agnostic stance is to consider an extremely broad range of possibilities. For example, EPA's recent handbook on benefit-cost analysis of land cleanup argues that "because there is no consensus in the literature about the average opportunity cost of labor under long-term unemployment, analysts are encouraged to consider multiple values between zero and the new wage rate to demonstrate a range of possible outcomes" (EPA 2011a, p. 16). While it is nice to consider a broad range of social values of job effects, it would be even nicer if this range could be narrowed.

The next section of the paper considers models of regulations' job effects and their social costs. I then use these models to provide estimates of social costs per lost job. I narrow the range of social costs, but the variance is still considerable. Following that section, I consider how these social costs affect benefit-cost analyses of environmental regulations. Some have argued that if costs of job loss were included in benefit-cost analysis, "many regulations would need to be revised and made less stringent" (Masur and Posner 2012, p. 583). I do not find such large effects of job loss on regulatory analysis. The conclusion suggests better policy directions for concerns about jobs. I also consider possibilities for future research.

MODELS OF REGULATORY JOB EFFECTS AND THEIR COSTS

Background on Issues in Measuring Social Costs of Job Effects of Regulations

Environmental regulation may cause a variety of job effects. Some effects are job losses and some effects are job gains. One issue is how to measure the job losses and gains; a second is how to measure the social value of whatever reallocation of labor is estimated or assumed.

The main topic of this paper is the social costs of some given reallocation of jobs. But before considering this, let's briefly consider what job reallocations might occur because of a pollution control regulation. Table 1 provides a summary.

The most obvious direct effect is that environmental regulation may increase regulated businesses' costs, and thereby reduce these industries' labor demand. But as Morgenstern, Pizer, and Shih (2002) have emphasized, the regulations may also increase demand for labor to be used in pollution control activities, both in the regulated industry and in companies that supply pollution control equipment or services. In addition, these direct labor demand effects will be accompanied by multiplier effects. For example, job losses in regulated industries will reduce demand for labor in suppliers to those industries or in businesses that produce goods or services for workers in the regulated industries. Similar multiplier effects, in the other direction, occur for job gains in pollution control.

Effects in regulated industry may also lead to general equilibrium or macro effects, which may affect labor demand in other industries. The consumer demand and capital supply that would otherwise have gone to the regulated industries are likely to go in part to other industries. This leads to some offsetting labor demand increases in other industries. These may be augmented due to Fed policies or other macro policies that seek to offset the reduced labor demand in the regulated industries.

Effects on regulated industries may also lead to general equilibrium effects on aggregate labor supply. As pointed out by Hazilla and Kopp (1990), increased consumer prices may lower real wages, which may reduce aggregate labor supply.

Amenity and health benefits of regulation may also affect labor demand or supply. Amenities may have substitution or complementary relationships with various goods and services or with leisure, which may affect demand for goods and services or the supply of labor. Health benefits of regulation may affect the quantity or quality of labor supply.

Conventional benefit-cost analysis would focus on the direct costs of the pollution control regulations in compliance costs, versus the direct benefits of the regulations in health benefits and improved amenities. All the various general equilibrium adjustments would be ignored, in the belief that in competitive markets, all these spillover effects represent optimal adjustment as prices change due to the regulation. Among the adjustments that are ignored are any job effects due to shifts in labor demand or supply.

My focus in this paper is on the value of job changes due to labor demand effects. Labor demand decreases may increase involuntary unemployment or underemployment. Labor demand increases may reduce involuntary unemployment or underemployment. Increases in involuntary unemployment or underemployment have social costs, and reductions in involuntary unemployment or underemployment have social benefits. In contrast, labor supply shifts involve voluntary changes in workers' choices, which do not imply the same social costs from shifts in involuntary unemployment or underemployment.[1]

[1]For example, in a model with fixed wages, and excess labor supply, shifts in labor supply do not affect the number of jobs, so there are no job creation or destruction effects. From other perspectives, there may be good reason to exclude labor supply effects. First, it is not implausible to assume that aggregate labor supply does not vary much with the real wage. Second, we do not have good estimates of the labor market effects of labor supply shocks, whereas we do have such models for labor demand shocks, as will be discussed later in this paper.

When analyzing labor demand effects, we have to consider both the obvious direct job effects and overall labor market effects. For example, there are direct job effects on workers displaced by regulation from polluting industries, but this negative labor demand shock also has broader effects on all workers. As displaced workers search for other jobs, they will compete with other workers in the labor market, which will tend to reduce other workers' employment rates and wage rates.

In benefit-cost analysis, social costs of labor demand shocks can be ignored from an economic efficiency perspective if the regulations move us instantly from one full-employment equilibrium to another full-employment equilibrium. In that case, all workers who want to be employed at the prevailing wage will always be employed in both the old and new equilibrium, and in the transition between the two equilibria. Even if there is still some temporary or permanent net job loss, the full employment assumption means that these additional nonemployed workers choose to be out of work. The regulatory induced net drop in labor demand reduces employment by slightly reducing the wage rate. This slight reduction in the wage rate induces some workers to drop out of the labor force. The value of their increased leisure time (time at nonpaid work), because it was voluntarily chosen by workers, must be in between the old and new wage rate, and thereby quite close to either wage rate. (Gains to leisure is labor economics jargon for any value to workers of whatever they do with their time while unemployed, including child care, work around the house, or education or job training, as well as other activities that may be more popularly called leisure, such as TV watching and socializing.) The reduction in the wage rate is a loss to workers, but an equal gain to firms. Therefore, there is no social cost even if there is regulatory-induced net job loss. The additional nonemployed workers will gain leisure (nonpaid work time) that they value at the wage rate, and firms' gains from reduced wages will perfectly offset worker losses.

But in an economy with involuntary unemployment, there may be social costs from regulatory-induced job loss. In a model with involuntary unemployment, many workers who are unemployed may place a value on their leisure time that is well below the market wage. (This would be impossible in a full employment equilibrium, as then all such workers could get a job.) As a result, many workers who end up being displaced from employment by the regulation, for at least some significant time period, may end up unemployed, with leisure that they value at considerably less than the market wage. How much less? That's hard to say. One could even argue that the value of involuntary leisure is negative. Negative leisure values may occur if involuntary unemployment has stigma effects, or if it leads to the loss of job skills, future reputation with employers, and the worker's self-confidence. There is considerable research literature that involuntary unemployment has negative effects on life satisfaction that exceed the earnings lost (Helliwell and Huang 2011; Tella, MacCulloch, and Oswald 2001). Research also shows that unemployment harms physical and mental health (Frey and Stutzer 2002). Finally, as I will explore in more detail later, being displaced from a job has large long-run effects in reducing future earnings (e.g., Davis and von Wachter 2011).

Furthermore, if jobs are in short-supply for willing and able workers, then many workers may be capable of being more productive than their current jobs allow. As a result, when workers are displaced from their original jobs into lower-paying jobs, they may be less productive in their new jobs than they are capable of being. In other words, they experience involuntary underemployment. (In a market where all labor markets clear, this would be impossible, as the worker's true productivity potential would always be realized by some alternative job. But in models with involuntary underemployment, these higher-wage and higher-productivity jobs are rationed so that not all qualified workers can access such jobs.) The loss in wages from their new to their old jobs may represent a genuine loss of productivity to the economy. In contrast, in full employment models, this loss of wages is simply a gain to employers. The loss of wages is either due to shifts in the market clearing wage, or the workers losing "rents" due to union-imposed or government-imposed wages that are artificially above the market-clearing level. In either case, the loss of wages is exactly matched by a gain to employers.

How much do firms gain when workers are downgraded to lower-wage occupations? That's hard to say. The productivity of a firm-worker match depends on both the job and worker. There is not much empirical literature that allows us to precisely quantify the relative contribution of the job and the worker to productivity.

Overcoming Confusions in Valuing Workers' Time

The research literature on social costs of jobs, when there is involuntary unemployment, is confusing and reaches contradictory conclusions. I review the literature in Bartik (2012). A key source of confusion is that the research literature uses different concepts of the opportunity cost of workers' time, their "reservation wage," or the lowest wage at which they would be indifferent between taking a paid job and being engaged in leisure. These different concepts of reservation wages are both correct, but from different perspectives.

The older perspective on the reservation wage is that it represents the value of the worker's time while unemployed (Haveman and Farrow 2011; Haveman and Krutilla 1967; Mishan and Quah 2007). This value may incorporate how much the worker values their leisure time activities, as well as any stigma effects of unemployment. Because stigma values may be negative and large, such "leisure value" reservation wages may be well below the market wage. The value of leisure may even be negative. These leisure values of time really shouldn't be viewed as true reservation wages. They are only reservation wages when compared with the option of never working again, which is typically not the option facing the worker.

The newer perspective on the reservation wage is that it represents an option value of the worker's time while unemployed, given the likely future job opportunities the worker faces (Mortensen 1986; Shimer and Werning 2007). In searching the labor market, an unemployed worker will set a reservation wage as the lowest wage at which she will accept a job offer. This reservation wage will depend in part on what future job offers she expects to get, not just on the value of leisure time. It can be shown that if market wages increase by \$*x* per hour, this reservation wage will increase by about the same \$*x* per hour (Mortensen 1986, p. 864). In addition, because reservation wages, when viewed as option prices that govern job search, are so tied to market wages, they tend to be close to market wages. The empirical literature suggests that such "job search" reservation wages, as a ratio to the worker's previous market wage, average 105 percent (Jones 1989), 107 percent (Feldstein and Poterba 1984), and 99 percent (Krueger and Mueller 2011). These ratios to previous market wages are high even if there is high unemployment that is plausibly involuntary; for example, the Krueger and Mueller study was carried out when the unemployment rate was in double digits in their study area (New Jersey).

The older perspective on the reservation wage is applicable from an ex post perspective on valuing some labor demand change, whereas the new perspective on the reservation wage is applicable from an ex ante perspective on valuing some labor market change. Consider some labor demand shock that changes the availability of jobs in a labor market. After the fact, we can compare the earnings and leisure experiences of all workers in two worlds: one world with the labor demand shock, and one world without the labor demand shock. The reservation wage that is used in job search as an option price becomes irrelevant after the fact, because the sequences of earnings and leisure that occur for each worker are simply what they are and cannot be changed. We could even view them as assigned by some central planner, and their value would be the same, so whatever option prices or reservation wages might be useful at some point as strategies for job search become irrelevant after the changes have been experienced. The value of these changes for workers can be evaluated as the change in earnings for all workers, plus the change in their leisure time evaluated at whatever value workers assign to leisure time, including possible stigma effects. (I ignore here the effect of the change on firms.)

In theory, we can also value the labor demand shock based on the “option value” reservation wage and the changed sequences of workers accepting and leaving jobs. Each such acceptance or departure from a job has a value to the worker of the wage rate minus their option value reservation wage. But the labor market change also changes each worker’s reservation wage, because option value reservation wages will vary with prevailing market wages and the ease of finding another job. This will change over time based on who exactly has found a job, which spills over into job availability for other workers. Therefore, in practice, evaluating the entire sequence of job changes using the option value reservation wage faces a difficult and perhaps impossible task of evaluating each worker’s gain or loss, equal to their wage paid minus their possibly changed reservation wage, as the sequence of job changes ripples through the labor market. In practice, such an approach appears empirically impossible to implement.

A more empirically practical use of the option value reservation wage is to provide an ex ante measure of the changing value of access to a labor market. As shown by Shimer and Werning (2007), the reservation wage represents the value of a worker’s access to a particular labor market. If a particular labor market experiences some labor demand shock that changes labor market conditions, this will immediately change reservation wages for all workers, both employed and unemployed. Reservation wages will change because market wages and unemployment rates have changed. The social value of the labor market change can be evaluated as the sum of changes in reservation wages over all workers, both employed and unemployed. These reservation wage changes would be evaluated after the labor demand shock has become apparent, but before the actual sequence of who gets what job has occurred. This change in reservation wages is hard to directly measure. But as argued in Bartik (2012), it is likely to be lower bounded by the predicted change in market wages due to the labor demand shock.

A Specific Example

Consider a specific example. Suppose the labor demand shock is simply the loss of one job. It might seem that the social cost of losing this one job is equal to the wages that are lost, with an adjustment for the "option value" reservation wage of the worker who loses a job, as that represents the minimum wage at which the worker will accept a job. But the social costs of this loss will not be accurately measured in that simple way.

Let us suppose this loss of one job is a subtraction of one job from total employment. Therefore, this job loss changes the employment rate, wage rate, and job offer density facing workers in an unfavorable direction. This unfavorable change is small for each individual worker if we're talking about one lost job in a big labor market. However, the value of the change summed over all workers is not necessarily a small number relative to the earnings of the lost job.

The question is how to value the net costs for all workers from that lost job. (There also is the issue of how employers are affected, which I ignore in this thought experiment.)

Prior to knowing which worker actually loses a job, we can value those benefits as the change in reservation wages for each individual worker, summed over all workers, both employed and unemployed. Reservation wages will go down because market wages will go down, and it will be harder to find jobs with a lower ratio of employment to population and a lower flow rate of job offers. The change in reservation wages for an individual worker will be small, but summed over all workers may not be a small number relative to the earnings associated with the lost job.

Once we know who actually loses this job, that worker has suffered a negative "surprise" of actually immediately losing the job. This increases the costs to this worker compared to her previous small reduction in reservation wage, when she only knew that she might lose her job. The revelation of who loses the job also lowers (in absolute value) the reduction in reservation wages for all other workers, as now these workers know they will not immediately lose a job.

However, all other workers should still have some reduction in their reservation wages for at least three reasons. First, the fact that the worker who loses the job has a reservation wage that is based on her likely future success in finding another job means that at some point, the worker who is displaced is likely to fill another job vacancy. Filling this job vacancy makes it slightly harder for other workers to find a job. In turn, there is a sequence of job chain displacement due to these other workers in the future not getting jobs that they otherwise would have obtained.

Second, unless the first worker who loses the job would have otherwise held that job forever, there would have been some positive probability for other workers holding that job in the future. This positive probability has some value to all other workers, and the loss of this job eliminates this positive probability and its value.

Third, the job loss has some effect, albeit very small, in reducing market wages, which will reduce reservation wages.

Therefore, the net social costs of a job offer, after the worker who will lose the job is identified, shifts from being a small reduction in reservation wages for all workers to being the wages of the lost job adjusted for the reservation wage of the worker who immediately loses the job, plus a slightly smaller (in absolute value) reduction in the reservation wage for all other workers. The two measures should sum to the same amount, at least in expected value terms. (That is, there may be differences depending upon how the probabilities of who gets what job are realized, but the expected value of all possible realizations should be the same.)

Finally, we can consider net worker costs ex post after we know the realizations of who actually gets what jobs when. Suppose we want to know the costs of this job being destroyed from the time the job was lost until some future time, and we are now looking back from the future time to consider the costs over this past period.

At this future date, we now know exactly how everyone's job history and wage history was affected by the one job that was lost. From an ex post perspective, we can calculate net costs without considering a reservation wage based on job search behavior. Ex post the universe is fixed and cannot be changed. In fact, we can imagine that some omniscient central planner has assigned people to the job sequences that were actually observed to be realized in the labor market. If people are assigned to the jobs they actually chose, their utility must be the same as if they had chosen those sequences. But if we view job sequences as assigned, reservation wages based on job search behavior become irrelevant. The cost of the job loss for each worker is the change in their earnings, minus whatever value they put on the change in their leisure time, but this time not adjusting for the value of job search, as I am assuming all jobs are simply assigned, or fixed by reality in that ex post what happened cannot be changed. Or in other words, the worker costs of the job loss are 1) earnings lost due to reduced employment rates because of the lost job, plus 2) earnings lost due to decreased wage rates, adjusted for 3) the value of the increased leisure time.

From an ex post perspective, the sequence of who is employed in each time period was realized only in one particular way from all the ways it could have been realized, given that job matches are stochastic. So this actual calculated social cost may be different from the ex ante measures given above. However, on average all three measures, the two ex ante measures and the one ex post measure, should be the same when we figure the average value over all possible job match realizations.[2]

Ex ante, the value of changes resulting from job losses for all workers can be evaluated by the changes in reservation wages for all employed and unemployed workers. This decline will have a lower bound (in absolute value) in the decline in market wages that would be predicted. Ex post, the value of these changes resulting from job loss for all workers can be evaluated as the decline in their earnings, minus some gain if increased leisure time has a net positive value after accounting for stigma effects.

Similar arguments can be applied for job gains. Ex ante, the job gains' benefits for workers can be evaluated as the increase in "option value" reservation wages summed over all workers. Ex post, the job gains' benefits for all workers can be evaluated by the increase in earnings for all workers, adjusted for the net value of the reduced leisure time.

[2]The ex ante and ex post perspectives could also be seen as the difference between evaluating some change in an individual's well-being based on an indirect utility function defined over prices versus a direct utility function defined over consumption bundles.

These relationships are developed more fully in Bartik (2012). The next section provides some specific equations for evaluating these changes.

Models of Social Values of Job Effects

My previous paper on jobs and benefit-cost analysis (Bartik 2012) provided two alternative equations that express the social value of job losses (or gains). The first method is based on the ex post approach outlined above. It starts by estimating job losses' effects on workers' earnings, due to declines in both employment rates and wage rates. This earnings loss is adjusted for the value of the increased leisure time of workers due to higher unemployment or declining labor force participation.

The second method is based on the "option value" approach to the reservation wage. This method values job loss based on the decline in reservation wages due to the job losses, evaluated over all workers, both employed and unemployed. This reservation wage decline will be understated, in absolute value, by the decline in predicted market wages for all workers.

Both of these methods adjust the losses to workers for possible gains by firms. A job loss leads to wage declines for at least two reasons. First, the loss of jobs leads to workers with particular educational and other credentials being forced to take lower-wage jobs. The jobs may be lower wage in that they are in lower-wage occupations, or be lower job levels within an occupation. Second, the job loss may lead to lower wages for the same type of job. The second source of wage decline clearly will benefit firms. The first type of job loss may not benefit firms. The key issue is the productivity of workers who downgrade to lower-wage jobs. If their productivity is normal for that job type, then the job downgrading has no corresponding benefits for firms. But if these higher credential workers are more productive than typical workers in these jobs, then firms may gain from the downgrading.

Both methods measure the same social costs of job losses. It is convenient to express these social costs as a percentage of the earnings reduction associated with the job losses. When this is done, either method shows that this percentage depends on various elasticities of how labor market outcomes respond to job loss. This percentage also depends upon parameters for the value of nonworking time and possible gains to firms.

Using method (1), the social costs of policy-induced job loss, as a percentage of the gross earnings associated with that job loss, can be written as follows:

$$[dY - f\,E\,(dW_m) - g\;W_m\,N\,(dER)\;]/[W_m\,(dE)] = (1 - f)\;S_{me} + [1 - g]\;S_{ere} \qquad \text{(Eq. 1)}$$

dY is the loss in earnings. E is employment. dE is the loss in employment due to the policy. W_m is the market wage rate. dW_m is the change in market wage rates, holding worker characteristics constant. dER is the change in the employment rate, defined with respect to the population. N is the population. f is the proportion of wage gains offset by employer losses. g is the proportion of earnings gains from new employment that represents a loss of valued nonmarket time, given stigma effects. S_{me} and S_{ere} are the elasticities of market wages and the employment rate with respect to the employment shock.[3]

Using method (2), the social costs of job loss can be expressed using the "option value" reservation wage concept as a percentage of the gross earnings loss as follows:

$$[dW_r\,(E + U) - f\,E\;dW_m\,]\;/\;(W_m\,dE\;) = [1 + (U/E)]\;(dW_r/dW_m)\;S_{me} - f\;S_{me} \qquad \text{(Eq. 2)}$$

[3]This Equation (1) is a simplified version of Equation (2) in Bartik (2012). I reordered the two methods for the present paper because it emphasizes the direct method of measuring social values of job effects.

W_r and W_m are the "option value" reservation wage and the market wage, holding worker characteristics constant. E is the number of employed. U is the number of nonemployed. dW_r and dW_m are the changes in reservation wages and market wages. dE is the policy-induced employment loss. S_{me} is the elasticity of market wages with respect to an employment loss.[4]

What intuition is behind the second method? The intuition is that the "option value" reservation wage, the lowest wage at which a worker is willing to work, represents the value of access to the labor market. The policy-induced job loss reduces the value workers place on access to the labor market. Labor market access is of lower value because wages are lower and jobs are harder to find. For a full social valuation, we also must consider effects on employers.

Both of these methods require more than knowing the elasticities of market wages and employment rates with respect to job loss. Both methods require us to decide what proportion of wage declines, which will hurt workers, will be offset by benefits to firms. There is not much empirical evidence on the magnitude of these possible benefits for firms.

Method (1) requires us to assign some opportunity cost to the workers' time in nonemployment. There is some evidence, from surveys, of how much value people place on time spent in involuntary unemployment or out of the labor force (Blanchflower and Oswald 2004; Frey and Stutzer 2002; Helliwell and Huang 2011; Knabe and Ratzel 2011; Knabe et al. 2009; Tella, MacCulloch, and Oswald 2001). In addition, the value of this time in nonmarket work is upward bounded by the worker's net take-home wage after all taxes.

Equation (2) can only be given a precise value with estimated effects on "option value" reservation wages. Unfortunately, there is little empirical evidence on how reservation wages respond to changing labor market conditions. However, as implied by the previous discussion,

[4]This Equation (2) is Equation (1) in Bartik (2012).

we would expect the observed decline in market wages to understate the decline in reservation wages. Holding employment rates constant, reservation wages would be expected to decrease about one-for-one with decreased market wages (Bartik 2012). But policy-induced job loss will lower employment rates, which would increase in magnitude the reservation wage decline, because declining employment rates reduce the value of labor market access. Therefore, method (2) allows us to put some lower bound to the social costs of job loss using observed effects on market wages.

Both of these methods are written in simplified form in the above equations. This simple formulation can be generalized. The simple formulation assumes that the environmental regulation just involves some job loss for which there are uniform values across workers of wage elasticities, employment rate elasticities, values of worker time, and offsets by firms. This could be generalized to writing many such equations for different groups of workers or even for each worker, allowing different groups of workers, or even each worker, to have their own elasticities, leisure time values, and firm offsets. The aggregate social cost of job loss would then sum over all workers these calculations for each worker or group. In addition, I am assuming just one type of job loss. There could be multiple types of job losses and gains in different labor submarkets because of the environmental regulation. We would then sum social values over each of these types of job losses and gains. Finally, the equation as written considers social costs for one time period. In the real world, there are dynamic responses to job losses and gains. We would sum each year's social costs over time using appropriate social discount rates.

ESTIMATES OF SOCIAL COSTS PER LOST JOB

Preliminary Social Cost Estimates

I now provide some estimates of social costs of job loss.

Initially, all these estimates assume that the job loss is permanent. This is a starting point for analysis. If the initial job loss is at least somewhat offset later by job gains, the value of these job gains could be added back in later on.

I also initially assume "average" costs of job loss. Later, I consider variations that may occur because of the size and sign of the job change, the nature of the job loss (e.g., industry mix or wage rate), the types of workers affected, and the labor market situation.

As a reference point, I first calculate the social costs of job loss if all of the associated earnings loss was a social cost. I assume, based on BLS statistics, average annual compensation (including benefits) of $59,997 (2012 dollars).[5] At a 3 percent discount rate, the present value of such an earnings loss over a 20-year future (an assumed time horizon) is $952,605. This present value is a little less than 16 times one-year's compensation. It is, by definition, equal to 100 percent of the gross earnings in the lost jobs (see Table 2).

I then consider the implications of some previous models of how job loss affects workers displaced from jobs. Walker (2012) considers workers who lost jobs because of the Clean Air Act. Davis and von Wachter (2011) consider displaced workers more generally. The resulting estimates of social costs of job loss are about 10 percent of the gross earnings loss associated with these jobs (Table 2). However, this is still a significant amount of money—over $75,000 in present value dollars per job loss.

[5] This figure comes from BLS's series for Employer Costs for Employee Compensation. I use figures on average compensation of private sector workers. I average the dollar cost per hour across the four quarters of 2011 to get $28.26 per hour. This hourly compensation figure times 2080 hours per year yields a $58,781 figure, which is then adjusted using the CPI to 2012 prices.

However, the displacement numbers in Walker (2012) and Davis and von Wachter (2011) have some limitations as measures of the social costs of job loss. First, these estimates do not adjust for the value of nonworking time for displaced workers, which may increase or decrease social cost estimates. Second, these estimates do not allow for employers to have any gains from any wage reductions for displaced workers. Third, if these estimates are applied only to workers directly displaced by environmental regulations, they omit possible multiplier effects. Finally, these estimates do not allow for possible spillover effects on other workers of the earnings and employment recovery experienced by displaced workers. Suppose the regulation-induced job loss is persistent. Then as the displaced workers recover from the job loss and obtain new jobs, some of that job-finding may come at the expense of reduced job availability for other workers.

Local Labor Market Estimates of Social Costs

To get more inclusive estimates of social costs, my remaining estimates of social costs are derived from local labor market models. The advantage of such models is that we have good estimates in local labor markets of how employment rates and wage rates respond to negative (or positive) labor demand shocks. Job loss due to environmental regulation ultimately does take place in specific local labor market areas. The total effects of some pattern of job loss due to environmental regulation can be derived by summing effects across affected local labor market areas.

My baseline estimates are based on new estimates using metro area data (Bartik 2013). These estimates update previous estimates in Bartik (1991, 2006). An appendix gives more detail on how these estimates are used to create social cost estimates.

The estimates are for the elasticities of a metro area's real earnings, and its components, in response to a one-time shock to metro employment growth (a once and for all shock to the metro employment level). Real weekly earnings is the product of the labor force participation rate, the employment to labor force ratio, weekly work hours, and the real wage rate per hour. Therefore, the elasticity of response of weekly earnings will be the sum of the elasticity of response of these components. In turn, real wages per hour are the sum of the real wages expected for this occupation based on national norms, and differences between actual real wages and this "occupational rank" wage rate.

The model is estimated using pooled cross-section time series data on year-to-year changes in the following dependent variables: real weekly earnings, real wages, unemployment rates, labor force participation rates, real wage rate predicted based on occupation and national wage rates. These dependent variables are adjusted for local demographic mix. The cross section is across 38 metro areas or 23 metro areas, depending on the availability of local price data that are needed for some of the dependent variables. The time series dimension is over year-to-year changes from 1979–1980 to 2010–2011. These dependent variables are explained as a function of the main independent variable of interest, which is current and lagged metro area annual employment growth. The regressions also control for year dummies to reflect national effects on labor market outcomes. Appendix A provides more detail and representative estimates.

The estimates are for the effects of a one-time growth shock on these various earnings components both immediately and for up to 10 years later. I use these estimates to project how earnings will respond to a job loss in a metro area for up to 20 years.

The initial estimates simply look at the effects of any type of employment growth shock. Later estimates are restricted to employment growth shocks that would be predicted if all local industries kept their shares of national employment. This industrial-mix-predicted growth is due to changes in demand for the area's specialized industries that sell their goods and services to a national market (Bartik 1991), which regional economists label as "export-base" industries. These estimates that use industry-mix-predicted growth as an instrument can be seen as restricting attention to one particular type of growth shock that is clearly due to labor demand.

I also look at how employment growth shock effects vary with the initial unemployment rate. However, the initial estimates are for a metro area with an average initial unemployment rate. For the metro areas and years in my sample, this is an unemployment rate of 6.7 percent.

The resulting estimates are discussed in more detail in Bartik (2013). The upshot, consistent with previous estimates (Bartik 1991), is that local job loss has initially strong effects in raising local unemployment rates and reducing weekly work hours, but these effects quickly fade. Labor force participation rates are also reduced, and these effects fade more slowly. Local job loss results in persistent effects in reducing local real wages. Some of these effects are due to workers being forced into occupations with lower national wage norms. Other real wage reductions are due to workers receiving lower local real wages than would be expected based on their occupations. Some of these negative real wage differentials from occupational averages are probably due to workers being forced into lower job levels within an occupation. Other negative real wage differentials are due to workers making less for the same job.

For effects in one labor market to accurately measure overall social costs, we must believe that if jobs are lost in one metro area, the labor market effects do not substantially spill over into other labor markets. This might appear implausible. Job loss in one metro area will lead to reduced in-migration from other metro areas, and increased out-migration to other metro areas. However, the best evidence is that the local labor market effects of such population shocks are slight. Migration shocks appear to yield similar changes in local employment (Greenwood and Hunt 1984; Muth 1971). As a consequence, we would not expect these migration shocks to cause substantial shifts in employment rates, wage rates, and other labor market outcomes in other metro areas.

The consequence of assuming no net labor market spillovers is that we can analyze the social costs of any national job loss using the local labor market model. The national job loss will be some pattern of local job losses. Each of these local job losses can be analyzed using the local labor market model. The national loss will be the sum of these local losses. If the elasticities are similar across local labor markets, then only the net national job loss must be known to evaluate national social costs.

To allow an apple to apple comparison of this local labor market model with the Walker (2011) and Davis and von Wachter (2011) results, I first simply provide estimates of the likely earnings effects under the local labor market model. These earnings costs are a little more than three times those estimated by Walker and Davis and von Wachter. However, these costs are still less than a third of the gross earnings associated with the lost jobs—workers in local labor markets do adjust to the loss of a job. However, the costs of job loss are greater in the local labor market model because the model allows for spillover effects of job loss on all workers. Job loss lowers wage rates and employment rates for workers other than those in the regulated industries.

However, these earnings loss numbers are not true social cost numbers. They do not adjust for the value of increased worker leisure or gains to firms. For better social cost figures, I must apply the two methods outlined above.

I initially assess social costs with the local labor market model using method (1). This involves looking at how job loss affects both employment rates and wage rates. To convert effects on these different components of earnings into social costs, I must make some additional assumptions. For my baseline social cost estimates, I assume a middle ground for the value of nonworking time. Knabe and Ratzel (2011) value nonworking time based on surveys of how life satisfaction responds to current income, permanent income, and labor force status. Their estimates imply that the value of worker time while involuntarily unemployed is equal to minus 50 percent of the market wage. The stigma effects of unemployment add about 50 percent to the direct earnings loss. The value of nonworking time while out of the labor force is estimated to be about minus 10 percent of the market wage. These estimates might be seen as providing relatively large estimates of stigma effects and social costs of nonemployment. On the other extreme, estimates suggest that it is likely that marginal taxes at all levels on labor earnings amount to at least 30 percent of labor earnings (CBO 2005; Kotlikoff and Rapson 2007). This suggests a maximum value of nonworking time of 70 percent of the wage rate.

For my baseline estimates, I assume an opportunity cost of nonworking time of halfway in-between these two figures. Thus, the net value of additional nonworking time in unemployment is assumed to be 10 percent of the wage rate (= halfway between −50 percent and +70 percent). The net value of additional nonworking time that is outside the labor force is assumed to be about 30 percent of the wage rate (= halfway between −10 percent and +70 percent). For reduced weekly work hours, the baseline middle of the road assumption is that the value of this time is 35 percent of the wage rate (halfway between 0 and 70 percent).

While these opportunity costs of labor assumptions are arbitrary, they appear reasonable. The public clearly views unemployment as a very damaging status. Our valuation of the unemployed’s time must be low enough to correspond to this public perception. If we fail to match public perceptions, our social cost estimates will be irrelevant to political debate.

I also need to make assumptions about what portion of wage reductions will be offset by gains to employers. For these baseline assumptions, I also make middle-of-the-road assumptions. For wage reductions due to occupational downgrading, I assume that half of these wage rate reductions will be offset by gains to employers in greater worker productivity. The estimates also show reduced wages due to differentials of local wages from occupational norms. Seventy-five percent of the wage reduction in these differentials is assumed to be offset by gains to employers.

Finally, I assume for these calculations that we are already working with job loss numbers that have been adjusted for possible multiplier effects. If this were not so, we would have to add in multiplier effects of the direct job loss before calculating social costs.

Obviously a number of assumptions are being made here to generate these estimated social costs of job loss. My defense is that the assumptions seem reasonable. Furthermore, I will consider alternative assumptions below.[6]

Social costs for the baseline version of this local labor market model are of similar magnitude to the estimates derived from displacement studies. Estimated social costs of job loss are about 14 percent of the gross earnings associated with the job loss. The present value of social costs due to the permanent loss of one direct job is around $134,000 (Table 2). These similar costs are due to the higher earnings effect being roughly offset by allowing for the opportunity costs of labor and benefits to firms.

[6]In the local labor market context, we might also wonder about the decrease in local prices, particularly in local housing prices, and the possible gains to employers of decreases in nominal wages due to decreases in local prices. I assume that these housing price effects net out from an economic efficiency perspective. Even if such effects were included, previous studies indicate that property value effects of local employment shocks have a much lower present value than real earnings effects of local employment shocks (Bartik 1991, 2011).

I can also calculate social costs of job loss using the method (2) approach. I use market wages to lower bound this reservation wage measure. The same offsetting firm benefits are assumed as with method (1).

The resulting social cost estimates are a little less than 9 percent of the earnings associated with these lost jobs. Because this is a lower bound, this implies that the 14 percent result from method (1) may be a reasonable estimate.

Alternative Estimates

The baseline estimates rely on one specific set of estimated effects of local employment shocks on local labor market outcomes (Bartik 2013). How sensitive are these estimated social costs to alternative estimates? Table 3 presents some alternatives.

I consider how estimates vary if we focus on the effects of local employment reductions that are due to local industry mix and national industry growth trends. These estimated effects are more clearly due to labor demand, whereas employment changes in general may be due to both labor demand shifts and labor supply shifts. These estimates show larger negative effects of local job losses. Other assumptions about offsets for firms and the social value of nonworking time are the same as before.

Moving to “demand shock” estimates more than doubles the estimated social costs of job loss. The present value of the social cost of one lost job increases to almost $300,000. The social costs of lost jobs are just below 32 percent of the earnings associated with these lost jobs (Table 3).

I also calculate social costs using the estimated effects of local growth in Bartik (1991). All other assumptions are the same. Social costs using these Bartik (1991) estimates are also somewhat higher than in the baseline estimates: $237,000 per job and about 25 percent of the gross earnings associated with the job loss.

Although these alternative estimates are higher, note that social costs are still considerably below the gross earnings associated with the loss jobs. Workers adjust to job loss, and there are some offsetting benefits to workers and firms. Thus, not all the earnings associated with lost jobs are a true social cost. In addition, all these estimates assume some permanent job loss. If the job loss leads to some offsetting job gains as capital and consumer demand shift to other industries, social costs will be even lower as a percentage of the earnings associated with the original job loss.

Alternative Assumptions about Opportunity Costs of Nonworking Time and Employer Offsets

The baseline estimates rely on hard-to-test assumptions about the social value of increased nonworking time that occurs due to job loss. The baseline estimates also rely on hard-to-test assumptions about how much of the wage reductions will be offset by gains to employers.

I consider effects on social cost calculations of more extreme assumptions in Table 4. One set of extreme assumptions pushes social costs down. I alter the estimates by assuming much higher social value to increased nonworking time and much higher employer offsets. I assume that the increased nonworking time due to job loss is valued at 70 percent of the wage rate, which reflects taxes on work. I assume that all wage reductions that exceed those predicted by occupational downgrading are fully offset by benefits for employers. And I assume that occupational downgrading results in productivity gains to employers that offset 75 percent of the costs of these wage reductions to workers.

Under this set of extreme assumptions, social costs of job loss are cut by more than two-thirds (Table 4). The social cost is about 4 percent of the associated reduction in earnings. On the other hand, this set of extreme assumptions still results in a social cost of over $38,000 per lost job.

I also go to another extreme. I make assumptions that dramatically increase social costs. I assume high stigma effects of nonworking times, and small offsetting employer benefits. I assume that increased time in involuntary unemployment has a social cost of 50 percent more than the associated earnings, based on estimates in Knabe and Ratzel (2011). I also assume that increased time outside the labor force has a social cost of 10 percent more than the associated earnings loss. Reduced weekly work hours are assumed to have a social cost just equal to the earnings lost. Finally, I assume that only one-quarter of wage reductions are due to occupational downgrading, and 50 percent of other wage reductions are offset by gains for employers.

These assumptions drive social costs up to about 24 percent of the associated earnings loss. Present value social costs per lost job are about $229,000.

More extreme assumptions about how workers value leisure and how much firms benefit from wage reductions can drive social cost estimates for job loss to near zero. However, these extreme assumptions are unlikely to increase social costs of job loss to anywhere close to the full value of the earnings associated with the job loss.

The Bottom Line on Social Costs of Typical Job Loss

These varying estimates and assumptions do yield varying results. But I think the estimates do help narrow the range of the plausible social costs of job loss for a typical job loss. By typical job loss, I mean that the jobs lost have employees with typical characteristics, that the jobs are average wage jobs, and that the unemployment rate is not extremely high. For this typical job loss, at one extreme it seems implausible that social costs could be much less than the lower bound provided by method (2), which relies on a reservation wage model. This social cost is 8 percent of the gross earnings associated with the direct job loss. As an upper bound, we can't rule out the estimates based on labor demand shocks due to local industry mix. This upper-bound measure has social costs of a little less than 32 percent of gross earnings associated with lost jobs.

A fourfold range from 8 to 32 percent could be argued to be wide; however, it is narrower than considering a range from 0 to 100 percent of the direct earnings effect, which is what the EPA Handbook (2011a) recommends.

Variations from Typical Job Loss Based on Who Loses Jobs, Types of Jobs, Size and Sign of Job Growth, and Labor Market Conditions

The above calculations ignore the potential for social costs of job loss to vary across different types of negative demand shocks. Social costs might vary with the characteristics of who loses the jobs, the types of jobs, the size and sign of job growth, and labor market conditions. Unfortunately, we do not have a huge amount of information how estimated labor market adjustments vary with these factors. I briefly review some of the research evidence for these variations from typical job loss.

Davis and von Wachter (2011) do consider how job loss effects vary across different types of workers. They find similar social costs as a percentage of the associated earnings of the lost jobs, with one important exception: older workers. For such workers, social costs are 100 percent greater as a percent of earnings (e.g., for men aged 51–60, versus men aged less than 50, they find lost earnings as a percent of counterfactual earnings of 24.0 percent versus 11.9

percent). Of course, it should be recognized that it would be unusual for some job loss to have 100 percent of its displaced workers be workers older than age 50.

Bartik (1993) has estimates that look at how effects of job growth shocks vary with different types of jobs. I find that effects do not vary much with whether the jobs tend to employ a particular education group, racial group, or age group, even when we focus on earnings effects on particular demographic groups. Bartik (1993, 1996) finds that effects of job growth shocks vary greatly with the average “wage premium” implied by the jobs’ industrial mix. The wage premium measures what that industry typically pays relative to the all-industry average, controlling for the demographics of the industry’s workforce. I find that a shift in a local labor market’s industry mix toward industries that pay an *x* percent lower wage premium tends to reduce overall area earnings by from two (Bartik 1993) to five (Bartik 1996) times *x* percent. It appears that a lower wage premium spills over into lower wage rates in other industries. In addition, a lower wage premium spills over into some decline in employment rates and annual hours worked. These spillover wage premium effects would imply possibly considerably higher social costs as a percent of earnings if the lost jobs have high wage premia. However, if one examines overall job loss including multiplier effects, wage premia effects may not be large. The manufacturing jobs lost might pay high average wage premia, but many of the multiplier jobs in retail and service industries will pay below average wage premia.

Davis and von Wachter (2011) also consider job loss effects during a recession. (The estimates above are for nonrecession years.) During a recession, social costs of job loss are over 60 percent greater as a percent of earnings (e.g., around 19 percent versus around 11 percent—see their Table 1). Somewhat smaller differentials are obtained in Bartik (2013) for variations with local labor market conditions. The baseline calculations above found social costs of 14.1

percent of gross earnings loss when the initial local unemployment rate was 6.7 percent (the sample average). However, social costs were 16.2 percent of gross earnings changes when the initial unemployment rate was 8.7 percent, and 11.9 percent when the initial unemployment rate was 4.7 percent.[7]

Several points should be noted here. First, social costs of job loss are large even when the macroeconomy is booming. Second, social costs might need to be blown up by 30 percent to 60 percent if either the national economy is distressed, or if the job loss happens to be in a high unemployment local economy. Third, if the job loss is in a high-unemployment local economy, there may be net costs of labor readjustment even if the job loss is immediately offset by job gains in lower-unemployment local areas. There is some net social cost of redistributing jobs from high-unemployment to low-unemployment areas.

Bartik (1991) examines whether the effects of local job growth on labor market outcomes varies with the sign and size of growth. I do not find strong and consistent variations of labor market effects with the size and sign of job growth.

What can we conclude from this analysis of variations in social costs of job loss? First, if we really want to get precise benefit-cost estimates that adjust for the effects of job loss or gains, we need to adjust for factors such as worker age, the wage premia paid for the jobs, and initial labor market conditions. Second, the existing research base is sparse in providing precise consensus estimates on how social costs vary. Third, it seems unlikely that these variations will do much more than double social cost estimates from the typical values given previously. This puts some likely upper bound on how important social costs of job loss can be.

[7] The standard deviation of the local unemployment rate in this 1979–2011 sample of 38 metro areas was 2.2 percent, so the range of unemployment rates considered is about plus or minus one standard deviation.

POTENTIAL EFFECTS OF JOB LOSS ON OVERALL SOCIAL COSTS OF REGULATIONS

How much of a difference do these estimates of job losses' social costs make to benefit-cost analysis? We have many benefit-cost analyses of environmental regulations and other regulations. These analyses typically do not assign any social costs to job losses (or gains) in calculating the net benefits or benefit-cost ratio for a regulation. The ideal benefit-cost analysis would include the social costs of job loss. If this were systematically done, would it make much difference in which regulations were judged to pass a benefit-cost test? Would it much affect our ranking of regulations?

To address these questions, I analyze a number of prominent regulations that have been discussed as cases in which job losses might be considered. In particular, I consider the environmental regulations analyzed by Masur and Posner (2012), and the Clean Air Act analysis of Walker (2012).

Appendix B presents more details on my results for each of these regulations. In Table 5, I present summary results for 12 of the regulations analyzed in Appendix B.

As Table 5 shows, for nonhabitat regulations, the social costs of job loss, as a percentage of total costs, are low. The average is 5 percent. The maximum calculated percentage boost to social costs is 13 percent.

For habitat regulations, the situation is different. Social costs of job loss are a far larger percentage of measured social costs. This might be attributable to the nature of these particular regulations. For most of the other environmental regulations, the regulation is applied to most of an industry or at least a large segment. Therefore, the increased regulatory costs are being imposed in a context in which many costs will be shifted forward into higher product prices. This forward shifting is likely to reduce direct job losses.

In contrast, for habitat preservation, we are imposing a regulation on a very tiny segment of an industry. Therefore, modest imposed regulatory costs could cause considerable direct job effects on that industry segment.

I now consider three regulations for which there has been particularly prominent discussion of job effects: 1) Walker's (2012) analysis of job effects of the Clean Air Act, 2) the industrial boiler regulations that have been attacked for causing job losses by industry groups, and 3) Masur and Posner's (2012) lengthy focus on effluent guidelines for pulp and paper manufacturing. Table 6 presents more details on these three regulations and their job effects.

Walker (2012) estimates that the direct effect of the Clean Air Act on regulated industries is a loss of 150,000 jobs. His job loss estimate is based on comparing employment trends for the polluting industries versus nonpolluting industries in newly designated nonattainment counties versus attainment counties. Because the comparison is in part relative to nonpolluting industries in nonattainment counties, it does not include a multiplier effect, but is only the estimated direct job loss in the polluting industries. Therefore, I use a multiplier of 2 to get an estimated job loss of 300,000 jobs. This results in a present value cost of the job loss due to the regulation of over $36 billion. This $36 billion figure multiplies 300,000 jobs by my estimated present value of social costs of job loss of $134,000 per job lost. This is a large number, but the Clean Air Act overall has a net present value of costs of over $423 billion. As a percentage of overall social costs, including job effects only raises social costs by 8 percent.

Therefore, I confirm Walker's (2012) conclusion that "the wage costs borne by workers [due to the Clean Air Act] are a small fraction of the benefits," as benefits are estimated to be over 31 times overall social costs. But I further strengthen his conclusion by arguing that the social costs of this job loss are also small compared to overall social costs. Furthermore, my conclusion follows even though I assume that the job effect with a multiplier is twice his estimated job loss, and I also assume higher social costs per job lost than in his model. As shown in Table 2, my local labor market social cost estimates per job lost are over 30 percent greater than Walker's (−$134,000 versus −$98,000). Finally, this job loss number assumes that the only job effects of the Clean Air Act are a permanent job loss of 300,000 jobs. Yet it is implausible that the Clean Air Act permanently reduces overall jobs in the United States by 300,000 jobs. Presumably the consumer spending and capital that went into some of these regulated industries will eventually find other uses.

Critics of the air pollution standards for toxic pollutants from industrial boilers have claimed that this regulation might cost around 50,000 jobs.[8] This is apparently based on unreleased research from the U.S. Commerce Department, which the outside critics claim "support[s] the findings of independent research conducted by . . . industry groups." I use this job loss number not because it is necessarily accurate, but rather because it is the kind of large job loss figure sometimes claimed by critics of environmental regulations. Fifty thousand jobs is clearly a large job loss number for these regulations. I assume that these claimed job losses already include multiplier effects, so the social cost of each lost job would be around $134,000 per job lost. The social cost of these lost jobs is considerable: over $6 billion in present value losses. However, this is still less than 13 percent of the overall present value costs of this regulation. Furthermore, these 50,000 lost jobs ignore the possibility that the consumer demand and capital involved in these regulated industries will go somewhere else in the economy.

[8]The specific claim by opponents is 40,000–60,000 jobs lost. I take the midpoint of these job loss estimates.

It might appear that my results are quite different from Masur and Posner (2012) for the regulation that is their special focus, effluent guidelines for pulp and paper manufacturing. They report that the regulatory option chosen by EPA “is no longer cost-benefit justified once . . . unemployment costs are figured into the equation” (p. 630). In contrast, I estimate that the social costs of job loss due to the regulation will increase overall social costs by less than 7 percent. This seems unlikely to tip any benefit-cost analysis.

Both of our analyses are using the same estimate of a loss of 5,711 jobs. These cost estimates start with judgmental engineering cost studies of what plants will close due to these regulations. These direct job losses are then combined with an input-output model to estimate the total job loss of 5,711.

The biggest reason that Masur and Posner (2012) got their results is that they compared the costs of job loss with a case in which what they call “median benefits” only slightly exceeded costs. They used the average present value of benefit number from the range of estimates presented in EPA (1997, Table 10-2 on p. 10-4). It so happens that this average benefit number is only 2.1 percent above EPA’s estimated present value of costs. As a result, even slight variations in costs are able to tip a benefit-cost analysis. In fact, given that I estimate that the job loss increases social costs by 6.8 percent, my estimated social costs of job loss are also enough to tip the benefit-cost analysis under Masur and Posner’s assumptions about median benefits. They actually use similar cost per job numbers to what I use. I assume a cost per job figure of $134,000; they use two possible costs per job figures, which, in 2012 dollars, are calculated to be $52,000 and $150,000.

However, it is highly unusual for the benefits and costs numbers to be so close in magnitude for an adopted regulation. In this particular case, this appears to be an accident of the range of benefit estimates produced by EPA, and the incompleteness of these estimates. First, these estimates are incomplete and underestimate benefits. EPA argued in their Federal Register filing on this regulation that an estimate of net benefits would be misleading for this regulation because too many categories of water quality benefits are not monetized: “EPA did not estimate annual net benefits . . . because so many categories of benefits are unmonetized that the comparison would be misleading” (p. 18590, 63 Fed. Reg.,1998). In EPA’s 1997 economic analysis of this regulation, EPA also argues that “monetized benefits are underestimated. Given this shortfall in the benefit estimates, it would be misleading to subtract benefits from the estimated costs and make conclusions about the net benefits of the regulation to society” (EPA 1997, p. 10-1). EPA obviously is unable to state the quantitative magnitude of benefits it doesn’t measure, but it would not be surprising if these unmeasured benefits are a larger percentage of benefits and costs than is true for the social costs of job loss.

Second, the median economic benefit presented by Masur and Posner (2012) is the average of widely varying estimates by EPA. In 2012 dollars, EPA estimates that the present value of social costs of the regulation is $11.312 billion. The present value of benefits is estimated to range from −$21.950 billion to +$45.051 billion. Masur and Posner average the two extremes of this benefit estimate range to get median benefits of $11.551 billion, which just so happens to be 2.1 percent greater than estimated social costs. And it also so happens that plausible costs of job loss are somewhat greater than the difference between costs and median benefits. But surely the more important issue is how to narrow down the range of benefit estimates. The social costs of job loss are dwarfed by the uncertainty in EPA’s benefit estimate—the range of EPA’s benefit estimates of $67 billion, from −$22 billion to +$45 billion, is over 80 times what I estimate the social costs of job loss to be, at $0.766 billion.

The main impediment to better benefit-cost analysis of these pulp and paper regulations is not EPA’s failure to include the social costs of job loss. Rather, the more important issue is the estimate of benefits, due to the wide range of possible estimates and the omission of benefits.

In sum, job losses from environmental regulation can be large. The associated social costs can also be large. However, under plausible estimates of typical social costs of job loss, it is unlikely that adding in social costs of job loss will cause a large percentage increase in overall social costs. Therefore, including typical social costs of job loss will rarely tip benefit-cost analyses of these regulations.

The caveat is that for some regulations, assuming the maximum plausible values of social costs of job loss could make a difference to benefit-cost analysis. For example, if we use the demand instrument estimates using local labor market data, costs per job loss approximately double. If we further assume that the jobs lost are in a severe recession or a severely depressed local labor market, we might get a further 30–60 percent increase in social costs of job loss. If the affected plants happened to employ a great many older workers, social costs of job loss might further increase. If we assume an extreme enough scenario, for at least some of the nonhabitat regulations in Table 5, we could push estimated social costs of job loss up to 20 percent or more of overall social costs.

On the other hand, these calculations assume that all of this job loss is permanent. In a more realistic scenario, the capital and consumer demand displaced in regulated industries will boost job growth elsewhere in the economy. As a result, even with involuntary unemployment, the most plausible conclusion is that social costs of job loss will rarely make a big difference to the overall costs of environmental regulation.

CONCLUSION

The social cost of a lost job is plausibly high. This corresponds to how the public and politicians perceive job loss. However, the estimates suggest that the social costs of a lost job are much less than 100 percent of the earnings associated with that lost job. A maximum plausible value for typical losses is 32 percent of the associated earnings. Other figures are significantly less than 20 percent of the associated earnings. A midpoint figure used in this report is 14 percent. A plausible minimum figure might be 8 percent of the earnings associated with the job loss. Estimating the bottom-line net job effects of environmental regulation is challenging. Determining direct effects on the regulated industry is difficult enough, but it is even more difficult to determine the level and timing of possible offsetting job gains in the overall national economy.

However, even if we only look at the direct job losses and don't consider possible offsets, in most cases the social costs of job loss due to regulation will add less than 10 percent to the measured social costs of the regulation. It takes quite a bit of regulatory costs to destroy one job. The social costs of job loss, although high, are not high enough to play a major role in driving benefit-cost analysis of environmental regulations.

One caveat is that social costs of job loss may loom higher for certain types of environmental regulation, such as some habitat regulations that entirely prohibit rather than regulate some economic activity.

Another caveat is that social costs of job loss vary with the age of the workers affected, the wage premia of the jobs lost, and with how high unemployment is in the national or local economy. When we combine this with the uncertainty in the general estimates of social costs of job loss, there are some extreme cases of job loss in which social costs will be more important than they are typically.

For research, this points to the need to improve our estimates of the social costs of job loss. In particular, we need more precise estimates about how social costs of job loss vary with worker demographics, the types of jobs, and economic conditions. We need better estimates of possible effects on firms of some of the occupational and job downgrading associated with job loss. We need better estimates of how quickly and to what extent the consumer demand and capital supply that is displaced by regulation leads to job gains in other industries.

What can we say to Congress about including the social costs of job loss in benefit-cost analysis of environmental regulation? I think we can definitely include job loss in benefit-cost analysis if that is demanded. Adding in the social costs of job loss would probably increase the uncertainty of the overall social cost figures. There is more uncertainty in the social cost of job loss figures than in most of the other regulatory costs. This uncertainty is due to uncertainty in both the job effects and the appropriate social cost per job lost. But although the resulting social cost figures would be more uncertain, these overall social cost figures would be more comprehensive in addressing the benefits and costs that the public values.

What also needs to be said is that if jobs gained or lost have a high value per job, the most efficient response is to have policies that specifically target job creation. Trying to create jobs through reforming environmental regulation is an inefficient way to address the need for jobs. If the economy is short of overall jobs, this can in many cases more effectively be addressed through monetary policy than through restructuring all the other operations of the government to address the jobs issue. If monetary policy is constrained by the zero bound on interest rates, or by other factors, then fiscal policy or other job creation policies can potentially address job creation in a cost-effective way. There are a number of overall job creation policies whose net fiscal costs will be less than $134,000 per job, including public spending on labor-intensive goods and services, public service jobs, wage subsidies, and work sharing (Bartik 2010). From a policy wonk perspective, it is completely inconsistent for a politician to argue against environmental regulations because they are "destroying valuable jobs" while also opposing policies that would create jobs at a lower cost than these jobs' value. But political stances are often inconsistent.

If monetary and other policies are effectively addressing the need for jobs, then including jobs in benefit-cost analysis of government regulation is less important in at least two senses. It is less important in that with lower unemployment, the costs of any job loss will be less. Therefore, benefit-cost numbers will be altered less by including the social costs of job loss. Including jobs in benefit-cost analysis will also then be less important because if we can count on public policy to maintain adequate overall employment, we can also count on any job loss from environmental regulation to be offset by job gains elsewhere. Net job effects will be small. There remains the distributional issue of some individuals being displaced by job loss, while other persons may gain from the offsetting job gains. But worker readjustment policies should have greater chance of success if the overall job market is maintaining adequate growth of overall employment.

The demand for including jobs in environmental benefit-cost analysis is just one of the more modest costs of the United States' failure to aggressively address the need for higher aggregate employment. Until we achieve and maintain a healthier aggregate labor market, we can expect the political and economic need for more jobs to distort many areas of U.S. public policy.

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Table 1 Benefits and Costs of Pollution Regulations Incorporating Job Effects

Category	Labor demand or supply	Sub-category	Direct job effects	Indirect job effects
Business regulatory effects				
	Labor demand	Direct cost effects on regulated industry	Job reduction in regulated industry, losses for affected workers	Affects overall labor market for all workers with reduced employment rates and wage rates
	Labor demand	Pollution compliance effects	Additional activity in regulated industry and suppliers to comply with regulation, which creates jobs	This job creation will affect overall labor market with increased employment rates and wage rates
	Labor demand	Multiplier effects of direct effects	Lower activity in regulated industries, and higher activity in pollution control industries, may have multiplier effects on suppliers to these industries and on suppliers to these industries' workers	Effects on supplier industries affects overall labor market, not just workers in supplier industries
	Labor demand	Displaced capital and consumer demand effects	Capital and consumer spending that would have gone to polluted industry go elsewhere, with job creation effects	This job creation affects not just hired workers, but overall labor market conditions
	Labor supply	Increased prices in regulated industry increases overall prices, which lowers real wages	Lower real wages may lower aggregate labor supply if labor supply responds to real wages	Lower labor supply of some workers affects labor market for other workers
Amenity and health benefits of reduced pollution				
	Labor demand and supply	Amenities may be complements or substitutes for leisure or various goods and services	Increased amenities may cause various shifts in consumer demands or supply of labor, with uncertain effects on overall labor demand and supply	Whatever labor demand or supply shocks occur will have effects on overall market equilibrium
	Labor supply	Health benefits of reduced pollution	May increase quantity or quality of labor supply	Addition to labor supply will possibly have some displacement effects in labor market, lowering others' real wages and employment rates

Table 2 Baseline Estimates of Social Costs of Job Loss

	Present value of social costs in dollars per lost job (2012 dollars)	Present value of social costs as ratio to annual earnings in lost jobs	Present value of social costs as % of present value of future earnings in lost jobs
Social cost = gross earnings	−952,605	−15.88	−100.0
Walker (2012) displacement estimates	−98,375	−1.59	−10.0
Davis and von Wachter (2011) displacement estimates	−76,845	−1.61	−11.4
Earnings estimates from local labor market model	−296,959	−4.95	−31.2
This paper's baseline estimates	−134,207	−2.24	−14.1
Reservation wage approach	−81,227	−1.35	−8.5

NOTE: Gross earnings figures assume all earnings associated with job loss are complete social loss. Walker figures are taken from dollar effects of displacement in column 5 of his Table 2, and percentage of earnings figures are taken from column 3 of his Table 2. I recalculate present values using a 3% discount rate. Davis and von Wachter figures are equally weighted averages of their results for men and women aged 21–50 with three or more years tenure, from their Tables 1 and 2, results for all years. The remaining estimates are based on local labor market model estimated in Bartik (2013) (see also Appendix A of the present paper). The earnings effects row estimates are comparable to Walker and Davis and von Wachter in not considering value of leisure or benefits for firms. The baseline estimates use method (1) from text, and baseline assumptions about leisure values and firm benefits. Reservation wage approach uses method (2) from text, and baseline assumptions about firm benefits. All estimates use 3% discount rate, except for Davis and von Wachter, which uses 5%. A 5% discount rate does not change other rows much.

Table 3 Alternative Social Cost Estimates, Using Different Local Labor Market Estimates

	Present value of social costs in dollars per lost job (2012 dollars)	Present value of social costs as % of annual earnings in lost jobs	Present value of social costs as % of present value of future earnings in lost jobs
This paper's baseline estimates	−134,207	−2.24	−14.1
Demand shock estimates	−298,658	−4.98	−31.4
Bartik (1991) estimates	−237,321	−3.96	−24.9

NOTE: Baseline estimates are same as in Table 2, and are based upon Bartik (2013) and assumptions outlined in text. Demand shock estimates are based on effects of growth estimated in Bartik (2013) based on instrumental variable estimates for effects of local job growth. Instrument for growth is predicted metro growth based on initial local industry mix and national industry growth trends. The last row uses estimates of growth effects from Bartik (1991). All other assumptions are same across all estimates in this table.

Table 4 Social Cost Estimates under Alterative Assumptions about Offsets

	Present value of social costs in dollars per lost job (2012 dollars)	Present value of social costs as % of annual earnings in lost jobs	Present value of social costs as % of present value of future earnings in lost jobs
This paper's baseline estimates	−134,207	−2.24	−14.1
Higher opportunity costs of labor and higher employer offsets	−38,941	−0.65	−4.1
Lower opportunity costs of labor and lower employer offsets	−229,473	−3.82	−24.1

NOTE: Baseline estimates are same as in Tables 2 and 3, and rely on baseline assumptions outlined in text and Appendix A. The next two rows alter those assumptions, as described in text, to higher or lower valuations offsets of the earnings loss for workers by either gains in nonwork time or gains for employers.

Table 5 Summary of Social Costs of Job Loss, as Percent of Total Estimated Social Costs of Environmental Regulations

	Average social costs of job loss as % of total measured social costs of environmental regulation	Range of social costs of job loss as % of total social costs, across regulations considered
Nine environmental regulations from Walker (2012) and Masur and Posner (2012) (nonhabitat)	5	1–13
Three habitat regulations (from Masur and Posner 2012)	84	24–167

NOTE: This summarizes information from Appendix B, Table B1. I consider percentage change in social costs due to job effects reported in that table, and summarize means and range. The three habitat regulations are identified in table. The nine nonhabitat regulations are all other regulations in Table B1 except for last two rows, which were suggested to me by EPA staff, and also other rows where percentage change in costs is zero or negative. In cases where range of social costs is reported in Table B1, I use largest positive percentage. The estimates used in this table end up being most of Masur and Posner's regulatory cases, and Walker's Clean Air Act analysis. Calculated mean percentage is unweighted mean across nine or three regulations.

Table 6 Social Costs of Job Loss Compared to Overall Social Costs for Three Prominent Regulations

Regulation	Source of benefit-cost and job info	Benefit-cost ratio	Overall social costs: present value (billions of 2012$)	Jobs lost (or gained)	Job effects: cost (or benefit) in present value (billions of 2012$)	% change in costs due to job effects
Clean Air Act	Walker (2012); EPA (2011b)	31.58	−432.663	−300,000	−36.640	8.5
Industrial boiler air pollution standards	76 Fed. Reg. 15,608 (2011); American Forest and Paper Assoc. (2010)	25.33	−53.311	EPA says small; others claim −50,000	0 to −6.710	0 to 12.6
Pulp/paper: total package of air and water pollution regulations	Masur and Posner (2012); EPA (1997)	?	−11.312	−5,711	−0.766	6.8

NOTE: This table is an excerpt of three rows from Table B1 in Appendix B.

APPENDIX A

MORE DETAILS ON ESTIMATED LOCAL LABOR MARKET MODEL AND ITS USE IN THIS PAPER

This paper's local labor market models of social costs are derived from new estimates of how local labor market outcomes respond to employment growth. The relevant "growth shock" is a one-time shock to growth, or a once and for all shock to the employment level. More details on this estimation are in Bartik (2013).

These local labor market elasticities are based on estimates of equations such as the following:

$$\ln Y_{mt} - \ln Y_{mt-1} = \mathrm{B}_0 + \mathrm{B(L)}G_{mt} + \mathrm{C(L)}\, G_{mt} * U_{mt-k} + \mathrm{F} * U_{mt-k} + D_t + e_{mt} \qquad \text{(Eq. A1)}$$

$\ln Y_{mt} - \ln Y_{mt-1}$ is the logarithmic change in some average labor market outcome variable in a metropolitan area m from year $t - 1$ to year t. G_{mt} is logarithmic metro employment growth from one year to the next. B(L) is a polynomial in the lag operator, which indicates that the equation includes both current and possibly several lags in employment growth. Some specifications include $G_{mt} * U_{mt-k}$, which is an interaction term between metro growth and the initial unemployment rate in the metro area. C(L) indicates some lags in growth are included in this interaction term. These terms are included in some specifications to see if the effect of growth on labor market outcomes varies with initial labor market conditions. The lagged unemployment rate variable is also included by itself in specifications that include initial unemployment rate's interaction with subsequent growth shocks. D_t is a set of year dummies, so that we are examining differentials in labor demand shocks across metro areas and how they are related to differentials in labor market outcomes across metro areas. e_{mt} is the disturbance term.

This model is estimated using pooled time series cross section data on average labor market outcomes for either 23 (for real wages) or 38 metro areas (for labor force variables) over the years 1979–2011. More details on the derivation of the data are in Bartik (2013).

The immediate effect of a growth shock is the coefficient on current period growth. The long-run cumulative effect of a one-time growth shock (a once and for all shock to the employment level) is the sum of all the B(L) coefficients up to the last lag of growth included. The cumulative effect after s years of a one-time growth shock (a once and for all shock to the employment level) is the sum of all the B(L) coefficients up to the sth lag in growth. In all models, we consider what lag length in growth optimizes the Akaike Information Criterion, a standard model selection criterion.

The estimates from this model are used in various Excel calculations to calculate social costs of job loss. The estimates from this model are used to derive an Excel table that looks like Table A1.

This table shows cumulative elasticities effects implied by "optimal" models from Bartik (2013) of cumulative effects after various years of a one-time negative reduction in employment. For example, the −0.278 for the year zero row, employment to labor force column, means that if there is a one-time reduction in metro employment of one percent in logarithmic terms (the log of metro employment declines by 0.01), then the natural logarithm of the metro area's ratio of employment to the labor force will decline by 0.278 times as much, or by −0.00278. This effect on the employment to labor force ratio diminishes over time and is estimated to disappear after five years.

Table A1 Job Loss Elasticities Used in Local Labor Market Baseline Model

Year after job loss	Weekly work hours	Employment to labor force ratio	Labor force participation rate	Real wage rate	Real wage rate predicted based on occupation	Wage differential from occupational prediction
0	−0.0724	−0.278	0.0167	−0.18	−0.0654	−0.1146
1	−0.0364	−0.25	−0.103	−0.248	−0.0542	−0.1938
2	−0.0174	−0.0908	−0.0763	−0.0662	−0.0545	−0.0117
3	−0.0974	−0.0719	−0.0899	−0.256	−0.0504	−0.2056
4	−0.0213	−0.113	−0.0379	−0.358	−0.0646	−0.2934
5	−0.0581	0.0111	−0.105	−0.319	−0.117	−0.202
6	0.00607	0	−0.0522	−0.16	−0.0481	−0.1119
7	0	0	0.0236	−0.226	−0.0606	−0.1654
8	0	0	0.0126	−0.337	−0.0934	−0.2436
9	0	0	−0.0137	−0.3	−0.0351	−0.2649
10	0	0	−0.00154	−0.197	−0.0449	−0.1521
11	0	0	0	−0.197	−0.0449	−0.1521
12	0	0	0	−0.197	−0.0449	−0.1521
13	0	0	0	−0.197	−0.0449	−0.1521
14	0	0	0	−0.197	−0.0449	−0.1521
15	0	0	0	−0.197	−0.0449	−0.1521
16	0	0	0	−0.197	−0.0449	−0.1521
17	0	0	0	−0.197	−0.0449	−0.1521
18	0	0	0	−0.197	−0.0449	−0.1521
19	0	0	0	−0.197	−0.0449	−0.1521
20	0	0	0	−0.197	−0.0449	−0.1521

NOTE: Estimates for first five columns (weekly work hours to real wage rate predicted based on occupation) come from Bartik (2013) but are multiplied by (−1) to correspond to job loss. Estimates are for elasticity of that labor market outcome with respect to one-time employment job loss shock; effects reported after s years represent cumulative elasticity after that many years. Wage differential is equal to difference between two preceding columns.

Because earnings is the product of weekly work hours, the employment to labor force ratio, the labor force participation rate, and the wage rate, the percentage change in earnings in response to some percentage job loss can be expressed as the sum of these various elasticities.

To translate Table A1 into social costs, I have to decide what proportion of the different components of earnings loss may be offset by various gains. I also have to decide on a discount rate. This is done in a combined calculation, in which the numbers in Table A1 are first multiplied by one minus an assumed offset factor, and then are discounted at a 3 percent real discount rate back to year zero, the year in which the job loss occurs.

The workforce activity elasticities are multiplied by various factors to reflect the value of nonworking time to workers. The weekly work hours' elasticities are multiplied by (1 − 0.35) to reflect an assumed value of increased weekly nonwork hours to workers of 35 percent of the wage rate. The employment to labor force ratio numbers are multiplied by approximately (1 − 0.10) to reflect the assumption that increased time in involuntary unemployment is valued at 10 percent of the market wage. The labor force participation rate numbers are multiplied by approximately (1 − 0.3) to reflect the assumption that increased time outside the labor force is valued at 30 percent of the market wage. These assumptions are discussed in more detail in the paper text.

The wage numbers are multiplied by various factors to reflect the value of wage reductions to employers. The reduction in wages due to occupational downgrading are multiplied by (1 − 0.50) to reflect the assumption that 50 percent of this wage reduction results in benefits to employers. The wage differential reduction is multiplied by (1 − 0.75) to reflect the assumption that 75 percent of this wage reduction results in benefits to employers.

After multiplying by these adjustment factors for offsets, I then discount each year's effects using a 3 percent annual discount rate back to year zero. I then sum the elasticities for each column, and then sum over all columns. The estimated effect summed over all variables is the social value of the reduction in earnings, expressed as a ratio to the initial percentage job loss. This initial percentage job loss is also the same percentage earnings loss. Therefore, this discounted sum over all variables is the social cost as a ratio to the annual earnings loss associated with the jobs loss.

This ratio is then multiplied by average compensation for one job of $59,997 to get the social cost associated with the loss of one job paying that amount. Finally, this ratio is divided by 15.88, which is the ratio of the present value at a 3 percent real discount rate of the gross earnings losses over a 20-year time horizon of the gross earnings losses that are directly due to a negative job loss. This shows the present value of social cost of job loss as a percentage of the present value of the gross earnings loss associated with the direct job loss.

Table A2 Elasticities Adjusted for Offset Factors and Discount Rate

Offset factor for each column	0.35	0.104061	0.298432	0.5	0.75
Year	Weekly work hours	Employment to labor force ratio	Labor force participation rate	Real wage rate predicted based on occupation	Wage differential
0	−0.04706	−0.24907	0.011716	−0.0327	−0.02865
1	−0.02297	−0.21746	−0.07016	−0.02631	−0.04704
2	−0.01066	−0.07668	−0.05046	−0.02569	−0.00276
3	−0.05794	−0.05895	−0.05772	−0.02306	−0.04704
4	−0.0123	−0.08995	−0.02362	−0.0287	−0.06517
5	−0.03258	0.008579	−0.06354	−0.05046	−0.04356
6	0.003304	0	−0.03067	−0.02014	−0.02343
7	0	0	0.013462	−0.02464	−0.03362
8	0	0	0.006978	−0.03687	−0.04808
9	0	0	−0.00737	−0.01345	−0.05076
10	0	0	−0.0008	−0.0167	−0.02829
11	0	0	0	−0.01622	−0.02747
12	0	0	0	−0.01575	−0.02667
13	0	0	0	−0.01529	−0.02589
14	0	0	0	−0.01484	−0.02514
15	0	0	0	−0.01441	−0.02441
16	0	0	0	−0.01399	−0.0237
17	0	0	0	−0.01358	−0.02301
18	0	0	0	−0.01319	−0.02234
19	0	0	0	−0.0128	−0.02169
20	0	0	0	−0.01243	−0.02105
Sum of column	−0.1802	−0.68354	−0.27218	−0.44121	−0.65975
			Sum of all columns	−2.24	

NOTE: Each column takes elasticities from corresponding variable in Table A1, and multiplies those elasticities by (1 minus offset factor) at top, and then divides by 1.03 (the discount rate) raised to the power of the corresponding year for that row. The sum of all these factors is the ratio of social cost to one-year's annual earnings. 2.24 times average compensation per worker of $59,997 results in the social cost implied by the loss of one job. 2.24 is divided by 15.88, the ratio if all gross earnings of the lost jobs are counted over 20 years, to get the ratio of the present value of social costs to the present value of the gross earnings associated with the lost jobs, which yields the 14.1% in the text Table 2.

APPENDIX B

MORE DETAILS ON THE ANALYSIS OF HOW JOB EFFECTS ALTER SOCIAL COSTS OF ENVIRONMENTAL REGULATIONS

This appendix summarizes some calculations on how job effects alter the social costs of various environmental regulations. I focus on some prominent regulations that have been discussed as cases in which job losses might need to be considered. I consider the Clean Air Act, which is obviously a major environmental regulation. More importantly, recent empirical work by Walker (2012) provides estimates of job loss for the CAA that were done independently of government regulatory officials. I also analyze 12 of the 13 regulatory examples listed by Masur and Posner (2012) in their recent article arguing that including social costs of job loss may often make a difference to benefit-cost analysis of regulations.[9] Masur and Posner give a special focus to effluent regulations for pulp and paper manufacturing; they argue that this is a case in which including job loss might tip the overall net benefits. Therefore, I devote some extra attention to these pulp and paper regulations. Finally, I consider two recent examples suggested by EPA officials: air toxic standards for utilities; the proposed cleanup of an ash spill by TVA.

I rely in most cases on the costs and benefits of the regulation that are reported in the official government analyses. I also rely in most cases on the job impacts reported by official government analyses. One exception is that I use Walker's estimates of job loss from the Clean Air Act. Another exception is emission standards for industrial boilers, for which I also consider

[9]One of their 13 examples, "conservation of roadless forest land," is omitted because the regulatory analysis does not estimate overall social costs, so it is impossible to calculate how including job loss would affect social costs.

the job impacts claimed by businesses opposed to these regulations. Finally, for the TVA ash cleanup, I do my own job effect analysis based on reported clean-up costs.

The job impacts for these regulations vary greatly in how they are calculated. In some cases, these are only direct job effects on the regulated industry due to the regulation. Some of these direct job loss numbers are due to engineering cost studies, which assume some number of plants will become uncompetitive due to regulations and therefore will close. In other cases these job effects include some multiplier effects, in many cases estimated using some input-output model. In still other cases these job effects include some offsets due to effects on pollution control jobs or effects on relocating consumption and output to other industries. Some of the models estimate direct job effects and these offsets using the model developed by Morgenstern, Pizer, and Shih (2002).

My focus is on how overall social costs would have been altered by including the social costs of job loss. To do this analysis, for each study I take the cost figure in the original study, which is typically an annual dollar figure, and use a 3 percent real discount rate to convert that cost estimate into a present value number. (I also convert all dollar figures to 2012 dollars.) If the job loss estimate of the original study only includes direct jobs, I assume a multiplier of 2.0 to calculate total jobs loss. This size multiplier is a conservative estimate for job losses in manufacturing (Crihfield and Campbell 1991, 1992; Grimes, Fulton, and Monardelli 1992; Moretti 2010; Rickman and Schwer 1995). I then take the total job loss estimate and multiply it by the $134,000 present value figure per lost job that is the baseline social cost per job estimate from the previous Table 2.[10]

[10]The social cost of jobs numbers assume a 20-year time horizon, whereas the overall social costs assume an infinite time horizon. I think this is realistic as regulatory costs will be quite persistent, whereas job costs should

What is most interesting from these calculations is the percentage effect of job loss on overall social costs. For many of these regulations, benefit-cost ratios might be 2-to-1, 3-to-1, or even 30-to-1. The bottom line of whether a regulation passes a benefit-cost test is not going to be altered unless there is a huge percentage effect of job loss on overall social costs. Even the relative ranking of regulations will not be much altered unless the job loss increases social costs of a regulation by more than 10 or 20 percent. The measurement error in social costs probably exceeds 10 or 20 percent.

For a wide variety of regulations, I find that including job loss usually increases social costs by less than 10 percent (Table B1). There are a few exceptions. For regulation of toxic air pollutants for industrial boilers, if one uses the job loss numbers of this regulation's critics, social costs increase by 13 percent. For some habitat preservation regulations, social costs of job loss are an even higher percentage. It is unclear whether this pattern is due to differences across government agencies in how economic effects are calculated, or due to differences in the nature of the regulations. The text presents some reasons why this difference might be related to the nature of the regulations.

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eventually fade. If we instead assume an infinite time horizon for the social costs of job loss, the social costs per job loss increase by 49.9 percent, based on calculations of social costs in the 20th year, extended into an infinite future. This 50 percent increase in social costs numbers would only modestly change the conclusions reached in Table B1. For example, the calculations in Table B1 for the Clean Air Act show that adding in job losses increases social costs by around 9 percent. If the social costs of jobs have an infinite time horizon, this figure would increase by 50 percent to around 13 percent.

Table B1 Social Costs of Job Loss Compared to Overall Social Costs of Various Regulations

Regulation	Source of benefit-cost and job info	Benefit-cost ratio	Overall social costs: present value (billions of 2012$)	Jobs lost (or gained)	Job effects: cost (or benefit) in present value (billions of 2012$)	% change in costs due to job effects
Clean Air Act	Walker (2012); EPA (2011b)	31.58	−432.663	−150,000	−36.640	8.5
Pulp/paper: total package of air and water pollution regulations	Masur and Posner (2012); EPA (1997)	?	−11.312	−5,711	−0.766	6.8
Desert tortoise habitat protection	59 Fed. Reg. 5,820 (1994)	?	−0.024	−310	−0.042	166.5
Landfills: wastewater discharges	65 Fed. Reg. 3,008 (2000)	?	−0.358	−109	−0.014	4.1
Aluminum production: hazardous air pollutants	65 Fed. Reg. 15,690 (2000)	?	−3.916	−94	−0.026	0.6
Coal mining effluent standards: discharges into water and drainage	67 Fed. Reg. 3,370 (2002)	Saves costs	0.572	−29	−0.004	−0.7
Peirson's milk-vetch (wildlife plant) habitat preservation—adopted alternative	69 Fed. Reg. 47,330 (2004)	?	−0.034	−60	−0.008	24.2
Peirson's milk-vetch—rejected alternative	69 Fed. Reg. 47,330 (2004)	?	−0.416	−1,896	−0.254	61.2
Fuel economy standards for cars and light trucks, for model year 2011 only	74 Fed. Reg. 14,196 (2009)	1.70	−1.268	−1,024	−0.008	0.6
Energy conservation standards for small electric motors	74 Fed. Reg. 61,410 (2009)	4.21	−4.163	0	0.000	0.0
Construction and development industries—Clean Water Act regulation of discharges	74 Fed. Reg. 62,996 (2009)	0.38	−34.073	−7,257	−1.947	5.7
Portland cement plants: air pollution standards	75 Fed. Reg. 54,970	13.54	−36.767	−807	−0.216	0.6%

Table B-1 (Continued)

Regulation	Source of benefit-cost and job info	Benefit-cost ratio	Overall social costs: present value (billions of 2012$)	Jobs lost (or gained)	Job effects: cost (or benefit) in present value (billions of 2012$)	% change in costs due to job effects
Industrial boiler air pollution standards	76 Fed. Reg. 15,608 (2011) ; American Forest and Paper Assoc. (2010)	25.33	−53.311	EPA says small; others claim −50,000	0 to −6.710	0 to 12.6
Incinerators: emission standards	76 Fed. Reg. 15,704 (2011)	2.79	−7.762	EPA central case: +200; worst case : −400	0.054 to −0.107	−0.7% to +1.4
Utilities: air toxic standards	77 Fed. Reg. 9,304 (2011)	6.61	-354.296	Central case: 8,000; worse case: −15,000	2.148 to -4.027.	−0.6% to 1.1
TVA ash cleanup	TVA (2010)	?	−0.296	Net job creation of 266 for four years, reduced to 2 jobs after that	0.004	−1.4

NOTE: This analysis was sped up by using Federal Register references from Masur and Posner (2012) for all except the Clean Air Act regulation, the utilities regulation of air toxic standards, and TVA ash cleanup. However, I did not use the net benefit figures from Masur and Posner, but rather used benefit-cost ratios and overall cost figures in present value terms. Also, although I looked at Masur and Posner’s estimated job loss figures, I independently examined these regulatory filings to determine the job loss, and my figures sometimes differ slightly from theirs. EPA analyses generally present annual costs and benefits for some typical future year when the regulation is fully effective. (One prominent exception is the pulp and paper regulation, for which I used the present value figures at a 3% discount rate from Table 10-4 of EPA (1997). EPA did not report a benefit-cost ratio for this regulation.). I used the annual benefit-cost ratio. I used a 3% real discount rate to convert annual costs to present values. This probably slightly increases present value given that regulations are often phased in. All costs are presented as negative numbers, and if instead there are cost savings or jobs created, these are presented as positive numbers. Present value figures for cost of job losses are calculated for all except the TVA case by directly using the baseline local labor market estimates from this study. The jobs numbers reported in the table are the jobs numbers reported by study, which in some cases included multiplier, but in other cases only included direct jobs affected. In calculating cost of job effects, I multiplied total job change by $134,000, from my baseline social cost estimates in Table 2. If the study did not include a multiplier, I assumed multiplier of 2.0 to get total job change. For the TVA case, I assume that TVA spending on project over 4 years, plus permanent spending, would have balanced budget multiplier effects in creating jobs. I assumed that spending would create jobs at $92,000 per job (in 2009 dollars), while increased taxes would destroy jobs at $145,000 per job (in 2009 dollars), based on Council of Economic Advisers (2009). I evenly spread TVA capital spending on this project over four years. The value of the temporary job creation for four years was calculated as present value of permanent job creation of 266 minus present value of permanent job destruction of 264 jobs four years from now, with appropriate discounting.

ENVIRONMENTAL REGULATION AND INDUSTRY EMPLOYMENT: A REASSESSMENT

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Abstract

This paper examines the impact of environmental regulation on industry employment, using a structural model based on data from the Census Bureau's Pollution Abatement Costs and Expenditures Survey. This model was developed in an earlier paper (Morgenstern, Pizer, and Shih (2002) - MPS). We extend MPS by examining additional industries and additional years. We find widely varying estimates across industries, including many implausibly large positive employment effects. We explore several possible explanations for these results, without reaching a satisfactory conclusion. Our results call into question the frequent use of the average impacts estimated by MPS as a basis for calculating the quantitative impacts of new environmental regulations on employment.

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1 INTRODUCTION

The "jobs vs. environment" debate has been raging in the United States and elsewhere since the 1970s, although interest has clearly intensified during the recent economic downturn. At the same time, conclusive evidence on the employment impacts of such regulation is quite limited, largely because the effects of environmental regulation on labor markets are so difficult to disentangle from other economic changes over time and across industries.

The policy debate has spawned alternative definitions of regulation-induced job loss. While an individual separated from an existing job because of an environmental regulation has clearly suffered a loss, pollution abatement activities themselves require labor input. Thus, environmental regulations may also create jobs – sometimes in the same industry, the same firm, or even the same plant. Although headlines rarely make the linkage, job loss in one area may be accompanied by job creation in another (e.g., when environmental regulation causes firms to shift production from counties not attaining one or more federal air quality standards to those in compliance). Henderson (1996), Becker and Henderson (2000), and Greenstone (2002) have found such job shifts using linear regression models based on these spatial, pollutant-specific differences in regulation. However, the number of jobs moving from non-attainment to attainment areas may overstate the effects on industry or economy-wide employment.

Labor unions and trade groups often focus on gross job changes and the cost of rearranging workers within an industry. However, *net* job loss within an industry – which recognizes all intra-industry employment changes associated with environmental regulation – is also an important metric. This definition recognizes that many regulated firms relocate employees in other units of the same company, and that plants remaining in the industry often expand output to make up for the reduced production due to exiting or shrinking plants in the same industry, thereby offsetting at least some of the initial job losses.

Morgenstern, Pizer, and Shih (2002) (hereinafter MPS) measured regulatory burden or stringency via a widely used proxy, pollution abatement operating costs (PAOC), reported in the Pollution Abatement Costs and Expenditures (PACE) Survey.[1] MPS developed a structural model to link PAOC and employment, and decomposed the employment consequences of PAOC into a cost effect, a factor shift, and a demand effect.[2] Standard theory predicts a positive cost effect and a negative demand effect, while the sign of the factor shift could go either way, making the direction of the net impacts indeterminate ex ante.

Using plant-level Census data from 1979–91 for four pollution-intensive industries, MPS estimated a cost function that allowed assessment of the first two components and then combined the results with estimates of industry-wide demand elasticities to calculate the third component. They

[1] As Gallaher, Morgan and Shadbegian (2008) noted, the PACE is "the only comprehensive source of pollution abatement costs and expenditures related to environmental protection in the manufacturing sector of the United States" (p 309). They also cited the now considerable literature examining the reasons why the PACE survey may either under- or overstate the true costs of pollution abatement. See also Becker and Shadbegian (2007).

[2] For a somewhat similar approach, see Berman and Bui (2001).

combined the components to estimate the net change in employment associated with changes in reported PAOC. Aggregating over four industries, they found a small, statistically insignificant, gain of jobs associated with PAOC. The positive value was driven by the results from the plastics and petroleum industries, which had significantly positive factor shifts coupled with relatively small demand effects.

Because of the importance of MPS in this debate, we used a similar methodology and addressed two key questions: (1) does the effect of environmental regulation vary across industries; and (2) has the nature or magnitude of the effect changed over time? Like MPS, we did not find any evidence of large negative effects. However, for some industries and time periods, we obtained very large positive effects. The magnitudes of these effects seem to imply that nearly all of the regulatory expenditure is used to hire workers. This is implausible because of the capital intensity of pollution abatement in these industries.

After reporting the main results, we describe extensive additional analysis trying to explain these results. One possibility is that the MPS methodology was sensitive to the sample, but in some cases we also obtained implausible results using a linear regression model rather than the model in MPS. Alternatively, there may have been an omitted variables problem that was apparent in our samples but less severe in the MPS samples. We were not able to identify suitable instruments or alternative strategies to address this possibility.

A key limitation of the MPS approach was the exclusive focus on continuing plants. Relying on a balanced panel, the approach excluded those facilities that exited the industry during the study period, thereby precluding analysis of the potential impact of regulation on exit. During our project we began to examine this issue by developing a preliminary analysis of the exit decision by plants in these industries. Perhaps unsurprisingly, we found a quite limited impact of regulation on exit probabilities, with mostly small and insignificant effects, including decreases as well as increases in exit associated with higher PAOC across the industries.[3]

The paper is organized as follows. The next section briefly lays out the framework for decomposing industry-level employment effects. Section 3 describes the methodology and data for estimating employment effects. Section 4 presents the results for these plants. Section 5 discusses possible explanations for the implausible results. Section 6 provides conclusions.

2 FRAMEWORK FOR DECOMPOSING INDUSTRY-LEVEL EMPLOYMENT EFFECTS

This section first provides an overview of the MPS approach and then discusses the extensions developed herein.

2.1 Overview of MPS Methodology

Recognizing that when environmental regulations change, both a rearrangement of production activities and a potential output contraction affect employment, MPS developed a structural model to estimate the relationship between regulatory costs and output. An advantage of the structural approach was that it enabled a decomposition of the employment effects into the cost, factor shift,

[3] Exit analysis results are available at http://yosemite.epa.gov/ee/epa/eerm.nsf/vwAN/EE-0572-07.pdf/$file/EE-0572-07.pdf

and demand components (further described below). As MPS emphasized, the public debate has focused mostly on the demand effect. However, this focus ignores the fact that employment could rise if demand is less than unit elastic or if production becomes more labor intensive. Thus, disentangling the three effects can help clarify the relationship between regulation and employment.

MPS defined their disaggregation as follows:

a) Cost effect: As production costs increase from added pollution abatement activities, plants use more of all inputs (including labor) to produce the same level of output.

b) Factor shift: Post-regulation production technologies may be more or less labor intensive (i.e., more or less labor may be required per dollar of output).

c) Demand effect: Higher production costs raise market prices. Higher prices reduce consumption (and production), thereby reducing demand for labor within the regulated industry.

The cost effect depends on the relationship between regulatory costs and total costs. The stronger the relationship is, the greater the effect. Theoretically, the cost effect is positive, meaning that an increase in regulatory stringency causes employment to increase via the cost effect. In contrast, the factor shift depends on whether regulatory costs induce substitution toward or away from labor while holding total costs constant. In principle, the factor shift could be either positive or negative.

MPS estimated these two effects by estimating a plant-level cost function that included regulatory costs as well as the costs of four productive inputs: capital, labor, energy, and materials. MPS showed that the cost effect and factor shift depend on the cost function parameters and input cost shares. We used the same functional form to estimate plant-level cost functions.

Assuming monopolistic competition among plants in an industry, MPS showed that the demand effect depends on the elasticity of total industry output demand with respect to the output price. The more elastic industry output demand is, the more an increase in costs reduces total industry output and thus employment. MPS estimated the demand elasticity using aggregate industry-level data. As the next section discusses, we made the same monopolistic competition assumption, but the estimation of demand elasticities differed in several important ways.

After estimating cost function parameters and demand elasticities, MPS estimated the employment effects of a hypothetical increase in regulatory costs. MPS made the not unreasonable assumption that the plant's share of regulatory costs was proportional to its share of total industry output – an assumption that we continued to employ.

2.2 Expanding the Time Period and Set of Industries Analyzed

We next discuss the extensions to MPS. MPS used plant observations from 1979–1981, 1985, 1989, and 1991. The MPS analytical datasets were assembled from several surveys, but two of them were not conducted continuously: the PACE survey, which collects information on expenditures related to environmental regulation, and the Manufacturing Energy Consumption Survey (MECS), which collects information on energy costs. MPS did not include all years in the 1979–1991 time period because they restricted the analysis to years in which both the PACE and MECS were conducted.

However, by performing some simple extrapolations (see Section 3 for more details), we were able to extend the analysis to all years from 1976 to 1991, with the exception of the two years the PACE survey was unavailable due to quality concerns (1983) or was not conducted (1987). Beyond the addition of years from the 1970s and 1980s, we extended the analysis forward to include the years 1992–1994, 1999, and 2005. This extension allowed us to examine whether the employment effects of PAOC have changed over time.

MPS chose their original four industries because their reported regulatory costs per value of output were among the highest in the manufacturing sector. However, plants in other industries also face stringent environmental regulation. Because of differences in production structure, industry organization, and location, the employment effects of environmental regulation are likely to vary across industries. Consequently, we generated the estimates for six additional industries as described in Section 3. These industries are also heavily regulated; have some of the highest ratios of reported regulatory costs to value of output; and, at least in some cases, are likely to be the focus of additional EPA regulations in the future.

3 METHODOLOGY AND DATA FOR ESTIMATING EMPLOYMENT EFFECTS

This section describes the details of the methodology for estimating employment. Our methodology made use of the same assumptions as MPS and introduced the extensions noted above. The section first defines the industries analyzed and then describes the demand elasticity and cost function estimation and data.

3.1 Industry Selection

To update MPS, we started with the original four industries: petroleum, plastics, pulp and paper, and iron and steel. The industry definitions for plastics and petroleum remained the same, while we dropped coke ovens from the steel industry (consistent with the industry definition in the North American Industry Classification System (NAICS)) and included pulp-only mills in the paper industry (because they face regulatory pressures similar to paper mills that produce their own pulp). We chose additional industries for analysis based on potential sample sizes of Census data and on informal consultation with technical experts to assess the likely degree of homogeneity of production functions within the selected industries.

The final set of 10 industries included the 4 from MPS plus 6 others. Table 1 lists these industries and their corresponding industry codes. One issue in dealing with these data was the switch of industry definitions from Standard Industrial Classification (SIC) to NAICS codes in 1997. This was less of a problem when dealing with the individual plant-level data, since we could identify the same plant over time even when it changed industries. However, some of our variables were based on industry-level information, so care was needed if industry definitions changed dramatically in 1997. As it turns out, of the four MPS industries, two (petroleum and plastics) were exact one-to-one matches between SIC and NAICS, one (steel) was near-exact (93–96 percent of SIC shipments were from a single NAICS industry), and the other (pulp and paper) had a somewhat weaker match (in the 82–88 percent range), largely because of the shifting in/out of paperboard/box plants.

3.2 Analysis

3.2.1 Estimation of Industry Demand Elasticities

The own-price elasticity of industry demand, reflecting the change in total industry output given a change in the average price of output, was an important parameter in the MPS model used to simulate the effect of PAOC on industry-level employment. The larger the elasticity (in absolute value), the more industry output falls when PAOC increases, and the larger the demand effect. Our estimation strategy used the same industry definitions as the cost function analysis. We estimated a simple demand equation and instrument for output price.[4]

3.2.1.1 Empirical Strategy

The industry demand elasticity is distinct from a plant's demand elasticity. The latter is much more commonly estimated in the literature. It is typically estimated using variation in output prices and output across plants, and the elasticity therefore reflects the change in demand for a plant's output given a change in its price relative to the prices of all other plants in the industry. For example, Foster, Haltiwanger, and Syverson (2008, henceforth FHS) estimated plant-level elasticities using the Census plant-level microdata from the Longitudinal Research Database (LRD). The industry demand elasticity should be smaller in magnitude (less elastic) than the plant-level demand elasticity because it corresponds to the reduction in total industry output if all plant input prices increase by the same amount.

We estimated the industry demand elasticity using industry-level variables. We began with the following equation for each industry:

$$\ln q_{jt} = \beta_{0j} + \beta_{1j} \ln p_{jt} + \varepsilon_{jt} \tag{1}$$

where q_{jt} is the output of industry j in year t, p_{jt} is the price of the output, ε_{jt} is an error term, and β_{0j} and β_{1j} are industry-specific coefficients to be estimated. The coefficient β_{1j} is the elasticity of output with respect to the price of output, and represents the percentage change in quantity demanded given a 1 percent price increase. That is, the elasticity captures movement along the aggregate industry demand curve caused by a price change.

Estimating equation (1) by ordinary least squares (OLS) using equilibrium prices and quantities is likely to yield an estimate of β_{1j} that is upward biased. The reason is the same as for a plant-level analysis: at least some of the variation in equilibrium prices is driven by shifting demand curves. For example, consider the petroleum refining industry. If a recession causes a decrease in demand for petroleum products, refineries are likely to cut their prices. Because the error term includes all determinants of equilibrium quantity besides the price, the error term is therefore positively correlated with the price, and the coefficient on the log output price is upward biased.

[4] By comparison, MPS used the Jorgenson KLEM dataset, which contains similar, although not identical industry definitions for the four MPS industries. (The details on the Jorgenson KLEM dataset are available in Appendix B.) Furthermore, MPS do not explicitly estimate a demand equation; instead, the main independent variable is the difference between the output price and an aggregate input price index.

One approach to reducing this bias is to control for demand shocks. When estimating plant-level demand elasticities, it is common to include year fixed effects or measures of total industry output, for example, as in FHS. However, we defined equation (1) at the industry level, and it would not have been possible to estimate industry-specific demand elasticities if we included year fixed effects.[5]

Instead, we constructed a measure of aggregate industry demand:

$$\bar{Q}_{jt} = \sum_{k \neq j} \bar{s}_{kj} q_{kt} \tag{2}$$

where $\bar{s}_{kj}$ is the share of output from industry j in industry k's total materials use and q_{kt} is the output of industry k in year t. The summation is taken over all industries other than industry j as well as final consumers, so that $\bar{Q}_{jt}$ is an estimate of the demand for industry j's output from all other industries and consumers.[6]

We added aggregate demand to equation (1) to obtain:

$$\ln q_{jt} = \beta_{0j} + \beta_{1j} \ln p_{jt} + \beta_{2j} \ln \bar{Q}_{jt} + \varepsilon_{jt} \tag{3}$$

Importantly, we constructed the aggregate demand measure using cost shares computed in a base year and changes in industry-level output over time. Using time-invariant shares alleviated concerns that the shares could be correlated with the error term. At the same time, because cost shares were fixed, $\bar{Q}_{jt}$ proxies for aggregate demand and measurement error for aggregate demand could bias other coefficients.

Given this concern, we also used an instrument for the output price. Appropriate instruments are correlated with the price but are uncorrelated with demand for industry output. Supply-side variables (i.e., cost-shifters) are commonly used in the literature on demand curve estimation. FHS estimated plant-level demand elasticities and used the plant's total factor productivity (TFP) as an instrument.

We could use the industry-level analog of plant-level TFP:

$$\ln TFP_{jt} = \ln q_{jt} - \sum_{z=k,l,e,m} \alpha_{jz} \ln x_{jzt} \tag{4}$$

where inputs, indexed by z, include capital (k), labor (l), energy (e), and materials (m); α_{jz} is the cost share of input z computed over all years; and x_{jzt} is the consumption of input z. Note that the cost shares needed to be multiplied by the returns to scale of the industry that was estimated as part of the cost function estimation.

[5] We could have pooled industries and include year fixed effects, which would have controlled for aggregate shocks that affect all industries proportionally. This would not have controlled for industry-specific demand shocks, however, and would have likely yielded biased estimates using OLS.

[6] Input-output tables from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA) indicate that manufacturing plants often consume output from other plants in the same industry. If we included output from industry *j* when computing demand for industry *j*, however, there would have been a mechanical relationship between the dependent variable and aggregate demand.

One concern with the instrument is that we computed it using the industry's output, which we also used to compute the dependent variable in equation (3). Measurement error in the input prices would therefore have biased the estimated coefficients.

Below we report results using a second set of instruments, which are the factor prices for industry j in year t. These instruments are also potentially problematic in that macro shocks may be correlated with factor prices. Because of the limitations of both types of instruments (industry TFP and factor prices), we compare results using one or the other.

3.2.1.2 Data

We performed the demand elasticity estimation using publicly available industry-level data from the National Bureau of Economic Research and U.S. Census Bureau's Center for Economic Studies (NBER-CES) Manufacturing Productivity Database (MPD), BEA input-output tables, and BEA gross output by industry.[7] The estimation sample included the years 1972–2005. For each six-digit NAICS industry, the MPD includes output; the output price; TFP; and prices of labor, energy, and materials. In cases where we estimated cost functions by aggregated six-digit NAICS industries, we aggregated the MPD variables by computing shipment-weighted averages.

We combined MPD and BEA data to construct aggregate demand. From the BEA input-output table, we computed the cost shares ($\bar{s}_{kj}$) in a base year for each manufacturing industry, for each non-manufacturing sector, and for end-use consumers. For each year from 1972 to 2005, we obtained output for each manufacturing industry from the MPD. We obtained output for non-manufacturing sectors and end-use consumers from the BEA gross output tables. We used a SIC-NAICS concordance to convert post-1997 output, which is on a NAICS basis, to a SIC basis. For each industry and sector, we computed annual growth rates as the difference in log output. We computed output in each year using the growth rates and the output in the base year. Finally, aggregate demand was the inner product of the cost shares and output.

3.2.2 Estimation of Cost Functions

3.2.2.1 Empirical Strategy

MPS built on the cost function-based model in Morgenstern, Pizer, and Shih (2001), which explored the relationship between PAOC and actual factor costs by explicitly distinguishing between environmental and non-environmental expenditures. Unlike some other papers that found reported PAOC understated true economic costs (e.g., Gray and Shadbegian, 1994; Joshi, Lave, Shih, and McMichael, 1997), Morgenstern, Pizer, and Shih (2001) found that, despite considerable variation at the industry level, the aggregate cost estimates did not appear to be under- or overstated on average, relative to reported PAOC. Importantly, their results hinged on the use of a fixed effects estimator that allowed for unspecified plant-level differences in productivity and factor intensities. This approach, they argued, corrected for an upward bias caused by plant-level omitted variables. See Appendix A for a description of the MPS cost function model.

[7] The NBER data are found at http://www.nber.org/data/nberces5809.html. BEA input-output data are available at http://www.bea.gov/industry/io_benchmark.htm.

An important consideration is whether sample selection affects the cost function estimates. For example, plants experiencing a negative shock to expected profitability are more likely to exit than other plants. Such exit could bias the cost function parameter estimates if unobserved and time-varying profitability shocks are correlated with other inputs; that is, the plant fixed effects control only for time-invariant shocks and not time-varying profitability shocks. Olley and Pakes (1996) used a model that allowed for time-varying profitability shocks and yielded unbiased estimates of production function parameters. Using the Olley-Pakes production function methodology to estimate the MPS cost function was outside the scope of this project, however.[8] Instead, we estimated a production function that was the dual of the MPS cost function in two ways: OLS with plant fixed effects and the Olley-Pakes model (available as a packaged Stata routine). Then, we compared the production function parameter estimates between the two estimations and assessed whether the estimated TFP from the Olley-Pakes model was stable over time, which would support the validity of using plant fixed effects to control for plant TFP when estimating the cost functions.

3.2.2.2 Data

Unfortunately, we did not have access to the original MPS data and code.[9] Using our data, we attempted to follow the data generation process as described in MPS in order to estimate the comparable cost model. This included re-estimation of the model using the MPS years and industries, as well as extending the data sample to include additional years and industries. Appendix B contains a description of the data generation process and a table with summary statistics for MPS industries and years as well as for all industries and years. Appendix C compares our process with the MPS process.

3.3 Estimation of Aggregate Effects on Employment

We used the empirical results to simulate the effect of a $1 million increase in PAOC on total industry employment. These simulations were modeled after those in MPS, in which the PAOC increase was apportioned to each plant and year in the sample. MPS apportioned the increase in proportion to the share in total costs for the entire sample. As MPS showed, the aggregate industry effect depended on the measured cost shares and other variables as well as on the estimated parameters from the cost function and from equation (3); see Appendix A for further details.

4 RESULTS

This section presents results, comparing with MPS and comparing across years and industries. For many industries we found small aggregate employment effects, but in several cases we found positive and implausibly large effects. We discuss possible explanations for these findings in Section 5.

4.1 Demand Elasticity Estimation

Tables 2–4 report the estimates of equation (3). Each panel contains a different industry; Table 2 contains the four MPS industries, and the other tables show the remaining six industries. For

[8] Petrin and Warzynski (2012) developed a methodology that allows for plant-specific and time-varying unobserved shocks to a Cobb-Douglas cost function. Applying the approach to the MPS cost function, in which one of the outputs is not observed, is not straightforward.

[9] The original datasets and data management code used by MPS in the Census Research Data Center were not available to us because of the failure of the backup drive at the Census on which they had been archived.

each industry, the estimation sample includes observations from the years 1972–2005. The dependent variable is the log of industry output, and Table 2 reports the coefficients on the log output price and log aggregate demand. Column 1 includes a linear time trend, and column 2 estimates equation (3) in first differences (omitting the time trend) to account for the strong persistence of the price and output variables.

In the first two columns in the tables, the estimates of the own-price elasticity are usually statistically significant at the 5 percent level and are almost always less than one in magnitude. The small magnitude implies that a 1 percent PAOC increase reduces industry output by less than 1 percent, so the demand effect is likely to be small. The small magnitude is also consistent with the interpretation of the coefficient as the own-price elasticity of industry output; plant-level elasticities (e.g., those reported in FHS) are typically much larger in magnitude. We observed that the coefficient on aggregate demand was positive and statistically significant in nearly all cases, as expected.

Estimating equation (3) by OLS, whether in levels or first differences, is likely to yield upward-biased (less negative) estimates for the reasons discussed above. This bias suggests that we would have underestimated the magnitude of the demand effect if we had relied on OLS estimates of the industry demand elasticity. Consequently, columns 3 and 4 report estimates using industry TFP (column 3) and input prices (column 4) as instruments. The equation was estimated in first differences, and the results should be compared to column 2. We observed that the estimates using the TFP instrument tended to be larger in magnitude than the corresponding OLS estimates, but the standard errors were also quite large. This was the case because the first stage was fairly weak for many of the industries. By comparison, the first stage using input prices was much stronger, and the standard errors were much smaller in column 4. Consequently, these estimates constituted our preferred estimates. For all industries, the instrumental variables estimates were quite close to the OLS estimates.

4.2 Cost Function Estimation

We briefly discussed the parameter estimates before focusing on the estimated employment effects. Appendix D, Table D1, reports the parameter estimates for the cost function along with the original MPS estimates. The current and MPS estimates differed considerably. A key parameter in the employment effects estimates is $\alpha_{\gamma r}$, which is the degree of interaction between environmental and non-environmental activities. The more positive the estimate is, the larger the cost effect. Therefore, a more positive (or less negative) estimate implies a more positive (or less negative) total employment effect. A negative $\alpha_{\gamma r}$ implies a *decrease* in production costs whenever the PAOC-to-production cost ratio increases. Our estimates of $\alpha_{\gamma r}$ were much larger in magnitude (and of opposite sign in two cases), compared to those originally estimated by MPS. For the paper industry, the coefficient changed from -0.62 to 1.19; for the petroleum industry from 0.59 to 1.18; for the plastics industry from 0.38 to 4.78; and for the steel industry from -0.07 to 3.27.

Appendix D, Table D2, reports the cost function estimates for all 10 industries using all available years of data. Estimates of $\alpha_{\gamma r}$ were greater than one for all MPS industries except paper (where $\alpha_{\gamma r}$ was negative and smaller than one in absolute value). Our estimate of $\alpha_{\gamma r}$ was negative for other electrical equipment, but for all other industries our estimate was positive.

4.3 Aggregate Employment Effects

4.3.1 MPS Industries and Years

Table 5 presents the estimated employment effects for MPS industries and MPS years. Panel A, columns (4)–(7), shows the original MPS estimates. MPS reported the employment effects of a $1 million PAOC increase measured in 1987 dollars. For consistency with the current estimates, we adjusted the MPS estimates to 1997 dollars using industry-level deflators. Panel B, columns (4)–(7), shows the estimates we obtained in our current analysis. Recall that our industry definitions for paper and steel are slightly different from those in MPS. However, we also estimated the model using the original MPS industry definitions, and the results were not materially different from the estimates reported here. The estimated cost effects and factor shifts in columns (5) and (6) do not depend on industry definition.

The total employment effect, in column (4), is positive in all four industries for the current estimates (Panel B). For plastics and steel, given average annual wages for production workers, the estimates suggested that most of the additional regulatory costs would be used for workers. This is implausible because of the capital intensity of pollution abatement expenditures in these industries.

Table 5 decomposes the total effects into the three components to further characterize the estimates. Looking first at the cost effects in column (5), it is evident that, except for the petroleum industry, the current estimates are substantially larger than the MPS estimates, particularly for plastics and steel. The differences between the current and MPS estimates for the factor shift and demand effects are smaller than those for the cost effect, except for the plastics industry, where we observed a large difference in the factor shift. Overall, the large cost effect explains much of the considerably larger total employment effect estimates reported in column (4).

For comparison with the structural estimates, we also reported estimated total employment effects using a reduced-form regression of log employment on PAOC and other variables included in the cost function estimation. The employment effects we estimated using the reduced-form equations, reported in column (3) of Panel B, are roughly similar to the estimates from the structural model, and are similarly implausibly large for the plastics and steel industries. This qualitative similarity between the structural and reduced-form estimates suggests that the implausibly large structural estimates are not simply an artifact of the complexities of the structural model; Section 5 further discusses potential explanations for these results.

Figure 1 provides additional insights into the drivers of the differences between the MPS and current estimates. Along with the current estimates (in red, labeled as #1) and MPS central estimates (in blue, labeled as #4), it plots estimates that we derived using the current cost function estimates and MPS demand elasticities (in green, labeled as #2) and estimates that we derived using available MPS cost function coefficients and MPS demand elasticities (in orange, labeled as #3). Note that the estimates in orange (#3) are an approximation using sample average cost shares from the current estimation sample rather than the MPS sample averages because MPS did not report all of the average cost shares.

Using MPS demand elasticities substantially changed the total effect estimate for the paper industry and steel industry. In Table 5, the demand effect in column (7) is fairly similar between the MPS and current estimations. The similarity is perhaps surprising because of the large differences in demand elasticities reported in column (8). However, the demand effect depends on the demand elasticities, the cost shares, and α_r. In this case, the differences happened to roughly cancel out, yielding similar demand effects. Therefore, differences in the MPS cost function estimates explain much of the difference in the employment effects (compare the red (#1) and the orange (#3) columns for the cost effect in each panel). Except for the steel industry, the differences in the total effect estimates that are due to differences in the sample average cost shares are also substantial.

4.3.2 Additional Years and Industries

Table 6 reports estimated employment effects based on all available years of data for the four MPS industries and an additional six industries. The table is structured similarly to Table 5. The large positive effects for the plastics and steel industries in the structural model are similar to those observed in Table 5, though the reduced-form estimate for the plastics industry is much smaller. Several of the additional industries exhibit large and positive estimated total employment effects in the structural model: rolling and drawing, pipe fitting, miscellaneous wood, and other electrical equipment. However, the effect is statistically significant only for the rolling and drawing industry. In addition, we observed sizable differences between the reduced-form and structural estimates for the six new industries. Three of the six reduced-form estimates are large and negative, while their structural estimates are large and positive, although neither is statistically significant. The results of the reduced-form regressions were stable across several alternative model definitions[10] for most industries and in all cases where we found statistically significant effects.

5 DISCUSSION

As reported in Section 4, we obtained different results when we estimated the employment effect of PAOC for the MPS industries, even when using the same years as MPS. Furthermore, for some industries and years we obtained implausibly large and positive estimates. We catalog a number of possible explanations for these results, although we are not able to provide a definitive explanation.

5.1 Variable Construction

Differences in variable construction could explain the differences between the current and MPS estimates in Table 5. We derived many variables from reported Census costs and values, and we had to construct appropriate price deflators from various sources. As Appendix B describes, we constructed variables somewhat differently from the MPS method because (1) after 1994, the MECS and PACE data were no longer collected in the same year (MPS relied on concurrent data), and (2) in recent years the Census Bureau has collected much less detailed data on materials. Consequently, the information needed to construct material price deflators was not fully available even for the original MPS industries, and for some of the additional industries such materials detail was never available. To test whether the new methodology affected the results, we constructed an alternative dataset that more closely followed the MPS methodology (see Appendix C). We re-estimated the models using these datasets, but still obtained results similar to those reported in Table 5, Panel B. We have concluded that the differences in variable construction are unlikely to explain much of the observed differences in Table 5.

[10] Along with the baseline reduced-form models, we estimated six other models that included leads and lags of PAOC-to-production cost ratio as well as leads and lags of log output.

5.2 Estimation Model

The MPS estimation model included multiple equations, cross- and within-equation parameter restrictions, and was estimated by maximum likelihood. MPS estimated the model in Time Series Processor (TSP) software, but because TSP is no longer available to Census researchers, we implemented our current estimation in Stata. The original TSP programs were lost along with the archived data, but we were able to find a printout of one of the original TSP programs that covered some parts of the estimation. Using a set of synthetic data outside the Census, we compared the results obtained by the new Stata procedure and the original TSP program. We obtained similar, though not identical, coefficient estimates using the original TSP code and our code. Specifically, out of 45 estimated coefficients, 20 differed by at most 10 percent, and 32 differed by at most 30 percent. Of the remaining coefficients, 7 were time fixed effects, and nearly all of the rest were not statistically significant. We have concluded that our estimation model is similar, if not identical, to that used by MPS.

5.3 Estimation Samples

Table 7 compares our sample with the MPS sample in terms of sample sizes as well as labor cost and PAOC shares (the only summary statistics provided by MPS). We observe several differences. As noted earlier, the MPS paper industry definition excluded pulp mills while we included them, and the MPS steel industry included coke ovens while we excluded them, explaining some of the differences in sample size.[11] Though labor shares for the petroleum and plastics industries were comparable for the two samples, labor shares for the paper and steel industries in our samples were about 50 percent and 30 percent lower than MPS. Finally, the PAOC share in our data was more than 50 percent smaller than the MPS PAOC share.

Differences in sample composition could arise for a variety of reasons, including data editing procedures that dropped some plants for missing or imputed values as well as changes in industry definitions. As discussed above, adopting the MPS SIC-based industry definitions did not substantially affect the results. There is no particular reason why differences in data editing or other aspects of sample construction would necessarily have resulted in substantial differences in the estimated results. Still, there are several possible reasons for different results for the two samples—they are not mutually exclusive, and their importance may differ across industries.

5.3.1 Heterogeneous Cost Function

If all plants had the same cost function parameters, changing the estimation sample would not be expected to result in substantially different coefficients. However, if the true parameters differed across plants, we could get different estimated parameters because the coefficient estimates would represent weighted averages of the plant-level parameters.

In fact, there is some indication that parameters may vary across plants. Plant age (as measured by a pre-1963 vintage dummy) significantly modifies the PAOC effect. We observed this modification for the petroleum and steel industries in the analyses using MPS years, and for all industries (except other electrical) in the analyses using the full range of years. While not conclusive,

[11] The summary statistics for the original MPS industry definitions are not available due to disclosure concerns.

this modification suggested some heterogeneity in cost function parameters across plants that could have contributed to different estimates for the two samples.

5.3.2 Sensitivity of Translog Cost Function to the Estimation Sample

The model estimated here includes a nonlinear cost function with many parameter restrictions. In such cases, substantial differences in coefficient estimates can result from small changes in the estimation sample. This potential sensitivity motivated the reduced-form approach reported in Tables 5 and 6, which yielded the same qualitative results for the MPS industries and years. Reduced-form models designed to minimize the impact of outliers also yielded similar results. These tests suggest that sensitivity of the cost function to sample composition may not be an important factor in explaining the differences in Table 5.

5.3.3 Endogeneity of PAOC and Other Variables

Because plants choose PAOC simultaneously with other variables, PAOC may be correlated with unobserved and time-varying plant-specific variables. This might help explain the large positive effects that we often observed in our results. Because the same could be true for the MPS analysis, such endogeneity by itself cannot explain the differences between the MPS and current results. However, it is possible that endogeneity caused greater problems in our sample than it did for MPS, although there is no specific reason to expect this to happen.

As noted above, it is not feasible within the confines of this research to adapt the Olley-Pakes production function estimation approach to the MPS cost function model. Instead, we used the Olley-Pakes production function model to investigate whether PAOC endogeneity was likely to explain the implausible results and the differences between the current and MPS estimates. If endogeneity were a concern, we would have expected to observe large within-plant variation in plant TFP, as estimated by the Olley-Pakes model. We compared the results of production function estimation with and without Olley-Pakes controls for endogeneity, without finding substantial differences. Table 8 shows the between- and within-plant variation on log-TFP that we generated using the Olley-Pakes model estimates (for samples including all available years of data). The within-plant variation was very close to the between-plant variation, which suggests that the plant fixed effects in the cost functions may not have fully controlled for plant-specific TFP. Table 8 also shows that the average estimated log-TFP declined over time for all industries.

In addition, we tried several instrumental variable (IV) versions of the reduced-form regression. We instrumented for PAOC using county-level dummy variables for non-attainment of National Ambient Air Quality Standards (NAAQS) and the League of Conservation Voters scorecard, which measures pro-environmental voting by the state's Congressional delegation. Unfortunately, neither of these instruments provided much explanatory power in the first stage, rendering the IV results effectively unusable (Bound, Jaeger, and Baker, 1995).[12]

[12] The first stage F-tests showed that dummy variables for county-level NAAQS non-attainment and the League of Conservation Voters scorecard were not statistically significant predictors of PAOC-to-production cost ratio for all industries and samples except the steel industry (all years sample) and the other electrical industry (all years sample). In both of these cases, the R^2 values were less than 1 percent, and the magnitude of the

It is also possible that multi-plant firms try to retain their labor by moving the employees around whenever there is a plant closure. Because we restricted the structural model estimation to plants that were continuing, these cross-plant spillovers might have confounded the PAOC effects if PAOC were correlated with the exit of other plants owned by the same firm. To examine this possibility, we created a variable that measured the potential spillover effects. The spillovers can occur only at plants belonging to multi-plant firms, and are related to the number of employees released by closing plants. We measured the magnitude of potential spillover to a plant in year t as the fraction of the firm's employment in year $t-5$ at plants that are no longer in operation by year t. This number was zero if none of the firm's plants closed between year $t-5$ and year t (no spillovers possible) and approached one if nearly all of the firm's plants closed during these five years.

We included the spillover measure as a regressor in the reduced-form regressions. We observed reductions in the magnitudes of the estimated PAOC effects for the paper, plastics, steel, pipe fitting, Portland cement industries, miscellaneous wood products (with a change in sign), and other electrical industry, but the effects of PAOC in the petroleum, pharmaceuticals, and rolling and drawing industries were similar to the baseline estimates. The spillover measure itself was not significant, but the results suggested that in many industries some employment was reallocated from exiting plants to continuing plants, possibly helping to explain the estimated positive employment effects from the structural model.

In sum, we examined a multitude of possibilities for the large estimated employment effects and the differences relative to MPS. Only two explanations were not rejected: heterogeneity of the cost function and endogeneity of PAOC.

6 CONCLUSION

Research on the link between environmental regulation and jobs is particularly challenging because of the difficulty of disentangling the effects of regulation from other key determinants of employment. Similar to other recent papers, the present analysis used plant-level information based on confidential Census data. The principal emphasis here was on a structural, as opposed to a reduced-form, model for continuing (non-exiting) plants, which allowed a decomposition of total employment effects into the cost, factor, and demand effects. We focused on net, as opposed to gross, job impacts within an industry. The metric of regulation, PAOC, is derived from the PACE survey, the most comprehensive source of pollution abatement costs and expenditures available. The data span more than 30 years, including the most recent information collected (2005), and cover 10 industries that have high levels of pollution abatement costs.

In many cases, we found implausibly large positive employment effects of abatement expenditures. For 6 of our 10 industries the structural model indicated total effects of 10–30 additional employees hired for each $1 million in additional abatement expenditures. This would imply that nearly all abatement spending is on labor, which is inconsistent with the observed capital intensity of abatement technologies. Using both reduced-form and structural models, we saw relatively similar results for the four MPS industries. In contrast, the other six industries showed considerable differences between the two modeling approaches, with some large positive structural estimates paired with large negative reduced-form estimates. Our results also tended to be substantially larger

instrumented PAOC impact was similar to that of the un-instrumented PAOC (for the steel industry this effect turned insignificant in the IV runs).

than the original MPS results. We explored several possible explanations for this difference without reaching a satisfactory conclusion. The surprisingly large positive effects overall might be due to endogeneity of PAOC, but our attempts to test for endogeneity with an instrumental variables approach failed due to a lack of valid instruments. Given these concerns, even the effects that are plausible in themselves should probably not be taken too seriously.

Finally, we address the issue of applying modeling results such as these to Regulatory Impact Analyses (RIAs) for new environmental rules. The application of analytical results from one situation to other, less studied areas is fairly routine, such as the use of benefits transfer in valuing environmental damages. However, the wide range of estimated values across industries observed here makes such an approach questionable. We emphasize the importance of making appropriate comparisons in RIAs, where the industry from which the estimates are derived is comparable to the one covered by the new rule and the impact of the new regulation on the production process is roughly comparable to the historical pattern of regulatory costs imposed on that industry. Even the smaller effects in the original MPS paper, which covered only the period 1979–91, showed considerable variability. Thus, using their average value to generate quantitative estimates of the employment effects of new rules in different industries is problematic. Specifically, even beyond the variability among the four principal industries, MPS found even larger differences between those four and a group of six additional industries for which the authors were unable to develop credible cost function estimates. For the four principal industries, MPS developed confidence intervals that included both positive and negative results in two cases. Thus, even without the additional results we report herein, the use of the original MPS results in RIAs would be questionable, especially without adequate qualification capturing the inherent uncertainty of the results. Now, with the added uncertainty introduced by the present results, the use of the work in RIAs is even more questionable.

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Appendix A: The Production Cost Model

MPS developed an expression for the entire employment effect,

$$\frac{\partial L_{agg}}{\partial RC_{agg}} = \underbrace{\frac{1}{TC_{agg}}\sum_{i=1}^{I}\frac{TC_i^2}{P_{l,i}}\frac{\partial v_{l,i}}{\partial RC_i}}_{\text{Factor Shift}} + \underbrace{\frac{\partial TC}{\partial RC}\frac{L_{agg}}{TC_{agg}}}_{\text{Cost Effect}} + \underbrace{(-\sigma_d)\frac{\partial TC}{\partial RC}\frac{L_{agg}}{TC_{agg}}}_{\text{Demand Effect}} \qquad \text{(A1)}$$

where L_{agg} is aggregate industry employment, RC_{agg} is the aggregate dollar measure of regulatory burden (PAOC) in the industry, TC_{agg} is the total industry-wide cost (including both conventional production and regulatory costs), $v_{l,i}$ is the labor cost share and $P_{l,i}$ is the wage at plant i, and $-\sigma_d$ is the industry-level demand elasticity. Unlike equations in studies that focus solely on negative demand effects, equation (A1) explicitly allows for supply-side labor effects that may offset any industry-wide contraction. Equation (A1) also allows one to consider each piece of the employment effect separately, assess its economic and statistical significance, and potentially design policy to properly address labor and industry concerns. Evaluation of this expression requires estimates of a structural model of production costs along with an industry-level demand elasticity.

The cost model is based on the assumption that the production of non-environmental outputs and environmental activities are distinct and are described by separate cost functions. Specifically, $PC = G(Y, \mathbf{P}, i, t)$ describes the cost (PC) of producing non-environmental output Y based on input price vector $\mathbf{P}$ at plant i at time t. Similarly, let $RC = H(R, \mathbf{P}, i, t)$ describe the cost (RC) of producing environmental "output" R similarly based on input price vector $\mathbf{P}$ at plant i at time t. Inputs include capital, labor, energy, and materials.

MPS allowed for the possibility that these two activities are not, in fact, distinct by rewriting $PC = G(Y, \mathbf{P}, i, t)[f(RC)]^{\alpha_r}$ where $f(RC)$ is an increasing function of regulatory expenditure. The parameter α_r describes the degree of interaction. A zero value indicates no significant interaction, negative values indicate cost savings, and positive values indicate additional burden.

MPS chose the following translog parameterization for $G(.)$ and $H(.)$:

$$\ln PC = \alpha_i + \alpha_t + \boldsymbol{\alpha}_{i,p}' \ln \mathbf{P} + \alpha_y \ln Y + \tfrac{1}{2}\ln \mathbf{P}' \boldsymbol{\beta}_{pp} \ln \mathbf{P}$$

$$+ \tfrac{1}{2}\beta_y (\ln Y)^2 + \boldsymbol{\beta}_{t,p} \ln \mathbf{P} + \boldsymbol{\beta}_{yp} \ln Y \ln \mathbf{P} + \beta_{yt} t \cdot Y + \alpha_r \frac{RC}{PC} \qquad \text{(A2)}$$

$$\ln RC = \gamma + \gamma_r \ln R + \boldsymbol{\gamma}_p' \ln \mathbf{P} + \tfrac{1}{2}\ln \mathbf{P}' \boldsymbol{\delta}_{pp} \ln \mathbf{P} + \gamma_t t + \boldsymbol{\delta}_{pt}' \ln \mathbf{P} \cdot t \qquad \text{(A3)}$$

where $\mathbf{P}$ is a vector of input prices (capital, labor, energy, and materials), PC are costs related to non-environmental output Y, RC are costs related to environmental output R, and t is time. The parameters have the following interpretations: α_i are plant-specific, Hicks-neutral productivity effects; α_t are time dummies, capturing aggregate Hicks-neutral productivity trends; $\boldsymbol{\alpha}_{i,p}$ are vectors of plant-specific cost-share parameters; $\boldsymbol{\beta}_{pp}$ is a matrix of share elasticities; α_y and β_y capture scale economies; $\boldsymbol{\beta}_{t,p}$ are year-specific productivity biases; $\boldsymbol{\beta}_{yp}$ reflects biases of scale; and β_{yt} captures any aggregate time trend in scale economies. All of these parameters refer to non-environmental production. The environmental production parameters have the following interpretations: $\boldsymbol{\gamma}_p$ is a vector of aggregate cost share parameters; $\boldsymbol{\delta}_{pp}$ is a matrix of share elasticities; γ_t describes the Hicks-neutral productivity trend; and $\boldsymbol{\delta}_{pt}$ captures factor trends. Finally, α_r describes any interaction between environmental and non-environmental activities.

The standard approach to estimate models such as those described in equations (A2) and (A3) is to specify a system of cost shares based on the first derivatives with respect to log prices. Stochastic disturbances are appended to each equation, and the system is estimated simultaneously (with cross-equation restrictions) in order to improve efficiency. The problem with this approach in the current context is that factor inputs used for environmental activities cannot be distinguished from those used for conventional production; and we have no direct measure of R, environmental output. Since factor inputs cannot be disaggregated in the data, the cost shares associated with equations (A2) and (A3) are not observed. Further, since there is no direct measure of R, equation (A3) cannot be estimated.

MPS circumvented these problems by assuming homothetic environmental costs $H(.)$. Environmental cost shares were solely a function of input prices and time (and not R):

$$\begin{aligned}
v_{k,r} &= \gamma_k + \boldsymbol{\delta}_k' \ln \mathbf{P} + \delta_{kt} t \\
v_{l,r} &= \gamma_l + \boldsymbol{\delta}_l' \ln \mathbf{P} + \delta_{lt} t \\
v_{e,r} &= \gamma_e + \boldsymbol{\delta}_e' \ln \mathbf{P} + \delta_{et} t \\
v_{m,r} &= \gamma_m + \boldsymbol{\delta}_m' \ln \mathbf{P} + \delta_{mt} t
\end{aligned} \tag{A4}$$

Coupled with non-environmental cost shares derived from equation (A2),

$$\begin{aligned}
v_{k,y} &= \alpha_{i,k} + \boldsymbol{\beta}_k' \ln \mathbf{P} + \beta_{yk} \ln Y + \beta_{t,k} \\
v_{l,y} &= \alpha_{i,l} + \boldsymbol{\beta}_l' \ln \mathbf{P} + \beta_{yl} \ln Y + \beta_{t,l} \\
v_{e,y} &= \alpha_{i,e} + \boldsymbol{\beta}_e' \ln \mathbf{P} + \beta_{ye} \ln Y + \beta_{t,e} \\
v_{m,y} &= \alpha_{i,m} + \boldsymbol{\beta}_m' \ln \mathbf{P} + \beta_{ym} \ln Y + \beta_{t,m}
\end{aligned} \tag{A5}$$

the observed total cost shares can be written as

$$\begin{aligned}
v_k &= \frac{RC}{PC + RC} v_{k,r} + \left(1 - \frac{RC}{PC + RC}\right) v_{k,y} \\
v_l &= \frac{RC}{PC + RC} v_{l,r} + \left(1 - \frac{RC}{PC + RC}\right) v_{l,y}
\end{aligned} \tag{A6}$$

$$v_e = \frac{RC}{PC + RC} v_{e,r} + \left(1 - \frac{RC}{PC + RC}\right) v_{e,y}$$

$$v_m = \frac{RC}{PC + RC} v_{m,r} + \left(1 - \frac{RC}{PC + RC}\right) v_{m,y}$$

These aggregate cost shares (over both non-environmental and environmental expenditures) are observable themselves and depend on other observable variables (prices, output, time, and regulation as a share of total costs). The equations in (A6) can therefore be estimated alongside the production cost function (A2) by treating each as a stochastic relation and adding random disturbances.

Because the endogenous variable PC appears on the right-hand side of the production cost function and aggregate share equations, MPS used a two-step approach. They first estimated the system of equations, setting $RC = 0$ (which eliminates PC on the right-hand side as well as the regulatory cost share parameters γ and δ). MPS used these parameter estimates to construct exogenous predicted values of $\widehat{PC}$ to replace the actual values of PC on the right-hand side of equations (A2) and (A6). MPS then used these predicted values to re-estimate the system without the endogeneity problem. At both estimation stages, MPS imposed symmetry ($\beta_{ij} = \beta_{ji}$ and $\delta_{ij} = \delta_{ji}$) and homogeneity of degree one in prices (which allowed us to arbitrarily drop a share equation). MPS used a maximum likelihood estimator that iterated on the covariance matrix estimate until it converged.

Appendix B: Census Microdata and Summary Statistics

We used the Longitudinal Business Database (LBD), as described in Jarmin and Miranda 2002)[13] to link data from the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM) to form a panel of plant-level data that includes costs, outputs, and inputs. More than 50,000 establishments are included each year, with a census of all plants occurring every 5 years. We obtained data on energy prices and quantities from the Manufacturing Energy Consumption Survey (MECS), collected by the Census Bureau for the Department of Energy every three years, beginning in 1985. Our measure of regulatory pressure came from the Pollution Abatement Costs and Expenditures (PACE) survey, collected annually by the Census Bureau from 1973 to 1994 (with two exceptions) but conducted only twice since then (1999 and 2005). We linked these plant-level data with other data (described below) to create the dataset we used in our analysis.

Because our work expanded that of MPS, our data construction process was similar to theirs. However, our expansion of the data to cover additional industries and additional years forced some modifications to the MPS process. First, MPS restricted their sample to years in which both the MECS and PACE surveys were collected, but none of the recent PACE years coincided with a MECS survey. We modified the construction of plant-level energy prices to allow us to work with non-MECS years, which greatly expanded our sample years – although most of those additional years fall in the 1974–1994 period. Second, MPS relied on material-specific quantity data collected by the Census to calculate their materials price deflators. Below we describe our approach for constructing materials prices. Our measure of plant output came from the value of shipments as reported in the Longitudinal Research Database, adjusted for inventory changes. The LRD also provided a breakdown of the total value of shipments into the values produced of each specific product, which we combined with the corresponding producer price indices (PPIs) from the Bureau of Labor Statistics (BLS) to form a plant-specific divisia index of output prices. We were able to get BLS PPI records to match the product categories almost perfectly. Labor input also came from the LRD, measured as the number of production workers and with the corresponding price index defined as labor cost (production worker wages plus their share of supplemental labor cost) per production worker. The “share” of supplemental labor cost is calculated from the share of production worker wages in total wages.

The LRD provided data on the plant’s energy spending, distinguishing between electricity and fuels and including the quantity of electricity purchased. In a few years (1979–1981) the LRD also provided separate cost and quantity data for several different fuel types, while more recently those data have been provided by the MECS. We first calculated plant-specific deflators for fuel prices and their cost shares for the MECS years. Then we used state-specific fuel prices from the SEDS (State Energy Data System from the Department of Energy) database to interpolate the changes in a plant’s fuel prices between the MECS years.[14] The plant-specific price of energy is a divisia index of the prices of these fuels and electricity (for which we have plant- and year-specific information).

The LRD provided expenditure data on total materials spending, as well as a breakdown of expenditures on specific materials every five years, at the time of Economic Census. For some materials, these data included the quantity of the material used, which MPS used to calculate a plant-specific materials price deflator. Unfortunately, in recent years the Census has dramatically reduced

[13] MPS used the manufacturing-only Longitudinal Research Database (LRD), the precursor to the LBD.
[14] The SEDS data are available at http://www.eia.gov/state/seds/.

the number of materials for which the quantity data are collected, even for the MPS industries. There are also some differences in the definitions of materials reported before and after 1997. Furthermore, the quantity data are not available for some of the additional industries in our sample for any of the years. These factors forced us to modify the construction of plant-specific materials price deflators. We used the Census material expenditure data to calculate plant-specific average cost shares for each reported material over the 1977–1997 period (up to five Census years of data) and used the cost shares to weight the corresponding producer prices from BLS. For those materials where BLS producer prices were not available, we used the industry-specific materials cost deflator from the Manufacturing Productivity Database as a substitute. To maintain consistency across industries and years, we used the modified deflators for all our analyses (for the MPS years and industries, the results were similar using the MPS methodology and the current methodology).

For capital input, the LRD provided annual data on new capital expenditures and some data on the (nominal) gross book value of a plant's capital stock, but these needed to be combined with other data to generate a measure of real capital stocks and capital services prices. We used the LRD-linked database created by John Haltiwanger for the real capital stock for each plant. Like the data in MPS, our capital services price data are not plant-specific. We took the corresponding capital services price series from the 35-KLEM sectoral input-output database for 1960–2005, developed by Dale Jorgenson and described in Jorgenson and Stiroh (2000), Jorgenson (1990), and Jorgenson, Gollop and Fraumeni (1987). We then calculated the plant's annual capital expenditures as the product of the capital services price and the plant's real capital stock.

The PACE survey provided our plant-specific measure of annual pollution abatement operating costs. These costs included costs for depreciation of the plant's stock of pollution abatement capital, and provided a relatively comprehensive measure of abatement costs. Since these were nominal data, we deflated them by the GDP deflator to generate a measure of real regulatory expenditure. The expansion of the MPS data to more recent years was limited by the availability of the PACE survey. We are aware that the 1999 PACE survey questionnaire was significantly different from the questionnaire in other years, as discussed in Becker and Shadbegian (2005). Some categories of abatement costs (e.g., depreciation) were not included in the 1999 PACE, while other previously separate categories (e.g., pollution prevention operating costs and capital expenditures) were combined, leading to potential difficulties in comparing costs across years. However, ignoring the 1999 PACE would create a decade-long gap in plant-level abatement cost data. We made plant-specific imputations (based on values reported in other PACE years) to fill in the missing categories of abatement costs. We also tested whether excluding 1999 from the analysis affected the overall results; doing so did not have a large impact.

Appendix Table B1. Summary Statistics

Industry:		Paper	Petroleum	Plastics	Steel	Paper	Petroleum	Plastics	Steel	Portland Cement	Rolling and Drawing	Pipe Fitting	Misc. Wood Products	Pharmaceuticals	Other Electrical Equipment
Years:		MPS years (1979, 1980, 1981, 1985, 1988, 1991)				All years (1976-1982, 1984-1986, 1988-1994 1999, and 2005)									
N		824	697	548	486	2928	2263	2515	1639	1032	1388	868	922	1579	1805
Variable	Units	Sample average (Sample Standard Deviation)													
Output	Thous. 1997$ / year	210,373	953,256	232,197	524,634	210,875	1,111,850	222,236	552,207	56,714	139,213	80,820	64,043	595,818	106,867
		(145,441)	(958,534)	(253,175)	(673,167)	(157,888)	(1,157,384)	(265,527)	(724,773)	(32,710)	(147,954)	(426,528)	(133,523)	(796,132)	(113,211)
Capital stock	Thous. 1997$	147,846	306,495	135,611	347,967	167,801	348,817	127,884	370,950	58,416	37,622	19,964	10,976	136,194	28,446
		(151,894)	(352,024)	(156,741)	(544,262)	(195,945)	(438,581)	(162,508)	(556,506)	(71,532)	(55,047)	(19,278)	(27,827)	(232,829)	(49,340)
Energy	Thous. 1997$ / year	18,019	32,507	10,624	45,806	16,630	33,162	9,404	43,049	10,023	2,492	917	422	4,459	1,409
		(15,418)	(60,796)	(10,803)	(70,110)	(14,532)	(63,856)	(13,377)	(68,880)	(7,663)	(2,757)	(1,186)	(698)	(7,851)	(1,301)
Employment	Production workers	580	373	557	1,985	543	360	414	1,803	140	376	349	340	512	414
		(406)	(364)	(627)	(2,696)	(402)	(350)	(539)	(2,453)	(84)	(361)	(296)	(502)	(592)	(422)
Materials	Thous. 1997$ / year	66,036	756,845	108,559	210,829	67,618	764,532	103,095	213,142	7,492	62,263	17,035	24,828	72,145	35,882
		(40,250)	(741,082)	(85,988)	(273,243)	(47,334)	(739,283)	(103,653)	(266,020)	(4,981)	(70,741)	(16,314)	(50,265)	(152,755)	(38,306)
Capital price index	Base=1997	0.66	0.97	0.52	0.53	0.72	0.96	0.64	0.60	0.77	0.58	0.53	0.76	0.62	0.56
		(0.18)	(0.14)	(0.16)	(0.10)	(0.20)	(0.61)	(0.20)	(0.30)	(0.29)	(0.29)	(0.17)	(0.26)	(0.22)	(0.17)
Energy price index	Base=1997	0.91	0.95	0.94	0.99	0.96	0.96	0.96	0.98	1.03	0.90	0.91	0.96	0.93	0.93
		(0.44)	(0.64)	(0.44)	(0.63)	(0.55)	(0.61)	(0.41)	(0.56)	(0.48)	(0.36)	(0.28)	(0.31)	(0.41)	(0.37)
Production labor cost	Thous. 1997$ / worker	35.98	39.66	33.94	39.26	40.22	44.02	40.88	42.07	39.31	27.92	26.85	21.94	33.59	26.82
		(10.48)	(10.79)	(11.39)	(10.01)	(16.30)	(22.28)	(19.00)	(16.24)	(12.46)	(11.93)	(10.94)	(9.92)	(17.99)	(12.59)
Materials price index	Base=1997	0.94	1.17	0.99	0.96	0.97	1.10	1.00	0.95	1.00	0.98	0.94	0.96	0.94	0.98
		(0.12)	(0.29)	(0.12)	(0.10)	(0.19)	(0.40)	(0.21)	(0.17)	(0.20)	(0.23)	(0.20)	(0.22)	(0.22)	(0.21)
PAOC	Thous. 1997$ / year	3,469	11,524	2,103	7,900	3,532	13,236	2,387	8,421	1,227	374	136	140	1,458	244
		(3,886)	(19,394)	(2,806)	(13,644)	(4,051)	(22,139)	(4,117)	(14,326)	(1,162)	(786)	(243)	(342)	(2,927)	(414)
Production costs	Thous. 1997$ / year	204,087	1,049,567	205,750	515,123	227,022	1,122,095	208,478	558,457	67,408	97,225	38,693	43,085	185,658	64,241
		(163,180)	(1,013,677)	(180,301)	(674,298)	(211,919)	(1,154,157)	(219,856)	(722,426)	(73,005)	(98,833)	(33,525)	(86,961)	(306,156)	(70,541)
Total costs	Thous. 1997$ / year	207,556	1,061,091	207,853	523,023	230,555	1,135,332	210,865	566,878	68,635	97,599	38,829	43,225	187,116	64,485
		(165,287)	(1,027,564)	(182,165)	(686,588)	(214,029)	(1,168,775)	(222,615)	(734,342)	(73,178)	(99,173)	(33,623)	(87,237)	(307,612)	(70,684)
PAOC-to-Prod. cost ratio	%	1.79	0.88	1.10	1.22	1.81	0.95	1.19	1.28	2.26	0.40	0.32	0.37	0.87	0.48
		(1.79)	(0.95)	(1.03)	(0.89)	(4.46)	(1.06)	(1.28)	(1.04)	(2.22)	(0.72)	(0.43)	(0.52)	(1.76)	(1.16)
PAOC share in total costs	%	1.73	0.87	1.07	1.20	1.69	0.93	1.16	1.25	2.17	0.40	0.31	0.37	0.84	0.46
		(1.63)	(0.91)	(0.99)	(0.86)	(2.37)	(1.01)	(1.19)	(0.99)	(1.93)	(0.68)	(0.43)	(0.51)	(1.46)	(0.97)
Labor cost share	%	11.66	1.58	8.25	17.25	11.16	1.75	7.22	15.95	9.91	12.58	25.13	19.83	12.60	18.85
		(4.33)	(1.22)	(4.71)	(7.12)	(4.49)	(1.27)	(4.47)	(7.58)	(4.96)	(6.37)	(7.98)	(8.21)	(6.56)	(9.48)
Capital cost share	%	42.93	23.63	29.72	31.60	46.30	25.04	33.80	35.28	60.77	22.25	28.95	18.11	44.26	23.13
		(15.15)	(11.29)	(13.24)	(12.93)	(15.75)	(12.85)	(15.17)	(14.59)	(14.88)	(13.58)	(12.33)	(13.56)	(18.44)	(12.54)
Energy cost share	%	8.05	2.07	4.36	8.10	7.17	2.20	3.79	7.36	15.64	2.40	2.17	1.19	2.30	2.24
		(3.75)	(1.83)	(2.52)	(4.41)	(3.63)	(1.78)	(2.63)	(4.30)	(7.11)	(1.77)	(1.55)	(1.29)	(1.89)	(1.45)

Appendix C: Differences between Current and MPS Dataset Construction

We started with the same Census datasets as MPS (i.e., LBD/ASM/CM data, MECS, and PACE) and tried to follow the same data construction process as much as possible, but some differences arose due to changes in data availability. The differences between our approaches are described below:

1. **Output** - No differences.

2. **Labor** - No differences.

3. **Materials** - Materials spending came from the cost of materials in the LRD in both MPS and our analysis. MPS derived the price of materials from the Census-year data on the cost and quantity for individual materials, allowing them to calculate a plant-specific price for each material. They then aggregated those individual materials prices into an aggregated divisia price index. This price index was linearly interpolated between the Census years. As noted earlier, Census cutbacks in collection of materials quantity data forced us to depend on BLS PPI data for specific materials.

4. **Energy** - MPS limited their analysis to years with plant-specific data on cost and quantity for several fuel types, either from the LRD itself (1979–1981) or the MECS data. These were used to calculate plant-specific fuel prices in each year, aggregated up to a divisia price index. After 1994 there were no years when both the energy and PACE data were collected, so we switched to an approach that interpolated energy prices between MECS years.

5. **Capital** - For capital input, the LRD provided annual data on new capital expenditures and some data on the (nominal) gross book value of a plant's capital stock, but these needed to be combined with other data to generate a measure of real capital stocks and capital service prices. MPS used their own perpetual inventory calculation to derive plant-specific real capital stocks. We relied on an LRD-linked database created by John Haltiwanger using a similar calculation for the real capital stock for each plant. MPS used industry-level capital service prices, taken from the KLEM sectoral input-output database for 1947–1991 (same vintage as used by MPS), developed by Dale Jorgenson and described in Jorgenson and Stiroh (2000), Jorgenson (1990), and Jorgenson, Gollop and Fraumeni (1987). Since we needed post-1991 prices, we used an updated version (also from Jorgenson). In both approaches, the plant's annual capital expenditures were calculated as the product of the service price and the plant's real capital stock.

6. **Regulation** - No differences.

Appendix D: Estimates of the Cost Function Coefficients

Appendix Table D1

Comparison between MPS[a] and Currently Estimated Cost Function Coefficients (MPS Industries and Years[b])

Industry:	Paper		Petroleum		Plastics		Steel	
Analysis:	MPS	Current	MPS	Current	MPS	Current	MPS	Current
Parameter[c]	Point Estimate (Standard Error in Parentheses)							
α_r	-0.6221	1.1914	0.5900	1.1814	0.3774	4.7784	-0.0726	3.2705
	(0.2746)	(0.4847)	(0.5905)	(0.8338)	(0.6958)	(1.0848)	(0.4671)	(0.9480)
α_y	0.7161	0.5355	0.7433	0.5944	0.8314	0.4190	0.7136	0.5675
	(0.0273)	(0.0302)	(0.0281)	(0.0252)	(0.0362)	(0.0341)	(0.0304)	(0.0215)
β_{ee}	0.0579	-0.0083	0.0128	-0.0014	-0.0027	-0.0096	0.0211	0.0029
	(0.0090)	(0.0037)	(0.0018)	(0.0018)	(0.0163)	(0.0039)	(0.0209)	(0.0064)
β_{kk}	0.1095	-0.2610	0.0070	0.0085	0.0029	0.0051	0.0664	-1.0383
	(0.0379)	(0.0460)	(0.0019)	(0.2174)	(0.0190)	(0.0639)	(0.0172)	(0.4306)
β_{ll}	0.1120	0.0633	0.0133	0.0060	0.0668	0.0410	0.0491	0.0835
	(0.0114)	(0.0061)	(0.0016)	(0.0015)	(0.0094)	(0.0075)	(0.0201)	(0.0215)
β_{ke}	-0.0116	-0.0012	0.0005	-0.0028	0.0103	0.0052	-0.0264	0.0273
	(0.0112)	(0.0084)	(0.0012)	(0.0071)	(0.0086)	(0.0100)	(0.0073)	(0.0099)
β_{le}	-0.0114	-0.0026	0.0003	0.0005	-0.0016	-0.0019	0.0156	-0.0131
	(0.0065)	(0.0026)	(0.0010)	(0.0007)	(0.0068)	(0.0038)	(0.0138)	(0.0073)
β_{kl}	-0.0347	0.0009	0.0017	0.0411	-0.0030	0.0106	-0.0035	0.0194
	(0.0128)	(0.0110)	(0.0008)	(0.0117)	(0.0092)	(0.0152)	(0.0088)	(0.0217)
β_{ey}	-0.0041	0.0062	-0.0104	-0.0024	0.0085	-0.0055	-0.0177	0.0124
	(0.0053)	(0.0037)	(0.0015)	(0.0017)	(0.0092)	(0.0020)	(0.0087)	(0.0034)
β_{ky}	0.0100	-0.0550	-0.0132	-0.1019	-0.0365	-0.0863	-0.0383	-0.1446
	(0.0071)	(0.0114)	(0.0021)	(0.0087)	(0.0049)	(0.0088)	(0.0031)	(0.0053)
β_{ly}	-0.0446	-0.0154	-0.0078	-0.0052	-0.0302	-0.0034	0.0066	0.0234
	(0.0052)	(0.0032)	(0.0010)	(0.0007)	(0.0041)	(0.0027)	(0.0072)	(0.0049)
β_{yt}	0.0041	0.0027	-0.0028	-0.0021	0.0110	0.0032	-0.0004	-0.0017
	(0.0014)	(0.0013)	(0.0013)	(0.0009)	(0.0020)	(0.0017)	(0.0014)	(0.0014)
β_y	-0.0336	-0.1090	0.0039	-0.0160	-0.0408	-0.1742	0.0389	-0.0110
	(0.0316)	(0.0243)	(0.0184)	(0.0097)	(0.0328)	(0.0303)	(0.0191)	(0.0147)
γ_e	0.1967	0.0102	-0.0225	-0.1019	0.2930	0.4974	-0.7126	0.0618
	(0.0846)	(0.0772)	(0.0387)	(0.0696)	(0.2028)	(0.0845)	(0.1952)	(0.1981)
γ_k	0.1276	0.7920	0.0532	0.9472	-0.0510	0.7190	0.1460	-0.8591
	(0.1085)	(0.2311)	(0.0545)	(0.3456)	(0.1053)	(0.3553)	(0.0715)	(0.3078)
γ_l	0.1531	0.1564	0.0748	0.0371	0.3621	0.4326	0.1565	0.3914
	(0.0770)	(0.0651)	(0.0292)	(0.0300)	(0.0914)	(0.1100)	(0.1610)	(0.2828)
δ_{ee}	0.4141	0.6028	-0.1483	0.2817	-0.3730	0.6348	-0.1428	-0.5693
	(0.1679)	(0.1333)	(0.0690)	(0.1077)	(0.5119)	(0.2972)	(0.5534)	(0.2428)
δ_{kk}	0.9811	2.0289	0.3400	0.2085	0.4311	1.5856	0.5153	-2.1443
	(0.4718)	(0.7747)	(0.0964)	(0.6933)	(0.4545)	(1.2929)	(0.2243)	(1.7474)
δ_{ll}	-0.3011	-0.0454	-0.2801	-0.3105	-1.1840	0.0236	1.4959	1.1337
	(0.3037)	(0.2165)	(0.0986)	(0.1111)	(0.3458)	(0.3391)	(0.5676)	(1.2513)
δ_{ke}	-0.1040	-0.1923	0.1260	-0.1519	0.1902	-1.2811	0.4567	-0.9256
	(0.1996)	(0.2321)	(0.0554)	(0.1399)	(0.2624)	(0.3223)	(0.1942)	(0.3668)
δ_{le}	-0.2485	-0.1664	0.0026	-0.0096	0.1503	0.1565	-0.8998	0.2076
	(0.1375)	(0.0951)	(0.0398)	(0.0421)	(0.2211)	(0.2213)	(0.3833)	(0.3067)
δ_{kl}	-0.0764	-0.0822	0.0078	0.0918	0.0251	0.0717	-0.1398	-3.6834
	(0.2554)	(0.2177)	(0.0394)	(0.0776)	(0.2843)	(0.4044)	(0.2375)	(1.0493)
δ_{et}	-0.0232	-0.0203	-0.0115	-0.0135	-0.0426	-0.0258	0.0501	-0.0723
	(0.0107)	(0.0108)	(0.0076)	(0.0138)	(0.0290)	(0.0163)	(0.0346)	(0.0332)
δ_{kt}	0.0013	-0.0541	-0.0043	0.0419	0.0627	-0.0358	-0.0122	0.2428
	(0.0171)	(0.0295)	(0.0110)	(0.0554)	(0.0186)	(0.0709)	(0.0160)	(0.0713)
δ_{lt}	-0.0154	-0.0082	0.0097	0.0207	0.0516	-0.0312	-0.0935	0.0381
	(0.0126)	(0.0093)	(0.0067)	(0.0082)	(0.0181)	(0.0213)	(0.0355)	(0.0585)

Notes: (a) We derived MPS estimates from MPS Table V, pp. 432–433. (b) The years included are: 1979, 1980, 1981, 1985, 1988, 1991. (c) We could not disclose time and plant dummies.

Appendix Table D2

Estimated Cost Function Coefficients for 10 Industries (using all available years[a])

Industry:	**Paper**	**Petroleum**	**Plastics**	**Steel**	**Portland Cement**	**Rolling and Drawing**	**Pipe Fitting**	**Misc. Wood Products**	**Pharmaceu -ticals**	**Other Electrical Equipment**
Parameter[b]	Point Estimate (Standard Error in Parentheses)									
α_r	-0.6136	3.3653	2.7525	3.5439	1.5405	3.1672	4.6354	2.2143	0.6368	-1.6668
	(0.1678)	(0.5269)	(0.4992)	(0.5723)	(0.6325)	(0.9613)	(2.3346)	(1.5843)	(0.6356)	(0.7265)
α_y	0.5397	0.5609	0.4512	0.5235	0.3031	0.6826	0.3159	0.6822	0.2663	0.4819
	(0.0157)	(0.0166)	(0.0152)	(0.0143)	(0.0377)	(0.0152)	(0.0189)	(0.0201)	(0.0171)	(0.0143)
β_{ee}	-0.0021	-0.0001	-0.0070	0.0009	-0.0506	0.0059	0.0055	-0.0009	-0.0012	0.0059
	(0.0018)	(0.0010)	(0.0017)	(0.0037)	(0.0079)	(0.0022)	(0.0017)	(0.0008)	(0.0015)	(0.0017)
β_{kk}	-0.2560	-0.1421	0.0893	-0.7138	-0.3185	0.1451	0.0951	0.0999	0.1205	0.1637
	(0.0276)	(0.1218)	(0.0332)	(0.2260)	(0.1494)	(0.0294)	(0.0691)	(0.0564)	(0.0607)	(0.0352)
β_{ll}	0.0487	0.0083	0.0365	0.0401	0.0535	0.0401	0.0880	0.0599	0.0577	0.0638
	(0.0031)	(0.0008)	(0.0028)	(0.0083)	(0.0061)	(0.0055)	(0.0116)	(0.0080)	(0.0046)	(0.0073)
β_{ke}	0.0103	0.0021	-0.0053	0.0002	0.0499	0.0109	0.0146	0.0045	-0.0014	0.0140
	(0.0048)	(0.0049)	(0.0048)	(0.0076)	(0.0136)	(0.0053)	(0.0058)	(0.0038)	(0.0060)	(0.0050)
β_{le}	-0.0041	0.0000	-0.0026	-0.0152	-0.0257	-0.0028	-0.0042	0.0004	-0.0018	-0.0035
	(0.0015)	(0.0004)	(0.0016)	(0.0038)	(0.0046)	(0.0021)	(0.0015)	(0.0009)	(0.0013)	(0.0017)
β_{kl}	-0.0049	0.0176	-0.0168	-0.0128	0.0136	0.0029	-0.0133	-0.0009	-0.0183	-0.0341
	(0.0068)	(0.0067)	(0.0060)	(0.0125)	(0.0142)	(0.0093)	(0.0153)	(0.0120)	(0.0108)	(0.0105)
β_{ey}	0.0018	-0.0014	-0.0021	0.0103	0.0368	-0.0044	-0.0027	-0.0018	-0.0022	-0.0019
	(0.0015)	(0.0010)	(0.0008)	(0.0016)	(0.0044)	(0.0008)	(0.0005)	(0.0003)	(0.0005)	(0.0006)
β_{ky}	-0.0396	-0.0861	-0.0885	-0.1177	-0.0989	-0.1058	-0.0515	-0.0947	-0.0594	-0.0619
	(0.0054)	(0.0058)	(0.0039)	(0.0035)	(0.0092)	(0.0043)	(0.0057)	(0.0048)	(0.0042)	(0.0036)
β_{ly}	-0.0052	-0.0046	-0.0008	0.0164	0.0084	-0.0021	0.0008	0.0027	-0.0002	-0.0016
	(0.0016)	(0.0005)	(0.0010)	(0.0022)	(0.0030)	(0.0020)	(0.0039)	(0.0031)	(0.0016)	(0.0024)
β_{yt}	0.0026	-0.0016	0.0006	-0.0024	-0.0174	-0.0028	-0.0037	0.0005	0.0046	-0.0021
	(0.0006)	(0.0005)	(0.0007)	(0.0007)	(0.0028)	(0.0009)	(0.0011)	(0.0009)	(0.0009)	(0.0008)
β_y	0.0023	-0.0152	0.0160	0.0469	-0.2097	0.0087	-0.0422	-0.0012	-0.0533	0.0311
	(0.0083)	(0.0057)	(0.0090)	(0.0063)	(0.0481)	(0.0107)	(0.0102)	(0.0109)	(0.0120)	(0.0115)
γ_e	0.1829	0.0149	0.2222	0.1056	0.3672	0.1268	0.1432	-0.0962	0.2086	0.1021
	(0.0289)	(0.0363)	(0.0363)	(0.1054)	(0.1005)	(0.0700)	(0.0757)	(0.0544)	(0.0402)	(0.0509)
γ_k	0.3194	1.5044	0.7258	0.3372	0.2946	0.8218	0.8822	0.7295	0.9830	0.5352
	(0.0938)	(0.2159)	(0.1881)	(0.2384)	(0.1979)	(0.3616)	(0.7904)	(0.7831)	(0.3030)	(0.3059)
γ_l	0.1944	0.0519	0.2367	0.7044	0.3089	0.5286	0.1994	0.2142	0.3048	0.5465
	(0.0297)	(0.0175)	(0.0482)	(0.1459)	(0.0692)	(0.1653)	(0.5614)	(0.4891)	(0.1243)	(0.2095)
δ_{ee}	0.2657	0.0735	0.2855	-0.4400	0.3926	0.1517	-0.0733	0.9780	-0.1574	0.1375
	(0.0589)	(0.0531)	(0.1007)	(0.1325)	(0.1884)	(0.1776)	(0.1936)	(0.1568)	(0.0721)	(0.0972)
δ_{kk}	0.2239	1.2674	0.3395	3.3141	1.7878	1.8314	5.7744	2.5047	0.6905	-2.3857
	(0.4621)	(0.3927)	(0.6820)	(0.7470)	(0.5604)	(1.9302)	(3.6306)	(2.4042)	(1.2071)	(1.3553)
δ_{ll}	0.2452	-0.1131	-0.3605	1.5972	0.1248	2.3706	2.2388	0.1637	0.5635	0.1086
	(0.0555)	(0.0435)	(0.0864)	(0.4070)	(0.1896)	(0.4835)	(2.0431)	(0.9073)	(0.2396)	(0.4925)
δ_{ke}	-0.0420	-0.1424	-0.4973	-0.1726	-0.3827	-0.5113	-0.8661	-0.2312	-0.5034	-0.2806
	(0.1185)	(0.0636)	(0.1252)	(0.2231)	(0.2394)	(0.3271)	(0.3152)	(0.1856)	(0.1332)	(0.2069)
δ_{le}	-0.0631	-0.0237	0.0265	0.3017	0.0880	0.3655	-0.4817	-0.0824	0.4039	0.1248
	(0.0419)	(0.0234)	(0.0581)	(0.1526)	(0.1123)	(0.2162)	(0.2566)	(0.1001)	(0.0717)	(0.1215)
δ_{kl}	0.0146	-0.0061	0.1966	-0.1681	-0.4937	-0.4784	-4.2189	1.1246	0.2312	1.0419
	(0.1184)	(0.0328)	(0.1541)	(0.3707)	(0.1825)	(0.6649)	(1.9225)	(1.0459)	(0.3701)	(0.5902)
δ_{et}	-0.0088	0.0020	-0.0038	-0.0402	-0.0253	-0.0172	-0.0102	0.0105	-0.0582	-0.0106
	(0.0037)	(0.0042)	(0.0046)	(0.0138)	(0.0098)	(0.0135)	(0.0076)	(0.0058)	(0.0053)	(0.0093)
δ_{kt}	-0.0178	0.0506	0.0325	0.0528	0.0341	0.0893	-0.3364	0.0411	0.0300	-0.1267
	(0.0118)	(0.0248)	(0.0237)	(0.0354)	(0.0192)	(0.0711)	(0.0846)	(0.0771)	(0.0413)	(0.0548)
δ_{lt}	-0.0084	0.0042	0.0140	-0.0436	-0.0304	-0.0728	0.0560	-0.0061	-0.0887	-0.0077
	(0.0037)	(0.0024)	(0.0061)	(0.0217)	(0.0066)	(0.0306)	(0.0584)	(0.0480)	(0.0161)	(0.0372)

Notes: (a) The years included are: 1976–1982, 1984–1986, 1988–1994, 1999, and 2005. (b) We could not disclose time and plant dummies.

FIGURES AND TABLES

Table 1
Industries in the Study

Industry Name	NAICS code
Original Industries	
1. Paper Mills	322110, 322121, 322130
2. Petroleum Refineries	324110
3. Plastics	3252
4. Iron and Steel Mills	331111
Additional Industries	
5. Portland Cement	327310
6. Rolling and Drawing	331421; 331422; 331491
7. Pipe Fitting	332911; 332912; 332919
8. Misc. Wood Products	321911, 321912, 321918, 321920, 321991, 321992, 321999
9. Pharmaceuticals	3254
10. Other Electrical Equipment	3359

Table 2

Elasticity Estimates for MPS Industries

Specification	(1) Levels	(2) First differences	(3) Instrument using TFP, first differences	(4) Instrument using input prices, first differences
		Panel A: Paper (SIC 2611, 2621)		
Log output price	-0.290	-0.456	-1.185	-0.270
	(0.136)	(0.192)	(0.264)	(0.244)
Log agg demand	0.609	0.887	1.749	0.667
	(0.100)	(0.323)	(0.382)	(0.399)
R squared	0.96	0.32		0.28
		Panel B: Plastic (SIC 2821-2824)		
Log output price	-0.260	-0.335	-0.945	-0.427
	(0.114)	(0.141)	(0.474)	(0.161)
Log agg demand	0.595	1.010	1.213	1.041
	(0.078)	(0.159)	(0.159)	(0.158)
R squared	0.97	0.57	0.29	0.57
		Panel C: Petroleum (SIC 2911)		
Log output price	0.121	-0.002	-0.050	-0.029
	(0.040)	(0.063)	(0.121)	(0.065)
Log agg demand	-0.473	0.424	0.538	0.488
	(0.152)	(0.287)	(0.335)	(0.267)
R squared	0.80	0.06	0.03	0.05
		Panel D: Steel (SIC 3312)		
Log output price	-1.012	-0.499	-4.455	-0.440
	(0.272)	(0.492)	(3.746)	(0.454)
Log agg demand	0.724	1.545	4.324	1.504
	(0.557)	(0.651)	(2.905)	(0.665)
R squared	0.56	0.35		0.32

Notes: The table reports coefficient estimates with standard errors in parentheses, robust to heteroskedasticity. Each panel includes results for the indicated industry. Besides the reported coefficients, column 1 also includes a linear time trend. Columns 1 and 2 are estimated by Ordinary Least Squares. Columns 3 and 4 are estimated by two-stage least squares. The instrument in column 3 is the 4-digit TFP growth rate from the MPD. The instruments in column 4 include the log capital price, log average payroll per employee, log energy price, and log materials price for the corresponding industry.

Table 3

Elasticity Estimates for Industries 5-7

	(1)	(2)	(3)	(4)
Specification	Levels	First differences	Instrument using TFP, first differences	Instrument using input prices, first differences
		Panel A: Portland cement (SIC 3241)		
Log output price	-0.749 (0.124)	-0.684 (0.147)	-1.658 (0.588)	-0.737 (0.193)
Log agg demand	0.850 (0.264)	0.825 (0.137)	1.049 (0.239)	0.837 (0.144)
R squared	0.53	0.57	0.10	0.57
		Panel B: Rolling and drawing (SIC 3351, 3356, 3357)		
Log output price	-0.503 (0.131)	-0.313 (0.177)	-1.097 (0.346)	-0.192 (0.203)
Log agg demand	0.263 (0.172)	0.867 (0.273)	1.377 (0.368)	0.788 (0.294)
R squared	0.45	0.29		0.28
		Panel C: Pipe fitting (SIC 3429, 3432, 3491, 3492, 3494, 3499, 3728)		
Log output price	-0.403 (0.146)	-0.565 (0.128)	-1.209 (0.439)	-0.572 (0.184)
Log agg demand	0.706 (0.115)	0.700 (0.204)	0.970 (0.224)	0.703 (0.233)
R squared	0.92	0.36	0.11	0.36

Notes: The table reports analogous specifications to Table 2 for the industries indicated in the panel titles.

Table 4

Elasticity Estimates for Industries 8-10

Specification	(1) Levels	(2) First differences	(3) Instrument using TFP, first differences	(4) Instrument using input prices, first differences
	Panel A: Misc. wood (SIC 2421, 2426, 2429, 2431, 2441, 2448, 2449, 2451, 2452, 2499, 3131)			
Log output price	-0.465	-0.100	-2.025	-0.057
	(0.152)	(0.107)	(1.295)	(0.100)
Log agg demand	0.356	0.823	1.793	0.801
	(0.181)	(0.149)	(0.939)	(0.156)
R squared	0.81	0.36		0.35
	Panel B: Pharmaceuticals (SIC 2833, 2834, 2835, 2836)			
Log output price	-0.172	-0.585	-2.657	-0.646
	(0.158)	(0.153)	(1.473)	(0.310)
Log agg demand	0.097	0.290	1.687	0.332
	(0.113)	(0.225)	(1.083)	(0.307)
R squared	1.00	0.24		0.24
	Panel C: Other electrical (SIC 3357, 3624, 3629, 3643, 3644, 3691, 3692, 3699)			
Log output price	-0.297	-0.255	-4.132	-0.335
	(0.196)	(0.146)	(3.337)	(0.168)
Log agg demand	0.472	1.036	2.512	1.066
	(0.184)	(0.334)	(1.371)	(0.362)
R squared	0.86	0.29		0.28

Notes: The table reports analogous specifications to Table 2 for the industries indicated in the panel titles.

Table 5
Change in Full-Time Jobs per Industry-Wide One Million Dollar[a] Increase in Environmental Expenditure: MPS Industries and MPS Years[b]

Industry	**Sample Size**	**Total Effect (reduced form)[c]**	**Total Effect**	**Cost Effect**	**Factor Shift**	**Demand Effect**	**Demand Elasticity[d]**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: MPS Estimates[e] (standard errors in parentheses)							
1 Paper	615	--	-0.89	1.73	-0.29	-2.33	*1.34*
			(2.15)	(1.25)	(1.63)	(1.99)	*(0.17)*
2 Petroleum	717	--	1.65	0.49	1.35	-0.2	*0.40*
			(0.67)	(0.18)	(0.62)	(0.17)	*(0.19)*
3 Plastics	404	--	4.61	2.16	3.51	-1.06	*0.49*
			(2.14)	(1.09)	(1.64)	(1.16)	*(0.29)*
4 Steel	536	--	0.30	3.14	3.01	-5.85	*1.86*
			(4.38)	(1.58)	(2.51)	(4.04)	*(0.35)*
Panel B: Current Estimates (standard errors in parentheses)							
1 Paper	824	1.58	6.43*	6.12*	2.72	-2.41	*0.27*
		(1.82)	(2.02)	(1.35)	(1.62)	(1.53)	*(0.24)*
2 Petroleum	697	0.43	1.11	0.77	0.37	-0.03	*0.03*
		(0.89)	(0.91)	(0.29)	(0.96)	(0.05)	*(0.07)*
3 Plastics	548	10.39	19.99*	15.48*	12.26*	-7.75	*0.43*
		(5.06)	(4.3)	(2.89)	(3.36)	(2.8)	*(0.16)*
4 Steel	486	38.57*	14.99	16.21*	7.58	-8.80	*0.44*
		(11.96)	(9.82)	(3.65)	(7.18)	(7.68)	*(0.45)*

Notes: (a) The $1M increase is in 1997$. (b) The years included are 1979, 1980, 1981, 1985, 1988, and 1991. (c) The dependent variable in the reduced-form model is the log of plant-level employment, and the independent variables include the plant-level ratio of PAOC to production costs, the logs of prices (energy, labor, capital) normalized with respect to price of materials, log capital stock, year fixed effects, and plant fixed effects. The equation is estimated by OLS, and heterogeneity-robust standard errors are reported. (d) MPS demand elasticities are from MPS Table II, p. 425; Current demand elasticities are negatives of “Log output price” coefficient from Table 2, column (4) of this document. Standard errors are reported in parentheses. (e) MPS estimates are derived from MPS Table III, p. 427. The original estimates were expressed per $1M increase in 1987$. For consistency with the rest of the results, the original MPS estimates were adjusted to represent changes in employment per $1M increase in 1997$, using industry-specific deflators. (*) Denotes a statistically significant estimate at 5% joint significance level. The Type I error was controlled using the Holm-Bonferroni procedure (Holm, 1979). The family of tests included all tests of employment effect significance in this table (36 tests) and in Table 6 (50 tests) to enable joint conclusions (Bender and Lange, 2001).

Table 6

Change in Full-Time Jobs per Industry-Wide One Million Dollar[a] Increase in Environmental Expenditure: All Industries and All Years[b]

Industry	**Sample Size**	**Total Effect (reduced form)[c]**	**Total Effect**	**Cost Effect**	**Factor Shift**	**Demand Effect**	**Demand Elasticity[d]**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: MPS Industries (standard errors in parentheses)							
1 Paper	2928	0.78*	2.68*	0.91	2.02	-0.25	*0.27*
		(0.19)	(0.64)	(0.4)	(0.65)	(0.27)	*(0.24)*
2 Petroleum	2263	0.61	2.66*	1.38*	1.31	-0.04	*0.03*
		(0.36)	(0.42)	(0.16)	(0.43)	(0.09)	*(0.07)*
3 Plastics	2515	1.08	31.21*	7.36*	27.01*	-3.17	*0.43*
		(1.38)	(5.19)	(0.97)	(5.05)	(1.25)	*(0.16)*
4 Steel	1639	28.55*	21.69	14.45*	13.59*	-6.36	*0.44*
		(5.29)	(7.2)	(1.78)	(3.25)	(6.6)	*(0.45)*
Panel B: Additional Industries (standard errors in parentheses)							
5. Portland Cement	1032	2.29	3.48	5.17*	2.14	-3.82	*0.74*
		(1.6)	(1.73)	(1.26)	(1.53)	(1.38)	*(0.19)*
6. Rolling and Drawing	1388	-3.88	22.68*	16.07*	9.66	-3.05	*0.19*
		(9.41)	(6.57)	(3.72)	(5.98)	(3.35)	*(0.20)*
7. Pipe Fitting	868	-54.35	16.14	50.65	-5.65	-28.87	*0.57*
		(25.11)	(21.55)	(21.63)	(18.78)	(16.25)	*(0 .18)*
8. Misc. Wood Products	922	-66.85	13.66	25.32	-0.52	-11.14	*0.44*
		(35.68)	(19.02)	(12.25)	(14.88)	(13.26)	*(0.45)*
9. Pharmaceuticals	1579	0.14	-1.66	4.48	-3.23	-2.91	*0.65*
		(1.69)	(3.29)	(1.73)	(3.11)	(1.86)	*(0.31)*
10. Other Electrical Equipment	1805	-11.32	10.17	-4.28	12.99	1.45	*0.34*
		(5.21)	(6.52)	(4.67)	(6.68)	(1.90)	*(0.17)*

Notes: (a) The $1M increase is in 1997$. (b) The years included are: 1976-1982, 1984-1986, 1988-1994, 1999, and 2005. (c) The dependent variable in the reduced-form model is the log of plant-level employment and the independent variables include the plant-level ratio of PAOC to production costs, the logs of prices (energy, labor, capital) normalized with respect to price of materials, log capital stock, year fixed effects and plant fixed effects. The equation is estimated by OLS and heterogeneity-robust standard errors are reported. (d) Demand elasticities are negatives of "Log output price" coefficient from Tables 3 and 4, column (4) of this document. Standard errors are reported in parentheses. (*) Denotes a statistically significant estimate at 5% joint significance level. The Type I error was controlled using the Holm-Bonferroni procedure (Holm, 1979). The family of tests included all tests of employment effect significance in Table 5 (36 tests) and in this table (50 tests) to enable joint conclusions (Bender and Lange, 2001).

Table 7
Characteristics of the Current Sample for MPS Industries and Years vs. MPS Sample[a]

Characteristic:	Sample Size		Labor as a Share of Total Costs		PAOC as a Share of Total Costs	
Analysis:	**MPS**	**Current**	**MPS**	**Current**	**MPS**	**Current**
1 Paper[b]	615	824	0.201	0.117	0.028	0.017
2 Petroleum	717	697	0.019	0.016	0.011	0.009
3 Plastics	404	548	0.085	0.082	0.020	0.011
4 Steel[c]	536	486	0.230	0.173	0.022	0.012

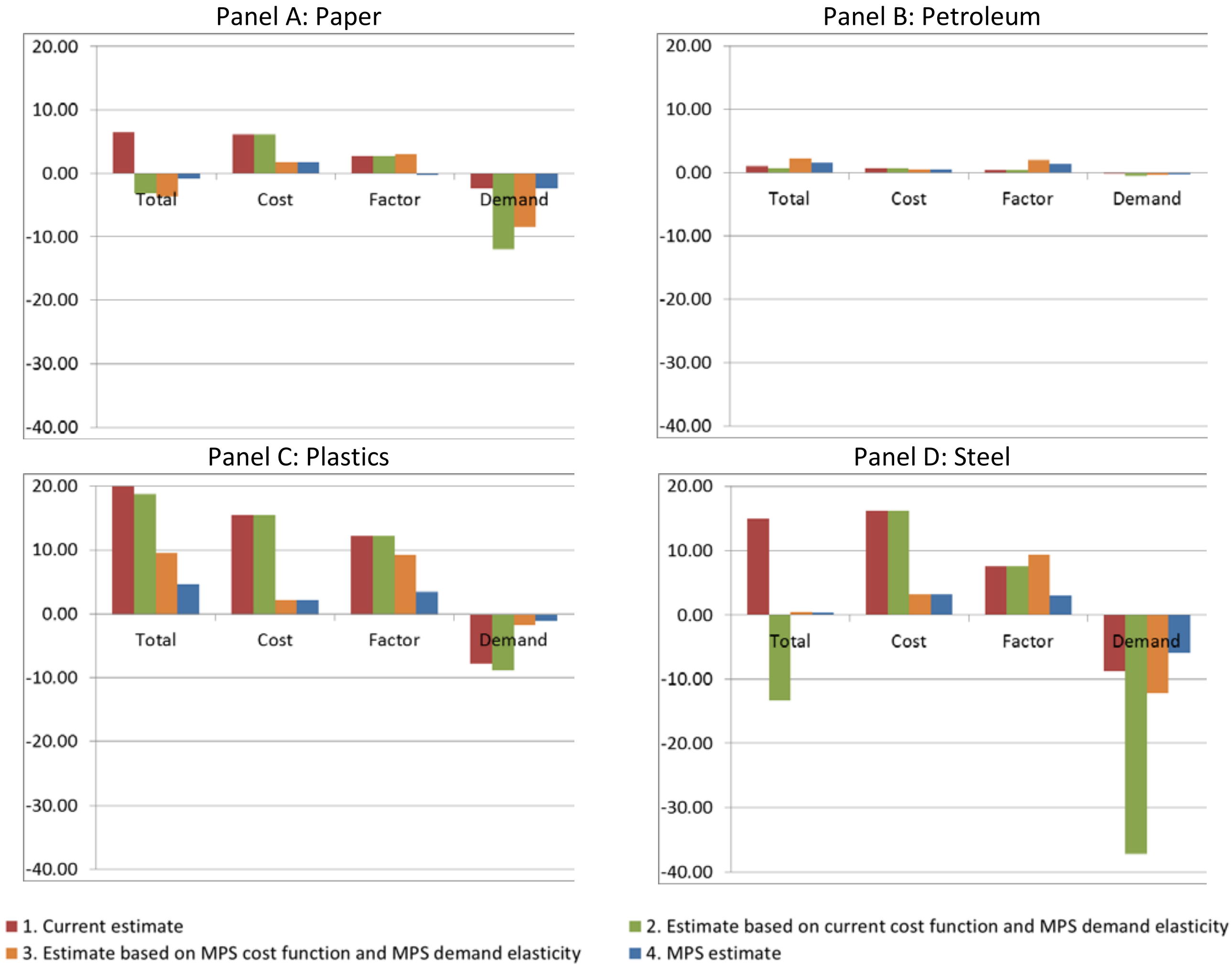
Notes: (a) MPS sample statistics is are from MPS Table I, p. 422. (b) Paper industry definition in MPS excluded pulp mills. (c) Steel industry definition in MPS included coke ovens.

Table 8
Estimated Total Factor Productivity[a] by Industry for All Available Years[b]

Industry	Standard Deviation			Mean	Mean by time period						
	overall	between	within	overall	1974-1977	1978-1982	1983-1987	1988-1992	1993-1997	1998-2002	2003-2005
1 Paper	0.29	0.24	0.19	2.17	2.19	2.19	2.17	2.15	2.14	2.15	2.14
2 Petroleum	0.42	0.44	0.31	1.42	1.43	1.42	1.46	1.42	1.37	1.38	1.35
3 Plastics	0.49	0.44	0.28	0.83	0.97	0.90	0.83	0.82	0.72	0.71	0.64
4 Steel	0.29	0.21	0.22	2.40	2.40	2.40	2.39	2.40	2.39	2.39	2.39
5 Portland cement	0.31	0.24	0.22	4.49	4.45	4.47	4.49	4.51	4.51	4.52	4.52
6 Rolling and drawing	0.31	0.23	0.22	1.49	1.50	1.50	1.49	1.48	1.47	1.46	1.44
7 Pipe fitting	0.68	0.52	0.32	2.74	2.79	2.79	2.74	2.70	2.66	2.60	2.41
8 Misc. Wood Products	0.32	0.26	0.19	0.65	0.76	0.72	0.68	0.61	0.59	0.49	0.50
9 Pharmaceuticals	0.98	0.87	0.52	-1.98	-1.79	-1.84	-1.90	-2.04	-2.26	-2.40	-2.36
10 Other electrical equipment	0.44	0.34	0.30	3.48	3.47	3.48	3.47	3.49	3.50	3.50	3.39

Notes: (a) Plant-specific TFPs were computed based on the production function estimates obtained from the Olley-Pakes model. The summary statistics reported are natural logs of TFP. (b) The years included are: 1976-1982, 1984-1986, 1988-1994 1999, and 2005.

Figure 1
Sources of Difference between Current and MPS Estimates of Employment Effects (MPS years)



Notes:
- The difference between (1) and (2) is that the MPS demand elasticity was used in combination with the current cost function estimate to derive the demand effect and the total effect. (There is no change in the cost effect and the factor effect.)
- The difference between (2) and (3) is that, in addition to MPS demand elasticities, MPS cost function estimates were used to decompose the employment impacts.
- The difference between (3) and (4) is that the current sample averages were used for the decomposition for (3), while (4) is the published MPS estimate, using the MPS data.

Environmental Regulations and Manufacturing Plant Exit: A Preliminary Analysis

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1 Introduction

Studies of the impact of environmental regulation on the output or employment levels of manufacturing plants have generally relied on a balanced panel that includes only facilities continuing to produce over the entire period. This is a preliminary analysis of the impacts of pollution abatement operating costs (PAOC) on plant exit probability and the associated changes in industry-wide employment in 10 manufacturing industries. It complements an updated analysis of the effects of PAOC on employment at continuing plants, which is summarized in a separate technical paper (see Belova, Gray, Linn, and Morgenstern, 2013; hereafter, BGLM). We describe the empirical strategy to estimate the effect of environmental expenditure on plant exit; the construction of the panel we used to estimate the exit regression models; and the results we obtained.

2 Empirical Strategy

Exit is a dynamic decision that depends on a plant's expectations of future changes in profitability as well as its current level of profitability. Our model builds on work by Olley and Pakes (1996), which specifies the plant's exit probability as a function of its efficiency (or productivity), age, and capital stock. We added the costs associated with environmental regulation as an explanatory variable.

Unlike factor prices and market structure, which vary little across plants within an industry, PAOC can vary quite a lot across plants. Because of this variation, PAOC can affect exit independently of the plant's age, capital stock, or efficiency, which motivates our inclusion of this variable. Environmental regulation could affect exit decisions through either the costs of current regulatory requirements or the expectations of future regulatory requirements. Consider a plant operating in period t. All else equal, the plant is less likely to continue operating into the next time period if it expects its future PAOC to be high, either because they are already high or because they will rise in the future.

We used two variables to proxy for the current and future regulatory requirements. For the current requirements, we used the ratio of the plant's PAOC to its production costs in period t. For the future requirements, we used the median increase in this PAOC ratio, calculated between the current and future period for all other plants in the industry that continue operating into the future period (in our data the future was the next Economic Census, five years later). We would expect both PAOC variables to have a positive effect on exit, although there are circumstances under which a negative relationship might be observed, at least for the current PAOC ratio. PAOC might be endogenous to the exit decision. For example, firms owning multiple plants may concentrate their PAOC on plants expected to continue operating. For example, Deily and Gray (1991) found evidence that firms allow plants on the verge of exit to slip into non-compliance. There might also be a negative relationship between a plant's current PAOC level and future changes in its PAOC, with some plants having adjusted to new regulatory requirements already, while others must increase their spending in the future. However, these concerns apply to the plant-level PAOC variable and not the industry-level variable, which motivated our inclusion of the latter.

A further concern is that a failure to control for unobserved profitability shocks could cause a spurious correlation between PAOC and exit if profitability and PAOC happen to be correlated. A positive profitability shock, combined with an increase in regulatory stringency, could cause a plant to increase its PAOC. The shock would also decrease the probability of exit, resulting in a negative correlation between PAOC and exit. As we discuss below, we added several variables to control for expected productivity.

Because our primary interest was in determining whether PAOC expenditure affects exit, we estimated the effect of expenditure on exit using a simple probit model:

$$P(EX_{it} = 1) = \Phi\left\{\left(\beta_0\left(\frac{RC_{it}}{PC_{it}}\right) + \beta_1 E\left[\mathrm{d}\left(\frac{RC_t}{PC_t}\right)\right] + \boldsymbol{X}_{it}\boldsymbol{\delta}\right)\right\} \qquad (1)$$

The dependent variable is a dummy equal to one if the plant exits between the current and subsequent Census year. The first two variables on the right-hand-side capture the effect of PAOC on exit. The first variable (denoted RC_{it}/PC_{it}) is the ratio of PAOC to production costs. The second PAOC variable (denoted $E[\mathrm{d}(RC_t/PC_t)]$) is the median increase, between the current period and five years later, among continuing plants in the industry for the ratio of PAOC to production costs.

The vector $\boldsymbol{X}_{it}$ includes a number of other variables that may affect exit. These include the plant's period t real capital stock and investment spending (in logs), a dummy to identify plants built after 1963, and second-degree polynomial expansion terms of these variables and the two PAOC expenditure variables (unfortunately, it is not possible to construct a precise age variable for all plants in the sample). The polynomials are included to allow for nonlinear effects of the variables on exit. The specification also includes output and input prices, capital's cost share, and annual industry growth. The industry growth variable was included only among the second degree polynomial expansion terms. The Olley and Pakes (1996) exit model includes only capital stock, age, and investment (which proxies for current and expected profitability), but we include other variables to control for industry or plant-level shocks (we cannot simply control for such shocks by adding year fixed effects because they would be collinear with the industry PAOC variable).

We estimated equation (1) separately for each industry. We then used the estimated coefficients to simulate the effect on exit probability of PAOC, which we expressed using either the plant's current PAOC or the industry's future growth in PAOC. Because the model includes second-degree terms involving the PAOC variables, the impacts are non-linear, and we considered the effects of both small and large changes in PAOC.

3 Data

The estimation sample for each industry consisted of all plants that appeared in any of the five Economic Census years from 1977 to 1997 (the time period for which we had relatively complete PACE survey data). Because the Economic Census includes all active plants in the particular year, we set the dependent variable, exit, equal to one if the plant did not appear in the following Census. We confirmed the quality of the exit variable by comparing it with flags in the Longitudinal Business Database that identified why the plant was not included in the subsequent Census (Jarmin and Miranda 2002), and by checking that the plant did not appear in any subsequent Census year.

Most of the explanatory variables we used in the analysis (real capital stock and investments, output and input prices, and capital's cost share) have already been described in some detail in BGLM. The exit analysis also includes a measure of plant age, which is a dummy for plants that began operating after 1963 (i.e., the dummy variable equals one for all plants that are not included in the 1963 Census of Manufactures). BGLM also provided summary statistics for the sample of continuing plants used in that analysis. Because of the substantial degree of overlap between the continuing plants used in BGLM and the set of plants used in the exit analysis, we have not presented summary statistics for the explanatory variables in the exit analysis. Table 1 provides information on the sample size for each industry, along with summary statistics for exit rates and median PAOC growth.

The first PAOC variable in equation (1) is the same as that used in the cost function estimation, measuring the plant's own abatement costs. For the second PAOC variable, we calculated the PAOC-to-production cost ratio (RC/PC) value for each plant in each Census year, then calculated the plant's growth in that ratio between Census years for plants with data in both years.[1] Finally, we calculated the median of these plant-level growth rates across all the other plants in the industry, excluding this particular plant, which we interpreted as the expected growth in PAOC over the next five years.

The limited years of PAOC data required some adjustment to the PAOC growth rate calculations. Because there was no PACE survey in 1987, we estimated PAOC in 1987 as the average of 1986 and 1988. The 1972-to-1977 growth rate used the growth rate measured from 1974 to 1977 and multiplied by 5/3; the 1992-to-1997 growth rate used the growth rate measured from 1992 to 1994 multiplied by 5/2; and the 1997-to-2002 growth rate used the growth rate measured from 1994 to 2005 multiplied by 5/11. We imputed the plant's own PAOC in 1997 using its own 1994 PAOC value. Note that we did not use the 1999 PACE data in the exit analysis. The 1999 survey reported much lower PAOC than in surrounding years (Becker and Shadbegian 2005). This discrepancy made it difficult to estimate growth rates using the 1999 survey.

4 Results

Table 2 presents the coefficient estimates for each industry for the basic model, including the full second-degree polynomial estimation. Because the coefficients in the nonlinear probit model were hard to interpret, we focused on simulations of the effects of PAOC on exit and employment.

Table 3 uses the estimated coefficients to predict the impact of a given change in PAOC abatement costs on the probability of plant exit in each industry. We considered three changes: a $1 million increase in PAOC spread proportionately across all plants in the industry, which matches the simulations for continuing plants in the BGLM but corresponds to a very small increase for the typical

[1] We measured growth as the change over the five years. For example, if the ratio of PACE to total costs increased from 1% to 2%, the increase would be measured as a 1% increase and not a 100% increase. To avoid reducing the sample size, we did not consider growth rates measured over longer periods of time.

observation; a 0.1% increase in the PAOC ratio for all plants in the sample; and a 1% increase in the PAOC ratio. Given that the industry average PAOC ratios ranged from 0.32% (for pipe-fitting) to 2.26% (for Portland cement), a 1% increase represents roughly a doubling of abatement costs for most of these industries. The first thing to note is that the effect of PAOC on exit probabilities is often negative. For a 0.1% increase in PAOC ratio, five of the current PAOC and only two of the future PAOC effects showed an increased probability of exit. There are only a few statistically significant effects of PAOC increases on exit probability. The impact of a 1% increase in current PAOC significantly reduced exit probability in the rolling and drawing industry (by 5.9%) and in the miscellaneous wood industry (by 8.7%). With the mean PAOC value in these industries being roughly 0.40%, such an increase represents a tripling of abatement costs and is therefore far out of sample. The impact of increase in expected future PAOC significantly decreases the probability of exit in the paper industry (by 0.2% for a 0.1% increase in PAOC and 1.7% for a 1% increase in PAOC) and increases this probability in the steel industry (by 0.4% for a 0.1% increase in PAOC).

We provided some support for the exit model results by simulating the effects of industry output growth on exit. Output growth is likely to be a strong predictor of future profitability, and we expected the variable to have a negative effect on exit. The last column of Table 3 shows much larger impacts of future industry output growth on exit probabilities. Many of the estimated effects are statistically significant, and a one standard deviation increase in industry output growth over the next five years is expected to reduce exit probabilities by 3.6% to 10.6%. This indicates that our model is capable of identifying factors that theory predicts should affect exit, and reinforces our conclusion that abatement costs, at least as captured by our measures of current and expected future PAOC, do not have a large effect on exit in these industries.

Figure 1 shows the non-linear nature of these exit effects for a range of increases in both current and expected future PAOC, with the horizontal axis measuring the increase in PAOC at the average plant and the vertical axis measuring the predicted change in exit probability. The first box on the left of the graph is the change caused by a $1 million aggregate PAOC increase, as displayed in columns 2–4 of Table 3; the other boxes show larger PAOC increases. Consistent with Table 3, none of the industries exhibit much of an increase in exit probability associated with PAOC, and several show decreases, especially for large increases in PAOC.

Table 4 translates the impacts on exit probability into impacts on expected industry employment, calculated by multiplying the change in each plant's exit probability by its employment level. Consistent with the earlier results in Table 3, most of these impacts on employment are positive, but all are relatively small. Except for the positive employment effect of expected future PAOC in the paper industry, none of these impacts are statistically significant. By contrast, the impacts of industry output growth on employment are generally larger, uniformly positive, and sometimes statistically significant. Figure 2 shows the non-linear impacts on employment for a range of increases in current and expected future PAOC, similar to Figure 1. Again we see very little impact of increased PAOC, this time on employment, unless the PAOC increases are very large.

5 Conclusions

For each of 10 industries we tested whether abatement spending reduces employment by increasing exit. None of our results support such a finding. Our models yielded relatively small impacts of abatement spending on exit, with most of those effects going in the opposite direction (reducing exit rather than increasing it), and nearly always statistically insignificant. When we translated these predicted exit effects into expected changes in industry employment, most industries showed employment increases rather than decreases, though none of the effects were statistically significant. This is not because our model is unable to predict exit decisions – we found that industry output growth has a large, statistically significant, and negative effect on exit. Some of the negative impacts of a plant's current PAOC might be driven by endogeneity; for example, a firm is more likely to invest in pollution abatement at plants it expects to continue operating. However, this concern should not affect the estimated effects of future PAOC increases, which are measured at the industry level. The consistently small exit effects of the plant and industry PAOC variables support our conclusion that PAOC has had a quite small effect on exit in the industries and time periods we examined.

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7 Tables and Figures

Table 1
Industry Definitions, Growth Data, and Available[a] Summary Statistics

Industry	NAICS Industry Definition	Compound Annual Industry Growth Rate of Real Shipments 1976–2005[b] (%)	Number of Observations in the Analysis	Probability of Exit during the Next 5 Years[c] (%)	Median Change in PAOC-to-production cost ratio over next 5 Years (%),
1 Paper	322110, 322121, 322130	1.71	924	6.06	-0.16
2 Petroleum	324110	3.77	658	4.48	0.17
3 Plastics	3252	1.41	1009	5.15	-0.10
4 Steel	331111	-1.46	469	4.05	-0.15
5. Portland Cement	327310	0.70	415	--	--
6. Rolling and Drawing	331421; 331422; 331491	-0.20	627	11.96	0.00
7. Pipe Fitting	332911; 332912; 332919	0.83	458	9.39	0.02
8. Misc. Wood Products	321911, 321912, 321918, 321920, 321991, 321992, 321999	1.83	736	12.50	0.01
9. Pharmaceuticals	3254	3.86	546	5.49	-0.04
10. Other Electrical Equipment	3359	1.08	839	10.97	0.04

Notes: (a) Because we concurrently disclosed descriptive statistics for the continuing plant analysis samples, only limited statistics could be disclosed for the exit samples. Descriptive statistics for continuing plants are reported in BGLM, Appendix Table A1. (b) These values were calculated based on industry-level growth rates from the growth rates of the underlying NAICS industries using NBER Productivity Database (Bartelsman and Gray, 1994). (c) That is, probability to exit during: 1977–1982, 1982–1987, 1992–1997, 1997–2002. (--) Values did not pass Census disclosure test.

Table 2 Estimated Parameters of the Probit Model for the Five-Year Exit Probability[a]

Industry:	Paper	Petroleum	Plastics	Steel	Portland Cement	Rolling and Drawing	Pipe Fitting	Misc. Wood Products	Pharmaceu-ticals	Other Electrical Equipment
Variable to which the effect corresponds	Point Estimates (Robust Standard Errors in Parentheses)									
Log of Capital	0.535	-5.509	-0.429	-4.443	50.806	-4.052	0.053	1.791	-2.919	-0.895
	(1.323)	(3.326)	(1.413)	(2.696)	(15.294)	(2.243)	(2.967)	(1.236)	(2.030)	(0.725)
Log of Investments	-0.712	5.218	1.098	6.186	-34.427	5.238	1.133	-0.284	2.827	1.499
	(0.613)	(2.796)	(0.905)	(1.588)	(11.740)	(2.047)	(1.043)	(0.512)	(1.688)	(0.552)
RC/PC	409.354	1,447.358	124.679	-850.059	401.060	-5,401.016	-999.148	102.183	204.349	-50.521
	(205.270)	(968.759)	(209.736)	(298.434)	(704.150)	(2,245.593)	(671.345)	(290.513)	(336.123)	(193.277)
Log of Capital Squared	-0.084	0.047	0.055	0.172	-4.244	0.098	-0.044	-0.127	0.338	0.103
	(0.092)	(0.059)	(0.088)	(0.121)	(1.309)	(0.129)	(0.189)	(0.090)	(0.133)	(0.060)
Log of Capital * Log of Investments	0.090	-0.078	-0.114	-0.350	4.966	-0.210	-0.138	0.054	-0.644	-0.247
	(0.096)	(0.086)	(0.111)	(0.091)	(1.905)	(0.118)	(0.135)	(0.081)	(0.199)	(0.082)
Log of Capital * (RC/PC)	-20.378	-99.337	-2.899	-5.979	17.404	-107.855	-9.578	-28.994	-27.916	-12.965
	(19.839)	(58.172)	(19.198)	(24.560)	(90.514)	(71.920)	(83.929)	(48.109)	(29.040)	(26.585)
Log of Investments Squared	0.022	-0.039	-0.003	0.065	-1.436	0.085	0.070	-0.013	0.195	0.062
	(0.033)	(0.050)	(0.045)	(0.054)	(0.739)	(0.042)	(0.047)	(0.031)	(0.086)	(0.031)
Log of Investments * (RC/PC)	-14.600	13.878	-5.708	-10.695	-117.034	101.623	84.302	-23.372	54.243	23.170
	(11.963)	(78.411)	(11.571)	(20.748)	(85.364)	(49.217)	(50.799)	(30.917)	(26.391)	(16.777)
(RC/PC) Squared	-4,509.774	-6,526.596	-18.891	380.653	-14,051.840	-3,210.292	-11,295.421	-6,325.462	-6,122.221	175.227
	(1,372.807)	(6,838.627)	(231.178)	(2,047.769)	(6,691.799)	(16,286.856)	(13,468.712)	(5,179.401)	(3,711.125)	(248.856)
Expected growth of PAOC-to-production cost ratio, E[d RC/PC]	-6,009.855	1,182.827	-1,272.231	-9,239.697	-8,510.768	-9,268.709	17,454.232	-3,742.265	-30,211.332	4,199.556
	(1,209.949)	(1,236.490)	(1,510.435)	(2,513.012)	(3,193.239)	(4,803.987)	(6,756.725)	(1,611.674)	(27,091.617)	(2,273.458)
Log of Capital * E[d RC/PC]	-0.855	296.580	83.480	260.629	32.798	2,031.681	642.074	333.830	816.546	187.920
	(46.226)	(205.578)	(74.001)	(113.415)	(112.427)	(940.759)	(376.276)	(163.308)	(891.274)	(100.096)
Log of Capital * E[d RC/PC]	-30.676	-264.575	5.880	-353.051	150.075	-2,889.368	-214.229	41.020	214.358	178.447
	(26.353)	(157.812)	(29.326)	(136.933)	(77.382)	(1,292.222)	(265.320)	(42.346)	(1,446.830)	(69.501)
(RC/PC) * E[d RC/PC]	-21,234.460	-21,152.401	19,857.268	77,820.968	31,750.640	3,697,359.600	160,364.990	37,448.551	-242,582.150	-15,102.324
	(8,335.555)	(59,035.489)	(30,381.909)	(27,355.041)	(11,384.042)	(1,472,404.200)	(101,625.310)	(23,642.213)	(111,299.840)	(7,162.457)

Industry:	Paper	Petroleum	Plastics	Steel	Portland Cement	Rolling and Drawing	Pipe Fitting	Misc. Wood Products	Pharmaceu-ticals	Other Electrical Equipment
Variable to which the effect corresponds	Point Estimates (Robust Standard Errors in Parentheses)									
E[d RC/PC] Squared	-361,588.230	-325,893.760	-138,706.800	-184,639.530	-148,271.150	-1,970,807.500	-4,983,921.700	-165,339.810	-4,501,034.800	-78,207.790
	(118,568.080)	(187,112.260)	(108,646.770)	(58,705.361)	(55,170.908)	(469,641.230)	(3,619,335.900)	(308,133.710)	(3,034,244.700)	(369,133.210)
Capital cost share	0.861	3.079	2.415	1.217	1.196	3.126	-0.344	2.139	1.727	2.256
	(0.967)	(0.964)	(0.746)	(0.891)	(2.482)	(0.699)	(1.043)	(0.658)	(0.844)	(0.601)
Log of Output Price	0.561	-1.801	0.274	2.591	-210.749	-0.913	-1.688	-0.267	0.676	-0.834
	(0.498)	(0.672)	(0.397)	(2.608)	(90.984)	(0.739)	(0.650)	(0.676)	(0.702)	(0.527)
Log of Capital Price	-306.656	9.853	-1.215	-105.569	229.046	-8.460	8.170	1.309	-8.459	-2.422
	(61.176)	(29.792)	(6.779)	(32.655)	(95.620)	(8.006)	(5.557)	(1.378)	(17.358)	(2.164)
Log of Production Labor Cost	-0.145	0.325	-0.152	0.053	2.269	-0.450	0.674	-0.204	0.260	-0.105
	(0.489)	(0.570)	(0.150)	(0.758)	(1.022)	(0.414)	(0.485)	(0.287)	(0.402)	(0.273)
Log of Energy Price	-0.615	0.838	0.137	-0.885	0.092	0.456	-1.592	1.103	-0.188	0.798
	(0.323)	(0.344)	(0.348)	(0.601)	(0.661)	(0.415)	(0.819)	(0.406)	(0.550)	(0.339)
Log of Materials Price	-0.064	15.711	0.160	-0.548	-7.669	3.597	-3.928	0.101	-2.608	3.712
	(2.328)	(7.113)	(1.427)	(19.609)	(10.355)	(1.305)	(4.311)	(0.827)	(2.354)	(1.113)
Log of Capital * Industry growth	0.979	--	-3.464	-8.911	--	-20.679	-3.030	-0.197	-38.625	-2.242
	(4.701)		(3.348)	(3.075)		(10.928)	(4.593)	(1.232)	(27.758)	(2.368)
Log of Investments * Industry growth	3.951	--	-0.404	10.347	--	29.372	1.902	-2.139	1.272	-5.527
	(3.107)		(2.026)	(3.834)		(15.034)	(3.758)	(0.990)	(45.499)	(1.920)
(RC/PC) * Industry growth	1,243.844	--	-930.631	-2,943.993	--	-39,577.372	2,909.695	-1,290.061	6,826.675	65.384
	(925.356)		(1,106.253)	(832.615)		(15,956.244)	(1,411.519)	(360.629)	(3,638.560)	(457.817)
E[d RC/PC] * Industry growth	8,112.428	--	-16,946.296	79,011.181	--	115,983.520	114,596.980	1,212.851	481,006.900	-94,904.165
	(17,698.164)		(11,238.137)	(20,444.447)		(46,642.260)	(93,129.007)	(21,428.501)	(427,609.130)	(48,690.711)
Industry Growth Squared	6,899.031	--	741.332	-2,224.007	--	-838.509	1,503.487	-19.797	-7,199.272	1,322.426
	(1,302.994)		(568.644)	(579.800)		(404.548)	(738.951)	(133.117)	(6,263.734)	(1,249.780)
Constant	-210.120	17.325	-10.204	-6.321	-117.603	7.970	-45.172	-5.683	25.250	-3.597
	(40.473)	(27.473)	(9.086)	(12.070)	(44.107)	(10.267)	(20.139)	(4.811)	(27.865)	(4.856)
Number of Observations	924	658	1,009	469	415	627	458	736	546	839
Log-likelihood	-106.866	-56.011	-126.143	-38.016	-17.819	-133.576	-95.693	-205.238	-55.240	-205.277

Notes: Coefficients of the dummy variable for post-1963 plant vintage could not be disclosed. (a) That is, probability to exit during: 1977–1982, 1982–1987, 1992–1997, 1997–2002. (--) Models with industry growth could not be estimated for the industry.

Table 3 Estimated Impacts of PAOC Increase on the Five-Year Plant Exit Probability[a]

Industry	Impact Type										
	I. $1M increase in aggregate PAOC for continuing plants (in all available years sample)[b]			II. Increase in plant-level PAOC by 0.1% of plant's total (production and compliance) cost			III. Increase in plant-level PAOC by 1% of plant's total (production and compliance) cost			IV. Increase in industry growth by one standard deviation	
	Average increase[c] in PAOC per plant (thous. 1997$)	Percent change[d] in 5-year exit probability due to change in:		Average increase[c] in PAOC per plant (thous. 1997$)	Percent change[d] in 5-year exit probability due to change in:		Average increase[c] in PAOC per plant (thous. 1997$)	Percent change[d] in 5-year exit probability due to change in:		Increase[e] in industry growth (%)	Percent change[d] in 5-year exit probability
		RC/PC	E[d RC/PC]		RC/PC	E[d RC/PC]		RC/PC	E[d RC/PC]		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1 Paper	0.3	0.0001	-0.0004*	216.8	0.0729	-0.2729*	2,167.8	-0.3750	-1.7814*	7.55	-6.8488*
		(0.0002)	(0.0001)		(0.1332)	(0.0615)		(1.0257)	(0.3830)		(0.7560)
2 Petroleum	0.4	0.0000	0.0000	1,035.5	-0.0659	-0.0093	10,354.9	-0.7751	-0.0842	--	
		(0.0001)	(0.0000)		(0.3336)	(0.0164)		(1.8112)	(0.1549)		
3 Plastics	0.3	-0.0001	-0.0002	179.5	-0.0286	-0.0822	1,795.0	0.0774	-0.7269	8.88	-5.2259
		(0.0003)	(0.0001)		(0.1365)	(0.0565)		(1.0506)	(0.4801)		(3.0643)
4 Steel	0.5	0.0002	0.0004*	508.7	0.3020	0.4144*	5,086.9	2.2425	0.5746	23.92	-4.0366*
		(0.0002)	(0.0001)		(0.1878)	(0.1203)		(1.0683)	(1.0937)		(0.9270)
5. Portland Cement	0.9	0.0010	-0.0007	60.6	0.0669	-0.0469	605.9	0.1732	-0.3564	--	
		(0.0015)	(0.0003)		(0.0983)	(0.0222)		(0.6457)	(0.1728)		
6. Rolling and Drawing	0.6	-0.0147	-0.0003	87.5	-1.3354	-0.0347	875.1	-5.9784*	-0.3331	9.25	-9.3078*
		(0.0086)	(0.0001)		(0.6467)	(0.0187)		(1.7265)	(0.1838)		(1.6631)
7. Pipe Fitting	1.0	0.0228	0.0010	35.4	0.7806	0.0338	353.8	-2.4141	0.3533	6.58	-10.4841*
		(0.0330)	(0.0009)		(0.9610)	(0.0305)		(2.5853)	(0.3110)		(2.7034)
8. Misc. Wood Products	0.7	-0.0333	-0.0001	29.8	-1.3461	-0.0050	298.2	-8.7740*	-0.0501	7.77	-3.6230
		(0.0145)	(0.0008)		(0.5207)	(0.0329)		(1.7582)	(0.3279)		(4.4375)
9. Pharmaceuticals	0.6	0.0007	-0.0001	181.2	0.2102	-0.0237	1,812.4	0.5640	-0.1854	2.94	-3.8573
		(0.0009)	(0.0001)		(0.2554)	(0.0300)		(1.5130)	(0.2719)		(1.9988)
10. Other Electrical Equipment	0.5	-0.0028	-0.0002	59.2	-0.3135	-0.0236	591.9	-2.2002	-0.2202	5.58	-10.6053
		(0.0037)	(0.0006)		(0.4253)	(0.0641)		(3.4052)	(0.6308)		(4.8400)

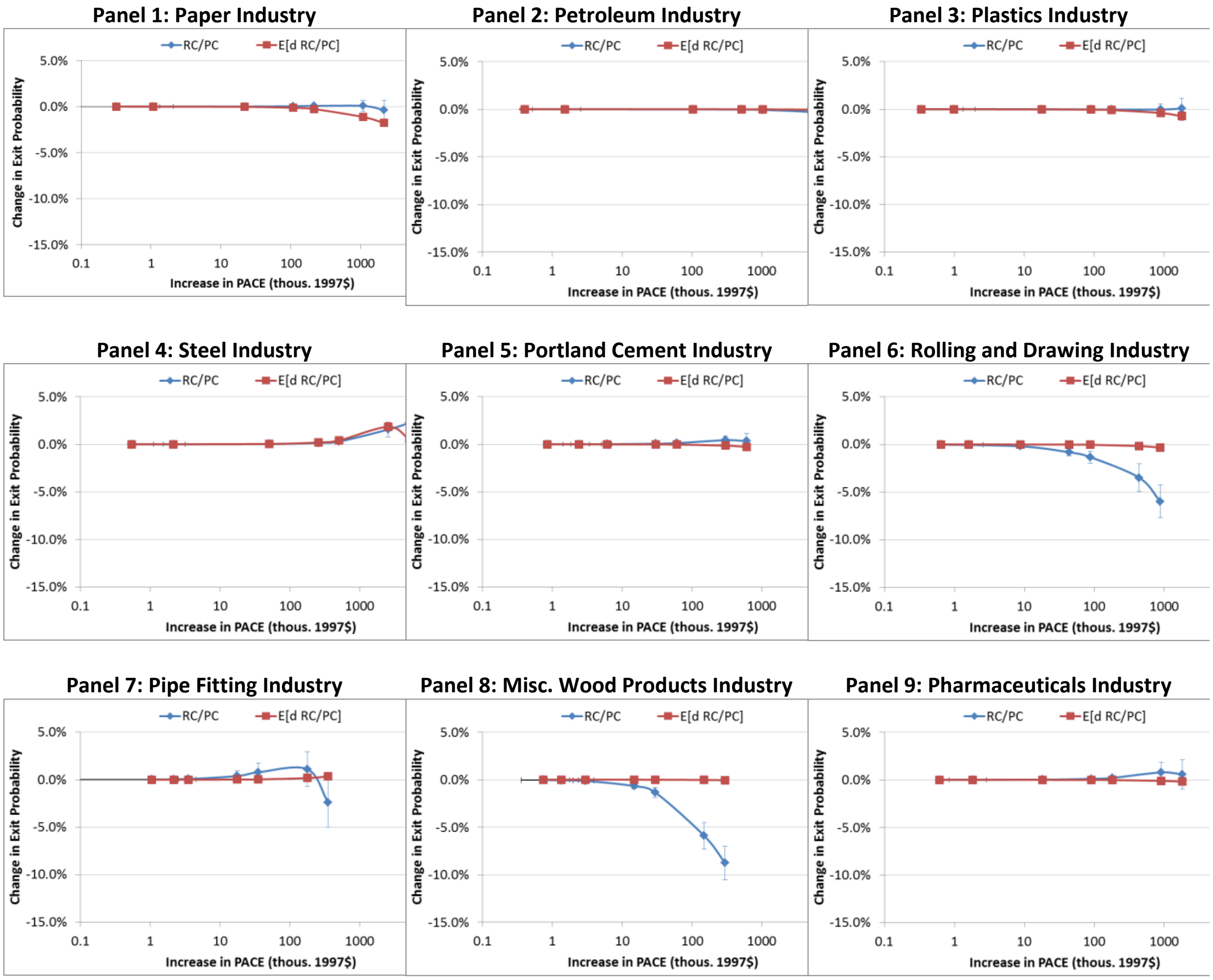
Notes: **RC/PC** – PAOC-to-production cost ratio; **E[d RC/PC]** – expected change in RC/PC in the next 5 years; (a) Probability of exit during 1977–1982, 1982–1987, 1992–1997, or 1997–2002. (b) For each industry, we calculated the ratio of average per-plant impact of $1M increase in aggregate PAOC to average total per plant cost for the continuing plants sample for all years (see BGLM for details). We used these industry-specific ratios to calculate corresponding per-plant increases in PAOC for the exit analysis sample. (c) The absolute increases in PAOC differ across plants because of variation in total costs. Sample averages are reported. (d) Changes in exit probability were calculated for each observation and then averaged. We report the point estimate and the robust standard error (in parentheses) of the average increase in exit probability. (e) In regression modeling, each plant-year observation was assigned the average annual industry-wide growth value. The values reported in this column represent standard deviation of annual industry growth in the estimation sample. A (--) indicates that the probit model with industry growth could not be estimated for the industry. (*) Denotes a statistically significant estimate at the 5% joint significance level. The Type I error was controlled using the Holm-Bonferroni procedure (Holm, 1979). To enable joint conclusions, all tests for a given category of impacts were considered a family (Bender and Lange, 2001). PAOC impact category (Types I-III) contained 60 tests, while industry growth impact category (Type IV) contained 8 tests.

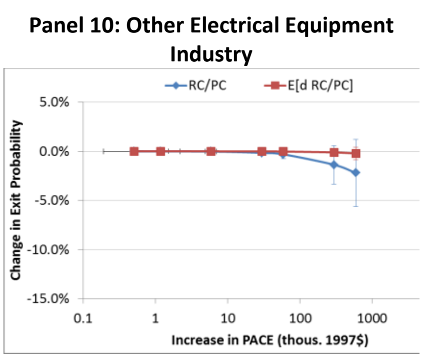
Table 4 Estimated Impacts of PAOC Increase on the Industry-Wide Employment through Changes in Exit Probability[a]

Industry	Impact Type										
	I. $1M increase in aggregate PAOC for continuing plants (in all available years sample)[b]			II. Increase in plant-level PAOC by 0.1% of plant's total (production and compliance) cost			III. Increase in plant-level PAOC by 1% of plant's total (production and compliance) cost			IV. Increase in industry growth by one standard deviation	
	Average increase[c] in PAOC per plant (thous. 1997$)	Change in industry-wide number of production workers[d] due to change in:		Average increase[c] in PAOC per plant (thous. 1997$)	Change in industry-wide number of production workers[d] due to change in:		Average increase[c] in PAOC per plant (thous. 1997$)	Change in industry-wide number of production workers[d] due to change in:		Increase[e] in industry growth (%)	Change in industry-wide number of production workers[d]
		RC/PC	E[d RC/PC]		RC/PC	E[d RC/PC]		RC/PC	E[d RC/PC]		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1 Paper	0.3	0.1	1.6*	216.8	81.6	998.6*	2,167.8	3,352.0	6,330.2*	7.55	19,109.2*
		(1.0)	(0.4)		(684.3)	(265.0)		(4,808.0)	(1,705.3)		(3,254.0)
2 Petroleum	0.4	0.2	0.0	1,035.5	369.8	4.4	10,354.9	968.5	31.2	--	
		(0.3)	(0.0)		(612.0)	(17.9)		(3,541.7)	(166.6)		
3 Plastics	0.3	0.1	0.2	179.5	46.4	95.9	1,795.0	-497.1	828.5	8.88	1,290.9
		(0.7)	(0.2)		(385.6)	(79.4)		(3,264.4)	(674.3)		(9,503.2)
4 Steel	0.5	-0.1	-1.4	508.7	-1,103.8	-1,310.9	5,086.9	-9,198.1	39.8	23.92	8,011.0
		(1.5)	(0.5)		(1,159.8)	(428.2)		(5,231.5)	(4,281.0)		(6,741.3)
5. Portland Cement	0.9	-0.3	0.4	60.6	-19.3	24.8	605.9	-83.5	184.3	--	
		(0.6)	(0.2)		(40.7)	(11.1)		(280.5)	(82.8)		
6. Rolling and Drawing	0.6	25.9	0.5	87.5	1,947.2	61.0	875.1	6,347.9	574.3	9.25	11,625.3*
		(22.9)	(0.2)		(1,220.9)	(28.0)		(3,346.8)	(267.9)		(3,036.3)
7. Pipe Fitting	1.0	-28.0	-1.1	35.4	-1,083.2	-37.9	353.8	143.8	-404.7	6.58	8,479.4*
		(33.8)	(0.9)		(1,026.0)	(29.4)		(2,955.1)	(303.5)		(2,769.7)
8. Misc. Wood Products	0.7	56.3	0.1	29.8	2,124.3	2.1	298.2	10,823.0	18.3	7.77	-129.1
		(30.0)	(1.1)		(1,070.0)	(42.4)		(3,994.5)	(422.7)		(7,151.6)
9. Pharmaceuticals	0.6	-1.2	0.1	181.2	-376.8	30.0	1,812.4	-3,051.5	205.7	2.94	1,178.6
		(1.4)	(0.2)		(398.6)	(48.7)		(3,654.2)	(442.3)		(4,209.7)
10. Other Electrical Equipment	0.5	4.5	0.3	59.2	486.7	38.2	591.9	1,810.8	333.1	5.58	16,201.8
		(9.0)	(1.1)		(1,028.0)	(132.3)		(8,940.2)	(1,301.0)		(11,390.9)

Notes: **RC/PC** – PAOC-to-production cost ratio; **E[d RC/PC]** – expected change in RC/PC in the next 5 years; (a) Changes in industry-wide due to changes in exit probability during 1977-1982, 1982-1987, 1992-1997, or 1997–2002. (b) For each industry, we calculated the ratio of average per-plant impact of $1M increase in aggregate PAOC to average total per plant cost for the continuing plants sample for all years. We used these industry-specific ratios to calculate corresponding per-plant increases in PAOC for the exit analysis sample. (c) The absolute increases in PAOC differ across plants because of variation in total costs. Sample averages are reported. (d) For each observation we calculated changes in exit probability and multiplied that by plant's employment. We then calculated the sum of plant-level employment changes. We report the point estimate and the robust standard error (in parentheses) of the total change in employment caused by change in plant exit rate. (e) In regression modeling, each plant-year observation was assigned the average annual industry-wide growth value. The values reported in this column represent the standard deviation of annual industry growth in the estimation sample. A (--) indicates that the probit model with industry growth could not be estimated for the industry. (*) Denotes a statistically significant estimate at the 5% joint significance level. The Type I error was controlled using the Holm-Bonferroni procedure (Holm, 1979). To enable joint conclusions, all tests for a given category of impacts were considered a family (Bender and Lange, 2001). PAOC impact category (Types I-III) contained 60 tests, while industry growth impact category (Type IV) contained 8 tests.

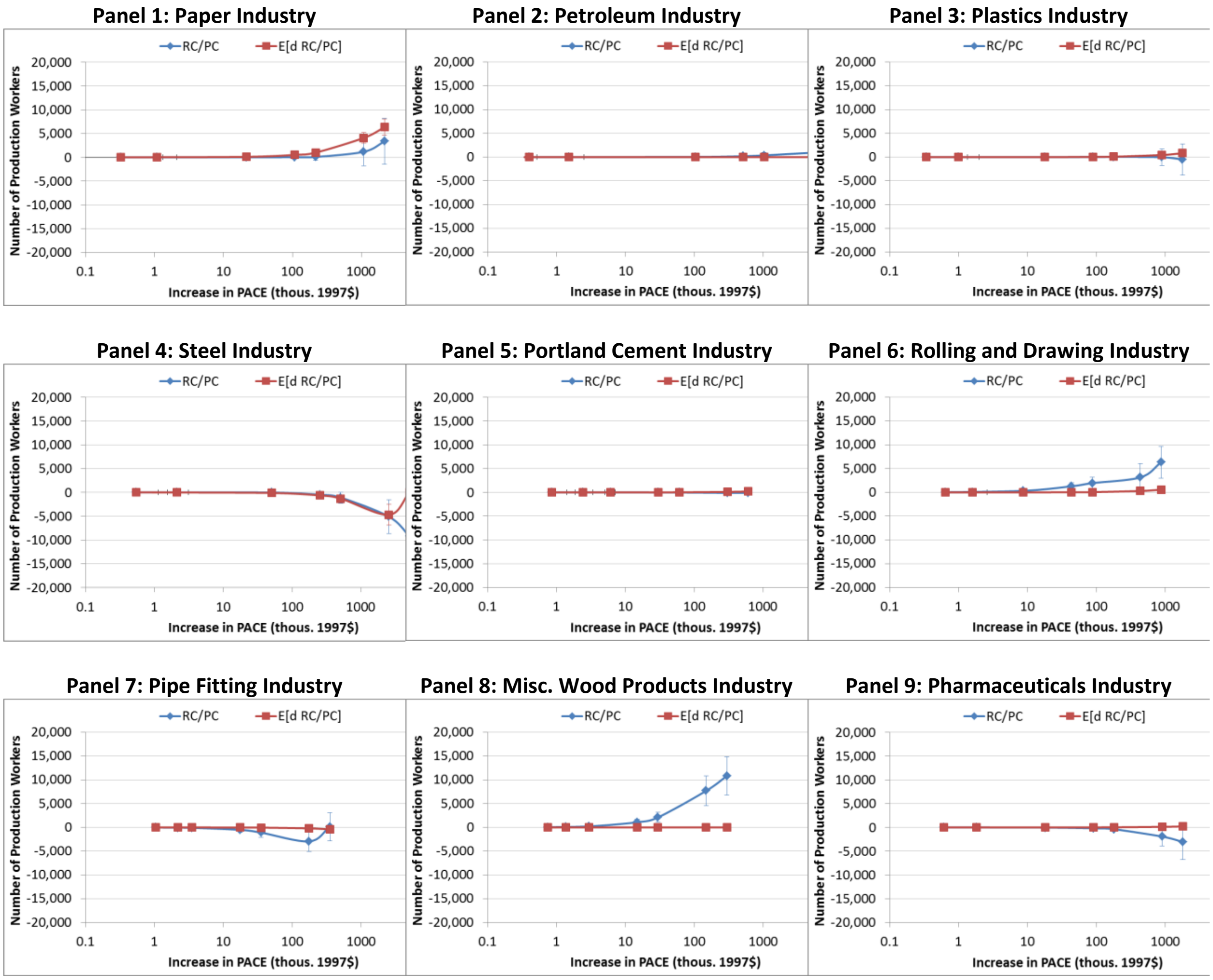
Figure 1 Estimated Impacts of PAOC Increase[a] on the Five-Year Plant Exit Probability[b]

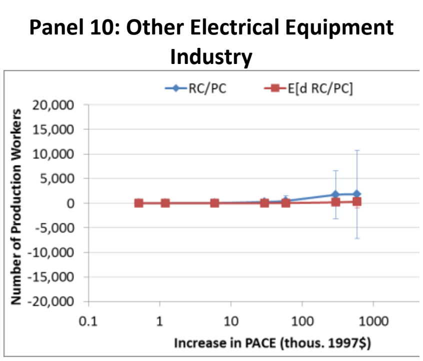




Notes: **RC/PC** – PAOC-to-production cost ratio; **E[d RC/PC]** – expected change in RC/PC in the next 5 years; (a) Changes were calculated for PAOC effect consistent with: $1M increase in aggregate PAOC (continuing plants sample); $1M increase in aggregate PAOC (exit analysis sample); and increases in plant-level PAOC corresponding to 0.01%, 0.05%, 0.1%, 0.5%, 1% of total costs. (b) Changes in probability of exit during 1977–1982, 1982–1987, 1992–1997, or 1997–2002, averaged over plant-year observations. Vertical bars represent robust standard errors that reflect sampling uncertainty.

Figure 2 Estimated Impacts of PAOC Increase[a] on the Industry-Wide Employment through Changes in Exit Probability[b]





Notes: **RC/PC** – PAOC-to-production cost ratio; **E[d RC/PC]** – expected change in RC/PC in the next 5 years; (a) Changes were calculated for PAOC effect consistent with: $1M increase in aggregate PAOC (continuing plants sample); $1M increase in aggregate PAOC (exit analysis sample); and increases in plant-level PAOC corresponding to 0.01%, 0.05%, 0.1%, 0.5%, 1% of total costs. (b) Changes in plant-level employment due to changes in plant-level probability of exit during 1977–1982, 1982–1987, 1992–1997, or 1997–2002, summed over plant-year observations. Vertical bars represent robust standard errors that reflect sampling uncertainty.