Title
Demand for Environmentally-Friendly Durables

Author
Martin, Leslie Aimee

Publication Date
2012

Peer reviewed|Thesis/dissertation

Demand for Environmentally-Friendly Durables

By

Leslie Aimée Martin

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Associate Professor Sofia Villas-Boas, Chair
Professor Peter Berck
Associate Professor Lucas Davis

Spring 2012

Demand for Environmentally-Friendly Durables

by

Leslie Aimée Martin

Abstract

Demand for Environmentally-Friendly Durables

by

Leslie Aimée Martin

Doctor of Philosophy in Agricultural and Resource Economics

University of California, Berkeley

Associate Professor Sofia Villas-Boas, Chair

This thesis addresses several aspects of the demand for environmentally-friendly durable goods. Chapter 2 asks how technological obsolescence affects how we should think about how much to promote the adoption of environmentally-friendly durables. If the purely social benefits improve quickly but private benefits only improve slowly, then subsidizing adoption now may delay upgrading in the future. As an example, I consider the impact of subsidizing the replacement of short-lived incandescent bulbs with long-lived CFLs even though we know that much better LEDs will soon be on the market. In the process, I provide some of the first publicly-available estimates of the elasticity of demand for CFLs and energy-saving in lighting.

Chapter 3 discusses the optimal timing of product introduction to market for goods that provide environmental benefits. Although a simple model argues for early introduction, if early-adopters have overly optimistic expectations about product quality, product launch decisions that are optimal for firms may be sub-optimal from a social point of view.

At the firm level, capital stock can vary widely in the intensity with which it uses fuels. Newer vintages are often associated with increased input use efficiency, leading to emissions reductions through energy savings. Chapter 4 analyzes the impact of trade liberalization in India on the greenhouse gas emissions of that country's manufacturing firms. I document that over a period of 13 years within-industry reallocation of market share to favor more energy-efficient firms produced a larger savings in greenhouse gases than is expected from all of India's Clean Development Mechanism energy efficiency and renewable energy projects combined. Using 19 years of firm-level data from India's Annual Survey of Industries and industry-level variation in policy reforms, I estimate the relative contributions of tariffs on final goods, tariffs on intermediate goods, FDI reform, and delicensing on increasing energy efficiency within firms and on reducing market share of energy-inefficient firms. I observe that reductions in tariffs on intermediate inputs led to a 23% improvement in fuel efficiency, with the entire effect coming from within-firm improvements. Delicensing and FDI reform, not tariffs on final goods, drove the reallocation effect, with post-liberalization changes in licensing requirements improving fuel efficiency an additional 7%.

Acknowledgements

I would like to thank my many formal and informal ARE advisors, namely Ann Harrison, Sofia Villas-Boas, Peter Berck, Anthony Fisher, David Zilberman, Larry Karp, Leo Simon, Christian Traeger and Max Auffhammer.

Throughout my time at Berkeley I benefitted greatly from amazing seminars and discussions at the UC Energy Institute and Energy Resources Group. A special thank you to Lucas Davis and Meredith Fowlie.

Thank you to my brilliant and generous classmates, particularly Shanthi Nataraj, Eric Hallstein, Pauline Grosjean, Jenny Ifft, and Abdoulaye Sy.

Thank you to Joanne Linnerooth-Bayer for inviting me to spend a semester working on this thesis at IIASA.

I will always be indebted to Jay W. Forrester and John Newman, who both contributed so much to how I think about and understand the world.

And last but not least, I would like to think my parents, grandmother, brother, and two favorite Bornstein men for their love, patience, and support.

Dedicated to JWF and JLN

Contents

Chapter 1

Introduction

This thesis addresses several aspects of the demand for environmentally-friendly durable goods. Examples of such goods include energy-efficient appliances such as air conditioners, refrigerators, TV monitors, light bulbs and fuel-efficient boilers, motor vehicles, and capital equipment. These products are not good for the environment when they displace other products whose use would generate worse environmental outcomes.

The consumption of electricity and fuels have social costs that are currently unpriced or under-priced. Electricity production from coal, oil, or natural gas feedstocks emit greenhouse gases that contribute to a changing climate. Coal mining and combustion releases mercury, lead, cadmium, arsenic, manganese, beryllium, chromium, and other toxic, and carcinogenic substances. Coal, oil, and gas combustion also result in emissions of NOx, sulfur dioxide (SO2), and particulate matter which affect local air quality.[1]

Although economists agree that the best way to deal with environmental externalities is an emissions tax, even better yet, a tax directly proportional to the incremental environmental damage that each source of emissions causes, efficiency standards and the promotion or subsidy of energy efficient products are tools frequently used by policy makers to obtain emissions reductions.[2]

Chapter 2 asks how technological obsolescence affects how we should think about how much to promote the adoption of environmentally-friendly durables. Durable goods yield services or utility over time. With durable goods existing stocks matter, both in terms of determining a household or firm's optimal timing of product adoption and in crediting what

[1]Source: (NRC 2010). Note that in some markets firms do internalize the social cost of their NOx and SO2 emissions.

[2]Lowest-cost policies are ones like taxes or cap-and-trade systems that equate marginal abatement costs across all taxed or capped sectors. Examples of energy efficiency standards include CAFE standards for motor vehicles and the Top Runner program in Japan. California adopted energy efficiency appliance standards for air conditioners, heat pumps, refrigerators, boilers, and laundry dryers in the late 1970s. The Federal government followed suit in the early 1990s. Examples of subsidy programs include the US $3.2 billion Energy Efficiency and Conservation Block Grant (EECBG) Program.

is displaced. The question of technological growth and the adoption of new technologies on environmental outcomes is particularly interesting when both private and public benefits associated with durables improve quickly but not equally fast. If purely social benefits improve a lot but private benefits only improve a little, then from the social planner's perspective too few 'early adopters' will upgrade. As an example, I consider the impact of subsidizing the replacement of short-lived incandescent bulbs with long-lived CFLs when we know that much better LEDs will soon be on the market. By thinking of adoption as a process that involves a sequence of generations of intermediate technologies, I provide another argument to question certain policies to promote widespread adoption of environmentally-friendly products.

Chapter 3 discusses the optimal timing of product introduction to market for goods that provide environmental benefits. Although a basic model argues for early introduction, if early-adopters have overly optimistic expectations about product quality, early introduction can prove to be significantly more costly from a social point of view. If firms only take into account the costs and risks faced by their own firm, then there might be a role for a social planner to intervene to discourage early introduction of products that will delay or block subsequent adoption.

Chapter 4 focuses on the environmentally-friendly technology adoption decisions of firms and market forces that favor or penalize firms with different environmental profiles. Specifically, I document the impact of trade liberalization in India on the greenhouse gas emissions of that country's manufacturing firms. The literature on the effect of globalization on pollution focuses to date on industry composition effects: whether pollution moves to countries with a comparative advantage in pollution-intensive industries, perhaps due to weak environmental regulation. In contrast I study what happens within industry. I ask whether opening up to trade increases competition domestically in a way that makes firms that use fuel inputs less efficiently more likely to be replaced by new entrants. I also document the extent to which opening up to trade encourages firms to upgrade to newer (often cleaner) technologies. I document these last aspects empirically using firm-level data from India's Annual Survey of Industries (ASI), using variation in the intensity of trade reforms across time and years to identify the effect of trade and industrial liberalization policies on firm-level pollution.

In the process of tackling these questions I make two additional technical contributions:

1. To calibrate a model of consumer upgrading environmentally-friendly products, I provide some of the first publicly-available estimates of the elasticity of demand for CFLs and energy-saving in lighting. Although many consumers value CFLs as one of few easy ways to be green, many also have a strong dislike for private characteristics of CFLs, like the tone of light or (previous) inability to dim. Understanding demand for private vs. externality characteristics of CFLs helps us forecast how many consumers will upgrade to the next generation technology (LEDs).

2. To estimate the impact of trade regulations on firm pollution, technology adoption,

and market share, I constructed a 19-year panel from the Annual Survey of Industries (ASI). I used a set of matching techniques to convert a repeated cross-section into a panel. This methodology could be applied by other researchers to datasets with similar characteristics.

One central theme in this thesis is that consumers and firms value a mix of product or capital stock attributes, only one of which is environmental-friendliness. In many cases, fuel or energy savings is a small factor in decision-making. But adoption of environmentally-friendly goods can take off when 'green' qualities are correlated with other dimensions of product quality.

Chapter 2

Promotion, obsolescence, and the environment

Are we over-promoting the adoption of intermediate environmentally-friendly technologies?

We actively promote adoption for two reasons: to bring forward the time at which subsequent generations of technology become cost-competitive, and to achieve environmental benefits from displacing dirtier technologies sooner. But not only is promoting widespread adoption today expensive, it can also delay future adoption of even better technologies, or increase the cost of widespread adoption of future technologies.

Consider the plan to install one million solar rooftops in California, or the proposed Senate bill 1108 for 10 million solar roofs nationwide. Large rounded numbers have political appeal, but are these anywhere near economically-efficient levels? Why one million or ten million? Why not 100,000? To what extent is it welfare improving to subsidize solar panels when we know that photovoltaic technology is rapidly improving, or to subsidize long-lived CFLs when we anticipate low-cost LEDs?

We want to promote adoption to the extent that the marginal benefits of displaced emissions and positive externalities associated with costs dropping as a function of installed base equals the marginal cost of adoption, including the cost associated with current adoption delaying future adoption. This delay becomes a real issue when two conditions are met: When environmental benefits grow quickly and private benefits don't,[1] and when there is a limited market for used product (in other words, when the scrap price is low).[2] If consumers are anticipate future regret, they will holding back on purchases today, and the cost of

[1]If environmental benefits grow slowly the social loss is small; if private benefits grow quickly then consumers will either chose to delay adoption despite the subsidies or will adopt and upgrade of their own accord

[2]There may be a significant used market for boilers or air conditioners, especially in developing countries. It is less likely that there will be a large market for used solar panels (which have high installation costs and are often installation-specific) or used light bulbs (for which transaction costs are high relative to product value).

subsidizing a set level of adoption will be higher than policy makers will anticipate if they fail to take regret into account. If consumers are not as forward-looking, then social planners may regret having subsidized as much as they did. They will either be faced with lower future adoption (if their subsidy budget is fixed) or will find that it will cost them more to obtain the same level environmental benefits in the future, relative to a scenario where they had not pushed as much adoption in early periods.

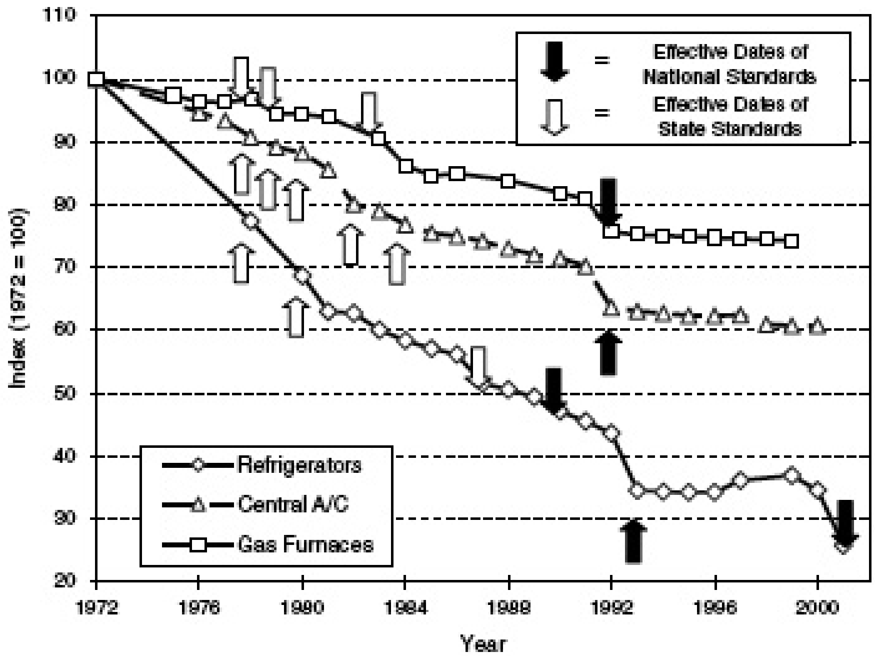
In this chapter I present a theoretical model of optimal promotion of environmentally-friendly durable goods in sectors with rapidly improving technology. I ask two important questions: What is the impact of current subsidies on subsequent adoption? and, How should the public sector allocate subsidies between extensive and intensive margins, that is, between encouraging new consumers to adopt and encouraging the existing consumer base to upgrade? Consumers may delay adoption in anticipation of technology growth. And because incentives to upgrade depend on current holdings, I discuss under what conditions it is welfare-improving to promote early adoption.

The social benefits of promoting the adoption of second-best technologies depends critically on ex-post rates of technology growth and distributions of private valuations for the different generations of technology. I propose to use a unique dataset to recover heterogeneous valuations for energy efficient light bulbs and simulate the extent to which current subsidies would delay adoption of subsequent lighting technologies. I take advantage of a two-year panel of supermarket purchases of light bulbs and other environmentally-friendly and cost-saving products to estimate private valuations of the product. I back out the extent to which purchases are driven by factors other than expected energy savings, using first a mixed logit model and then a dynamic structural model. I will also use the estimates to simulate the effects of a set of policy questions specific to light bulbs.

This research is the first to my knowledge to model the impact of technological obsolescence on how best to promote the adoption of environmentally-friendly durable goods. The research is important because current policies rely heavily on technology-specific promotion, as evidenced by tax credits of the purchase of hybrid vehicles, incentives for installation of residential solar panels, and extensive programs to promote adoption of CFLs. Given increasing demand for green and other socially-conscious products, there is also value in developing a better understanding of voluntary adoption of environmentally-friendly products, in the vein of (Kahn 2007).

There is renewed interest in technological obsolescence due in part to the recent development of empirical techniques for estimating dynamic structural demand models; see (Gordon forthcoming) on the market for personal computers, (Prince 2009) for PC processors, (Gowrisankaran and Rysman 2009) for digital camcorders, and (Schiraldi and Street 2008) for automobiles. The literature on the adoption of environmentally-friendly products, however, has lagged behind in addressing product durability.

Durable goods yield services or utility over time. Durability affects adoption dynamics in two ways. First of all, consumers have an incentive to delay purchases of durables if



Electric Technologies in EU, 1980-1995

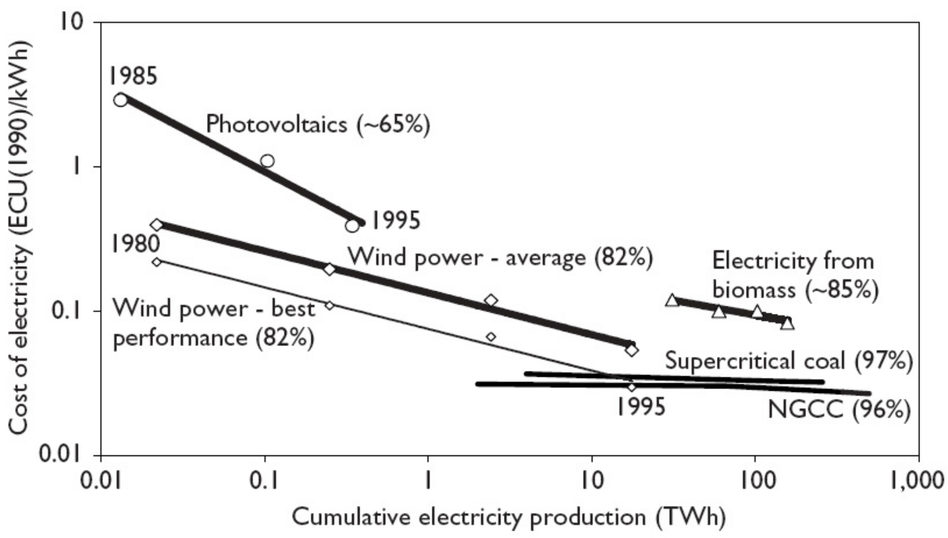


Figure 2.1: Technology is rapidly improving in sectors relevant for energy-efficiency and clean energy production (Source: Jaffe et al, IEA *Experience Curves for Energy Technology Policy*)

purchase prices are expected to decrease over time (say, due to technology growth or because a monopolist is expected to decrease prices to capture residual demand).[3] Second, the relative utility that a consumer derives from a prospective purchase depends on their current holdings. Adopting today increases the value of tomorrow's outside option, especially if the adopted asset is long-lived. Consider solar panels. A household has only one roof; when it decides whether or not to upgrade it takes into account the opportunity cost of the stream of benefits from any existing installation. Alternately, consider CFLs: Demand for replacement light bulbs depends on how often bulbs burn out, which depends on lifespan of bulbs a household has installed. With durable goods, the decision to make a replacement purchases is intrinsically different from the decision to make a new purchase.

Type of asset	Typical service life (years)
Household appliances	8-12
Automobiles	10-20
Industrial equipment/machinery	10-70
Aircraft	30-40
Electricity generators	50-70
Commercial/industrial buildings	40-80
Residential buildings	60-100

Note: Product life in sectors that are frequently the source of energy efficiency projects. Source: (Jaffe *et al.* 2002)

2.0.1 Environmentally-friendly durable goods

The early energy-efficiency literature modeled product durability as a trade-off between up-front capital costs and subsequent savings in operating costs. Authors described the 'surprising' underinvestment in energy-saving capital in terms of discount rates implied by observed adoption decisions. The seminal paper by (Hausman 1979) uses household-level data on residential air-conditioners to estimate an implied discount rate of 20%, decreasing with income. (Train 1985) provides a survey of the implicit discount rate literature. He reports implied rates of 10-35% for measures to improve thermal integrity of dwellings, 4-36% for space heating systems, 3-29% for air conditioning, 39-100+% for refrigerators and 18-67% for other appliances (water heating, cooking, food freezing). More recent energy efficiency literature debates the extent to which market failures that may be responsible for

[3] The IO literature on durable goods has focused on markets in which there is monopoly power. The Coase conjecture proposes that if the new goods market is dominated by a monopolist, and the monopolist cannot credibly commit to not decreasing prices in subsequent periods to capture residual demand, then he can only charge high prices to consumers with very high discount rates. Bulow 1986 endogenizes the supply of durability: monopolist who rents provides optimal durability, monopolist who sells provides short product life to minimize competition from used goods.

what appear to be high implied discount rates. (Levine *et al.* 1995) and (de T'Serclaes and Jollands 2007) describe a few such failures, like principal-agent problems, credit constraints, and information asymmetries.

(Jaffe *et al.* 2002) provide an overview of the literature that combines environmental policy and technological change. Environmental costs or benefits are a function of joint decisions of technology choice and intensity of input use. The putty-clay framework that distinguishes between ex ante ("putty") and ex post ("clay") technology decisions can be applied to the joint decision of which durable to adopt and how intensely to use it, given uncertainty about future factor or input prices. Zilberman and Caswell show in a series of papers that drip irrigation is adopted (over sprinkler) only by farmers with medium range land qualities; decreases in technology costs increases the range of land qualities where drip is adopted; and when there is uncertainty in water prices, farmers are less likely to adopt water-saving technologies. (For a summary see (Sunding and Zilberman 2001) and (Dinar *et al.* 1992)). The recent energy-efficiency literature estimates a small role for induced innovation, that is, on the effect of increases in factor prices on adoption of durable goods that use those factors less intensively. (Jaffe and Stavins 1995) find a positive but small response in the adoption of residential thermal insulation technology to energy prices. Several authors find more significant responses on the part of firms ((Popp 2002), (Linn 2008)). The result of this literature has been to recommend purchase subsidies as an expensive but effective policy tool (Jaffe *et al.* 2005).

There is recognition that the durability of environmentally-friendly goods leads to a 'lock-in' effect that discourages adoption. This lock-in is not the same as lock-in due to increasing returns, as discussed in (Arthur 1989). It is closer to lock-in due to switching costs, as described in (Farrell and Klemperer 2009), though durability in itself is probably not a switching cost in the technical sense. (Hassett and Metcalf 1993) call lock-in 'irreversibility' and argue that irreversibility and uncertainty regarding future energy prices can entirely explain low observed rates of adoption of certain energy-efficient appliances. (Sanstad *et al.* 1995) disagree with their analysis, arguing that price variation observed in data may have be viewed by consumers as temporary.

The incipient 'carbon lock-in' literature ((Philibert 2006), (Unruh 2000)) also acknowledges that the durability of consumer goods delays diffusion of new technologies, but focuses on functional obsolescence, that is, product break down. (Jaffe *et al.* 2002) identify that "a primary driver of replacement purchases for durable energy-using goods is the goods useful lifetime" but don't connect durability to optimal policy decisions.

Technology adoption has a long history in the agricultural economics literature. David 1975 described the transition farmers made from reaping by hand to using a mechanical reaper via a 'threshold model' whereby an agent adopts a new technology only if it allows him to cross the 'threshold' of profitability with the traditional technology. This model had little explanatory power; later studies were more successful in explaining observed diffusion with models of investment under uncertainty, as described in Dixit and Pindyck 1994.

Finally, the environmental literature on waste disposal that discusses product durability at length, but the focus is on the impact of planned obsolescence on increasing flow of toxic components into landfills.

2.0.2 Estimating demand for durable goods

(Chen *et al.* 2008) use simulations to demonstrate the bias introduced into elasticity estimates when models for durable goods are estimated using static techniques. There has recent been a number of empirical IO models that estimate demand for durable goods taking into account household inventories or vintages of current holdings. The only paper to my knowledge on thats study the adoption of durable goods that provide positive externalities, is by David Rapson, as of yet unpublished, and it focuses on the environmental externality as a an ancillary benefit.

The most relevant papers that use individual-level data and account for current consumer holdings are all based on (Rust 1987)'s optimal stopping problem. (Hendel and Nevo 2006) develop a household inventory model of stockpiling during sales to demonstrate that static demand estimates may overestimate price sensitivity. The authors have to make assumptions about initial stock values. In their model consumers face two sources of uncertainty: utility shocks and future prices. Consumers tradeoff the cost of holding an additional unit of inventory with the potential benefit of buying at the current sale price instead of at future expected prices.

(Prince 2009) uses cross-sectional data on personal computer holdings by vintage for two years (including whether last purchase was a first time purchase or a replacement purchase) to estimate variation in marginal valuation of PC quality across households. His identification relies on variation across holdings, and he demonstrates that failing to take into account forward-looking behavior biases estimates of price sensitivity.

The research that is closest to mine is (Gordon forthcoming). The author distinguishes between demand for new purchases and demand for upgrades, or replacement purchases. His analysis, however, is limited by only having access to market-level data and two observations per household (holdings for two different years). (Gowrisankaran and Rysman 2009) has the seminal work using aggregate-level data. Their paper is a structural dynamic model heterogeneous consumer tastes, rational expectations about future products (falling prices and improving features), repeat purchases over time. They estimate a distribution of consumer preferences for digital camcorders using market-level data, in an approach that combines a BLP framework with an optimal stopping problem.

2.1 Theoretical model

The following models describe the adoption and upgrade decisions for durable products that provide social benefits which are not entirely internalized by adopters. I present first a two-period model then extend the analysis to an infinite horizon. Consumers can only adopt one product at a time (each roof can only have one solar panel system, each hilltop one wind turbine, each socket one bulb), and private and/or additional social benefits increase over time. Private benefits are modeled separately from externality benefits. I aggregate several effects into private benefits: operating cost savings, warm glow or altruistic benefits from being green, less dislike for the product for whatever reason (for example, non-environmental dimensions of quality). Net private benefits can be negative.

2.1.1 Two period model

In the first period a durable good is available that lasts two periods. In the second period, a better good becomes available. Each good provides private benefits α_{ti} to consumer i, additional social benefits $\overline{\alpha}_t$, and receives a purchase subsidy s_t in period t. Both goods are priced at a constant, common, marginal cost c. Say that the planner is able to observe private valuations.[4]

The consumer's optimal adoption decision as a function of his private valuations α_{1i} and α_{2i} is presented graphically in Figure 2.2. If his private valuations in both periods are low, he never adopts: region (0,0). If his private valuations in both periods are very high, he adopts in $t = 1$ and upgrades in $t = 2$: region (1,1). In the area labeled 'delay' consumers who would have adopted in the first period had the second generation technology not existed chose to delay adoption to the second period (subset of region (0,1) where private valuations for α_{1i} greater than $\frac{c-s_1}{1+\delta}$. The area labeled 'lock-in,' a subset of region (1,0) with private valuations of α_{2i} greater than $c - s_2$, represents the private valuations of consumers who would have adopted the second technology had they not already adopted the first generation technology.

The mismatch between the social planner's incentives and the consumer's incentives for adoption in the two periods comes from overlaying the above figure with one that looks at full social benefits, $\alpha_{ti} + \overline{\alpha}_t$, and ignores subsidy transfers. In the first period, the social planner wants to provide purchase subsidies to individual i if his private valuation is high enough that it's socially optimal for him to adopt, but low enough that he wouldn't adopt without a subsidy $s_1 \geq c - \alpha_{1i}(1 + \delta)$, that is, to:

$$\frac{c}{1+\delta} - \overline{\alpha}_1 < \alpha_{1i} < \frac{c}{1+\delta}$$

[4] The lock-in effect is only accentuated when the public sector is unable to distinguish which agents are on the margin in the first period.

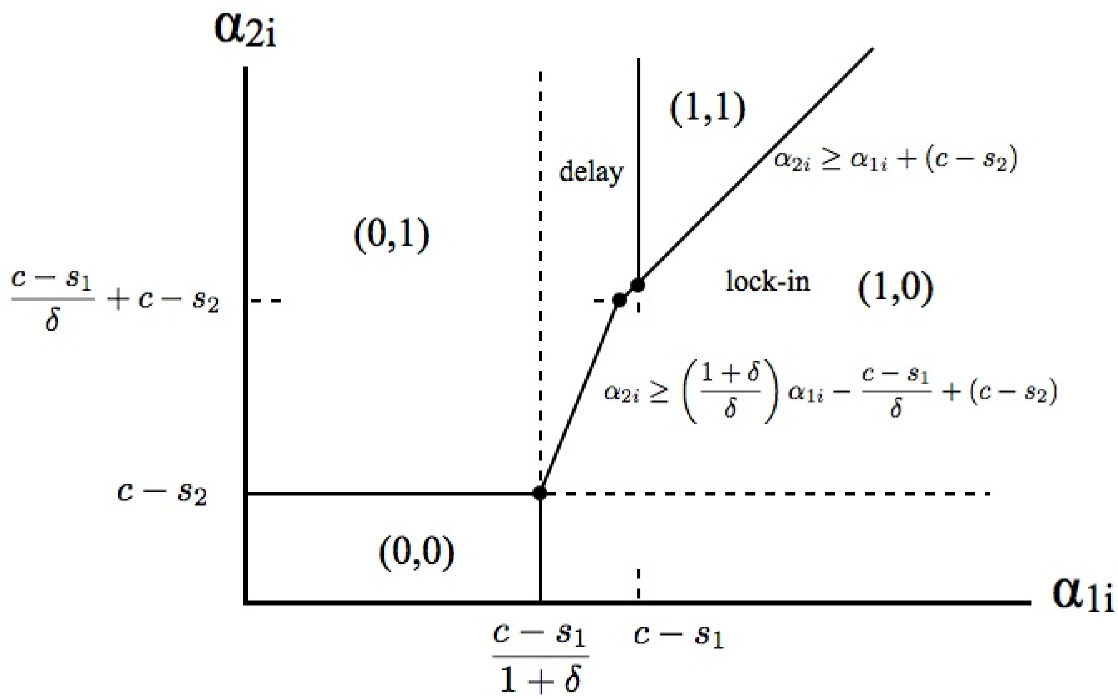


Figure 2.2: Optimal adoption $(t = 1, t = 2)$ as a function of private valutions

In the second period, the social planner wants individuals who adopted in the first period to upgrade if:

$$\overline{\alpha}_2 - \overline{\alpha}_1 > c - (\alpha_{2i} - \alpha_{1i})$$

To get early adopters to voluntarily upgrade need to provide $s_2 \geq c - (\alpha_{2i} - \alpha_{1i})$. On the other hand, to get people who did not adopt in the first period to adopt in the second period, the planner only needs to provide $s_2 \geq c - \alpha_{2i}$. To get people to upgrade after they've adopted, the planner needs to increase purchase subsidies by the discounted stream of private benefits they would otherwise receive from intermediate technology. The smaller the increase in private benefits between first durable adopted and latest technology, the more he needs to compensate. This makes intuitive sense: when deciding to upgrade you take into account the opportunity cost of the stream of benefits from your existing installation. Your outside option changes.

If private benefits are not high enough to warrant first period adoption and subsequent upgrading, the social planner would prefer delayed adoption to second period if discounted technology growth is greater than the discounted cost of upgrading and the foregone net benefits in the first period, that is:

$$\delta(\overline{\alpha}_1 + \alpha_{1i}) - (\overline{\alpha}_0 + \alpha_{0i}) > \delta c + (\overline{\alpha}_0 + \alpha_{0i} - c)$$

Table 2.1: Consumer and social surplus

	Private	Social
Don't adopt	0	0
Adopt today and don't upgrade	$\alpha_{0i} - (c - s_0)$ $+\delta\alpha_{0i}$	$\overline{\alpha}_0 + \alpha_{0i} - c$ $+\delta(\overline{\alpha}_0 + \alpha_{0i})$
Adopt only tomorrow	$\delta(\alpha_{1i} - (c - s_1))$	$\delta(\overline{\alpha}_1 + \alpha_{1i} - c)$
Adopt today and upgrade tomorrow	$\alpha_{0i} - (c - s_0)$ $+\delta(\alpha_{1i} - (c - s_1))$	$\overline{\alpha}_0 + \alpha_{0i} - c$ $+\delta(\overline{\alpha}_1 + \alpha_{1i} - c)$

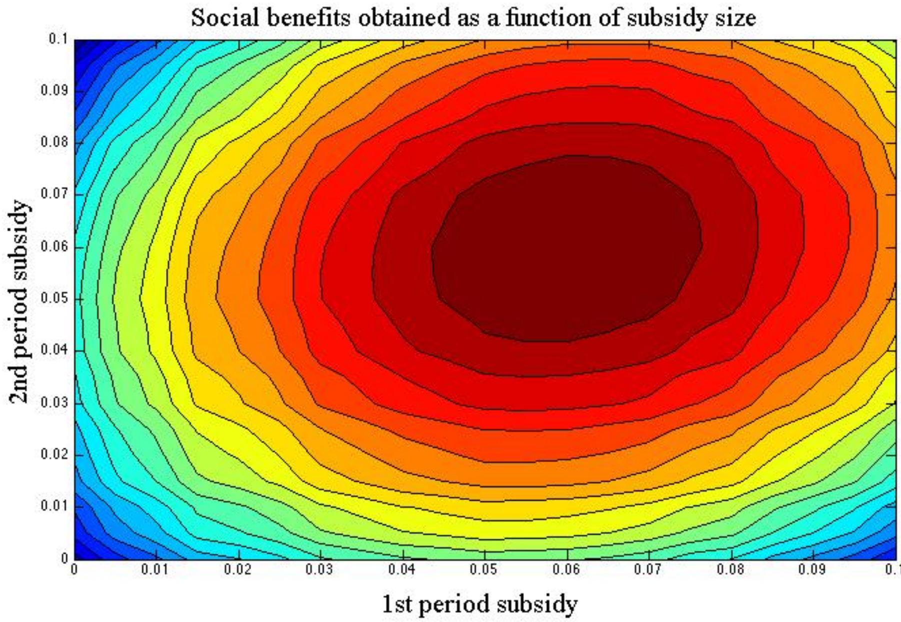
When technology is rapidly improving, increases in private benefits give forward-looking consumers an incentive to further delay adoption relative to socially-optimal levels. Improvements in additional social benefits can cause social planners to prefer scenarios with less initial adoption and more subsequent adoption.[5]

Consider situations where externality benefits increase along with private benefits. Take for example the case of installation of wind turbines in Europe, where there are a scarce number of good sites. (A good site has a lot of wind, is far enough from population centers such that zoning is not a problem but not so far that transmission costs become an issue.) The best sites have the highest benefits both to firms and social planners. As the best spots are taken up by earlier vintages of technology, there comes a point where it's more cost effective to encourage a firm to upgrade the technology at an existing site than to encourage expansion to the next best site. The extent of this trade-off depends on the distribution of private and social benefits across the different sites.

2.1.2 Infinite horizon model

Durable goods last an indefinite number of periods, consumers take into account the discounted value of all future replacement decisions. I propose a discrete time, infinite horizon model with two discrete states: annual experienced benefits of adoption α and time t and a binary decision variable {do nothing, upgrade}. The potential benefits of adoption, $f_\alpha(t)$ increase over time.

[5] I can extend the framework to include ex-ante uncertainty in technology growth. Say $\overline{\alpha}_1$ and α_{1i} can take on two values: high and low, with known probability. The social planner only wants consumers to upgrade in second period in the high benefit state of the world. Consumers take expectations over second period states to make first period adoption decision.



Writing the Bellman equation:

$$V(\alpha, t) = \max \left\{ \begin{array}{ll} \alpha + \delta V(\alpha, t+1) & \text{do nothing} \\ f_\alpha(t) - c + \delta V(f_\alpha(t), t+1) & \text{upgrade} \end{array} \right\}$$

I solve the infinite horizon Bellman equation via policy iteration so that:

$$V - \max_x \{f(x) + \delta P(x) V\} = 0$$

which is computed numerically via Newton's method in Matlab.[6]:

$$x \leftarrow \arg\max_x \{f(x) + \delta P(x) V\}$$

$$V \leftarrow [I - \delta P(x)]^{-1} f(x)$$

I plot the results under two assumptions of technology growth: constant rate of technology increase (left) and technology increasing at decreasing rate (right). The social planner's solution is plotted in blue; the result of a private actor's decision process in red. The graphs show that with externalities, private agents upgrade less than socially optimal. They delay adoption and hold on to each generation of the durable good longer.

Figure 2.4 demonstrate results for the scenario where private benefits represent only 30%

[6] I use Miranda & Fackler's *comp econ* toolbox

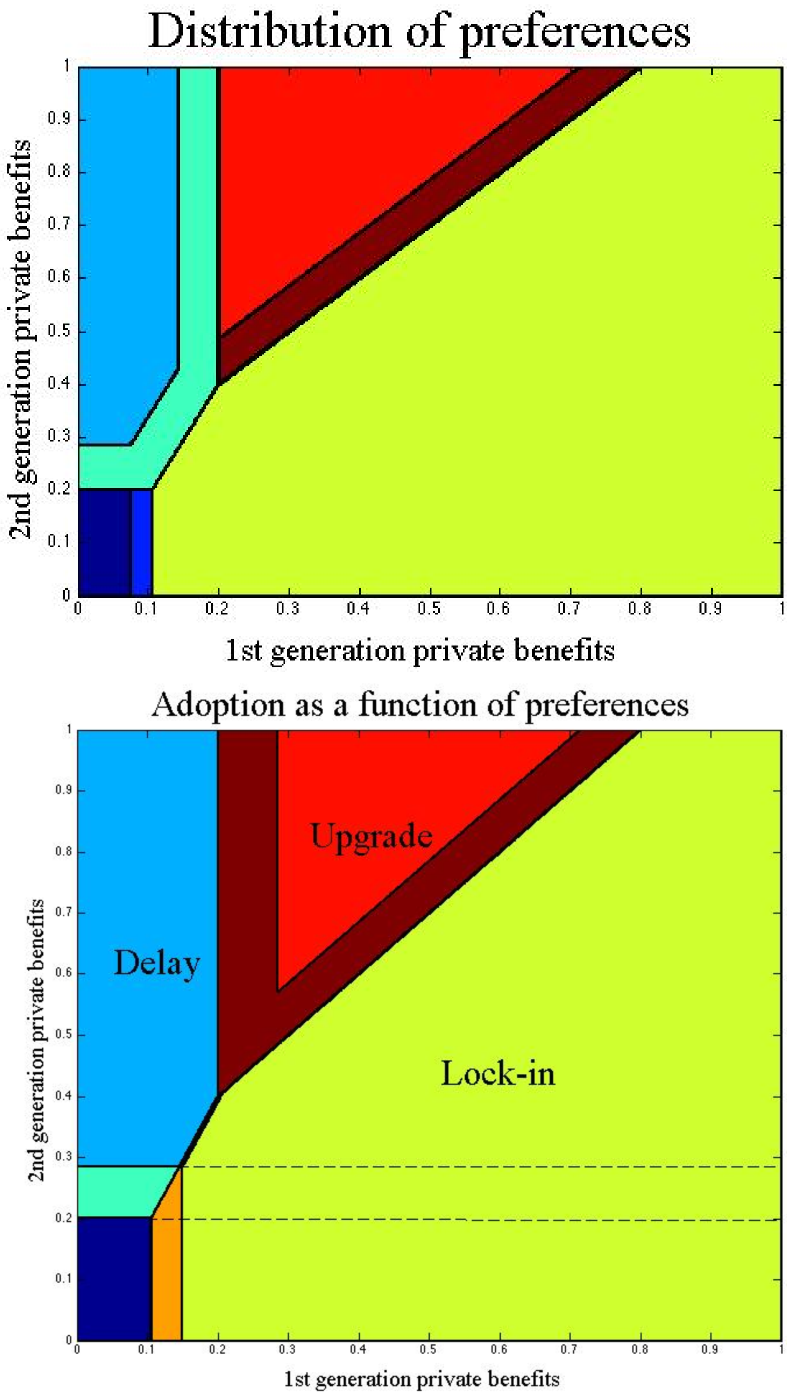
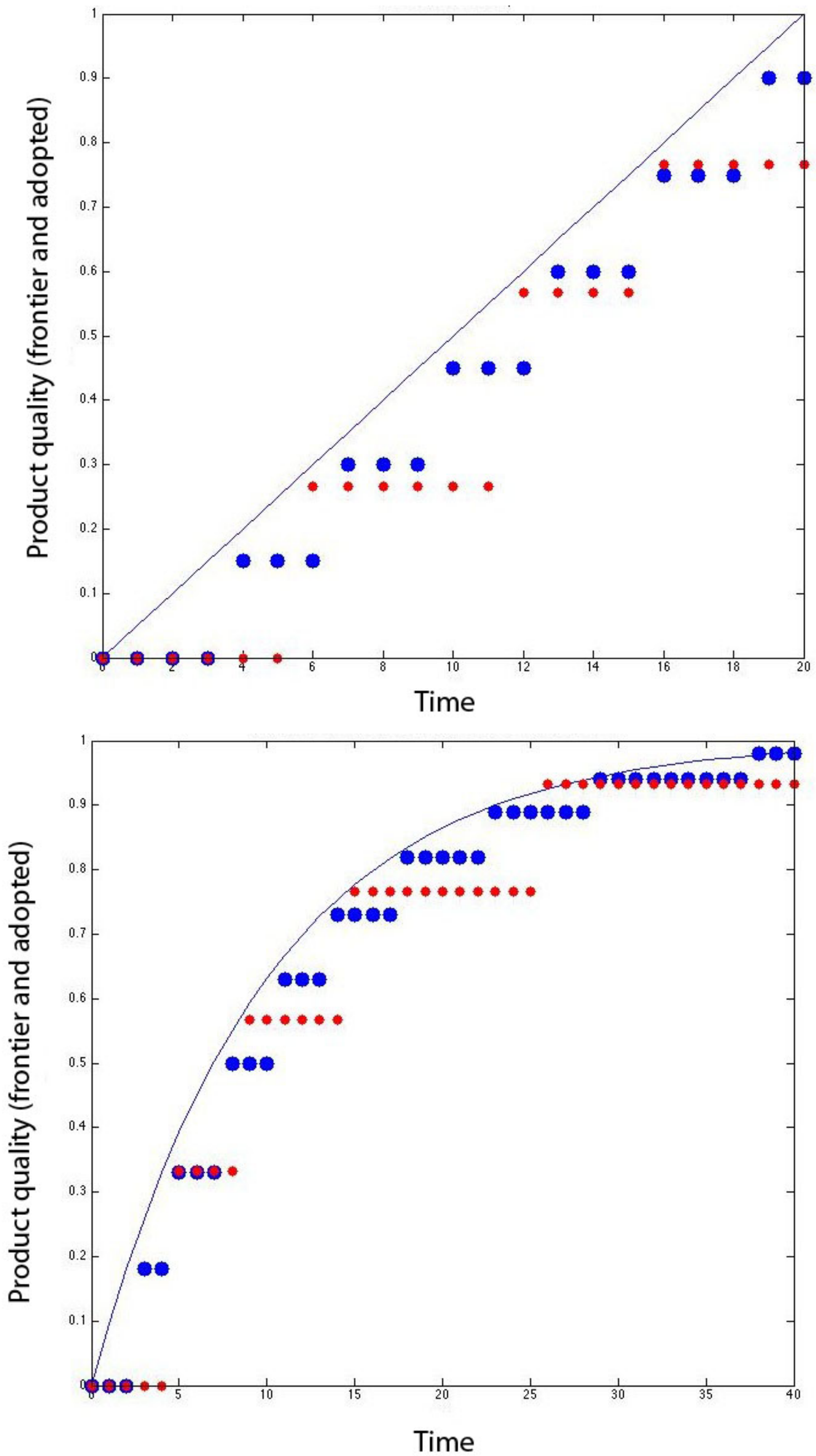


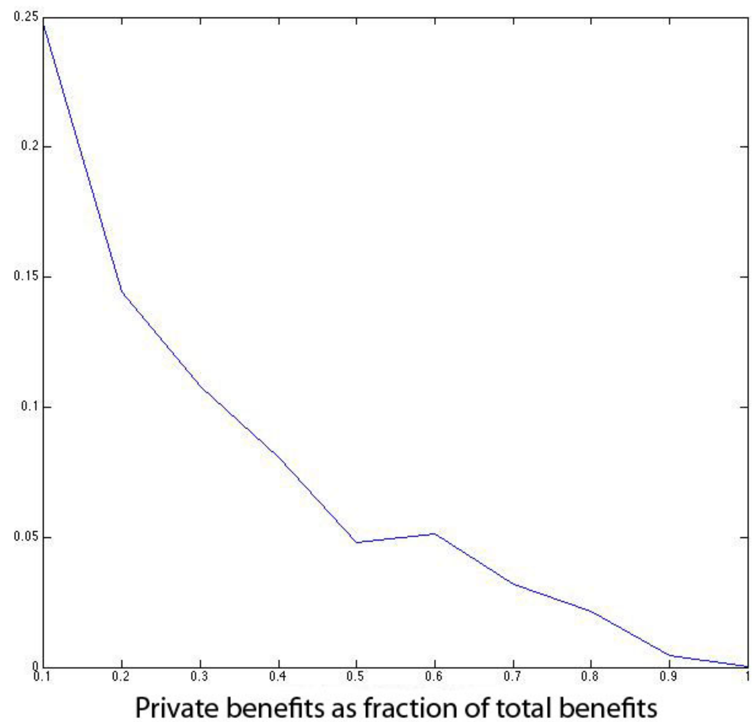
Figure 2.3: With (above) and without (below) first period subsidy

Figure 2.4: Quality: optimal upgrading of social planner (blue) vs. private agents (red) when technology improves at a rate that is constant (above) or decreasing (below)



of total benefits. Then the net present value (NPV) of social benefits are 15% (left) and 11% (right) lower under private decision-making than socially-optimal. Figure 2.5 demonstrates how the NPV of social benefits lost decreases as relative size of private benefits increases for each technology growth scenario.[7]

Figure 2.5: Net present value (NPV) of lost social benefits as a function of the size of private benefits relative to total benefits (including purely social benefits), case where technology improves at a decreasing rate



I can loop over subsidy levels to identify optimal trajectory of subsidies, subject to an intertemporal budget constraint.[8] These curves highlight the unsurprising result that the welfare cost associated with adoption of intermediate technologies highly depends on private valuations of the environmentally-friendly good.

[7]The choppiness in the curves is due to the fact that agents in the model only have the opportunity to re-optimize once a year.

[8]I can also easily extend the dynamic control problem to take into account uncertainty in rates of technology growth.

2.2 Data

Compact Fluorescent Light bulbs (CFLs) are a good example of an intermediate technology that by virtue of being so long-lasting may delay adoption of subsequent generations of energy efficient lighting, like Light Emitting Diodes (LEDs). Characteristics of three generations of bulb technology are presented in Table 2.2.[9] CFLs) are energy-efficient (15 watt CFL for 60 watt incandescent bulb), durable (minimum of 7000 hours in contrast to 1000 for incandescent bulbs), and expensive (regular retail is \$7 compared to \$0.75 per incandescent bulb).

The most likely next technology is Light-Emitting Diodes (LEDs). These bulbs are even more energy efficient (4 W LED for 15 W CFL replacing a 60 watt incandescent bulb), even more durable (25000 hours vs 7000 hours CFL and 1000 for incandescent bulb), and even more expensive (regular retail \$35 vs \$7 CFL and \$0.75 incandescent). LEDs have additional private benefit of improved quality of light, and additional environmental benefit of not containing mercury (that CFLs contain).

By using sales data to estimate private valuations of CFLs relative to the social benefits provided by CFLs, I can estimate how much of an issue, if at all, lock-in may be in this sector.

Table 2.2: Comparing subsequent generations of lighting technology

	Incandescent	CFL	LED
Power	60 W	15 W	5 W
Durability	1000 hours	7000 hours	25,000 hours
Price	\$0.75	\$6	\$35
Savings		\$0.57	\$0.70

Note: CFL= Compact Fluorescent Light, LED = Light Emitting Diode. At a national average of 630 g/kWh, each 60W incandescent bulb used 3 hours a day produces 37.8 kg of CO2 and each 60 W equivalent (i.e. 15 W) CFL produces 9.5 kg of CO2 per year. If CFLs are not disproportionately installed in high-use sockets, each installed CFL displaces 28.3 kg of CO2 per year. (Source: Environmental Protection Agency (EPA) eGRID)

One advantage to using CFLs as a case study is that light bulbs are purchased relatively frequently (unlike, say, refrigerators, boilers, or cars). The main disadvantage of using CFLs as a case study is that the results may not extrapolate well to the purchase decisions of significantly more expensive environmentally-friendly durable goods. Stock-piling is also an issue that appears relatively unique to CFLs.

I requested and received a unique supermarket scanner dataset of weekly light bulb sales covering 210 stores in 13 states over a period of 4 years, from March 2005 through March

[9]Savings are calculated per month, bulb used 3 hours/day, average residential rate of \$0.14/kWh

2009. Up until now, publicly available research on CFL demand has surprisingly been limited to stated-preference recall survey methods like (Itron 2007). Using store-week scanner data from 2003 to 2005 for the same 210 stores as in my later sample, Martin 2008 suggests own-price elasticities for CFLs at -1.5 (with a 95% confidence interval of -1.1 to -1.9). Average residential electricity prices did not significantly influence the likelihood of purchase. The estimates were obtained using a nested logit model with a control function that instruments with average out-of-state prices.

One caveat that may turn out to pose less of a problem than I initially anticipated is package size. At the time that the data was collected, most if not all CFLs were sold in individual packages.[10] Incandescents, on the other hand, are frequently sold in packages of two or four bulbs. I have replicated the analysis imputing product quantity from price segments, using personal observation in local stores that four-packs of traditional incandescent light bulbs range from $2.50 to $3.00 per pack. The results are robust to all of the package specifications that I tried.[11] I suspect that the small difference is due to the fact that very high and very low-priced packages make up a very small fraction of incandescent bulb sales.

The bigger concern that I have with the scanner data is that there is no indication of when items were temporarily out of stock. I make the conservative assumption that a bulb is present in a store every week between the time of its first sale and its last sale, including intermediate weeks in which no sale of that product type is observed.

For the estimation, I match the scanner data with demographics associated with the zip code in which each store is located. Most of the demographic data comes from 2000 Census zip code tabulation areas (ZCTA). Demographic data includes median household income, household size, average commute time, and race and age distribution variables. Average retail energy prices were obtained from the Department of Energy's (DOE) Energy Information Agency (EIA). Unlike the other consumer variables, retail energy prices vary at the state-level. I also include an estimate of CO2 emissions associated with energy generation in each state, also obtained from the EIA website. This variable varies only by state and by year.

2.3 Empirical framework

My goal is to answer the following questions:

- What fraction of CFL sales can not be explained by a desire to save money? (i.e. is

[10] (Pulliam 2006)

[11] For example, assuming that 1028 of the packages with prices greater than $3.50 represent 8-packs instead of 4-packs and that the 1307 packages with prices less than $1.50 represent 2 packs. I also simulated the discrete choice models under the assumption that packages of standard bulbs include twice as many bulbs as do packages of other incandescent bulb types. As expected the price coefficient changed, but all of the coefficients maintained the same sign.

probably explained by green preferences, warm glow, trendiness, etc)

- How much adoption is likely with smaller point-of-sale subsidies?
- How much would promoting CFLs delay adoption of LEDs? What is the associated welfare cost, as a function of when LEDs become price-competitive?
- What is (a lower bound on) the welfare loss associated with a product ban?[12]

I can also use existing estimates of the elasticity of residential electricity demand to estimate how large a carbon tax would be needed to produce equivalent energy savings to that obtained by promoting CFL purchases.

I adopt a random utility model that models demand for product characteristics. I assuming a structural form for indirect utility:

$$U_{ijm} = \beta_i X_{jm} - \alpha_i p_{jm} + \xi_{km} + \epsilon_{ijm}$$

Explanatory variables are estimated energy savings, CFL, generic-brand, wattage-equivalent, package count, interactions between market segments and CFL and interactions between zip-code demographics (median income and education) and CFL. ξ_{jm} is a product-market fixed effect. The coefficient on price, α_i, represents the marginal utility of income. In my primary specification I fix the coefficient on price and assume that the coefficients on the other variables are normally or lognormally distributed.[13]

I use DOE state-month average residential energy rates to estimate expected energy savings. More disaggregated data may be available, but I have to proxy household location by store location, so imperfect disaggregation may not be worth the collection effort. I would prefer to use data on marginal electricity rates, but I do not know household energy consumption. The biggest worry that I have about assigning average rates to all consumers is that I want to make sure to not attribute expectations of above average use to green preferences. I also assume that households use current energy prices to form expectations of future energy prices.

Assuming utility is linear in product attributes and random effects and that preferences can change over time, I write consumer i's utility from product j in store-week market m as:

$$u_{ijm} = \beta_i X_{jm} + \xi_j + \epsilon_{ijm}$$

where X_{jm} are product and market observable covariates, ξ_j is an unobserved, product-specific covariate and ϵ_{ijm} is an idiosyncratic error shock that is identically and independently

[12]The 2007 federal Energy Bill bans future sales of incandescent light bulbs: sales of 100-watt bulbs will be banned as of 2012 and 40-watt bulbs will be gone by 2014.

[13]Energy savings, promotion, wattage, and package count should be lognormal (strictly positive coefficients).

distributed across markets and products. The probability of consumer i choosing product j in market m is:

$$P(y_{ijm}=1)=P(U_{ijm}\geq U_{ikm})=P[\epsilon_{ikm}<\epsilon_{ijm}+\beta_i(X_{jm}-X_{km})+\xi_j-\xi_k]\ \forall k\neq j$$

If the unobservable components of utility are distributed extreme value, the probability that consumer i choses product j is:

$$P(y_{ijm}=1)=\frac{e^{\beta_i X_{jm}+\xi_j}}{\sum_l e^{\beta_i X_{lm}+\xi_l}}$$

(Villas-Boas and Winer 1999) have demonstrated that endogenous prices and promotion may bias elasticity estimates. I instrument for price endogeneity using average out-of-state CFL prices, as recommended by (Nevo 2000). This approach is widely used, though not robust to aggregate demand-side shocks. Better instruments would be gross margins (highly correlated with price and uncorrelated with the error) or the price of neon phosphors (neon phosphors are a large component of the cost of producing CFLs and do not factor into the cost of producing traditional incandescent light bulbs).

2.3.1 Berry logit

My first specification is a conditional logit model as presented in Berry 2004. If consumers have identical preferences, observed market shares s_{jm} directly reflect choice probabilities:

$$s_{jm}=I_m P(y_{jm}=1)=I_m\left(\frac{e^{\beta X_{jm}+\xi_j}}{\sum_l e^{\beta X_{lm}+\xi_l}}\right)$$

where I_m is the size of the market. I run the model with several assumptions about total market size, and the results are remarkably robust to my different assumptions. I assume the utility associated with outside options is zero, and I normalize all coefficients relative to that option. Then for the outside option,

$$s_{0m}=I_m\left(\frac{1}{\sum_l e^{\beta X_{lm}+\xi_l}}\right)$$

Taking natural logs of each equation and subtracting,

$$\ln s_{jm}-\ln s_{0m}=\ln I_m+(\beta X_{jm}+\xi_j)-\ln\left(\sum_l e^{\beta X_{lm}+\xi_l}\right)-\ln I_m+\ln\left(\sum_l e^{\beta X_{lm}+\xi_l}\right)$$

Terms cancel out and I'm left with:

$$\ln s_{jm} - \ln s_{0m} = \beta X_{jm} + \xi_j$$

I estimate the β coefficients with OLS and 2SLS. Results of the regression analysis are presented in Section 2.4.

I can then use the estimated coefficients to calculate elasticities:

$$\eta_{jm} = \frac{\partial s_{jm}\, p_{km}}{\partial p_{km}\, s_{jm}} = \begin{cases} -\alpha\, \hat{s}_{jm}\,(1 - \hat{s}_{jm}) & \text{if } j = k \\ \alpha\, \hat{s}_{jm}\, \hat{s}_{km} & \text{otherwise} \end{cases}$$

$$\text{where } \hat{s}_{jm} = \frac{e^{\hat{\beta} X_{jm}}}{\sum_l e^{\hat{\beta} X_{lm}}}$$

and α is the estimated coefficient on price.

Unfortunately the log functions restrict my dataset to observations for which market shares are non-zero. I'm effectively estimating the effect of characteristics on choice probabilities, conditional on at least one sale of a product taking place. In my case this restriction is problematic because CFLs are only purchased in 35% of the store-weeks for which I have data. Aggregating data over similar products or over multiple weeks can partially mitigate this problem, but both approaches involve taking weighted averages across product prices.[14]

2.3.2 Market share logit

I then consider a traditional logit model that I adapted to use market shares instead of individual purchase decisions. Similarly to the case with individual-level data, the loglikelihood function is:

$$LL(\beta) = \sum_m \sum_j \left(\frac{N_{jm}}{N_m}\right) \ln P_{jm} = \sum_m \sum_j \left(\frac{N_{jm}}{N_m}\right) \ln \left(\frac{e^{\beta X_{jm} + \xi_j}}{\sum_l e^{\beta X_{lm} + \xi_l}}\right)$$

I implement the market share logit by adapting the loglikelihood function used in Ken Train's maximum likelihood optimization, changing the dependent variable from a 0/1 binary to market share. The MATLAB code for my adapted loglikihood function is presented in the Appendix.

I then implement a two-stage control function approach. I decompose ϵ_{ijm} into a mean conditional on μ_{jm} and a variation around the mean:

$$\epsilon_{ijm} = E[\epsilon_{ijm}|\mu_{jm}] + \tilde{\epsilon}_{ijm}$$

[14]Non-zero sales take place in 55% of market observations.

By construction the remaining error term, $\tilde{\epsilon}_{ijm}$, is uncorrelated with p_{jm}. Substituting in to the utility equation:

$$U_{ijm} = \beta_i X_{jm} + \gamma_i p_{jm} + E[\epsilon_{ijm}|\mu_{jm}] + \tilde{\epsilon}_{ijm}$$

Following the control function approach I first regress price on a set of instruments and use the residuals to create the control function $E[\epsilon_{ijm}|\mu_{jm}]$. I then estimate the discrete choice model as written above, including the control function as one of the right hand side variables.

Results of the maximum likelihood estimation are presented in Section 2.4. A major disadvantage specific to the logit approach is the assumption of the independence of irrelevant alternatives (IIA). The IIA assumption implies fixed substitution patterns proportional to market shares. The other disadvantage to both aforementioned approaches is that they do not allow me to take into account heterogeneous preferences across individuals.

2.3.3 Random coefficient mixed logit

Finally I estimate a mixed logit model with random coefficients. In a mixed logit model, the likelihood of choices j_i of consumers $i = 1 \ldots N$ is:

$$L(\gamma) = \prod_{i=1}^{N} \int_{\beta} \frac{exp(x_{ij_i}\beta)}{\sum_{k=1}^{J} exp(x_{ik}\beta)} f(\beta|\gamma) d\beta$$

Let A_{jm} be the set of individuals who chose product j in market m. For a given set of parameters, the predicted market share of the jth product is the integral over the consumers in that market:

$$s_{jt} = \int_{A_{jm}} dP_{\epsilon}(\epsilon|D,\nu) dP_{\nu}(\nu|D) dP_D(D)$$

The BLP model is a generalized method of moments (GMM) estimation of coefficients of utility that consumers derive from product characteristics, where each moment condition is derived from the assumption that the instruments are actually good instruments (that they are orthogonal to unobserved characteristics common to all consumers in a particular market). For each coefcient vector guess, the BLP approach backs out the endogenous component of utility by inverting market shares. More specifically, for every set of parameter coefcients checked in the GMM minimization, BLP iterates to nd the value of utility of unobserved characteristics common to all consumers in each market for each product that implies market shares similar to those observed.

The BLP approach is to re-write utility to separate out market- and individual-specific components:

$$U_{ijm} = \underbrace{\beta_0 X_{1jm} + \xi_{jm}}_{\delta_{jm}} + \underbrace{(\Sigma v_i + \Pi D_i) X_{2jm}}_{\mu_{ijm}} + \epsilon_{ijm}$$

δ_{jm} is the utility associated with a product that's common to all consumers in a market (includes the utility effect of both observable and unobservable characteristics). μ_{ijm} is the individual-specific component of utility that depends on simulated observables.

If I can estimate δ_{jm} then I can back out ξ_{jm} by definition: $\xi_{jm} \equiv \delta_{jm} - \beta_0 X_{1jm}$. I get δ_{jm} by inverting market shares: that is, iterating to find δ_{jm} such that $\hat{s}_{jm}(\delta, \theta) = s_{jm}$. I know that:

$$s_{jm}\left(\delta_{jm}, \mu_{ijm}\right) = \int P(y_{jm}|\delta_{jm}, \mu_{ijm})\, dF(v_i) = \int \left(\frac{e^{\delta_{jm}+\mu_{ijm}}}{\sum_l e^{\delta_{lm}+\mu_{ilm}}} \right) dF(v_i)$$

So I estimate share of product j in market m with:

$$\hat{s}_{jm}\left(\delta_{jm}, \mu_{ijm}\right) = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{e^{\delta_{jm}+\mu_{ijm}}}{\sum_l e^{\delta_{lm}+\mu_{ilm}}} \right)$$

Note that this approximation induces additional estimation error.

This iteration to find δ_{jm} is the key component of BLP. The authors show that the iteration is a contraction mapping (i.e. should converge, eventually):

$$\delta_{jm}^{h+1} \leftarrow \delta_{jm}^{h} + \ln s_{jm} - \ln \hat{s}_{jm}\left(\delta_{jm}^{h}, \mu_{ijm}\right)$$

Once we have ξ_{jm} I can set up the GMM objective function. By assumption, at the true parameter values, the population moments equal zero. I look for coefficients θ that set the sample analog of the moments to zero.

$$E[Z\,\xi] = 0$$

$$\text{GMM objective } = \xi\, Z\, \Phi^{-1}\, Z\, \xi$$

where Z are instruments and Φ^{-1} are weights, metric by which we measure how close to zero we are. By using the inverse of the variance-covariance matrix of the moments for the weights, we give less weight to those moments (equations) that have a higher variance.

The Jacobian of the GMM objective function at $\hat{\theta}$ provides the standard errors of the coefficient estimates. I bootstrap to find standard errors for $\hat{\delta}$.

To estimate elasticities, I first note that each individual has a different probability of purchase (and price sensitivity):

$$s_{ijm}\left(\delta_{jm}, \mu_{ijm}\right) = \frac{e^{\delta_{jm}+\mu_{ijm}}}{\sum_l e^{\delta_{lm}+\mu_{ilm}}}$$

I replace integrals with expectations:

$$\eta_{jkm} = \frac{\partial s_{jm} p_{km}}{\partial p_{km} s_{jm}} = \begin{cases} -\frac{p_{jm}}{s_{jm}} \frac{1}{Ns} \sum_{i=1}^{Ns} \alpha_i \, s_{ijm} \,(1 - s_{ijm}) & \text{if } j = k \\ \frac{p_{km}}{s_{jm}} \frac{1}{Ns} \sum_{i=1}^{Ns} \alpha \, s_{ijm} \, s_{ikm} & \text{otherwise} \end{cases}$$

Recent studies have shown that BLP coefcient estimates can be very sensitive to optimization algorithm used and starting values (see Knittel & Metaxoglou 2008 and Dube, Fox, & Su 2009). As with many other structural models, results are also sensitive to structural assumptions (eg. additively linear utility, Bertrand vs. Cournot competition on the supply side). Also, as with other maximum likelihood and GMM techniques, BLP models are not guaranteed to converge in nite time, which can be pretty frustrating for the researcher.

2.4 Results

To interpret my results, I divide the distribution of the coefficient on CFL by the coefficient on price to find the distribution of WTP for CFLs, controlling for private benefits from energy savings. I interpret this WTP as an amalgam of warm glow associated with being green, altruism for providing a positive externality, and value consumers get from impressing others with their green choices, all net of personal dislike for quality issues associated with CFLs: tone of light, etc.

The results of the logit estimation are presented in Table 2.3 below. Standard errors estimated from the diagonal values on the inverse of the Hessian associated with the likelihood function evaluated at the set of optimal coefficients. The coefficients presented in Table 2.4 represent the contribution of each variable to increasing a consumer's utility. Individual coefficients have limited significance however because utility is ordinal: observed choices cannot simultaneously determine both coefficients and the variance of the unobserved portion of utility. Because only differences in utility matter for choice, each product-specific effect should also be interpreted as an effect relative to a base case alternative - in this case, standard incandescent light bulbs.

The sign of each estimated coefficient, however, is important, and can be shown to be the same sign as the marginal effect of each explanatory variable on the likelihood of purchase.[15] In addition, relative coefficients, that is, coefficient ratios, are cleanly identified. I considering first the signs of the coefficients. As expected, higher prices decrease the likelihood of a given bulb being chosen and being on promotion increases that likelihood. Bulbs with higher associated annual energy costs appear less likely to be chosen, which could be a sign that consumers are indeed taking into account the bulb's potential cost savings, but this effect is not statistically significant. After controlling for price, CFLs are less likely to be chosen

[15]Demonstrated in (Train 2003) by taking total derivative of utility function.

Table 2.3: Berry logit using lightbulb data

	OLS	OLS	2SLS	2SLS
	Market size 1	Market size 2	Market size 1	Market size 2
Price per bulb	-.461	-.459	-.559	-.557
	(.002)***	(.002)***	(.002)***	(.002)***
CFL	-.466	-.481	-.342	-.356
	(.012)***	(.012)***	(.012)***	(.012)***
Watts saved	.021	.021	.026	.026
	(.0002)***	(.0002)***	(.0003)***	(.0002)***
Halogen	.009	-.008	.273	.259
	(.011)	(.011)	(.012)***	(.011)***
Enhanced tone	-.027	-.029	-.0007	-.002
	(.003)***	(.003)***	(.003)	(.003)
Generic	.029	.034	-.030	-.026
	(.003)***	(.003)***	(.003)***	(.003)***
R^2	.357	.369	.357	.369
Wattage FE	yes	yes	yes	yes
Obs.	629702	629702	629262	629262
R^2	.414	.485	.412	.485

Note: Two-stage least squares (2SLS) use out-of-state product-week prices as instruments, with Northern California and Southern California counting as two separate states. CFL, Halogen, Enhanced tone, and Generic are indicator variables. Enhanced tone designates primarily GE "Reveal" type bulbs but also other bulbs specifically labeled "Enhanced". Columns (1) and (3) use maximum store weekly sales plus an increment of 100 bulbs to estimate total market share for each store. Columns (2) and (4) define total market as maximum market share across all stores.

than incandescent bulbs. This coefficient on the CFL constant represents the average effect of unincluded factors on the utility associated with CFLs, above and beyond the average effect of unincluded factors on the utility associated with standard incandescent bulbs.

Table 2.4: Market share maximum likelihood with control function

Price bulb	-0.874	-0.922
	(0.0105)***	(0.0109)***
Control function		0.642
		(0.0308)***
CFL	0.383	0.437
	(0.1092)***	(0.1095)***
Watts saved	0.022	0.024
	(0.002)***	(0.002)***
Halogen	-0.656	-0.485
	(0.1201)***	(0.121)***
Enhanced tone	-0.090	-0.066
	(0.0194)***	(0.0194)***
Generic	-0.112	-0.140
	(0.0161)***	(0.0161)***
Wattage FE	yes	yes
Product alternatives	86	86
Markets	40,134	40,134
Parameter tolerance	0.000001	0.000001
Convergence criterion	0.000001	0.000001
Value log likelihood function at convergence	-77248.1439	-77027.716

Relative coefficients represent how consumers tradeoff factors that give them utility. For example, the ratio between the coefficients on promotion and price in the control function estimation is about one third, implying that consumers are willing to pay 0.33 cents less for a bulb that is on promotion. Although the coefficient on energy cost is not statistically significant, the ratio using that point estimate would have suggested that consumers were willing to pay an additional 6 cents for a bulb in order to avoid one dollar in annual energy cost. If bulbs last 7 years, $0.06 = \frac{1}{r}\left(1 - \frac{1}{(1+r)^7}\right)$, which would imply a discount rate of 160%. Consumers may be unaware of electricity prices or responding to other factors that are also correlated with average residential electricity rates.

Comparing the standard logit and the control function approach, I observe that, as expected, controlling for endogenous prices increases the relative negative effect of price on sales. The elasticity of P_{jm} with respect to x_{jm} is:

$$\epsilon_{j,x_{jm}} = \frac{\partial P_{jm}}{\partial x_{jm}} \frac{x_{jm}}{P_{jm}} = \frac{\partial U_{jm}}{\partial x_{jm}} P_{jm}(1 - P_{jm}) \frac{x_{jm}}{P_{jm}} = \beta_x (1 - P_{jm}) x_{jm}$$

where P_{jm} is the estimated market share, or probability of choosing product j, and x_{jm} is the price of the product in market m. So the own-price elasticities for CFLs at average prices is estimated at $-0.325 \times (0.9879) \times 4.317 = -1.39$ in the standard model and at $-1.034 \times (0.9879) \times 4.317 = -4.41$ after controlling for price endogeneity.

As can be expected, the reliability of the control function approach depends on the function being correctly specified. If retail stores are exercising market power, that is, if markups are a function of a product's elasticity, then the control function approach would not fully capture the endogeneity.

The other concern, particularly for the elasticity estimates, is that the logit model assumes IIA and by definition produces price sensitivity estimates that are fixed proportions of each products market share. The following model moves towards relaxing this assumption, and takes advantage of additional variation in attributes and observed sales within types of incandescent bulbs.

2.5 Discrete time discrete state dynamic programming model

Now consider a household with preferences for product characteristics as described in the previous section. Express the household's utility as a function of state variables, $U_i(S_t)$. Households benefit from market-specific cost savings α associated with lower operating costs. CFL prices are stochastic (price with and without sale), with a known decreasing trend. Consumers want to take advantage of sales, but anticipate future price decreases, so there is a trade-off between purchasing early and taking advantage of sales.

Each week households observe current prices, need for replacement, and decide how many CFLs to purchase and replace. Any socket not filled with a CFL is filled with an incandescent bulb, purchased when needed at current (constant) prices.

$$\max_{x_{1t}} \sum_{t=0}^{\infty} \delta^t E \left[U(S_t) + \alpha S_t - C(I_t) - p_0 \left(\frac{S_t}{\tau_1} + \frac{\overline{S} - S_t}{\tau_0} - r_t \right) - p_{1t} x_{1t} \mid S_{t-1}, I_{t-1}, p_{1t} \right]$$

$$\text{subject to } S_t = S_{t-1} + r_t - \frac{S_t}{\tau_1} \qquad I_t = I_{t-1} + x_{1t} - r_t \qquad r_t = \min \left\{ \frac{S_t}{\tau_1} + \frac{\overline{S} - S_t}{\tau_0}, I_t \right\}$$

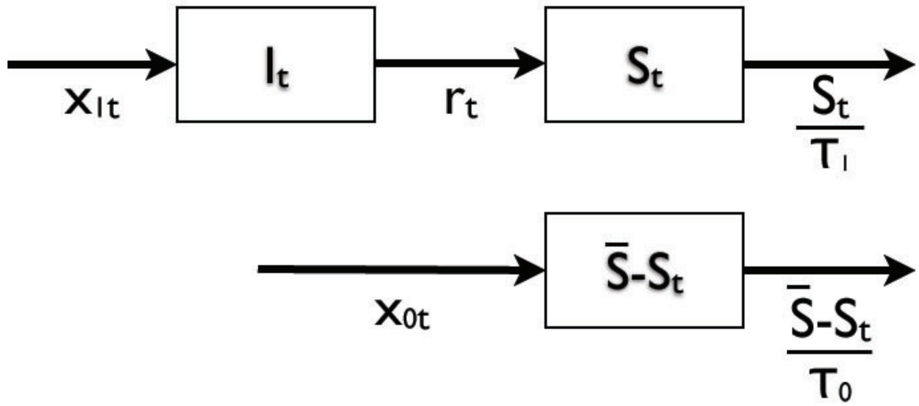


Figure 2.6: Stock and flow diagram of household CFL purchases and stockpiling

$$I_t, S_t, x_{jt}, r_t \geq 0$$

Where I_t, S_t are state variables: household inventories of CFLs and number of sockets in a household filled with CFLs, x_{1t} is the control variable: CFL purchases, price p_{1t} is a discrete random variable, τ_j is the average lifetime of each bulb type, and $C(I_t)$ is a strictly increasing cost of holding inventory.

I solve the above model by setting up the Bellman equation:

$$V(I,S,p) = \max_x \left\{ f(I,S,p,x,r) + \delta E_p V\left(I + x - r, S + r - \frac{S}{\tau_1}\right)\right\}$$

where

$$f(I,S,p,x) = U(S) + \alpha S - C(I) - p_0\left(\frac{S}{\tau_1} + \frac{\overline{S} - S}{\tau_0} - r\right) - px$$

subject to the constraints

$$I,S,x,r \geq 0 \qquad x + I \geq r \geq \frac{S}{\tau_1} - S \qquad r = \min\left\{\frac{S}{\tau_1} + \frac{\overline{S} - S}{\tau_0}, I\right\}$$

Value function and CFL purchases plotted as a function of stocks of CFLs (inventories and installed in sockets):

The collocation method gives me optimal $x_0(S,I,p), x_1(S,I,p)$ as a function of $U(S)$ and $C(I)$. I assume $C(I)$ and initial values for I_0 and S_0: then I have optimal $x_0(t), x_1(t)$ as a function of $U(S)$ and observed prices. I can then use household-level scanner data to fit parameters of $U(S)$. Finally, I can run out-of-sample simulations: impact of changing subsidies, banning incandescent bulbs, to what extent 2nd generation promotion creates

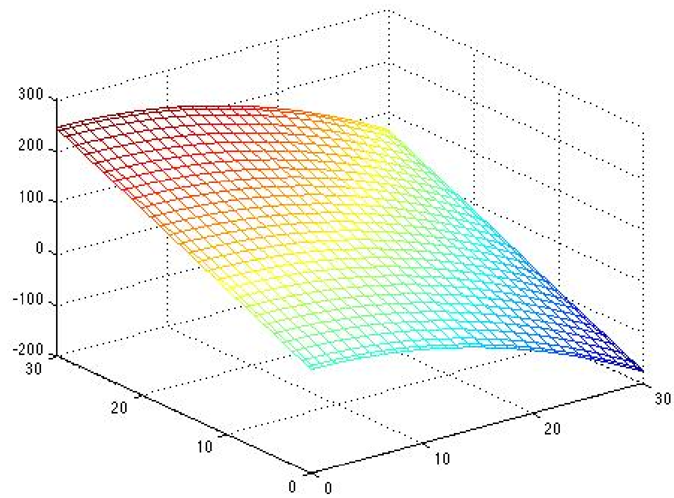


Figure 2.7: Value function as a function of stocks of CFLs

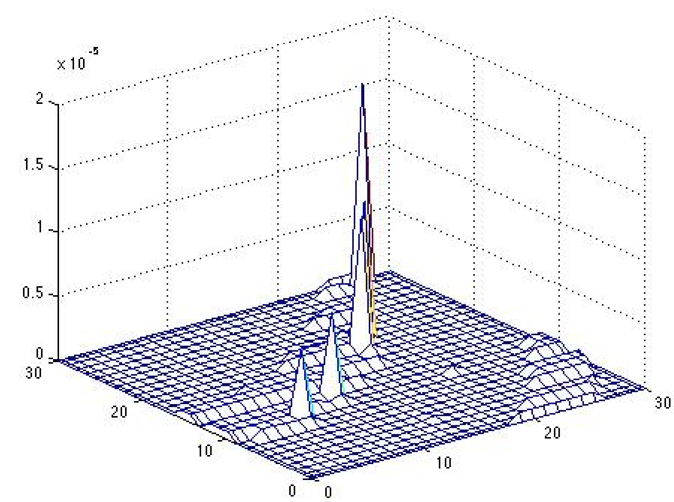


Figure 2.8: CFL purchases as a function of stocks of CFLs

potential lock-in.

Chapter 3

Rushing environmentally-friendly technologies to market

High efficiency motors, T-8 lamps and electronic ballasts, compact florescent light bulbs, passive solar homes, and solar water heaters are all examples of energy efficient technologies that had reliability and other problems at introduction. After bad initial experiences, there is anecdotal evidence of early adopters resisting later adoption.[1] In an exploratory survey that I conducted this fall, consumer dislike and refusal to adopt CFLs was highly correlated with the year in which respondents first installed CFLs in their home. Early consumer adoption of experience goods with quality levels that improve over time but may be initially inadequate can lead to a net loss in environmental benefits due to drop-out and limited subsequent adoption. The problem is particularly acute if later adopters form quality expectations based on the unfortunate experience of early adopters.

This chapter combines an experience good quality model and a technology adoption model to study the net welfare impact of early adoption of technologies with environmental benefits. The proposed theoretical model is similar to the Akerlof's "Market for Lemons" model, except that instead of consumer quality expectations based on a distribution of sellers, quality expectations are formed over time based on the experiences of early adopters.

3.1 Theoretical model

An energy efficient appliance is supplied in a competitive market at an incremental price P above the price of the non-energy-efficient alternative. The incremental price P is effectively the cost of the energy efficiency embodied in the appliance. The marginal cost of energy efficiency c is constant per unit supplied and decreases exogenously over time at a

[1] Peters 2007 Lessons Learned After 30 Years of Process Evaluation, white paper for the Nov 7 Behavior, Energy and Climate Change Conference.

constant rate α. This assumption is consistent with a market in which there is significant public sector support for reseearch and development. Because the market is competitive, $P(t) = MC = c(t)$.

The energy efficient appliance yields social benefits β per adopter per period of time. Willingness to pay (WTP) for embodied energy efficiency is distributed Uniform $(0, a)$ across a population of size n. This WTP includes among other things the altruism associated with environmental preferences and discounted expected future energy cost savings.

The appliance has a level of quality $s(t)$. In the case of compact fluorescent energy efficient light bulbs (CFLs), quality includes features like the color of the light (CFLs use a different spectrum), the frequency at which bulbs die before their expected life, and the whether the bulbs fit into regular fixtures. Quality $s(t)$ increases exogenously over time at a constant rate γ.[2]

Consumer preferences for quality are modeled as a discrete threshold. In other words, consumers are not willing to substitute quality for lower prices. This assumption clearly holds for small purchases like CFLs where even charging a negative incremental price, up to the cost of a traditional light bulb (i.e. making CFLs free), is unlikely to sufficiently compensate consumers who dislike the color of the light emitted. The assumption also holds for durable experience goods: because consumers do not know quality levels at the time of purchase, they are unable to make a real quality-price tradeoff. I consider two cases: first a single threshold M common to the entire population, and second a threshold distributed Uniform (b, d) across consumers, independent of the distribution of WTP for energy efficiency.[3]

The model relies on asymmetric information. The quality of the energy efficient appliance is an experience good. Consumers know their threshold for quality, but do not know the quality of the appliance until after their purchase. Early adopters initially assume that quality of energy-efficient appliances will be equal to the quality level of the non-energy-efficient alternative s_A. Also, the government knows the initial level of quality, but is uncertain about how that level compares to consumer thresholds. No one knows ex-ante how fast costs decreases (α) or quality increases (γ) so there is little strategic benefit to delaying purchases.

[2] Endogenous decreases in marginal cost and endogenous increases in quality would accentuate the negative impact of initial low quality on ability of subsequent increases in quality to lead to adoption.

[3] There's no reason why environmentalists would have more or less dislike for, for example, a tone of light, all other things equal.

3.1.1 Adoption when quality is not an issue

Maximum welfare benefits are achieved when quality is always adequate, that is, when the initial quality of the energy-efficient product s_0 is above the consumer threshold for quality M. When the energy-efficient appliance is first released, $p_0 = c_0$ and, if $a > c_0$, the population q_0 adopts the appliance. Because WTP is uniformly distributed across n consumers, $q(p) = n - \frac{n}{a}p$. Figure 3.1 shows WTP for embodied energy efficiency and, shaded in blue, the consumer surplus associated with the release and adoption of an energy efficient appliance with initial unit cost c_0. As time progresses, $c(t) = c_0 - \alpha t = p(t)$ and an increasing number of consumers adopt:

$$q(t) = n - \frac{n}{a}p(t) = n - \frac{n}{a}(c_0 - \alpha t) = n\left(1 - \frac{c_0}{a}\right) + \alpha\frac{n}{a}t$$

The WTP of the marginal adopter follows over time the line highlighted in red in Figure 3.1. The subsequent adoption does not generate any additional consumer surplus, but provides environmental benefits $\beta\, q(t)$ in each period.[4]

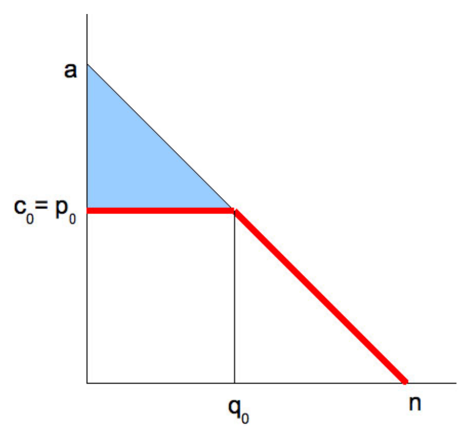


Figure 3.1: WTP for embodied energy efficiency: initial adoption is q_0

$$\begin{aligned}\text{Total welfare } &= \frac{1}{2}(a - c_0)\, q_0 + \int_0^T \beta\, q(t)\, dt \\ &= \frac{1}{2}(a - c_0)\, n\left(1 - \frac{c_0}{a}\right) + \int_0^T \beta\left[n\left(1 - \frac{c_0}{a}\right) + \alpha\frac{n}{a}t\right] dt \\ &= \frac{1}{2}(a - c_0)\, n\left(1 - \frac{c_0}{a}\right) + \beta n\left(1 - \frac{c_0}{a}\right)T + \beta\alpha\frac{n}{2a}T^2\end{aligned}$$

[4]Discounting future environmental benefits does not add significantly to the conclusions, other than to further penalize delayed adoption

As can be seen in the equation for total welfare, adoption incentive programs clearly have a positive impact. Lowering c_0 increases consumer surplus and accumulated environmental benefits and increasing α increases accumulated environmental benefits.

3.1.2 Adoption when quality matters

Now consider cases for which quality $s(t) = s_0 + \gamma t$ is for some time below acceptable thresholds for some consumers. In the case of a common threshold, this implies that $s_0 < M$. In the case of a threshold distribution Uniform (b, d), $s_0 < d$.

3.1.2.1 Case: Perfect information

If consumers had perfect information about quality, or if they could purchase an appliance, experience, and return it costlessly, *without holding a grudge against the product*, then they would wait or effectively wait until quality reached their threshold to adopt. In the case of a common threshold, quality reaches the threshold at: $M = s_0 + \gamma t_M$ so $t_M = \frac{M - s_0}{\gamma}$. At that point,

$$q(t_M) = n\left(1 - \frac{c_0}{a}\right) + \alpha\frac{n}{a}\left(\frac{M - s_0}{\beta}\right)$$

The net welfare effect of lower initial quality is ambiguous. Earlier adopters receive higher consumer surplus because costs are lower $c(t_M) = c_0 - \alpha t_M = c_0 - \alpha\frac{M - s_0}{\gamma}$, but environmental gains from the new energy-efficient appliance are delayed. Figure 3.2 shows the impact on consumer surplus.

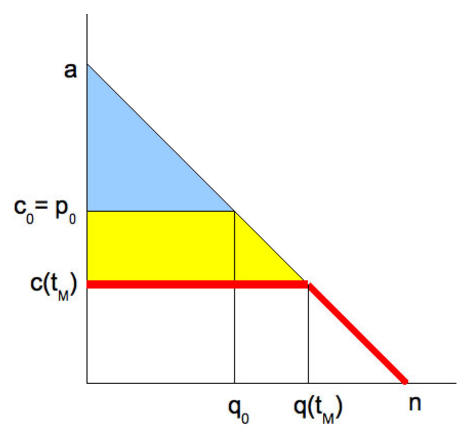


Figure 3.2: WTP for embodied energy efficiency: low quality and constant threshold increases consumer surplus but delays adoption and associated environmental benefits

$$\text{Total welfare} = \frac{1}{2}\left[a - c(t_M)\right] q(t_M) + \int_{t_M}^{T} \beta\, q(t)\, dt$$

The net loss in welfare relative to the high quality case is:

$$\int_{0}^{t_M} \beta\, q(t)\, dt + \frac{1}{2}\left[a - c(t_M)\right] q(t_M) - \frac{1}{2}(a - c_0)\, q_0$$

The expression for adoption is more complicated if the threshold is instead distributed Uniform (b, d) across consumers.

$$q'(t) = \phi(t)\left[n\left(1 - \frac{c_0}{a}\right) + \alpha \frac{n}{a} t\right] \text{ where } \phi(t) = \begin{cases} 0 & s(t) < b \\ \frac{s(t)-b}{d-b} & b < s(t) < d \\ 1 & s(t) > d \end{cases}$$

In the cases described above, consumers can obtain perfect information about quality or can purchase an appliance, test it, and return it costlessly without forming expectations about future quality. In each case there is no cost to society to early adoption. Regardless of how many consumers adopt early, environmental benefits begin to accrue to the entire consumer base with a high enough WTP once quality has reached to threshold levels.

3.1.2.2 Case: Early adopters who discover quality below their threshold never adopt again

Say that early adopters who discover quality below their threshold never adopt again. If the threshold is common across the population, then the population of early adopters who will refuse re-entry is:

$$q(t_M) = n\left(1 - \frac{c_0}{a}\right) + \alpha \frac{n}{a}\left(\frac{M - s_0}{\gamma}\right)$$

Total welfare is calculated:

$$\text{Total welfare} = \int_{t_M}^{T} \beta\ \left[q(t) - q(t_M)\right]\ dt$$

Relative to the previous case where early experiences do not undermine subsequent willingness to adopt, total welfare is lower by:

$$\frac{1}{2}\left[a - c(t_M)\right] q(t_M) + q(t_M)(T - t_M)$$

where $t_M = \frac{M - s_0}{\gamma}$ as defined above.

3.1.2.3 Case: Early adopters may adopt again if perceived quality exceeds their threshold for quality

Now consider the case in which early adopters may adopt again if perceived quality exceeds their threshold for quality. Initial adopters assume that quality is equal to the quality of the non-energy efficient alternative s_A. All subsequent adopters incrementally adjust quality expectations based on the experience of earlier adopters.

Formally, every individual i in the population n is indexed by their WTP for embodied energy efficiency w_i and a quality threshold m_i. Expected quality $\hat{s}(t)$ is updated to match average actual quality experienced by those who tried the product $\bar{s}(t)$:

$$\hat{s}(t=0) = s_A \text{ and } \frac{d\hat{s}(t)}{dt} = \frac{\bar{s}(t) - \hat{s}(t)}{\tau}$$

$$\bar{s}(t) = \frac{\int_0^t \sum_i \left(s(t) I_{E(t)} \right) \, dt}{\int_0^t \sum_i I_{E(t)} \, dt}$$

where τ is the average time to update expectations, I represents the indicator function and $E(t)$ is the set of those who have experienced the product, that is, for whom:

- $w_i \geq c(t)$: cost does not exceed willingness to pay, and
- $m_i \geq \hat{s}(t-1)$: expected quality is not below quality threshold

The MATLAB code associated with numerical simulations of the model is presented in the appendix. Figures 3.3 and 3.4 present the simulation output.

Figure 3.3 shows that expected quality levels can drop and lag below actual quality levels. If consumers form expectations based on low initial quality levels and limit future adoption, then even when actual quality improve dramatically, expected quality levels adjust slowly because few consumers experience the higher quality levels.

Figure 3.4 shows how environmental benefits may suffer when low levels of expected quality hinder adoption. Note that in Figure 3.4 actual quality trajectories are identical in both simulations. The longer the time to adjust expectations (the less consumers react to the experience of earlier adopters), the less incomplete information has a negative environmental impact. The net impact of quality perceptions on environmental benefits depends on the relative rates of quality increases, cost decreases, and the time to form quality expectations. If costs are initially quite high, then there will be low adoption at the initial low quality levels, and later adoption may have less of a reputation effect.

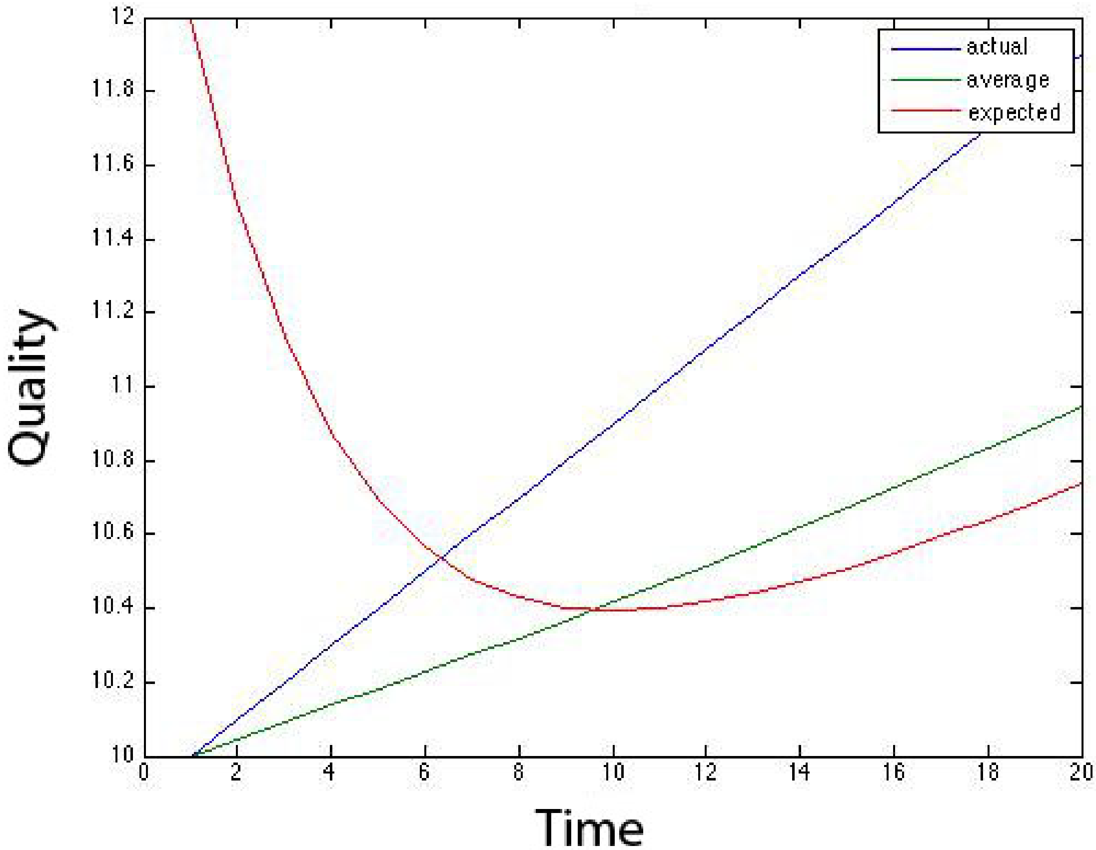


Figure 3.3: Expected quality levels can drop and lag below actual quality levels: quality levels are actual (blue, increasing at a constant rate), average (green, increasing at a constant rate but below actual), and expected (red, starting high but dropping, eventually growing slower than average)

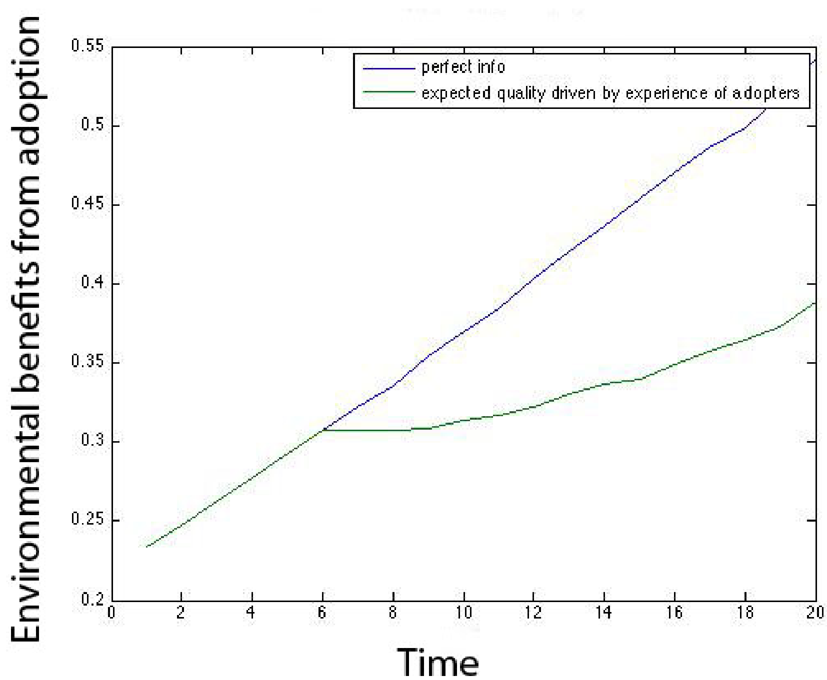


Figure 3.4: Environmental benefits suffer when low levels of expected quality hinder adoption. Blue (benefits increasing at a constant rate) represents benefits obtained under perfect information. Green (benefits growing at a slower rate after period 6) represents a simulation where expected quality is driven by the experience of adopters. Actual quality trajectories are identical in both simulations.

3.2 Policy implications

By definition of environmental externality, social planner's optimal timing of product introduction to market for goods that provide environmental benets will differ from that of the firm. Although a basic model would argue for early introduction, if private benets improve slower than purely social benets, or if early-adopters have overly optimistic expectations about product quality, early introduction can prove to be signicantly more costly from a social point of view. If rms only take into account the costs and risks faced by their own rm, then there might be a role for a social planner to intervene to discourage early introduction of products that will delay or block subsequent adoption.

Early consumer adoption of experience goods with quality levels that improve over time but may be initially inadequate can lead to a net loss in environmental benefits due to drop-out and limited subsequent adoption. The problem is particularly acute if later adopters form quality expectations based on the unfortunate experience of early adopters.

This effect is a problem even without policies to promote adoption. Because of the environmental benefit associated with consumer adoption, there is a role for the public sector to support firms. Using tax incentives or other consumer subsidies that lower initial purchases costs aggravates the problems associated with premature adoption. The obvious, but expensive, solution would be for the public sector to help firms engage in detailed market research pre-launch. Alternately, the public sector could in lieu of consumer adoption subsidies support research and development, thereby helping to lower production costs or improve quality. The government could also encourage the promotion of in-house demonstrations, where appropriate, and "no questions asked" returns policies. Firms could distinguish future generations of technology as entirely separate goods. Finally, for some products consumers may have different thresholds for different uses. For example CFL use on porches, garages, basements are potentially held to a lower standard of light quality. In that case technology promotion should be targeted initially at encouraging uses associated with low quality thresholds.

Chapter 4

Energy efficiency gains from trade

Recent trade theory describes how trade liberalization increases competition and favors the growth of high-productivity firms. In this chapter I argue that because total factor productivity and efficient energy use frequently go hand-in-hand, within-industry reallocation of market share favors energy-efficient firms and can have significant benefits of avoided fuel use and greenhouse gas emissions. Using 19 years of firm-level data from India's Annual Survey of Industries, I document that over a period of 13 years within-industry reallocation of market share produced a larger savings in greenhouse gases than is expected from all of India's Clean Development Mechanism energy efficiency and renewable energy projects combined. Using industry-level variation in policy reforms, I estimate the relative contributions of tariffs on final goods, tariffs on intermediate goods, FDI reform, and delicensing on increasing energy efficiency within firms and on reducing market share of energy-inefficient firms. I observe that reductions in tariffs on intermediate inputs led to a 23% improvement in fuel efficiency, with the entire effect coming from within-firm improvements. Delicensing and FDI reform, not tariffs on final goods, drove the reallocation effect, with post-liberalization changes in licensing requirements improving fuel efficiency an additional 7%. All else equal, decreases in tariffs on intermediate inputs led to reallocation of market share to firms that used inputs less efficiently.

4.1 Liberalization and pollution

Recent trade models that take into account firm heterogeneity ((Melitz 2003) and (Bernard *et al.* 2003)) propose that trade liberalization increases aggregate productivity in part because liberalization-induced reallocation of market share favors firms that use inputs efficiently. To the extent that reallocation favors firms that consume *fuel* inputs more efficiently, we should expect that trade-induced reallocation of market share also yields environmental benefits in terms of avoided greenhouse gas emissions. In this paper, I document trends in greenhouse gas emissions and fuel use in India, estimate the environmental gains associated with across-firm reallocation of market share, and analyze how much of these gains can be attributed to India's trade policy reforms. I pick India for a case study for two reasons: first of all, it is a fast-growing economy whose greenhouse gas emissions are expected to grow 4-7 fold in the next 20 years.[1] Second, India experienced a dramatic trade liberalization in the 1990s. I use the arguably exogenous variation in intensity of reforms across industries and years to infer causal effect of liberalization on pollution intensity.

The impact of trade liberalization on the environment can be broken down into three effects: scale, composition, and technique[2]. *Scale* represents the expansion of economic activity. *Composition* captures the reallocation of market share across industries. *Technique* represents all of the effects that change average industry pollution intensity. The technique effect is typically described in terms of technology adoption,[3] but by definition it aggregates within-firm changes due to the use of different technologies, changes in process efficiency, and changes in fuel mix, as well as across-firm effects of market share reallocation.

To date, theoretical papers concerned with the environmental impact of trade have focused on the composition effect.[4] Low trade costs could cause polluting industries to move from advanced economies into countries with lax environmental regulation and older and less-efficient capital stock, like China and India.[5] There is furthermore a concern that some countries may proactively loosen existing regulations in order to attract scarce foreign capital, becoming "pollution havens" and creating an environmental "race to the bottom." Large industrializing countries such as India are considered to be potential candidates for attracting pollution-intensive industries.

I find no evidence, however, of Indian manufacturing shifting towards pollution-intensive sectors after 1991, despite the country experiencing one of the most dramatic increases in trade liberalization in recent history.[6] In Section 4.3 I decompose trends in fuel combustion in India to estimate the relative size of the scale, composition, and technique effects of trends in greenhouse gas emissions from fuel use in India's manufacturing sector. I show that scale is the driver for most of the growth in fuel combustion. Indian manufacturing has grown at close to 5% per year over the period between 1985 and 2005. I estimate that the expansion of economic activity increased greenhouse gas emissions 270% over that 20-year period. The composition effect, however, decreased greenhouse gas emissions in manufacturing by 37%

[1] IEA 2011 estimates 4-fold, TERI 2011 estimates 7-fold.

[2] (Grossman and Krueger 1991) and (Copeland and Taylor 2003)

[3] (Levinson 2009)

[4] (Karp 2011) provides an excellent review of the theoretical work.

[5] See NY Times Dec 21, 2007 "China Grabs West's Smoke-Spewing Factories" followed by "As Industry Moves East, China Becomes the World's Smokestack." The concern is not necessarily that individual firms will relocate, but that firms in pollution-intensive domestic industries will contract output while firms abroad expand output and increase exports, effectively allowing wealthy countries to outsource pollution-intensive activities.

[6] This result is consistent with (Levinson 2010) that finds that the composition of US imports has become cleaner, not dirtier, as tariffs on imports have dropped.

relative to a counterfactual in which industry shares in output had remained unchanged.[7]

In contrast to the experience of many countries that face more reliable power supply and low levels of generator use,[8] I also find that although within-industry trends decreased emissions slightly in the years following India's trade liberalization, the technique effect was responsible for a 25% *increase* in emissions in subsequent years. [9]

New theoretical models in the trade and productivity literature have provided a framework for understanding the mechanisms by which the technique effect operates.[10] In these models, opening up to trade creates competitive pressure to improve the allocation of existing resources across heterogeneous firms within each industry. High productivity firms expand output and export while low productivity firms drop out of the market, increasing aggregate productivity. One version of this model, (Bustos 2011), explicitly incorporates technology adoption. In her model of heterogeneous firms, even absent changes in capital costs trade-liberalization increases the number of firms that stand to benefit from upgrading technology, leading to within-firm driven improvements in aggregate productivity.

The predictions of the recent trade models have clear implications for environmental outcomes, especially with regards to greenhouse gases. Fuel combustion is a major source of greenhouse gas emissions. Policies that give firms incentives to use fuel inputs efficiently and policies that reinforce market mechanisms that shift market share away from input-inefficient firms both reduce greenhouse gas emissions.[11]

In the second section of this paper I develop and apply a unique decomposition methodology that explores the drivers of the technique effect. I first use this methodology to estimate the environmental impact of within-industry reallocation of market share. I show that post-liberalization increases in average firm fuel intensity were counterbalanced in large part by reallocation of market share to more fuel-efficient firms. I use this decomposition to create counterfactuals: how emissions would have grown had it not been for increased reallocation in the domestic market after liberalization. By comparing the actual trends to the counterfactuals, I estimate the avoided fuel use and avoided greenhouse gas emissions associated with reallocation. Specifically, I posit that had it not been for within-industry reallocation

[7]These avoided emissions are from manufacturing alone. The relative growth of services in GDP has further acted to improve the economy-wide ratio of greenhouse gas emissions to output.

[8](Ang and Zhang 2000)

[9]Until now data availability has limited the ability of most studies to accurately measure the technique impact of pollution on the environment. (Levinson 2009) and all of the studies in the comprehensive survey of the literature by (Ang and Zhang 2000) use industry-level data and estimate technique as a residual. As recognized by the above authors, this approach attributes to technique any interactions between the scale and composition effects and any potential mismeasurement associated with broad industry classifications. When using decompositions that rely on partial differentiation, the technique effect also contains any differences between the infinitesimal changes used in theory and the discrete time steps used in practice. With firm-level data, I am able to reduce these sources of bias.

[10](Melitz 2003) and (Bernard *et al.* 2003)

[11]Fuel switching is the other source of emissions reductions. Fuel switching can also play a key role in reducing greenhouse gas emissions, but is not a focus of this paper due to data limitations.

of market share after liberalization, within-industry emissions would have been 16% higher.

I then investigate to what extent India's emissions trends were driven by the trade reforms. Following an econometric approach similar to that used by three recent papers which document the impact of trade reforms on productivity of Indian firms,[12] I use variation in the intensity of trade reforms across industries and years to identify the impact of different trade and industrial reform policies.

The empirical literature on the environmental impact of trade liberalization has focused primarily on cross-country and cross-city comparisons that attempt to control for endogeneity between income levels, trade flows, and pollution outcomes.[13] In contrast, this paper takes the experience of one country, India, and uses both a growth accounting approach and then an econometric analysis to identify effects at the firm level, using industry-level variation in the timing and intensity of trade reforms to attribute changes to trade policies. Using three metrics of trade liberalization and controlling for simultaneous dismantling of a system of industrial licenses, I observe that reductions in tariffs on intermediate inputs led to a 23% improvement in fuel efficiency, with the entire effect coming from within-firm improvements. Delicensing and FDI reform, not decreases in tariffs on final goods, drove the reallocation effect, with post-liberalization changes in licensing requirements improving fuel efficiency by an additional 7%.

Looking at heterogeneous impacts across firms, the data shows a stronger role of trade policies. FDI reform led to improvements in the fuel efficiency of older firms (5% improvement for firms founded before 1967). FDI reform also led to increases in market share of fuel-efficient firms and decreases in market share of fuel-inefficient firms—on the order of 7% lost each year for fuel-inefficient firms and 11% gained each year by fuel-efficient firms. This effect is compounded by investment: of all the firms that made large investments after liberalization, the most market share reallocation was experienced by the most energy-efficient firms, and of all the firms that didn't invest, the strongest losses in market share

[12](Topalova and Khandelwal 2011) use the Prowess dataset, a panel of approximately 4000 of the largest firms in India, and find a positive effect of trade liberalization on productivity, particularly in industries that are import-competing and not subject to excessive domestic regulation. (Sivadasan 2009) uses the ASI dataset, as I do, which is a repeated cross-section of more than 30,000 firms per year to study the impact on productivity of both liberalization of FDI and reduction in tariff rates. He finds improvements in both levels and growth rates of liberalized sectors, the later primarily driven by within-plant productivity growth. (Harrison *et al.* 2011) construct a panel of ASI firms and document a similar result: that reallocation increased productivity after liberalization, but that trade reforms were not the main drivers of the productivity reallocation.

[13](Grossman and Krueger 1991) regress city-level SO_2, particulate matter, and dark matter concentrations on trade indicators to estimate the size of the technique effect. (Copeland and Taylor 2004) similarly use cross-country variation to identify the scale effects and within-country across-city variation to identify the technique effects. They find that a 1% increase in scale raises SO_2 concentrations by 0.25-0.5% but the associated increase in income lowers concentrations by 1.25-1.5%. (Shafik and Bandyopadhyay 1992) and (Suri and Chapman 1998) also take a cross-country regression approach to estimate similar effects. (Frankel and Rose 2005) find that trade reduces SO_2 concentrations when controlling for income per capita.

were experienced by the least energy-efficient firms.

Investigating the environmental effect of reducing tariffs on intermediate inputs is particularly interesting because the theoretical prediction is ambiguous. On one hand, if environmentally-friendly technologies are embedded in imported inputs, then increasing access to high-quality inputs can improve fuel intensity within-firm and reduce pollution. Even if imports involve used goods, they may displace even older, less-efficient alternatives. On the other hand, decreasing the price of intermediate inputs disproportionately lowers the variable costs of firms that use intermediate inputs less efficiently. If all else equal inputs are cheaper, there will be less post-liberalization competitive pressures faced by those firms, thereby diminishing the potential beneficial effect of reallocation of market share to favor cleaner firms. I find that, in India, input-inefficient firms gained market share in industries that experienced the largest decreases in tariffs on intermediate inputs.

The paper is organized as follows. Section 4.2 provides a theoretical argument for why trade liberalization would reallocate market share to favor energy-efficient firms. Section 4.3 describes a methodology for decomposing energy trends that isolates within-firm and reallocation effects within industry. Section 4.4 describes data on Indian manufacturing and policy reforms, and Section 4.5 applies the decomposition methodology to the data. Section 4.6 uses industry-level variation in the timing and intensity of trade policies to argue for a causal connection between trade reforms, within-firm fuel intensity, and market share reallocation.

4.2 Why trade liberalization would favor energy-efficient firms

This section explains why trade liberalization is likely to reallocate market share to energy-efficient firms. I first document the empirical evidence of a strong correlation between high productivity (overall input use efficiency) and fuel efficiency. I then describe two theoretical models that demonstrate how trade liberalization can lead to both reallocation of market share to firms that use inputs most efficiently and to inducing more productive firms to adopt new technologies. Finally, I discuss the environmental implications of policies that favor firms that use fuel inputs most efficiently, and describe the hypotheses that I will test in Section 4.6.

In India fuel costs represent on average only 5-10% of expenditures on materials and labor. But even in industries where fuel costs make up a small fraction of variable costs, firm-level data for India shows a high correlation between low variable cost and efficient energy use. Firms with low total factor productivity (TFP) are almost 3 times as likely to have high fuel intensity than low fuel intensity, where TFP and fuel intensity rankings are both calculated within industry-year.[14] Similarly, and firms with high TFP are almost 3 times as likely to have low fuel intensity than high fuel intensity. Table 4.1 shows that an increase in TFP from the 25th to 75th percentile range is associated with a 20% decrease in fuel intensity of output.[15]

A few theories can explain the high correlation. Management quality, for example, is likely to increase the efficiency of input use across the board, in energy inputs as well as non-energy inputs. Technology can also explain the correlation: newer vintages typically use all inputs, including energy inputs, more efficiently. The energy savings embodied in new vintages can be due to local demand for energy savings, or due to increasing international demand for energy savings based on stricter regulation abroad and subsequent technology transfer.[16]

Recent trade theory models demonstrate how reducing trade costs can lead to reallocation of market share to firms with high input use efficiency. (Melitz 2003) presents a model of monopolistic competition in which many competing producers sell differentiated products and consumers value variety. Firms face identical and fixed production costs, costs to enter, and costs to export. After entry each firm observes a stochastic productivity draw φ and decides whether to produce or exit the industry. As shown in the equation for total cost, in this model a high productivity draw is equivalent to low variable cost.

$$TC(q, \varphi) = f + \frac{q}{\varphi}$$

Each firm faces downward sloping residual demand and sets prices equal to marginal revenue

[14] Author's own calculations. The exceptions appear to be primarily driven by generator use (for example, in explaining why young, high productivity firms are still energy-intensive. I calculate total factor productivity within industry using the Aw, Chen & Roberts 2003 index method. The TFP index for firm i in year t with expenditure on input X_{imt} expressed as a share of total revenue S_{imt} is:

$$\begin{aligned}\ln \mathrm{TFP}_{it} = \quad & \ln Y_{it} - \overline{\ln Y_t} + \textstyle\sum_{s=2}^{t} \left(\overline{\ln Y_s} - \overline{\ln Y_{s-1}}\right) - \textstyle\sum_{m=1}^{M} \frac{1}{2}\left(S_{mit} + \overline{S_{mt}}\right)\left(\ln X_{mit} - \overline{\ln X_{mt}}\right) \\ & - \textstyle\sum_{s=2}^{t} \sum_{m=1}^{M} \frac{1}{2}\left(\overline{S_{ms}} + \overline{S_{ms-1}}\right)\left(\overline{\ln X_{ms}} - \overline{\ln X_{ms-1}}\right)\end{aligned}$$

[15] Industries that pre-reform contain a relatively large fraction of firms that are high TFP but also high fuel intensity are, in decreasing order: starch, ferroalloys, cotton spinning weaving, chocolate, plaster, clay, sugar (indigenous), cement, nonmetal minerals other, and explosives. Industries that contain a relatively large fraction of firms that are low TFP but also low fuel intensity are for the most part skilled labor-intensive: musical instruments, engraving, made-up textiles, ferroalloys, ceramics, cameras, spirits, glass, chocolate, and specialty paper. In both cases, 'large fraction' means 9-11% of firms in the industry are in these categories. Across the population, 6% of firms are in each of these categories.

[16] Consider two examples. In cement, switching from wet kiln process to dry kiln process halves non-energy materials costs, halves heat consumption, and reduces electricity use by 10%. ((Mongia *et al.* 2001)) In machine parts and tools, shifting from traditional lathes to Computer Numerical Controlled (CNC) lathes increases throughput, guarantees uniform quality standards, and additionally requires less electricity per unit produced.

Table 4.1: Correlation coefficients between Total Factor Productivity (TFP) and log fuel intensity of output 1985-2004

Dependent variable: log fuel intensity of output	
TFP × 1985	-.484 (.006)***
TFP × 1992	-.529 (.007)***
TFP × 1998	-.492 (.009)***
TFP × 2004	-.524 (.008)***
Industry-region FE	yes
Obs.	570520
R^2	.502

Note: All years interacted, selected years shown. TFP calculated via Aw, Chen & Roberts index decomposition. Fuel intensity is factor cost share at 1985 prices. Median TFP is .09; the 25 to 75 percentile range is -.12 to .30. An increase in TFP from the 25th to 75th percentile range is associated with a 20% decrease in fuel intensity of output. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

(isoelastic demand implies a fixed markup over marginal cost). Firms enter as long as they can expect to receive positive profits. All firms except for the cutoff firm receive positive profits.

In the Melitz model trade costs are represented as a fraction of output lost, representing ad valorem tariffs on final goods or value-based shipping costs. In the open economy all firms lose market share to imports in the domestic market. Firms that export, however, more than make up for the domestic profit loss due to additional profits from exporting. As the cost of trade decreases, exporters experience higher profits, more firms enter the export market, and wages increase. Competition from imports and higher wages drive firms with high variable costs out of the market. Firms with low variable costs, on the other hand, expand output.[17]

(Bustos 2011) refines the Melitz model to incorporate endogenous technology choice.[18] In her model, firms have the option to pay a technology adoption cost that lowers the firm's variable cost. The fixed production cost increases by a multiplicative factor $\eta > 1$ and variable costs are reduced by a multiplicative factor $\gamma > 1$:

$$TC_H(q, \varphi) = f\eta + \frac{q}{\gamma\varphi}$$

Bustos shows that decreasing trade costs induce high productivity firms to upgrade technology because they benefit the most from even lower variable costs. When trade costs drop, more firms adopt the better technology, expected profits from exporting increase, encouraging entry into the industry, causing aggregate prices to drop and more low productivity firms drop out. Her model also predicts that during liberalization both old and new exporters upgrade technology faster than nonexporters.

The Melitz and Bustos models predict that lowering trade barriers increases rewards for efficient input use. If increased efficiency of input use implies increased efficiency of fuel use, as argued above, and if fuel mix choices are correlated with firm-level productivity in a way that makes the more productive firms opt for dirtier fuels, then trade liberalization favors, within each industry, firms with relatively low greenhouse gas emissions per unit output and encourages within-firm improvements. [19] If ξ represents an industry-specific mean factor cost

[17]An alternative model that also explains why so few firms export and why exporters are more productive than non-exporting firms is (Bernard *et al.* 2003). This model is also based on heterogeneous firms, but the trade impact is driven by heterogeneous trade costs across countries.

[18](Rud 2011) also extends the Melitz model to incorporate technology adoption and applies the model to India using ASI data for 1994. Strangely, though, the paper applies the extended Melitz model exclusively to the adoption of generators, which indeed reduce variable costs relative to the infinite cost associated with the no-generator-in-times-of-blackouts counterfactual but significantly increase variable cost relative to counterfactual of fewer power cuts.

[19]Some pollutants may be optimally abated by end-of-pipe treatments, like the installation of scrubbers to remove SO_2 from the smokestacks of coal-fired power plants and common effluent treatment facilities to treat industrial water discharge. But CO_2, the dominant greenhouse gas from manufacturing, once emitted

share of energy inputs in variable costs and g represents the average greenhouse gas intensity of the energy mix, then total greenhouse gas emissions associated with manufacturing energy use can be represented as:

$$GHG = \int_0^{\infty} g\xi \frac{q(\varphi)}{\gamma(\varphi)\mu(\varphi)} d\varphi$$

where $\gamma(\varphi)$ takes on a value of 1 if the firm does not upgrade technology and a value of $\overline{\gamma} > 1$ if it does, $0 < \xi < 1$, and $\mu(\varphi)$ represents the distribution of firms that choose to remain in the market. Pro-trade liberalization policies can provide environmental benefits both by reinforcing market incentives for adoption of input-saving technologies (increasing the density of firms for which $\gamma(\varphi) > 1$), increasing the share of total output produced by firms with high input use efficiency, and increasing attrition of most input-inefficient firms.

Although the Melitz and Bustos models do not directly address the issue of changes in tariffs on intermediate inputs, these changes are particularly important when thinking about technology adoption and input-use efficiency. When tariffs on imports drop, there should be differential impacts on sectors that produce final goods that compete with those imports and sectors that use those imports as intermediate goods. The theoretical predictions of changes in tariffs on intermediate inputs on input-use intensity is mixed. On one hand, decreasing tariffs on inputs can increase the quality and variety of inputs, improving access to environmentally-friendly technologies embodied in imports. (Amiti and Konings 2007) find that in Indonesia decreasing tariffs on intermediate inputs had twice as large an effect in increasing firm-level productivity as decreasing tariffs on final goods. On the other hand, decreasing the price of intermediate inputs disproportionately lowers the variable costs of firms that use intermediate inputs least efficiently, mitigating competitive pressures these firms may face post-liberalization. In the Indian context, (Goldberg *et al.* 2010) show that they also increased the variety of new domestic products available and (Topalova and Khandelwal 2011) show that decreases in tariffs on intermediate imports increased firm productivity.

In the context of the Melitz and Bustos models, we can think about the impact of tariffs on intermediate inputs as shifts in the firm's total cost function:

$$TC_H(q, \varphi) = f\eta(1 + \tau_K) + \frac{q}{\gamma\varphi}(1 + \tau_M)$$

Tariffs on capital good inputs τ_K effectively increase the cost of upgrading technology whereas tariffs on materials inputs τ_M increase variable costs. Reductions in tariffs on capital goods increase the number of firms that chose to adopt new technology. Unlike reductions in tariffs

can only be removed from the atmosphere by carbon capture and sequestration, which is still in experimental stages. The Melitz and Bustos models say nothing about incentives to install end-of-pipe measures. These measures increase variable costs, so absent binding regulation firms would be highly unlikely to install them, especially in a Melitz world in which high variable costs are clearly associated with loss of market share.

in final goods that directly affect only the profits of exporting firms, reductions in tariffs on material inputs decrease the variable cost of all firms, potentially offsetting the productivity and input-use efficiency benefits of trade liberalization.

The extension of the Melitz and Bustos models to firm energy input use provides a few hypotheses that I test in Section 4.6. First of all, I expect to see increases in market share among firms with low energy intensity of output and decreases in market share among firms with high energy intensity of output.

Second, if low variable cost is indeed driving market share reallocations, I expect that industries with highest correlation with energy efficiency and low overall variable costs will exhibit the largest within-industry reallocation effect. I proxy high overall productivity with total factor productivity (TFP). TFP is the efficiency with which a firm uses all of its inputs, that is, the variation in output that can not be explained by more intensive use of inputs. TFP embodies effects such as learning by doing, better capacity utilization, economies of scale, advances in technologies, and process improvements.

Third, I explore the input tariff mechanism by disaggregating input tariffs into tariffs on material inputs like cotton and chemicals and tariffs on capital inputs like machinery, electronic goods, and spare parts. I also identify the effect separately for industries that import primarily materials and those that import a significant fraction of capital goods. I expect that decreases in tariffs on capital inputs would lead to within-firm improvements in fuel efficiency, whereas decreases in tariffs in material inputs could relax competitive pressure on firms to adopt input-saving technologies.

4.3 Decomposing fuel intensity trends using firm-level data

I first replicate (Levinson 2009)'s index decomposition analysis for India. Levinson identifies scale, composition, and technique effects for air pollution trends in United States manufacturing. For total pollution P, total manufacturing output Y, industry j share in manufacturing $s = \frac{v_j}{V}$, and industry j average pollution intensity of output $z_j = \frac{p_j}{y_j}$, he writes aggregate pollution as the product of output and the output-weighted share of pollution intensity in each industry:

$$P = \sum_j p_j = Y \sum_j s_j z_j = Y s' z$$

He then performs a total differentiation to get:

$$dP = s' z dY + Y z' ds + Y s' dz$$

The first term represents the scale effect: the effect of increasing output while keeping each industry's pollution intensity and market share constant. The second term represents the composition effect: the effect of industries gaining or losing market share, holding pollution intensity and output constant. The third term represents the technique effect: the effect of changes in industry-average pollution intensity, keeping output and industry market share constant.

(Levinson 2009) uses industry-level data and estimates technique as a residual. As he recognizes, this approach attributes to technique any interactions between scale and composition effects. It also reflects any differences between the infinitesimal changes used in theory and discrete time steps used in practice. With firm-level data, I am able to reduce these sources of bias.

A major contribution of this paper is that I also disaggregate the technique effect into within-firm and market share reallocation components. Within-firm pollution intensity changes when firms make new investments, change capacity utilization, change production processes with existing machines, or switch fuels. Reallocation refers to the within-industry market share reallocation effect described in (Melitz 2003). I disaggregate these effects using a framework first presented by Olley & Pakes and applied empirically by (Pavcnik 2002) and most recently (McMillan and Rodrik 2011).[20] The Olley Pakes approach decomposes aggregate (output-share weighted) productivity into average unweighted productivity within firm and reallocation of market share to more or less productive plants. I use the same approach, but model trends in industry-level fuel and greenhouse gas intensity of output instead of trends in total factor productivity.

$$\begin{aligned} dz &= z_{j1} - z_{j0} = \sum_i s_{i1} z_{ij1} - \sum_i s_{i0} z_{ij0} \\ &= \bar{z}_{j1} - \bar{z}_{j0} + \sum_i \left(s_{ij1} - \bar{s}_{j1}\right)\left(z_{ij1} - \bar{z}_{j1}\right) - \sum_i \left(s_{ij0} - \bar{s}_{j0}\right)\left(z_{ij0} - \bar{z}_{j0}\right) \end{aligned}$$

The output-share weighted change in industry-level pollution intensity of output, dz_{jt}, is the Technique effect. It can be expressed as the sum of the change in average unweighted pollution intensity within firm, $\bar{z}_{jt}$, and the change in allocation of market share to more or less polluting firms, $\sum_i \left(s_{ijt} - \bar{s}_{jt}\right)\left(z_{ijt} - \bar{z}_{jt}\right)$. The reallocation term is the sample covariance between pollution intensity and market share. A negative sign on each period's reallocation term is indicative of a large amount of market share going to the least pollution-intensive firms.

I decompose fuel intensity and greenhouse gas intensity trends at the industry-level for each industry. In section 4.6 I regress those trends on policy variables.

To estimate the aggregate effect of within-industry reallocation and contrast its size to across-industry reallocation, I then extend the Olley Pakes approach in a unique decompo-

[20]The Olley Pakes decomposition was subsequently refined for use with panel data by Bailey et. al., Ziliches-Regev, and Melitz Polanec. I opted against using the Melitz Polanec approach because it is constructed in such a way to attribute to entry and exit only the behavior of firms in their first and last years, which means that these components are primarily measuring the effect of start-up and ramp down activities.

sition. My disaggregation proceeds as follows. For each firm i of n_{jt} firms at time t that are in industry j of a total of N industries, firm output is represented y_{ijt} and firm pollution intensity is z_{ijt}. Let firm share within industry $s_{ijt} = \frac{y_{ijt}}{y_{jt}}$, industry share within manufacturing $s_{jt} = \frac{y_{jt}}{y_t}$, average firm share within each industry $\overline{s}_{jt} = \frac{1}{n_{jt}} \sum_{i \in j} \frac{y_{ijt}}{y_{jt}}$, average share of an industry within manufacturing $\overline{s}_t = \frac{1}{N} \sum_j \frac{y_{jt}}{y_t}$, and average pollution intensity in each industry $\overline{z}_{jt} = \frac{1}{n_{jt}} \sum_{i \in j} z_{ijt}$. Then I can write each period's aggregate pollution intensity z_t as:

$$
\begin{aligned}
z_t &= \sum_i \frac{y_{ijt}}{y_t} z_{ijt} = \sum_j \frac{y_{jt}}{y_t} \sum_{i \in I_j} \frac{y_{ijt}}{y_{jt}} z_{ijt} = \sum_j s_{jt} \Phi_{jt} \\
&= \frac{1}{N} \sum_j \Phi_{jt} + \sum_j \left(s_{jt} - \overline{s}_t\right) \left(\Phi_{jt} - \frac{1}{N} \sum_j \Phi_{jt} \right) \\
&= \frac{1}{N} \sum_j \left(\overline{z}_{jt} + \sum_{i \in I_j} \left(s_{ijt} - \overline{s}_{jt}\right) \left(z_{ijt} - \overline{z}_{jt}\right) \right) + \sum_j \left(s_{jt} - \overline{s}_t\right) \left(\Phi_{jt} - \frac{1}{N} \sum_j \Phi_{jt} \right) \\
&= \underbrace{\frac{1}{N} \sum_j \overline{z}_{jt}}_{\text{within}} + \underbrace{\frac{1}{N} \sum_j \sum_{i \in I_j} \left(s_{ijt} - \overline{s}_{jt}\right) \left(z_{ijt} - \overline{z}_{jt}\right)}_{\text{across firms}} + \underbrace{\sum_j \left(s_{jt} - \overline{s}_t\right) \left(\Phi_{jt} - \frac{1}{N} \sum_j \Phi_{jt} \right)}_{\text{across industries}}
\end{aligned}
$$

The first term represents average industry trends in energy efficiency. The second term represents reallocation between firms in each industry. It is the sample covariance between firm market share within-industryand firm energy efficiency. The third term represents reallocation across industries. It is the sample covariance between industry market share within manufacturing and industry-level fuel intensity.

I then apply these decompositions to an extensive dataset of firms in India's manufacturing sector.

4.4 Firm-level data on fuel use in manufacturing in India 1985-2004

India is the second largest developing country by population and has significant potential for future greenhouse gas emissions and avoided emissions. India's manufacturing sector is responsible for over 40% of its energy use, and fuels used in manufacturing and construction are responsible for almost half of the country's greenhouse gas emissions.

My empirical analysis is based on a unique 19-year panel of firm-level data created from India's Annual Survey of Industries (ASI). The ASI provides detailed firm-level data from

1985-1994 and 1996-2004 for over 30,000 firms per year. The survey includes data on capital stock, workforce, output, inventories, and expenditures on other inputs. It also contains data on the quantity of electricity produced, sold, and consumed (in kWh) and expenditures on fuels. I define output to be the sum of ex-factory value of products sold, variation in inventories (semi-finished good), own construction, and income from services. Fuels include electricity, fuel feedstocks used for self-generation, fuels used for thermal energy, and lubricants (in rupees). When electricity is self-generated, the cost is reflected in purchases of feedstocks like coal or diesel. Fuels that are direct inputs to the manufacturing process are counted separately as materials. Summary statistics on key ASI variables are presented in Table 4.2. I exclude from the analysis all firm-years in which firms are closed or have no output or labor force.

I measure energy efficiency as fuel intensity of output. It is the ratio of real energy consumed to real output, with prices normalized to 1985 values. In other words, I equate energy efficiency with the cost share of energy in 1985. Over 1985-2004 fuel intensity in manufacturing decreases at a very slight rate, from .070 to .065. In contrast, the IEA estimates that in China fuel intensity in manufacturing was close to .20 in the mid-1980s but decreased dramatically to close to .04 over that same period. (Figure B.2) Currently India's fuel intensity of manufacturing output is about three times as high as in OECD countries. (IEA 2005)

This measure of energy efficiency is sensitive to the price deflators used for both series. I deflate output using annual 14-sector wholesale price index (WPI) deflators and fuels using the fuel deflator provided by India's Ministry of Commerce and Industry. Ideally I would use firm-specific price deflators. Unfortunately the ASI only publishes detailed product information for 1998-2004, and many firms respond to requests for detailed product data by describing products as "other." The main advantage to firm-level prices is that changes in market power post liberalization could lead to firm-specific changes in markups, which I would incorrectly attribute to changes in energy efficiency. In section 4.6 I test for markups by interacting policy variables with measures of industry concentration. Almost all of the trade reform effects that I estimate are also present in competitive industries. Figure B.3 shows that average industry output deflators and fuel deflators evolve in similar ways.

I unfortunately can not analyze the effect of changes in fuel mix with the available data. Fuel mix has a large impact on greenhouse gas emission calculations, but less impact on fuel intensity because if firms experience year-to-year price shocks and substitute as a result towards less expensive fuels, the fuel price deflator will capture the changes in prices.

Lacking exact fuel mix by firm for each year, I estimate the greenhouse gas emissions associated with non-electricity fuel use by extrapolating the greenhouse gas intensity of fuel use from detailed fuel data available for 1996. The 1996 ASI data includes highly disaggregated data on non-electricity fuel expenditures, both in rupees and in quantities consumed (tons of coal, liters of diesel, etc.). I use values from the US EPA and Clean Development Mechanism project guideline documents to estimate the greenhouse gas emissions from each

Table 4.2: Summary statistics

	Estimated population	Sampled firms	Panel
Firm-years	1,410,341	580,122	413,758
Firms per year, mean	82,961	34,124	24,338
Census firm-years	276,278	276,278	246,881
Census firms per year, mean	16,251	16,251	14,522
Unique firm series			147,838
Output, median (million Rs.)	2.6	3.6	5.3
Fuels, median (millions Rs.)	.12	.15	.24
Capital, median (million Rs.)	0.4	0.5	0.8
Materials, median (million Rs.)	1.9	2.6	3.9
Labor, median (no. employees)	21	31	33
In panel, as fraction of total in sampled population:			
Output			0.93
Fuels			0.93
Capital			0.94
Labor			0.92
Firm-years > 100 employees			0.94
Firm-years > 200 employees			0.96
Firm-years			0.71
Census firm-years			0.89

Note: Annual Survey of Industries (ASI) data for 1985-1994 and 1996-2004. Detailed data and ASI-supplied panel identifiers for 1998-2004. Panel reflects all firm series with 2 or more matched years.

type of fuel used. Coefficients are displayed in Table 4.3. I then aggregate the fuel mix data by industry to estimate greenhouse gas emissions factors for each industry's expenditures on non-electricity fuels.

Electricity expenditures make up about half of total fuel expenditures. I follow the protocol recommended by the Clean Development Mechanism in disaggregating grid emissions into five regions: North, West, East, South, and North-East. I disaggregate coefficients across regional grids despite the network being technically national, and most power-related decisions being decided at a state level, because there is limited transmission capacity or power trading across regions. I use the coefficient for operating margin and not grid average to represent displaced or avoided emissions. The coefficient associated with electricity on the grid, close to 1 metric ton CO2 equivalent per MWh, is more than 40% higher than in the US.[21]

I measure industries at the 3-digit National Industrial Classification (NIC) level. I use concordance tables developed by (Harrison *et al.* 2011) to map between 1970, 1987, 1998, and 2004 NIC codes. Table B.4 presents fuel use statistics for India's largest industries. The industries that uses the most fuel are cement, textiles, iron & steel, and basic chemicals (chloral-alkali), followed by paper and fertilizers & pesticides. These six sectors are responsible for 50% of the country's fuel use in manufacturing. Other large consumers of fuels include nonferrous metals, medicine and clay. Other important sectors important to GDP that are not top fuel consumers include agro-industrial sectors like grain milling, vegetable & animal oils, sugar, plastics, and cars. The sectors with the highest fuel cost per unit output are large sectors like cement, paper, clay, and nonferrous metals, and smaller sectors like ferroalloys, glass, ceramics, plaster, aluminum, and ice.

4.5 Decomposition results

This section documents trends in fuel use and greenhouse gas emissions associated with fuel use over 1985-2004 and highlights the role of within-industry market share reallocation. Although only a fraction of this reallocation can be directly attributed to changes in trade policies (Section 4.6), the trends are interesting in themselves.

4.5.1 Levinson-style decomposition applied to India

The results of the Levinson decomposition are displayed in Table 4.4 and Figure 4.1. The scale effect is responsible for the bulk of the growth in greenhouse gases over the period from 1985 to 2004, growing consistently over that entire period. The composition and technique effects played a larger role after the 1991 liberalization. The composition effect reduced emissions by close to 40% between 1991 and 2004. The technique effect decreased emissions

[21] US EPA guidelines: 0.69 metric tons CO2 per MWh for displaced emissions.

Table 4.3: Coefficients used to calculate greenhouse gas emissions associated with fuel use

Fuel	Region	% Exp	Factor	tons CO2 per
Coal		14.6	2.47	ton
Lignite		0.9	1.40	ton
Coal gas		0.4	7.25	1000 m3
LPG		0.6	2.95	ton
Natural gas		2.2	1.93	1000 m3
Diesel oil		8.7	2.68	1000 liters
Petrol		1.9	2.35	1000 liters
Furnace oil		7.5	2.96	1000 liters
Other fuel oil		2.9	2.68	1000 liters
Firewood		1.5	1.80	ton
Biomass		0.3	1.10	ton
Other		2.1	0.40	1000 Rs
Electricity grid	North	13.1	0.72	MWh
	East	22.2	1.09	MWh
	South	14.3	0.73	MWh
	West	6.2	0.90	MWh
	Northeast	0.4	0.42	MWh

Source: UNEP for all except for grid coefficients. Grid coefficients for 2000-2001 from CO2 Baseline Database for the Indian Power Sector User Guide, June 2007: North represents Chandigarh, Delhi, Haryana Himachal Pradesh, Jammu & Kashmir, Punjab, Rajasthan, and Uttar Pradesh. East represents Bihar, Orissa, and West Bengal. South represents Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu. West represents Chhatisgarh, Goa, Gujarat, Madhya Pradesh, and Maharashtra. Northeast represents Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland and Tripura. Fraction of total expenditures on fuels based on 1996-1997 ASI data. The value for "Other fuels" is the median value obtained when applying all other coefficients to fuel expenditures in the dataset.

by 2% in the years immediately following the liberalization (between 1991 and 1997), but increased emissions by 24% in the subsequent years (between 1997 and 2004).

Table 4.4: Levinson decomposition applied to greenhouse gases associated with fuel use in manufacturing in India, 1985-2004, selected years shown

	1985	1991	1997	2004
Scale	100	155.4	210.8	270.3
Composition	100	99.6	77.4	63.1
Technique	100	103.2	101.3	125.4
Technique as residual	100	102.9	95.9	108.7
Composition and technique	100	102.8	78.7	88.5
Total	100	158.2	189.5	258.9

Note: Greenhouse gas emissions in tons of CO2 equivalents, normalized to 1985 values. On average, half of emissions are associated with electricity use. Does not include industrial process emissions. Estimates based on actual usage of fuel and estimates of greenhouse gas intensity of fuel use based on industry fuel mix prevalent in 1996.

To highlight the importance of having data on within-industry trends, I also display the estimate of the technique effect that one would obtain by estimating technique as a residual. More specifically, I estimate trends in fuel intensity of output as a residual, given known total fuel use, and then apply the greenhouse gas conversation factors presented in Table 4.3 to convert fuel use to greenhouse gas emissions. I find that the residual approach to calculating technique significantly underestimates the increase in emissions post-liberalization, projecting a contribution of less than 9% increase relative to 1985 values instead of an increase of more than 25%.

4.5.2 Role of reallocation

Table 4.5 summarizes the savings in greenhouse gas emissions and fuel use, in absolute and percentage terms, due to reallocation of market share across industries and within industry. In aggregate, across-industry reallocation over the period 1985-2005 led to fuel savings of 50 billion USD, representing 469 million tons of avoided greenhouse gas emissions. Reallocation across firms within industry led to smaller fuel savings: 19 million USD, representing 124 million tons of avoided greenhouse gas emissions.

The Kyoto Protocol's Clean Development Mechanism (CDM) is a good benchmark for the emissions reductions obtained over this period. In contrast to the total savings of almost 600 million tons of CO_2 from avoided fuel consumption, 124 million of which is within-industry reallocation across firms, the CDM is projected to obtain between 2003 and 2012 reductions of 13 million tons of CO_2 over all residential and industrial energy efficiency projects combined. The CDM plans to issue credits for 86 million tons of CO_2 for renewable

Figure 4.1: Levinson decomposition applied to India, technique effect calculated both directly and as a residual

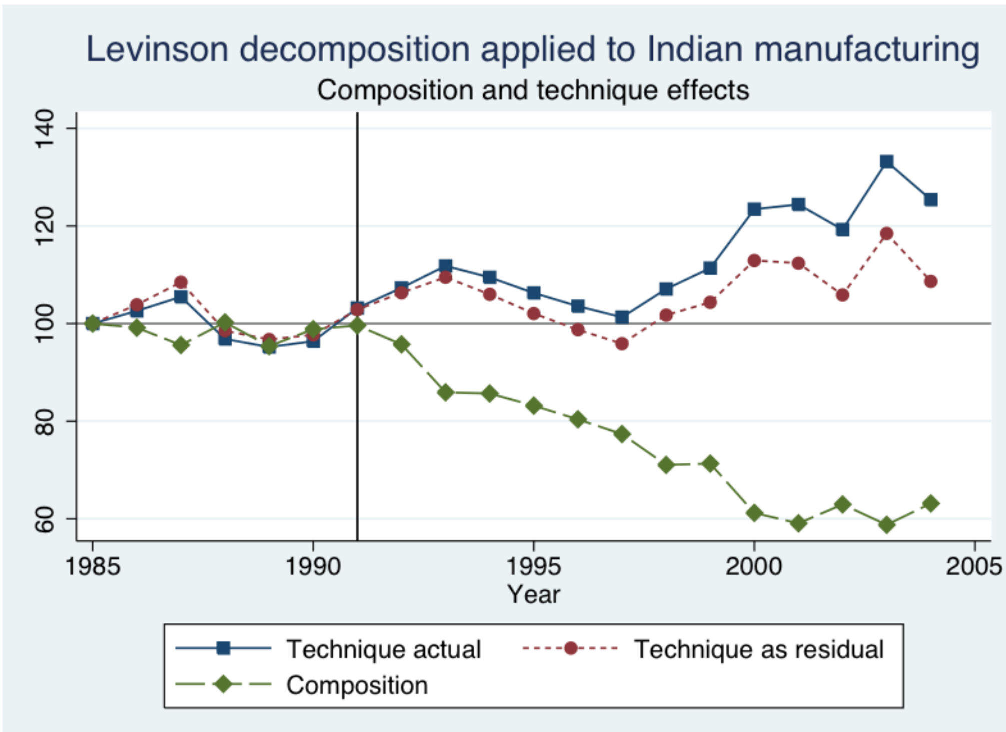


Table 4.5: Fuel and GHG savings from reallocation within industry and reallocation across industries

	GHG emissions		Fuel Expenditures		
	million tons CO2e	as % of counterfact	billion Rs (1985)	billion USD (2011)	as % of counterfact
Across industry reallocation	469	15%	340	50	13%
Within industry reallocation	124	4%	130	19	5%
Total savings	593	19%	470	70	18%

energy projects, and a total of 274 million tons of CO_2 avoided over all projects over entire period (includes gas flaring and removal of HFCs). Table B.3 in the Appendix describes projected CDM emissions reductions in detail.

The results of the fuel decomposition are depicted in Figure 4.2 and detailed in Table B.2. The area between the top and middle curves represents the composition effect, that is, the fuel savings associated with across-industry reallocation to less energy-intensive industries. Even though fuel-intensive sectors like iron and steel saw growth in output over this period, they also experienced a decrease in share of output (in the case of iron and steel, from 8% to 5%). Cotton spinning and weaving and cement, sectors with above-average energy intensity of output, experienced similar trends. On the other hand, some of the manufacturing sectors that grew the most post-liberalization are, in decreasing order: plastics, cars, sewing, spinning and weaving of synthetic fibers, and grain milling. All of these sectors have below average energy intensity.

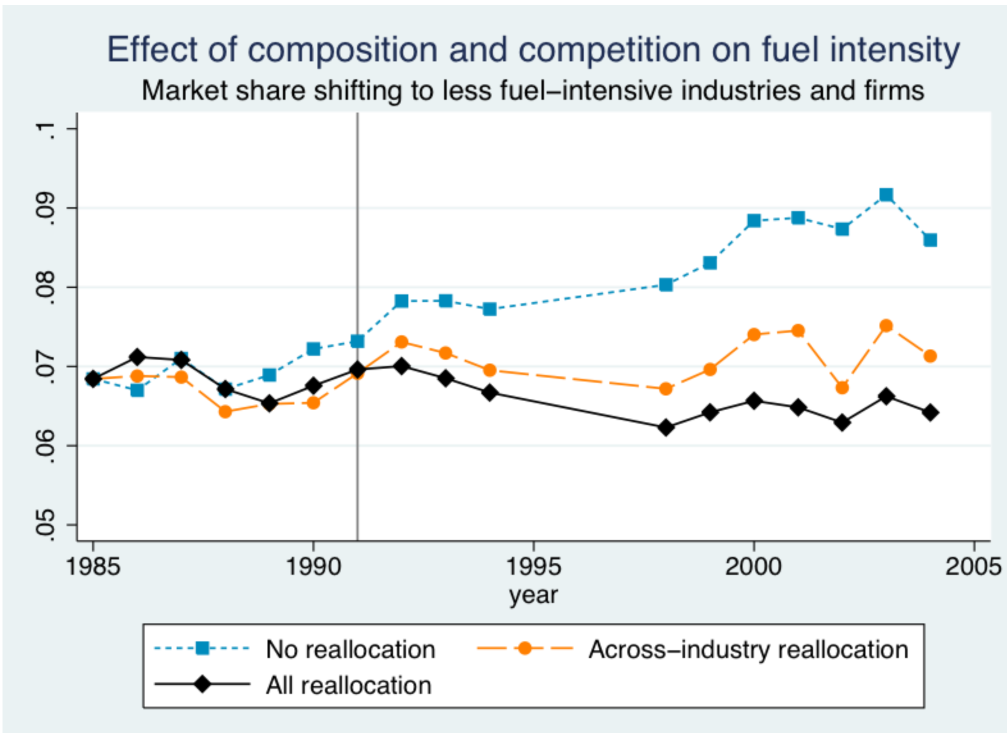
The within-industry effect is smaller in size, but the across-industry effect still represents important savings. Most importantly, it is an effect that should be able to be replicated to a varying degree in any country, unlike the across-industry effect which will decrease emissions in some countries but increase them in others.

4.6 Impact of policy reforms on fuel intensity and reallocation

The previous sections documented changes in trends pre- and post- liberalization. This section asks how much of the within-industry trends can be attributed to different policy reforms that occurred over this period. I identify these effects using across-industry variation in the intensity and timing of trade reforms. I first regress within-industry fuel intensity trends (the technique effect) on policy changes. I show that, in the aggregate, decreases in intermediate input tariffs and the removal of the system of industrial licenses improved within-industry fuel intensity. Using the industry-level disaggregation described in the previous section, I show that the positive benefits of the decrease in intermediate input tariffs came from within-firm improvements, whereas delicensing acted via reallocation of market share across firms. I then regress policy changes at the firm level, emphasizing the heterogeneous impact of policy reforms on different types of firms. I show that decreases in intermediate tariffs improve fuel intensity primarily among older, larger firms. I also observe that FDI reform led to within-firm improvements in older firms.

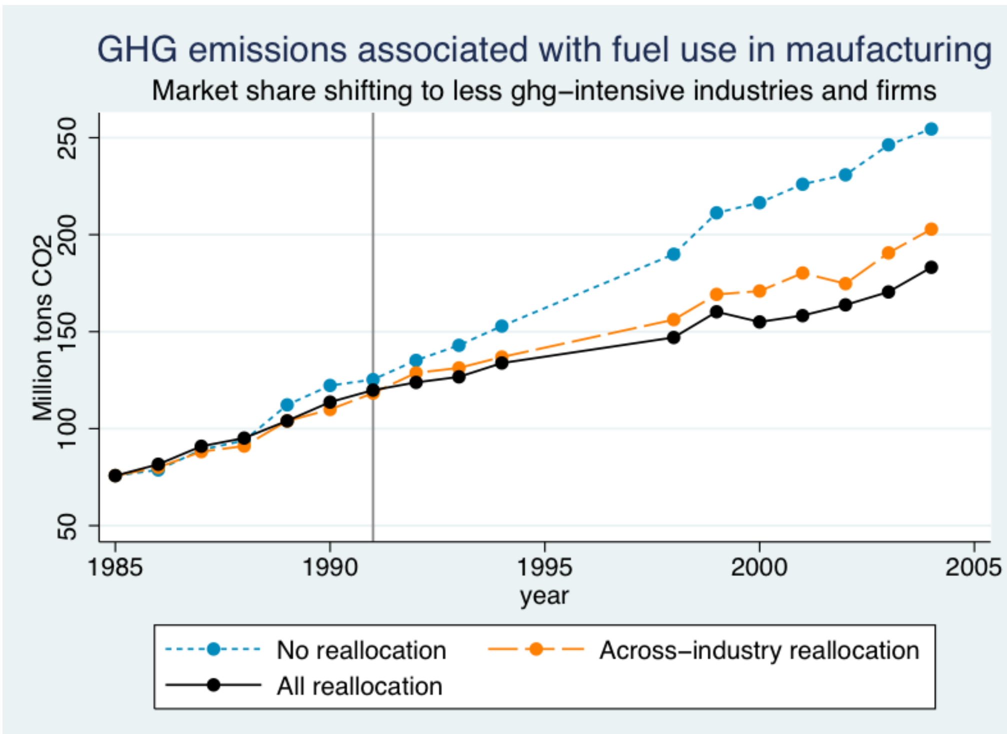
I then test whether any of the observed within-industry reallocation can be attributed to trade policy reforms and not just to delicensing. Using firm level data, I observe that FDI reform increases the market share of low fuel intensity firms and decreases the market share of high fuel intensity firms when the firms have, respectively, high and low TFP. Reductions in input tariffs on material inputs, on the other hand, appears to reduce competitive pressures

Figure 4.2: Fuel decomposition that highlights relative role of across-industry and within-industry reallocation



Note: The top curve represents the counterfactual trajectory of fuel intensity had there been no reallocation of market share. The middle curve represents the counterfactual fuel intensity trajectory had across-industry reallocation taken place as it did, but had there been no within-industry reallocation. The bottom curves represents actual fuel intensity experienced (with actual levels of both across-industry and within-industry reallocation).

Figure 4.3: Millions of tons of CO2 from fuel use in manufacturing



Note: The area between the top and middle curves represents the emissions avoided due to across-industry reallocation. The area between the middle and bottom curves represents emissions avoided due to within-industry reallocation.

on fuel-inefficient firms with low TFP and high fuel intensity.

4.6.1 Trade reform data

India experienced a dramatic IMF-driven trade liberalization in 1991. Prior to liberalization, India's trade regime was highly restrictive, with average tariffs above 80%. In 1991 India suffered a balance of payments crisis triggered by the Golf War, primarily via increases in oil prices and, lower remittances from Indians in the Middle East. ((Topalova and Khandelwal 2011)) The IMF Stand-By Arrangement was conditional on a set of liberalization policies and trade reforms. As a result there were in a period of a few weeks large, unexpected decreases in tariffs and regulations limiting FDI were relaxed for a number of industries. In the period of industrial licenses, known as the "license Raj", non-exempt firms needed to obtain industrial licenses to establish a new factory, significantly expand capacity, start a new product line, or change location. With delicensing, firms no longer needed to apply for permission to expand production or relocate, and barriers to firm entry and exit were relaxed. During the 1991 liberalization reforms, a large number of industries were also delicensed.

I proxy the trade reforms with three metrics of trade liberalization: changes in tariffs on final goods, changes in tariffs on intermediate inputs, and FDI reform. Tariff data comes from the TRAINS database and customs tariff working schedules. I map annual product-level tariff data at the six digit level of the Indian Trade Classification Harmonized System (HS) level to 145 3-digit NIC industries using Debroy and Santhanam's 1993 concordance. Tariffs are expressed as arithmetic mean across six-digit output products of basic rate of duty in each 3-digit industry each year. FDI reform is an indicator variable takes a value of 1 if any products in the 3-digit industry are granted automatic approval of FDI (up to 51% equity; non-liberalized industries had limits below 40%). I also control for simultaneous dismantling of the system of industrial licenses. Delicensing takes a value of 1 when any products in an industry become exempt from industrial licensing requirements. Delicensing data is based on (Aghion *et al.* 2008) and expanded using data from Government of India publications.

I follow the methodology described in (Amiti and Konings 2007) to construct tariffs on intermediate inputs. These are calculated by applying industry-specific input weights supplied in India's Input-Output Transactions Table (IOTT) to tariffs on final goods.[22] In regressions where I disaggregate input tariffs by input type, I classify all products with IOTT codes below 76 as raw materials, and products with codes 77 though 90 as capital inputs. To classify industries by imported input type, I use the detailed 2004 data on imports and assign ASICC codes of 75000 through 86000 to capital inputs.

Summary statistics describing India's policy reforms are presented in Table 4.6.

[22] An industry that spends 40% of its input expenditures on product A and 60% on product B would have an overall input tariff rate of 0.4 times the final goods tariff for product A and 0.6 times the final goods tariff for product B.

Table 4.6: Summary statistics of policy variables

	Final Goods Tariffs		Intermediate Input Tariffs		FDI reform		Delicensed	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1985	.893	.335	.583	.115	0.00	0.00	0.33	0.47
1986	.961	.387	.608	.109	0.00	0.00	0.34	0.48
1987	.955	.383	.591	.099	0.00	0.00	0.34	0.48
1988	.956	.383	.598	.102	0.00	0.00	0.34	0.48
1989	.963	.412	.599	.103	0.00	0.00	0.35	0.48
1990	.964	.414	.599	.103	0.00	0.00	0.35	0.48
1991	.964	.414	.599	.103	0.36	0.48	0.83	0.37
1992	.637	.283	.400	.530	0.36	0.48	0.83	0.37
1993	.640	.318	.387	.530	0.36	0.48	0.85	0.36
1994	.644	.369	.374	.620	0.36	0.48	0.85	0.36
1995	.534	.316	.302	.540	0.36	0.48	0.85	0.36
1996	.421	.254	.228	.510	0.36	0.48	0.85	0.36
1997	.340	.190	.184	.400	0.43	0.50	0.89	0.31
1998	.346	.180	.191	.390	0.43	0.50	0.92	0.27
1999	.356	.168	.202	.390	0.43	0.50	0.92	0.27
2000	.351	.156	.213	.410	0.93	0.26	0.92	0.27
2001	.343	.165	.206	.460	0.93	0.26	0.92	0.27
2002	.308	.159	.188	.540	0.93	0.26	0.92	0.27
2003	.309	.159	.189	.530	0.93	0.26	0.92	0.27
2004	.309	.159	.190	.530	0.93	0.26	0.92	0.27

Source: Tariff data from TRAINS database and customs tariff working schedules: SD = standard deviation

My preferred specification in the regressions in Section 4.6 uses firm level fixed effects, which relies on correct identification of a panel of firms from the repeated cross-section. The ASI supplies panel identifiers for 1998-2005 but the 1985-1994 ASI does not match firm identifiers across years. I match firms over 1985-1994 and on through 1998 based on open-close values for fixed assets and inventories and time-invarying characteristics: year of initial production, industry (at the 2-digit level), state & district. (Harrison *et al.* 2011) describes the panel matching procedure in detail. With the panel I can use firm-level fixed effects in estimation procedures to control for firm-level time-unvarying unobservables like quality of management.

4.6.2 Potential endogeneity of trade reforms

According to (Topalova and Khandelwal 2011), the industry-level variation in trade reforms can be considered to be as close to exogenous as possible relative to pre-liberalization trends in income and productivity. The empirical strategy that I propose depends on observed changes in industry fuel intensity trends not being driven by other factors that are correlated with the trade, FDI or delicensing reforms. A number of industries, including some energy-intensive industries, were subject to price and distribution controls that were relaxed over the liberalization period.[23] I am still collecting data on the timing of the dismantling of price controls in other industries, but it does not yet appear that industries that experienced the price control reforms were also those that experienced that largest decreases in tariffs. Another concern is that there could be industry selection into trade reforms. My results would be biased if improving fuel intensity trends encouraged policy makers to favor one industry over another for trade reforms. As in (Harrison *et al.* 2011), I check whether pre-liberalization industry-level trends in any of the major available indicators can explain the magnitude of trade reforms each industry experienced. I do not find any statistically significant effects. The regression results are shown in Table 4.7.[24]

4.6.3 Industry-level regressions on fuel intensity and reallocation

To estimate the extent to which the technique effect can be explained by changes in policy variables, I regress within-industry fuel intensity of output on the four policy variables: tariffs on final goods, tariffs on intermediate inputs, FDI reform and delicensing. To identify

[23] Price and distribution controls, year relaxed: Aluminum: 1989. Cement: 1982, last controls relaxed in 1989. Fertilizer: 1992 on. Iron & steel: 1992. Paper: 1987. (Mongia *et al.* 2001), TEDDY 2003, TEDDY 2005

[24] (Sivadasan 2009) checks for endogeneity in industry selection on productivity trends by identifying proxies for four different sources of selection bias (pre-reform trends, export orientation, capital intensity, distance from productivity frontier). In one formulation he uses these proxies as controls, and in the other he uses them to create propensity scores of being selected for reform. In (Sivadasan 2009) the effect of tariff liberalization on productivity is unaffected; the FDI liberalization effect is halved.

Table 4.7: Changes in Reforms and Pre-Reform Trends in Industry Characteristics

	ΔFinal Goods Tariffs	ΔInput Tariffs	ΔFDI Reform	ΔDelicensing
Δ Fuel Intensity	-0.60	0.17	0.37	-0.86
	(0.151)	(0.40)	(2.04)	(0.99)
Δ Production Share	-0.052	-0.16	0.17	0.82
	(0.92)	(0.25)	(0.12)	(0.26)
Δ log(wage)	0.002	-0.042	0.088	-0.14
	(0.19)	(0.052)	(0.60)	(1.27)
Δ log(K/L Ratio)	-0.12	0.007	0.041	0.043
	(0.080)	(0.022)	(0.052)	(0.11)
Δ log(Employment)	-0.062	-0.024	-0.0085	-0.034
	(0.061)	(0.016)	(0.04)	(0.084)
Δ log(Firm Size)	-0.096	-0.035	0.018	-0.026
	(0.12)	(0.032)	(0.077)	(0.16)
Δ log(Output)	-0.037	-0.0088	0.02	-0.0028
	(0.040)	(0.011)	(0.026)	(0.055)
Δ TFP (Total)	0.038	-0.0066	0.062	0.014
	(0.072)	(0.020)	(0.047)	(0.099)
Observations	136	136	136	136

Source: (Harrison et al. *2011):* Results are coefficients from regressions of the change in reforms (final goods tariffs, input tariffs, delicensing, FDI reform) from 1990 to 2004 on changes in industry characteristics from 1985 to 1989. Each value represents a result from a separate regression. Standard errors are in parentheses.

the mechanism by which the policies act, I also separately regress the two components of the technique effect, average fuel-intensity within-firm and reallocation within-industry of market share to more or less productive firms, on the four policy variables. I include industry and year fixed effects to focus on within-industry changes over time and control for shocks that impact all industries equally. I cluster standard errors at the industry level. Because each industry-year observation represents an average and each industry includes vastly different numbers of firm-level observations and scales of output, I include analytical weights representing total industry output.

Formally, for each of the three trends calculated for industry j I estimate:

$$\text{Trend}_{jt} = \beta_1 \text{Tariff FG}_{jt-1} + \beta_2 \text{Tariff II}_{jt-1} + \beta_3 \text{FDI}_{jt-1} + \beta_4 \text{Delic}_{jt-1} + \eta_j + \tau_t + \epsilon_{jt}$$

Results are presented in Table 4.8. The drop in tariffs on intermediate inputs and delicensing are both associated with statistically-significant improvements in within-industry fuel intensity. The effect of tariffs on intermediate inputs is entirely within-firm. The effect of delicensing is via reallocation of market share to more fuel-efficient firms.

Table 4.9 interprets the results by applying the point estimates in Table B.5 to the average change in policy variables over the reform period. Effects that are statistically significant at the 10% level are reported in bold. I see that reduction in input tariffs improves within-industry fuel efficiency (the technique effect) by 23%. The input tariffs act through within-firm improvements – reallocation dampens the effect. In addition, delicensing is associated with a 7% improvement in fuel efficiency. This effect appears to be driven entirely by delicensing.

To address the concern that fuel intensity changes might be driven by changes in firm markups post-liberalization, I re-run the regressions interacting each of the policy variables with an indicator variable for concentrated industries. I expect that if the results are driven by changes in markups, the effect will appear primarily in concentrated industries and not in more competitive ones. I define concentrated industry as an industry with above median Herfindahl index pre-liberalization. I measure the Herfindahl index as the sum of squared market shares in 1990. Table B.6 in the Appendix shows the results of the concentration distinction. The impact of intermediate inputs and delicensing is primarily found among firms in competitive industries. There is an additional effect in concentrated industries of FDI reform improving fuel intensity via within firm improvements.

I then disaggregate the input tariff effect to determine the extent to which firms may be responding to cheaper (or better) capital or materials inputs. If technology adoption is playing a large role, I would expect to see most of the effect driven by reductions in tariffs on capital inputs. Because capital goods represent a very small fraction of the value of imports in many industries, I disaggregate the effect by industry by interacting the input tariffs with an indicator variable. Industries are designated “low capital imports” if capital goods represent less than 10% of value of goods imported in 2004, representing 112 out of

Table 4.8: Extent to which within-industry trends can be explained by changes in policy variables

	Fuel Intensity (1)	Within Firm (2)	Reallocation (3)
Final Goods Tariff	-.008	-.004	-.004
	(.008)	(.006)	(.006)
Input Tariff	.043	.050	-.008
	(.019)**	(.031)*	(.017)
FDI Reform	-.0002	.0004	-.0006
	(.002)	(.002)	(.002)
Delicensed	-.009	.002	-.011
	(.004)**	(.004)	(.003)***
Industry FE	yes	yes	yes
Year FE	yes	yes	yes
Obs.	2203	2203	2203
R^2	.086	.286	.167

Note: Dependent variables are industry-level fuel intensity of output, average fuel-intensity within-firm within-industry, and reallocation of market share to more or less productive firms within-industry. Fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Regression restricted to balanced panel of 145 industries. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table 4.9: Aggregate within-industry trends explained by policy variables 1991-2004

	Fuel Intensity (technique effect)	Within Firm	Reallocation
Final Goods Tariff	6.3%	3.2%	3.2%
Input Tariff	**-22.9%**	**-26.6%**	4.3%
FDI Reform	-0.3%	0.5%	-0.8%
Delicensed	**-7.3%**	1.6%	**-8.9%**

Note: Changes relative to average post-liberalization fuel intensity of .0732. Represents 0.58 point decrease in tariffs on final goods, .39 point decrease in tariffs on intermediate inputs, FDI liberalization in 93% of industries and additional delicensing of 59% of industries.

145 industries. I unfortunately cannot match individual product imports to firms because detailed import data is not collected until 1996 and not well disaggregated by product type until 2000.

Table 4.10: Decreases in tariffs on both capital and materials inputs drive within-firm improvements in fuel intensity; the effect is slightly mitigated by decreases in tariffs on materials inputs reallocating market share towards firms that use inputs less efficiently

	Fuel Intensity	Within	Reallocation
	(1)	(2)	(3)
Industry High Capital Imports:			
Tariff Capital Inputs	.037	.028	.009
	(.014)***	(.015)*	(.011)
Tariff Material Inputs	.022	.039	-.017
	(.010)**	(.013)***	(.009)*
Industy Low Capital Imports:			
Tariff Capital Inputs	.013	.013	-.0008
	(.009)	(.008)*	(.008)
Tariff Material Inputs	.035	.040	-.006
	(.013)***	(.017)**	(.012)

Note: Full results shown in 4.10. Dependent variables are industry-level fuel intensity of output, average fuel-intensity within-firm within-industry, and reallocation of market share to more or less productive firms within-industry. Industries are designated "low capital imports" if capital goods represent less than 10% of value of goods imported in 2004, representing 112 out of 145 industries.

Table B.5 shows that the within-firm effect of decreasing input tariffs acts almost equally within-firm for capital and material inputs. If anything the effect of decreasing tariffs on material inputs is larger (but not significantly so). There is however, a counteracting reallocation effect in industries with high capital imports when the tariffs on material inputs drop – market share shifts in favor more fuel-inefficient firms, mitigating the positive effect of within-firm improvements.

As a robustness check, I also replicate the analysis at the state-industry level, mirroring the methodology proposed by (Cai *et al.* 2011). Table B.9 presents the impact of policy variables on state-industry fuel intensity trends. Reducing the tariff on capital inputs, reforming FDI, and delicensing all lower fuel intensity, though the effects are only statistically significant when I cluster at the state-industry level. The effect of material input tariffs and capital input tariffs are statistically-significant within competitive and concentrated industries, respectively, when I cluster at the industry level.

The next two subsections examine within-firm and reallocation effects in more detail, with firm level regressions that allow me to estimate heterogeneous impacts of policies across different types of firms by interacting policy variables with firm characteristics.

4.6.4 Firm-level regressions: Within-firm changes in fuel intensity

In this section I explore within-firm changes in fuel intensity. I first regress log fuel intensity for firm i in state s in industry j in year t for all firms the appear in the panel, first using state, industry, and year fixed effects (Table 4.4 columns 1 and 2) and then using firm and year fixed effects (column 3), my preferred specification, on the four policy variables:

$$\log f_{ijt} = \beta_1 \text{Tariff FG}_{jt-1} + \beta_2 \text{Tariff II}_{jt-1} + \beta_3 \text{FDI}_{jt-1} + \beta_4 \text{Delic}_{jt-1} + \eta_i + \tau_t + \epsilon_{ijt}$$

In the first specification I am looking at the how firms fare relative to other firms in their industry, allowing for a fixed fuel intensity markup associated with each state, and controlling for annual macroeconomic shocks that affect all firms in all states and industries equally. In the second specification I identify parameters based on variation within-firm over time, again controlling for annual shocks.

Table 4.4 shows within-firm fuel intensity increasing with age and decreasing with firm size (output-measure). In the aggregate, fuel intensity improves when input tariffs drop: a 10 pt drop in tariffs lead to 3% reduction in fuel intensity; representing a 12% improvement in fuel efficiency associated with the average 40 pt drop experienced in India's manufacturing industries. Public sector rms are more fuel intensive. More fuel intensive firms are more likely to own generators.

4.6.4.1 Fuel intensity and firm age

I then interact each of the policy variables with an indicator variable representing firm age. I divide the firms into quantiles based on year of initial production. Table 4.12 disaggregates the fuel intensity effect by firm age. The strongest effects of input tariffs on improving fuel efficiency are found in the oldest firms (4.8% and 3% drop in fuel intensity for every 10 pt drop in input tariffs). FDI reform also improves fuel efficiency among the oldest firms: FDI reform is associated with a 4% decrease in within-firm fuel intensity for firms that started production before 1976. Note that the oldest firms were also the most fuel-inefficient firms, so the effect of input tariffs and FDI reform is that older firms that remain active post-liberalization do so in part by improving fuel intensity.

4.6.4.2 Fuel intensity and firm size

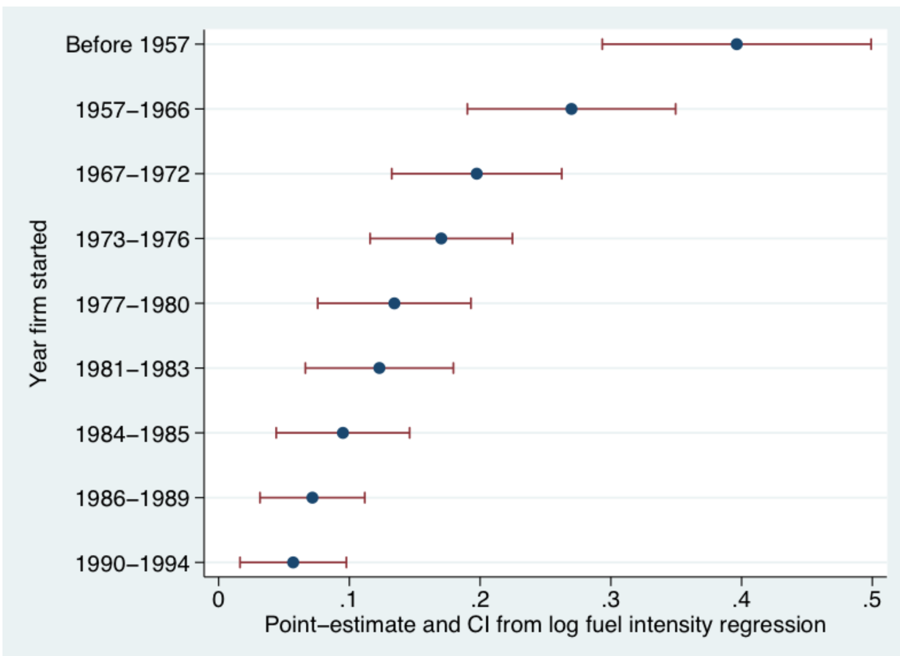
I then interact each policy variable with an indicator variable representing firm size, where size is measured using industry-specic quantiles of average capital stock over the entire period

Table 4.11: Within-firm changes in fuel intensity as a function of policy reforms

Dependent variable: log fuel intensity of output	(1)	(2)	(3)
Final Goods Tariff	.012	.008	-.026
	(.070)	(.068)	(.019)
Industry High Capital Imports:			
Tariff Capital Inputs	.194	.207	.033
	(.100)*	(.099)**	(.058)
Tariff Material Inputs	.553	.568	.271
	(.160)***	(.153)***	(.083)***
Industry Low Capital Imports:			
Tariff Capital Inputs	.119	.135	.037
	(.091)	(.086)	(.037)
Tariff Material Inputs	.487	.482	.290
	(.200)**	(.197)**	(.110)***
FDI Reform	-.018	-.020	-.017
	(.028)	(.027)	(.018)
Delicensed	.048	.050	.007
	(.047)	(.044)	(.022)
Public sector firm		.133	
		(.058)**	
Newly privatized		.043	.010
		(.033)	(.016)
Has generator		.199	
		(.024)***	
Using generator		.075	.026
		(.021)***	(.005)***
Medium size (above median)		-.393	
		(.044)***	
Large size (top 5%)		-.583	
		(.049)***	
Age cohort FE	no	yes	no
Firm FE	no	no	yes
Industry FE, State FE	yes	yes	no
Year FE	yes	yes	yes
Obs.	544260	540923	550585
R^2	.371	.401	.041

Note: Dependent variable is log fuel intensity, where fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Size indicator variables represent top 5% of firms (large) and 50-95% percentile (median) by output within each industry-year. Standard errors clustered at the industry level.

Figure 4.4: Estimated coefficients: effect of age cohort on log fuel intensity



Note: Coefficients on and 95% confidence intervals around the age cohort fixed effects included in the regression with results displayed in Column 2 of Table .

Table 4.12: Within-firm: input tariff decrease and FDI reform improve fuel efficiency in oldest firms

Dependent variable:	Year Firm Entered				
log fuel intensity	Pre 1967	1967-76	1977-83	1984-90	1991-03
Final Goods Tariff	-.049	-.006	-.0004	-.039	.029
	(.035)	(.031)	(.024)	(.028)	(.070)
Industry High K Imports:					
Tariff Capital Inputs	.069	.012	.018	.011	.317
	(.067)	(.047)	(.078)	(.145)	(.198)
Tariff Material Inputs	.291	.231	.290	.257	-.029
	(.097)***	(.092)**	(.102)***	(.123)**	(.184)
Industry Low K Imports:					
Tariff Capital Inputs	.029	.031	.041	.037	.025
	(.047)	(.028)	(.035)	(.084)	(.128)
Tariff Material Inputs	.369	.347	.234	.231	.144
	(.127)***	(.132)***	(.125)*	(.145)	(.140)
FDI Reform	-.051	-.040	-.020	-.001	.045
	(.022)**	(.019)**	(.021)	(.019)	(.016)***
Delicensed	-.005	.034	-.005	.014	-.121
	(.025)	(.022)	(.024)	(.024)	(.088)
Newly privatized	.009				
	(.016)				
Using generator	.025				
	(.005)***				
Firm FE, year FE	yes				
Obs.	547083				
R^2	.042				

Note: Single regression with policy variables interacted with firm age. Dependent variable is log fuel intensity, where fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Entry date from stated year of initial production. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

that the firm is active. Table 4.13 shows the results of this regression. The largest firms have the largest point estimates of the within-firm fuel intensity improvements associated with drops in input tariffs (though the coefficients are not significantly different from one another). In this specification delicensing is seen to lead to a 4% improvement in fuel efficiency among the largest firms and, surprisingly, FDI reform is associated with close a to 4% improvement in fuel efficiency for the smallest firms.

4.6.5 Firm-level regressions: Reallocation of market share

This subsection explores reallocation at the firm level. If the Melitz effect is active in reallocating market share to firms with lower fuel intensity, I would expect to see that decreasing final goods tariffs, FDI reform, and delicensing increase the market share of low fuel efficiency firms and decrease the market share of high fuel efficiency firms. The expected effect of tariffs on firm inputs is less clear: on one hand, a decrease in input tariffs is indicative of lower input costs relative to other countries and hence lower barriers to trade. On the other hand, lower input costs may favor firms that use inputs less efficiently, mitigating the Melitz reallocation effect.

I regress log within-industry market share s_{ijt} for firm i in industry j in year t for all firms that appear in the panel using firm and year fixed effects, with interactions by fuel intensity cohort:

$$\log s_{ijt} = \beta_1 \,\text{FI cohort}_{it} \times \text{Tariff FG}_{jt-1} + \beta_2 \,\text{FI cohort}_{it} \times \text{Tariff II}_{jt-1}$$

$$+\beta_3 \,\text{FI cohort}_{it} \times \text{FDI}_{jt-1} + \beta_4 \,\text{FI cohort}_{it} \times \text{Delic}_{jt-1} + \eta_i + \tau_t + \epsilon_{ijt}$$

The main result is presented in Table 4.14 below. FDI reform and delicensing increase within-industry market share of low fuel intensity firms and decrease market share of high fuel intensity firms. Specifically, FDI reform is associated with a 12% increase in within-industry market share of fuel efficient firms and over 7% decrease in the market share of fuel-inefficient firms. Delicensing has a similar impact on increasing the market share of fuel efficient firms (10% increase) but an even stronger impact on decreasing market share of fuel-inefficient firms: greater than 16% reduction in market share. There is no statistically significant effect of final goods tariffs (though the signs on the coefficient point estimates would support the reallocation hypothesis).

The coefficient on input tariffs, on the other hand, suggests that the primary impact of lower input costs is to allow firms to use inputs inefficiently, not to encourage the adoption of higher quality inputs. The decrease in input tariffs increases the market share of high fuel intensity firms.

Table 4.13: Within-firm: input tariff decrease improves fuel intensity mostly in larger firms

Dependent variable:	Firm Size				
log fuel intensity	Small	Med-small	Medium	Med-large	Large
Final Goods Tariff	.014	-.044	-.023	-.069	-.001
	(.041)	(.031)	(.035)	(.038)*	(.034)
Industry High K Imports:					
Tariff Capital Inputs	.014	.038	-.046	.091	.026
	(.084)	(.067)	(.070)	(.050)*	(.106)
Tariff Material Inputs	.247	.240	.280	.238	.314
	(.094)***	(.101)**	(.091)***	(.092)***	(.105)***
Industry Low K Imports:					
Tariff Capital Inputs	.038	.006	.031	.050	.048
	(.041)	(.045)	(.041)	(.042)	(.058)
Tariff Material Inputs	.222	.306	.272	.283	.318
	(.122)*	(.114)***	(.125)**	(.124)**	(.125)**
FDI Reform	-.035	-.015	-.005	-.009	-.017
	(.021)*	(.020)	(.019)	(.020)	(.021)
Delicensed	.034	.020	.022	.006	-.046
	(.026)	(.023)	(.025)	(.025)	(.025)*
Newly privatized	.010				
	(.015)				
Using generator	.026				
	(.005)***				
Firm FE, year FE	yes				
Obs.	550585				
R^2	.042				

Note: Single regression with policy variables interacted with firm age. Dependent variable is log fuel intensity, where fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Firm size measured as industry-specific quantiles of average capital stock over the entire period that the firm is active. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table 4.14: Reallocation: FDI reform and delicensing increase within-industry market share of low fuel intensity firms and decrease market share of high fuel intensity firms. The decrease in tariffs on materials inputs increases the market share of high fuel intensity firms.

Dependent variable: log within-industry market share		by fuel intensity		
		Low	Avg	High
	(0)	(1)	(1)	(1)
Final Goods Tariff	.011	.004	-.035	.006
	(.054)	(.081)	(.064)	(.055)
Industry High Capital Imports:				
Tariff Capital Inputs	.204	.489	.246	.039
	(.139)	(.313)	(.155)	(.126)
Tariff Material Inputs	-.289	-.236	-.247	-.388
	(.132)**	(.237)	(.138)*	(.130)***
Industry Low Capital Imports:				
Tariff Capital Inputs	-.049	-.113	-.040	.010
	(.045)	(.085)	(.051)	(.067)
Tariff Material Inputs	-.068	.235	.025	-.352
	(.101)	(.167)	(.116)	(.124)***
FDI Reform	.017	.109	.034	-.074
	(.022)	(.028)***	(.025)	(.026)***
Delicensed	-.029	.110	-.011	-.174
	(.040)	(.049)**	(.041)	(.045)***
Newly privatized	-.004	.012		
	(.027)	(.028)		
Firm FE	yes	yes		
Year FE	yes	yes		
Obs.	550584	530882		
R^2	.023	.069		

Note: Dependent variable is log within-industry market share. Column (0) represents a base case with no quantile interactions. Columns labeled (1) represent the result of a second regression where all policy variables are interacted with firm-level fuel intensity indicator variables. Firms are divided into 3 fuel intensity quantiles at the industry-current year level. Fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

4.6.5.1 Fuel intensity and total factor productivity

I then re-run a similar regression with interactions representing both energy use efficiency and TFP. I divide firms into High, Average, and Low TFP quantiles in each industry-year. I then create 9 indicator variables, representing whether a firm is Low Fuel Intensity and High TPF or Average Fuel Intensity and Average TFP, etc. I then regress log within-industry market share on the policy variables interacted with the 9 indictor variables. Table B.7 shows the results. The largest effects of reallocation away from fuel-intensive rms occur when high fuel intensity firms also have low total factor productivity (TFP). This set of regressions supports the hypothesis that the firms that gain and lose the most from reallocation are the ones with lowest and highest overall variable costs, respectively. The effect of FDI reform and delicensing favoring fuel efficient firms and punishing fuel-inefficient ones is concentrated among the firms that also have high and low total factor productivity, respectively. Firms with high total factor productivity and high energy efficiency (low fuel intensity) see 18% and 17% increases in market share with FDI reform and delicensing, respectively. Firms with low total factor productivity and poor energy efficiency (high fuel intensity) see market share losses of close to 18% and 32% with FDI reform and delicensing, respectively. Although firms with average fuel intensity still see positive benefits of FDI reform and delicensing when they have high TFP and lose market share with FDI reform and delicensing when they have low TFP, firms with average levels of TFP see much less effect (hardly any effect of delicensing and much smaller increases in market share associated with FDI reform). Although TFP and energy efficiency are highly correlated, in cases where they are not, this lack of symmetry implies that TFP will have significantly larger impact on determining reallocation than energy efficiency.

Table 4.14 and Table B.7 separate firms into cohorts based on simultaneous values of fuel intensity and total factor productivity. The main rationale for this approach is to include firms that enter after the liberalization. The effect that I observe conflates two types of firms: reallocation of market share to firms that had low fuel intensity pre-liberalization and did little to change it post-liberalization, and reallocation of market share to firms that may have had high fuel-intensity pre-liberalization but took active measures to improve input use efficiency in the years following the liberalization. To attempt to examine the complementarity between technology adoption, within-firm fuel intensity, and changing market share, Table B.8 disaggregates the effect of fuel intensity on market share by annualized level of investment post-liberalization. Low investment represents below industry-median annualized investment post-1991 of rms in industry that make non-zero investments. High investment represents above median. The table shows that low fuel intensity firms that invest significantly post-liberalization see increases in market share with FDI reform and delicensing. High fuel intensity firms that make no investments see the largest reductions in market share. The effect of drop in input tariffs of increasing market share of fuel-inefficient firms is concentrated among firms making large investments. Fuel-efficient firms that don't

Table 4.15: Reallocation: Largest effects of reallocation away from fuel-intensive firms occur when high fuel intensity is correlated with low total factor productivity (TFP)

Dependent variable: log within-industry market share		Fuel Intensity Low	Fuel Intensity Avg	Fuel Intensity High
FDI Reform	Low TFP	-.052	-.073	**-.174**
		(.037)	(.032)**	(.028)***
	Avg TFP	.094	.060	-.002
		(.028)***	(.025)**	(.031)
	High TFP	**.165**	.093	.072
		(.029)***	(.025)***	(.033)**
Delicensed	Low TFP	-.066	**-.147**	**-.334**
		(.055)	(.044)***	(.047)***
	Avg TFP	.093	.009	-.036
		(.051)*	(.042)	(.050)
	High TFP	**.186**	.081	-.006
		(.051)***	(.044)*	(.053)

Note: Full results shown in Table B.7. Firms are categorized into current-year within-industry fuel intensity and TFP quantiles. TFP is estimated via Aw, Chen & Roberts index method.

make investments see decreases in market share as tariffs on inputs drop.

Table 4.16: Reallocation: high fuel intensity firms not making investments lose market share; low fuel intensity firms making investments gain market share; tariff on material inputs again an exception

Dependent variable: log within-industry market share		Fuel Intensity: Low	Avg	High
FDI Reform	No investment	-.080 (.040)**	**-.105** (.035)***	**-.215** (.038)***
	Low investment	.024 (.033)	-.030 (.029)	**-.123** (.030)***
	High investment	**.185** (.025)***	**.125** (.022)***	.032 (.029)
Delicensed	No investment	-.075 (.061)	**-.200** (.047)***	**-.344** (.071)***
	Low investment	.059 (.050)	-.069 (.037)*	**-.263** (.042)***
	High investment	**.282** (.052)***	**.109** (.050)**	-.080 (.068)

Note: Full results shown in Table 4.16. Firms are divided into 3 fuel intensity quantiles at the industry-current year level. Low investment represents below industry-median annualized investment post-1991 of firms in industry that make non-zero investments. High investment represents above median.

4.7 Concluding comments

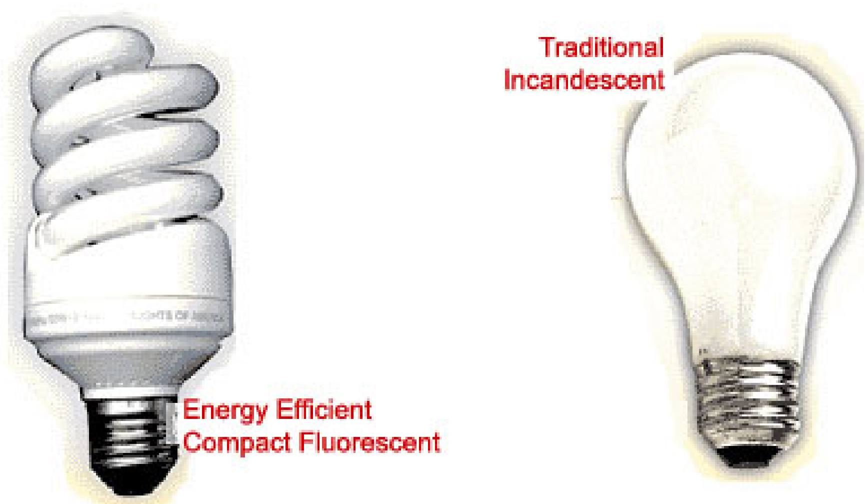
This paper documents evidence that the competition effect of trade liberalization is significant in avoiding emissions by increasing input use efficiency. In India, FDI reform and delicensing led to increase in within-industry market share of fuel efficient firms and decrease in market share of fuel-inefficient firms. Reductions in input tariffs reduced competitive pressure on firms that use inputs inefficiently; all else equal, it led these firms to gain market share.

Although within-industry trends in fuel intensity worsened post-liberalization, there is no evidence that the worsening trend was caused by trade reforms. On the opposite: I see that reductions in input tariffs improved fuel efficiency within firm, primarily among older, larger firms. The effect is seen both in tariffs on capital inputs and tariffs on material inputs, suggesting that technology adoption is only part of the story.

Traditional trade models focus on structural industrial shifts between an economy producing “clean” labor-intensive goods and “dirty” capital-intensive goods. Although I think that the structural shift between goods and services plays a large role, there is just as much variation, if not more, between goods manufactured with “clean” processes vs. “dirty” processes as there is variation across industries. Within-industry, capital acquisition tends to reduce fuel-intensity, not increase it, because of the input savings technologies embedded in new vintages. For rapidly developing countries like India, a more helpful model may be one that distinguishes between firms using primarily old, depreciated capital stock (that may appear to be relatively labor intensive but are actually materials intensive) and firms operating newer, more expensive capital stock that uses all inputs, including fuel, more efficiently.

Appendix A

CFLs



A.1 Background on CFL demand

For most of the last decade CFLs made up approximately 5% of total light bulb sales; by 2006 CFL market share was more than twice as high. Sales in 2007 totaled approximately 290 million bulbs.[1] There are several theories as to what drives demand for CFLs. Consumer information campaigns like the EPA and DOE's ENERGY STAR *Change a Light, Change the World* campaign promote CFLs as a cheap and easy way to be green, that is, to feel and demonstrate to others one's concern for the environment. Consumer subsidies, increased production, and the introduction of large retailer generics have also led to significant price

[1](EPA 2008)

decreases. The low prices may tip the scale for consumers who are comparing upfront purchase costs to a discounted stream of future energy cost savings. A 60-watt equivalent CFL is expected, at current energy prices, to save a user over $50 over the life of the product. Other consumers may purchase CFLs to benefit from needing to change light bulbs less frequently. On the other hand, some dislike CFLs because of the spectrum of the light and poor fit with existing fixtures and dimmers. Some environmentalists worry about the trace amounts of mercury contained in the bulbs and uncertainty about how best to dispose of them if they break.

Given the considerable expenditures on consumer purchase price subsidies for CFLs,[2] it is surprising how little research on consumer demand for CFLs is publicly available. To my knowledge the best available analysis about consumer demand for energy efficient light bulbs are two recent PUC-sponsored Itron and KEMA joint reports: (Pulliam 2006) and (Itron 2007). The 2006 study uses point-of-sale data, but only provides descriptive statistics of trends in prices and sales; the study does not couple volume of sales to prices paid. The 2007 report attempts to estimate individual responses to price, but uses a retrospective stated preference approach. The authors conducted a phone survey of over 2500 California households. The authors summarize their findings as follows:

"The average self-reported price paid for CFLs by 2004/2005 purchasers ranged from $0.25 to $12.00 and averaged $2.50 per bulb. [...] To elucidate whether 2004/2005 CFL purchasers would still have purchased CFLs in absence of this discount, interviewers asked whether they would still have purchased the CFLs if each bulb cost $2.00 more. Nearly half of purchasers said they would have purchased the CFLs for $2.00 more per bulb (46%) while a similar proportion said they would not have purchased the CFLs (44%). These results indicate that a $2.00 discount has some level of influence on the CFL purchasing decisions of approximately 2 out of 5 CFL purchasers."

Unfortunately the Itron 2007 analysis looks at a single threshold price point ($2) and does not associate the level of subsidy with the actual price that the consumers paid. The analysis also suffers from the problems typically encountered in stated preference work: respondents being unable to recall, unwilling to answer in ways that would make them seem un-environmental, and responding without taking into account real world budget constraints.

This paper improves on existing research by using grocery supermarket scanner data with price quantity pairs to estimate demand for CFLs.

[2]In California, for example, PG&E, SCE, and SDG&E all provide manufacturer buydown incentives for lighting measures. In 2004-2005 the three utilities spent $14 million, $11 million and $3 million respectively. Through the program utilities paid manufacturers $1 to $2.50 per bulb (based on wattage) upon receiving retail sales data of ENERGY STAR qualified CFLs from stores in their districts. The state also provided $3 million of direct point-of-sale rebates to selected retailers, and conducted a widespread *Flex-Your-Power* information campaign. (Pulliam 2006)

A.2 MATLAB code for loglikelihood function

```
function ll=loglik(coef);

global NCS NROWS IDDEP VARS

NALT=NROWS/NCS;
v=VARS*coef;
ev=exp(v);
v=reshape(v,NALT,NCS);
ev=reshape(ev,NALT,NCS);
% Making sure to sum only over available alternatives
ev( (ev-1))=0;
denom=log(sum(ev,1));
denom=repmat(denom,NALT,1);
s=reshape(IDDEP, NALT,NCS);
val = s.*(v - denom);
% Negative since neg of ll is minimized
ll=-sum(sum(val));
```

A.3 Hedonic regression

In the Rosen hedonic price model,[3] the hedonic price schedule is the result of equilibrium interactions of consumers and producers. A consumer's decision involves maximizing a utility function that is a function of product attributes interacted with consumer attributes, subject to a budget constraint. First order conditions imply that the marginal price of the characteristic is equal to the marginal rate of substitution between a characteristic and the numeraire good. The observed price schedule is formed by tangencies between consumers' bid and suppliers' offer functions. At each point on the price schedule, the marginal price of a characteristic is equal to an individual's marginal willingness to pay for that characteristic and an individual supplier's marginal cost of producing it.

[3](Rosen 1974)

Table A.1: Determinants of bulb price: advertised prices vs. prices at which sales occurred

	Advertized	Sales-Weighted
	(1)	(2)
CFL	3.683	3.404
	(.006)***	(.010)***
Energy-saving	.769	.627
	(.006)***	(.010)***
Halogen	2.727	2.913
	(.004)***	(.014)***
Enhanced tone	.243	.387
	(.002)***	(.003)***
Generic	-.813	-.482
	(.002)***	(.002)***
Wattage 15	-.164	.055
	(.004)***	(.009)***
Wattage 25	-.160	.052
	(.004)***	(.008)***
Wattage 40	-.571	-.296
	(.003)***	(.004)***
Wattage 75	.252	.096
	(.002)***	(.003)***
Wattage 100	.091	.070
	(.002)***	(.003)***
Wattage 150	.741	1.183
	(.003)***	(.008)***
Wattage 200	-.223	-.012
	(.004)***	(.011)
Wattage 240	2.051	2.112
	(.005)***	(.018)***
Obs.	1098085	629702
R^2	.828	.723

Appendix B

Indian firms and greenhouse gas emissions

B.1 Forming the panel

The ASI data provide unique firm identifiers beginning in 1998. However, it has not previously been possible to track firms prior to 1998, and thus to follow them during the most significant period of reforms. I overcome this challenge by matching individual firms from one year of the survey to the next between 1985 and 1998. I then combine this constructed panel with the pre-formed panel provided by the ASI from 1998-2004.

I construct my panel in three steps. First I pair firms that appear in consecutive years. I search for exact duplicates in Open and Close values between one year and the next (e.g. I look for a match between the Close value in 1985 and the Open value in 1986) in one of the following six variables: stock of raw materials, fuels, and stores; stock of semi-finished goods; stock of finished goods; inventory; loans; and fixed capital. I count the number of digits across all exact matches in Open and Close variables, excluding non-trailing-zero digits, and take every pair of firms that has more than 6 non-trailing-zero digits of exact matches.[1] In the case of conflicting firm matches, I take the pair that matches the largest number of digits over the six variables. On average, matched firms have 24 non-trailing-zero digits in common. I apply this technique from 1985-1994 and from 1996-1998.[2]

Second, I attempt to link firms over 1995, a year for which firm-level data have not been

[1]For example, two firms that report 10000 rupees of fixed capital would match 1 digit for this variable. Two firms that report 10003 rupees of fixed capital are credited for 5 digits. However, two firms that report 10002 and 10003 rupees, respectively, receive no credit (though could be matched based on other variables or in subsequent steps).

[2]As discussed above, I do not construct TFP directly from the firm-level data in 1996 and 1997 given the way in which several inputs were reported in those years. However, I are able to perform the matching procedure using the variables listed above, and I impute TFP for these years as discussed below.

released, and over other years in which individual firms may not have been sampled. In this step, I consider matches within state, 2-digit industry code, and permanent serial number. Though the ASI provides a permanent serial number for each firm, this number is not unique; however, I find that the numbers are consistent across previously matched firms from 1990 onwards. Excluding two periods in which permanent serial numbers also appear to have changed, in all other years permanent serial numbers are equal across known matches more than 90% of the time. I therefore use the permanent serial number along with state and 2-digit industry codes to bridge gap years.

Third, I validate matches by checking the year of initial production, district, ownership, 3-digit industry and growth in labor and fixed capital. [3] For the growth in labor and fixed capital, I use known matches from the first step to establish confidence intervals for subsequent period values as a function of the number of years elapsed between observations. I break each variable into 500-unit increments, and require potential matches in non-adjacent years to fall within a 5th degree polynomial fit of the 10th and 90th percentiles of observed growth in that variable. Based on my analysis of the pre-formed panel, for the year of initial production I allow for variation of up to two years. I accept matches that are exact in state, 2-digit industry, permanent serial number, and either exact year of initial production and at least two other variables, or without year of initial production but with at least five other variables. Conflicting matches are resolved by taking the match with the largest number of successfully matched variables. [4]

Since I observe each firm's year of initial production, I are confident that I can correctly identify survivors and entrants in my panel. However, given the substantial fraction of firms that are not surveyed every year, I are more reserved about my ability to identify exiting firms. The rates of exit that I observe in my panel are significantly higher than the rates that I extrapolate from the observed distribution of years of initial production. Therefore, in estimating productivity, I avoid methods that rely on accurately identifying firm exit, and instead employ an index number method that is robust to potentially spurious exit.

Summary statistics for the panel (to which I do not apply sampling multipliers) are presented in the final column of Table 4.2. Larger firms (those that are in the "census" sector and are surveyed every year) make up more than 60% of the firm-year observations in the panel, 45% of firm-year observations in the full sample of firms, and only 20% of firm-year observations in the estimated population. The panel should not be seen as representative of the population, but rather as a selection of relatively large firms. Nonetheless, the bottom

[3] The mapping of district codes to geographical regions changes frequently over the period of my survey, so I generate a concordance of district codes over time, using existing concordances as well as the changing codes observed in my known panel matches. I thank Pauline Grosjean and Ben Crost for providing us with their district code concordance, which formed a basis for mine.

[4] The pre-formed 1998-2004 panel dataset does not contain similar permanent serial numbers or district identifiers, but I also have an older, cross-sectional dataset, which does have permanent serial numbers and district codes, covering the same years. I merge permanent serial numbers and district identifiers into the pre-formed panel dataset using a sample of common variables.

rows in Table 4.2 show that 71% of firm-year observations that appear in the sample, representing 93% of total deflated output over the entire period and 92% of the labor force, are captured for at least two years in the panel.

B.2 Additional figures and tables

Table B.1: Logit regression to identify likelihood that pre-reform firms would have (1) high TFP and high fuel intensity and (2) low TFP and low fuel intensity

	High TFP and high fuel intensity	Low TFP and low fuel intensity
	(1)	(2)
Year Initial Production (quantile)	-.010	.014
	(.000)***	(.000)***
Capital stock (quantile)	-.006	.006
	(.000)***	(.000)***
Public sector firm	-.007	.028
	(.001)***	(.003)***
Has generator	.012	-.016
	(.001)***	(.002)***
Using generator	.006	-.021
	(.001)***	(.002)***
Obs.	231238	231238

Note: Marginal effects relative to mid-aged, medium-sized private sector firm with no generator. 1985-1990 data. TFP and fuel intensity stratified Low-Average-High with quantiles calculated within industry-year. Year of initial production is stratified across the population into 10 quantiles. Capital stock is stratified within each industry-year into 5 quantiles. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

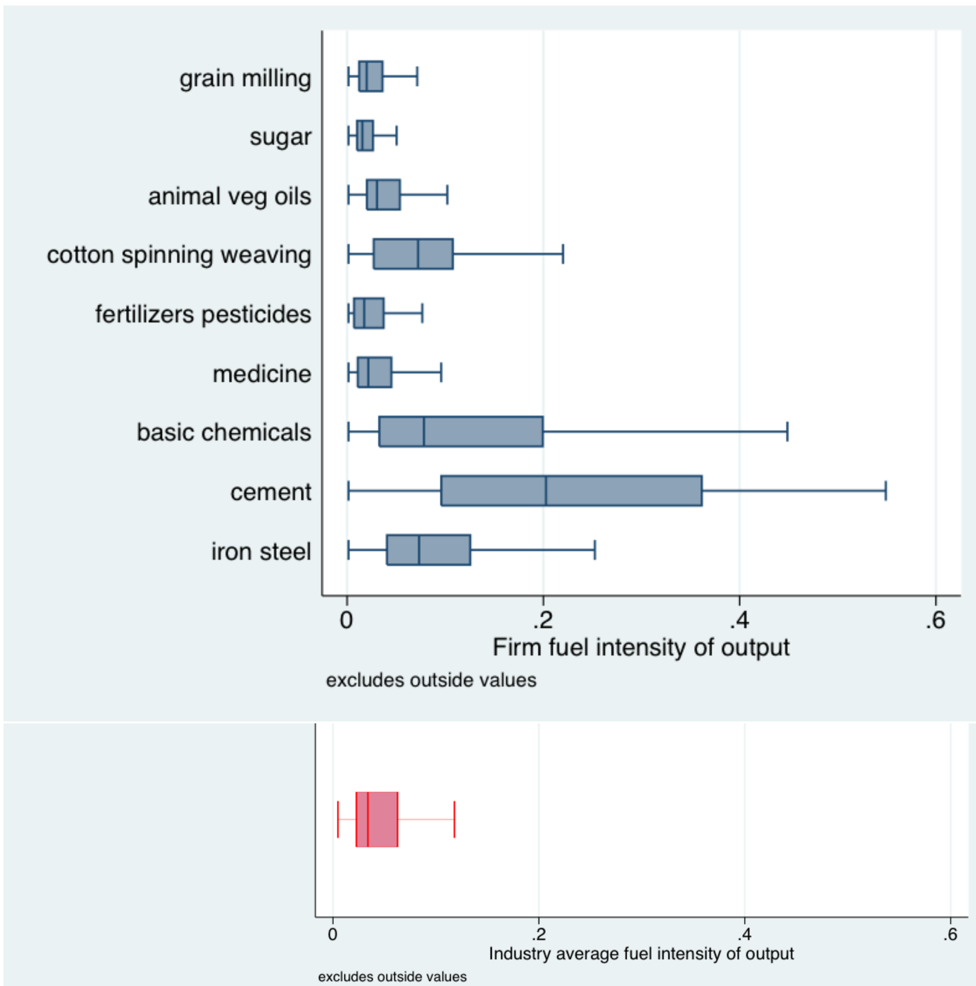


Figure B.1: Comparing variation within industry (above) to variation in averages across industries (below). 1990 data used for both figures. Firm fuel intensity of output shown for 10 largest industries by output, ordered by NIC code.

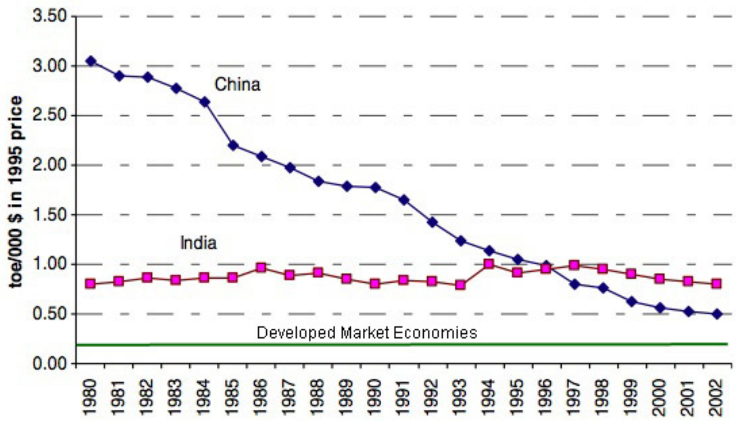


Figure B.2: Energy intensities in the industrial sectors in India and China

Source: IEA 2005: Average energy intensity of output decreased rapidly for China to levels well below India's levels. India's energy intensity of output stayed more or less constant. toe = tons of energy equivalents

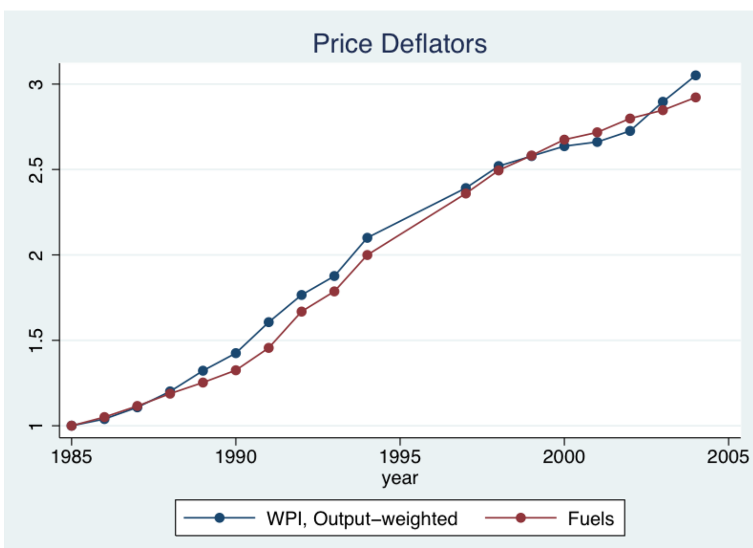
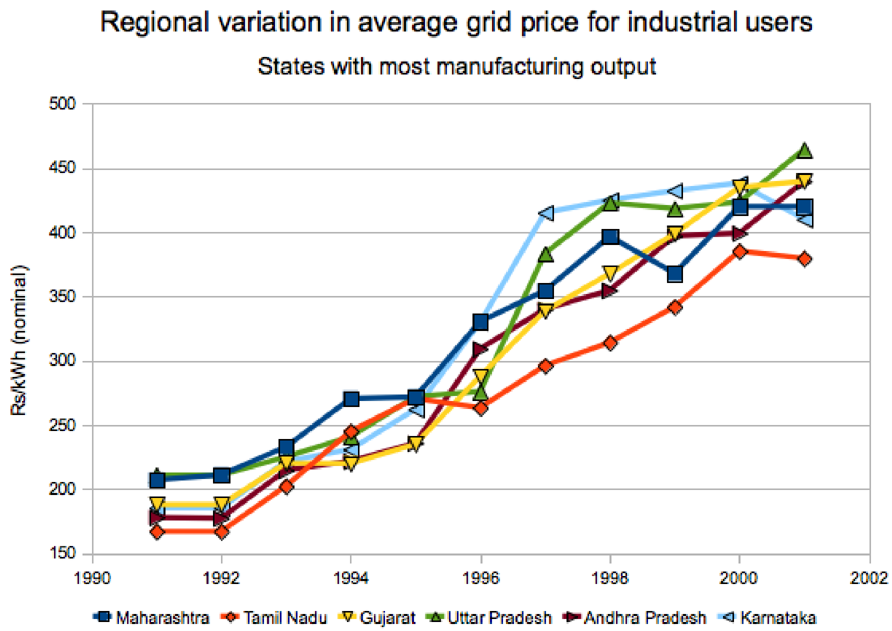


Figure B.3: Output-weighted average price deflators used for output and fuel inputs



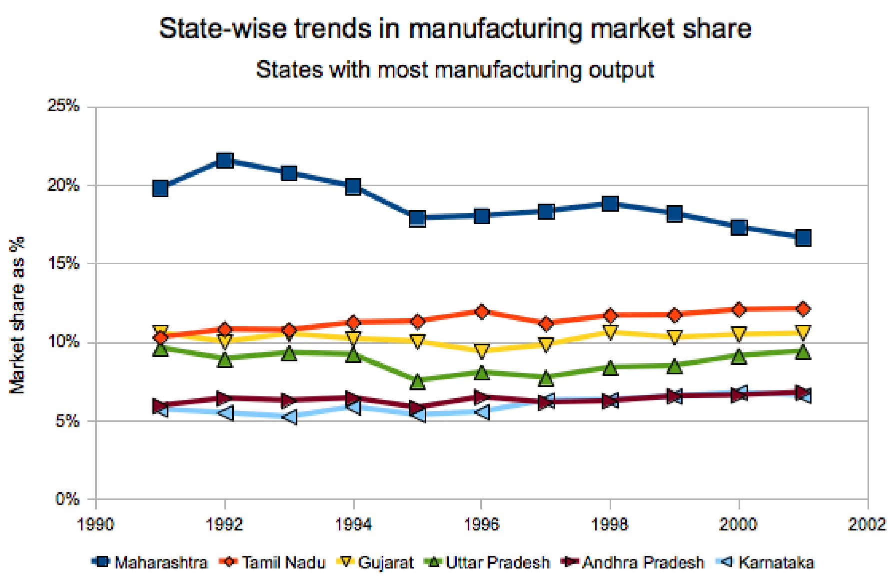


Figure B.4: Regional differences in fuel prices unlikely to be driving results

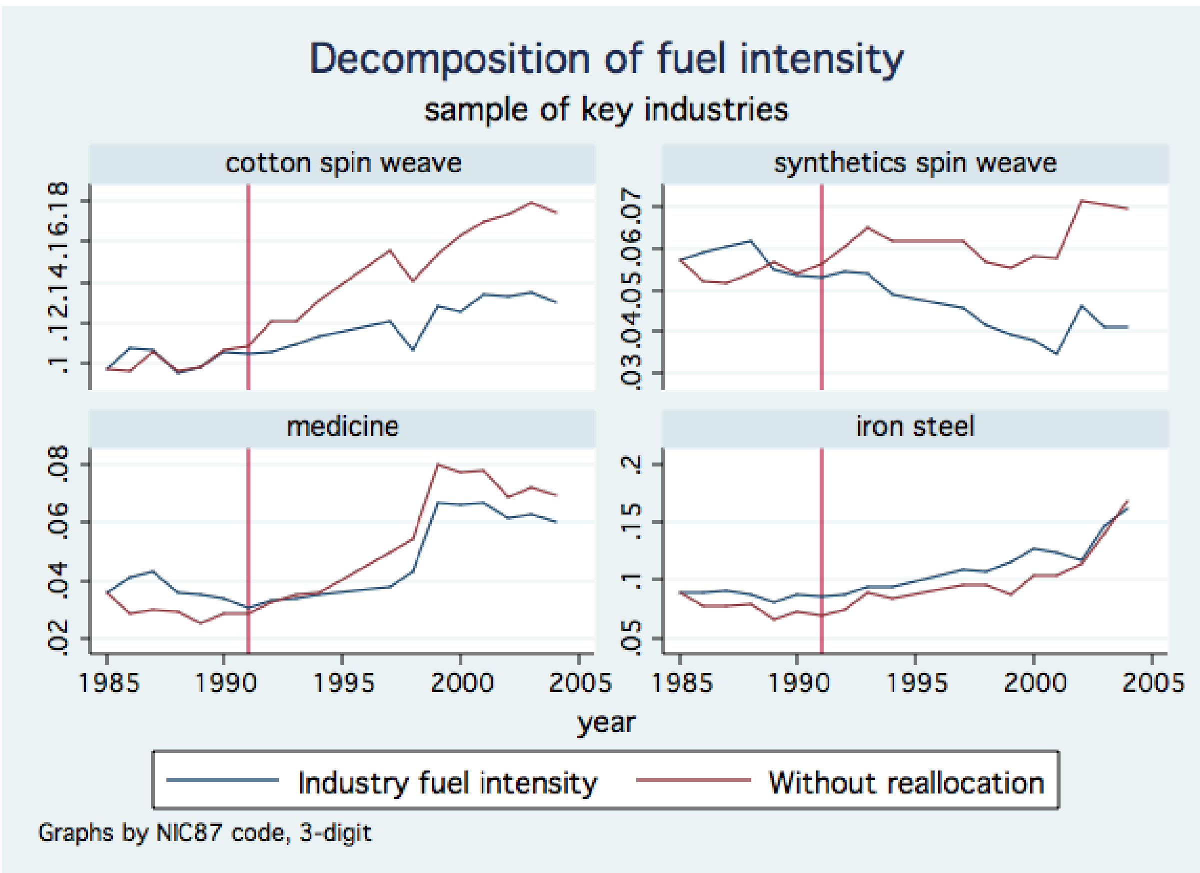

Decomposition of fuel intensity
sample of key industries
cotton spin weave
synthetics spin weave
medicine
iron steel
.1 .12 .14 .16 .18
.03 .04 .05 .06 .07
.02 .04 .06 .08
.05 .1 .15 .2
1985 1990 1995 2000 2005
year
Industry fuel intensity
Without reallocation
Graphs by NIC87 code, 3-digit

Table B.2: Decomposition of aggregate fuel intensity into normalized contributions from within-industry improvements, reallocation within industry, and reallocation across industries

year	Aggregate	Within	Reallocation within	Reallocation across
1985	0.068	0.000	0.000	0.000
1986	0.071	-0.001	0.002	0.002
1987	0.071	0.003	0.002	-0.002
1988	0.067	-0.001	0.003	-0.003
1989	0.065	0.000	0.000	-0.004
1990	0.068	0.004	0.002	-0.007
1991	0.070	0.005	0.000	-0.004
1992	0.070	0.010	-0.003	-0.005
1993	0.069	0.010	-0.003	-0.007
1994	0.067	0.009	-0.003	-0.008
1995				
1996				
1998	0.062	0.012	-0.005	-0.013
1999	0.064	0.015	-0.005	-0.013
2000	0.066	0.020	-0.008	-0.014
2001	0.065	0.020	-0.010	-0.014
2002	0.063	0.019	-0.004	-0.020
2003	0.066	0.023	-0.009	-0.017
2004	0.064	0.018	-0.007	-0.015

Table B.3: Projected CDM emission reductions in India

	Projects	CO2 emission reductions	
		Annual (10^3 tons)	Total (10^6 tons)
Wind power	168	36.03	31.11
Biomass	163	38.18	36.76
Hydro power	76	58.6	17.66
Waste gas/heat utilization	70	76.22	35.54
Energy efficiency	**67**	**74.64**	**12.72**
Cement	17	114.71	16.81
Fuel switching	16	393.47	25.62
Biogas	15	28.33	2.5
Methane avoidance	13	82.5	2.43
HFC reduction/avoidance	7	1577.42	82.71
N2O decomposition	5	406.92	6.14
Other renewable energies	5	20.63	0.41
Afforestation & reforestation	3	25.02	0.64
Methane recovery & utilization	2	94.25	1.17
Transportation	2	32.05	0.28
PFC reduction	1	433.55	1.3
Total	630	80.56	273.78

Source: UNFCCC, as of 31 March 2011, Registered CDM projects: Average annual emissions reductions in thousands of tons of CO2 equivalents. Total Emission Reductions (ERS) by 2012 in millions of tons of CO2 equivalents.

Table B.4: Indicators for industries with most output or fuel use

Industry (NIC87 3-digit)	Fuel intensity of output				Share of output in manufacturing (%)				Greenhouse gas emissions from fuel use (MT CO2)			
	1985	1991	1998	2004	1985	1991	1998	2004	1985	1991	1998	2004
iron steel	0.089	0.085	0.107	0.162	8.4	8.0	5.0	5.3	8.7	12.3	14.2	28.3
cotton spinning & weaving in mills	0.098	0.105	0.107	0.130	6.9	5.2	5.7	4.0	5.2	6.7	10.7	11.6
basic chemicals	0.151	0.142	0.129	0.111	4.4	4.6	3.0	3.1	6.1	9.4	7.9	8.9
fertilizers pesticides	0.152	0.122	0.037	0.056	4.2	2.5	1.5	1.0	7.8	5.7	1.6	1.9
grain milling	0.018	0.024	0.032	0.039	3.6	3.0	3.4	3.7	0.4	0.8	1.7	2.8
synthetic fibers spinning weaving	0.057	0.053	0.042	0.041	3.4	4.3	3.9	4.0	1.6	3.0	3.2	3.9
vacuum pan sugar	0.023	0.019	0.016	0.024	3.0	4.6	3.9	3.0	0.7	1.3	1.4	1.9
medicine	0.036	0.030	0.043	0.060	3.0	4.1	3.5	3.0	0.9	1.6	2.8	4.3
cement	0.266	0.310	0.309	0.299	2.7	3.1	2.2	1.7	12.6	25.9	27.0	24.2
cars	0.032	0.035	0.042	0.034	2.7	2.4	2.6	4.4	0.6	0.9	1.6	2.8
paper	0.193	0.227	0.248	0.243	1.9	1.9	1.3	1.1	5.5	10.1	10.8	10.8
vegetable animal oils	0.019	0.040	0.038	0.032	1.8	3.0	3.5	2.5	0.4	2.2	3.4	2.6
plastics	0.029	0.033	0.040	0.037	1.3	2.2	3.7	5.1	0.2	0.7	2.1	3.3
clay	0.234	0.195	0.201	0.205	0.6	0.7	0.5	1.0	2.7	4.1	4.5	10.7
nonferrous metals	0.049	0.130	0.138	0.188	0.2	1.4	1.2	1.2	0.1	2.3	2.9	5.1

Note: Data for 10 largest industries by output and 10 largest industries by fuel use over 1985-2004. Fuel intensity of output is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Plastics refers to NIC 313, using (Aghion *et al.* 2008) aggregation of NIC codes.

Table B.5: Decomposing input tariff effect into tariff on capital inputs and tariffs on materials inputs

	Fuel Intensity	Within	Reallocation
	(1)	(2)	(3)
Final Goods Tariff	-.012	-.008	-.004
	(.008)	(.006)	(.007)
Industry High Capital Imports:			
Tariff Capital Inputs	.037	.028	.009
	(.014)***	(.015)*	(.011)
Tariff Material Inputs	.022	.039	-.017
	(.010)**	(.013)***	(.009)*
Industy Low Capital Imports:			
Tariff Capital Inputs	.013	.013	-.0008
	(.009)	(.008)*	(.008)
Tariff Material Inputs	.035	.040	-.006
	(.013)***	(.017)**	(.012)
FDI Reform	-.0009	-.00002	-.0008
	(.002)	(.002)	(.002)
Delicensed	-.011	-.001	-.010
	(.005)**	(.004)	(.003)***
Industry FE	yes	yes	yes
Year FE	yes	yes	yes
Obs.	2203	2203	2203
R^2	.107	.315	.171

Note: Dependent variables are industry-level fuel intensity of output, average fuel-intensity within-firm within-industry, and reallocation of market share to more or less productive firms within-industry. Industries are designated "low capital imports" if capital goods represent less than 10% of value of goods imported in 2004, representing 112 out of 145 industries. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table B.6: Effect of liberalization policies on within-industry trends, depending on whether industry is competitive or concentrated pre-reform

	Fuel Intensity (1)	Within Firm (2)	Reallocation (3)
Final Goods Tariff	-.010	-.004	-.006
	(.009)	(.007)	(.007)
Input Tariff	.045	.050	-.005
	(.020)**	(.030)*	(.017)
FDI Reform	.001	.002	-.001
	(.002)	(.003)	(.003)
Delicensed	-.007	.005	-.012
	(.005)	(.005)	(.004)***
Concentrated X Final Goods Tariff	.013	.003	.010
	(.011)	(.009)	(.008)
Concentrated X Input Tariff	-.024	-.008	-.016
	(.018)	(.015)	(.017)
Concentrated X FDI Reform	-.007	-.009	.002
	(.003)**	(.003)***	(.003)
Concentrated X Delicensed	-.006	-.010	.004
	(.006)	(.006)*	(.005)
Obs.	2203	2203	2203
R^2	.096	.306	.173

Note: Dependent variables are industry-level fuel intensity of output, average fuel-intensity within-firm within-industry, and reallocation of market share to more or less productive firms within-industry. Concentrated takes a value of 1 if industry had above median Herfindahl index over 1985-1990 period. Regression restricted to balanced panel of 145 industries. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table B.7: Reallocation: Largest effects of reallocation away from fuel-intensive firms occur when high fuel intensity is correlated with low total factor productivity (TFP)

Dependent variable: log within-industry market share		Fuel Intensity Low	Fuel Intensity Avg	Fuel Intensity High
Low TFP	Final Goods Tariff	-.175 (.097)*	-.175 (.070)**	-.104 (.069)
	Industry High Capital Imports:			
	Tariff Capital Inputs	.455 (.281)	.299 (.142)**	-.029 (.152)
	Tariff Material Inputs	-.298 (.225)	-.345 (.121)***	-.410 (.142)***
	Industry Low Capital Imports:			
	Tariff Capital Inputs	-.168 (.090)*	-.068 (.066)	-.051 (.090)
	Tariff Material Inputs	.144 (.133)	-.031 (.109)	-.455 (.147)***
	FDI Reform	-.052 (.037)	-.073 (.032)**	-.174 (.028)***
	Delicensed	-.066 (.055)	-.147 (.044)***	-.334 (.047)***
Avg TFP	Final Goods Tariff	-.012 (.075)	-.026 (.064)	.075 (.058)
	Industry High Capital Imports:			
	Tariff Capital Inputs	.437 (.332)	.231 (.173)	-.038 (.110)
	Tariff Material Inputs	-.195 (.248)	-.226 (.150)	-.298 (.116)**
	Industry Low Capital Imports:			
	Tariff Capital Inputs	-.087 (.076)	-.027 (.052)	.013 (.056)
	Tariff Material Inputs	.226 (.147)	.045 (.117)	-.264 (.108)**
	FDI Reform	.094 (.028)***	.060 (.025)**	-.002 (.031)
	Delicensed	.093 (.051)*	.009 (.042)	-.036 (.050)

continued next page...

Table B.7 continued...

Dependent variable: log within-industry market share		Fuel Intensity Low	Avg	High
High TFP	Final Goods Tariff	.043	.044	.098
		(.086)	(.072)	(.062)
	Industry High Capital Imports:			
	Tariff Capital Inputs	.620	.237	.172
		(.310)**	(.171)	(.096)*
	Tariff Material Inputs	-.279	-.172	-.326
		(.231)	(.146)	(.112)***
	Industry Low Capital Imports:			
	Tariff Capital Inputs	-.095	-.022	.053
		(.098)	(.058)	(.076)
	Tariff Material Inputs	.324	.081	-.144
		(.187)*	(.128)	(.147)
	FDI Reform	.165	.093	.072
		(.029)***	(.025)***	(.033)**
	Delicensed	.186	.081	-.006
		(.051)***	(.044)*	(.053)
	Newly privatized	.014		
		(.027)		
	Firm FE, Year FE	yes		
Obs.	530882			
R^2	.135			

Note: Dependent variable is log within-industry market share. Firms are categorized into current-year within-industry fuel intensity and TFP quantiles. Fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. TFP is estimated via Aw, Chen & Roberts index method. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table B.8: Reallocation: high fuel intensity firms not making investments lose market share; low fuel intensity firms making investments gain market share

Dependent variable: log within-industry market share		Fuel Intensity Low	Avg	High
No investment	Final Goods Tariff	.042	.037	.045
		(.095)	(.088)	(.113)
	Industry High K Imports:			
	Tariff Capital Inputs	.397	.373	.090
		(.437)	(.254)	(.222)
	Tariff Material Inputs	.094	-.202	-.234
		(.409)	(.273)	(.236)
	Industry Low K Imports:			
	Tariff Capital Inputs	-.183	-.240	-.185
		(.177)	(.112)**	(.110)*
	Tariff Material Inputs	.797	.704	.238
		(.243)***	(.227)***	(.246)
	FDI Reform	-.080	-.105	-.215
		(.040)**	(.035)***	(.038)***
	Delicensed	-.075	-.200	-.344
		(.061)	(.047)***	(.071)***
Low investment	Final Goods Tariff	.083	-.014	.010
		(.080)	(.063)	(.077)
	Industry High K Imports:			
	Tariff Capital Inputs	.530	.309	.214
		(.350)	(.188)	(.174)
	Tariff Material Inputs	-.229	-.220	-.397
		(.237)	(.143)	(.158)**
	Industry Low K Imports:			
	Tariff Capital Inputs	-.220	-.063	.090
		(.119)*	(.069)	(.118)
	Tariff Material Inputs	.477	.234	-.200
		(.219)**	(.159)	(.171)
	FDI Reform	.024	-.030	-.123
		(.033)	(.029)	(.030)***
	Delicensed	.059	-.069	-.263
		(.050)	(.037)*	(.042)***

continued next page...

Table B.8 continued...

Dependent variable: log within-industry market share		Fuel Intensity Low	Avg	High
High investment	Final Goods Tariff	-.103	-.078	-.054
		(.089)	(.080)	(.073)
	Industry High K Imports:			
	Tariff Capital Inputs	.636	.230	.032
		(.352)*	(.171)	(.141)
	Tariff Material Inputs	-.425	-.285	-.400
		(.261)	(.144)**	(.158)**
	Industry Low K Imports:			
	Tariff Capital Inputs	-.123	-.001	.037
		(.089)	(.095)	(.114)
	Tariff Material Inputs	.064	-.229	-.501
		(.127)	(.107)**	(.146)***
	FDI Reform	.185	.125	.032
		(.025)***	(.022)***	(.029)
	Delicensed	.282	.109	-.080
		(.052)***	(.050)**	(.068)
Newly privatized	.018			
	(.026)			
Firm FE, year FE	yes			
Obs.	413759			
R^2	.081			

Note: Dependent variable is log within-industry market share. Firms are divided into 3 fuel intensity quantiles at the industry-current year level. Fuel intensity is measured as the ratio of energy expenditures in 1985 Rs to output revenues in 1985 Rs. Low investment represents below industry-median annualized investment post-1991 of firms in industry that make non-zero investments. High investment represents above median. Standard errors clustered at the industry level. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Table B.9: Industry-state regression: Reducing the tariff on capital inputs, reforming FDI, and delicensing lowers fuel intensity

Dependent variable: industry-state annual fuel intensity (log)	(1)	(2)	(3)	(4)
Final Goods Tariff	.053	-.078	-.187	-.187
	(.107)	(.117)	(.110)*	(.233)
Input Tariff	-1.059			
	(.597)*			
Tariff Capital Inputs		.481	.466	.466
		(.165)***	(.171)***	(.355)
Tariff Materials Inputs		-.370	-.433	-.433
		(.289)	(.276)	(.338)
FDI Reform	-.102	-.091	-.048	-.048
	(.044)**	(.041)**	(.044)	(.061)
Delicensed	-.068	-.090	-.145	-.145
	(.084)	(.083)	(.076)*	(.133)
State-Industry FE	yes	yes	no	no
Industry FE	no	no	yes	yes
Region FE	no	no	yes	yes
Year FE	yes	yes	yes	yes
Cluster at	state-ind	state-ind	state-ind	ind
Obs.	18188	18188	17795	17795
R^2	.253	.254	.507	.507

Note: Dependent variable is industry-level fuel intensity of output. Concentrated takes a value of 1 if industry had above median Herfindahl index over 1985-1990 period. One, two, and three stars represent significance at 10%, 5% and 1% levels, respectively.

Bibliography

(Aghion *et al.* 2008) Philippe Aghion, Robin Burgess, Stephen J. Redding, and Fabrizio Zilibotti. The unequal effects of liberalization: Evidence from dismantling the license raj in india. *American Economic Review*, 98(4):1397–1412, 2008.

(Amiti and Konings 2007) Mary Amiti and Jozef Konings. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *AER*, 97(5):pp. 1611–1638, 2007.

(Ang and Zhang 2000) B.W Ang and FQ Zhang. A survey of index decomposition analysis in energy and environmental studies. *Energy*, 25(12):1149–1176, 2000. Notes paper I received from Meredith Fowlie.

(Arthur 1989) W.B. Arthur. Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, pages 116–131, 1989.

(Bernard *et al.* 2003) Andrew B. Bernard, Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum. Plants and productivity in international trade. *The American Economic Review*, 93(4):pp. 1268–1290, 2003.

(Bustos 2011) Paula Bustos. Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *American Economic Review*, 101(1):304–40, 2011.

(Cai *et al.* 2011) Jing Cai, Ann Harrison, and Justin Lin. The pattern of protection and economic growth: Evidence from chinese cities. working paper, October 2011.

(Chen *et al.* 2008) J. Chen, S. Esteban, and M. Shum. Demand and supply estimation biases due to omission of durability. *Journal of Econometrics*, 147(2):247–257, 2008.

(Copeland and Taylor 2003) B.R. Copeland and M.S. Taylor. *Trade and the Environment*. Princeton Univ. Press, 2003.

(Copeland and Taylor 2004) Brian R. Copeland and M. Scott Taylor. Trade, growth, and the environment. *Journal of Economic Literature*, 42(1):pp. 7–71, 2004.

(de T'Serclaes and Jollands 2007) P. de T'Serclaes and N. Jollands. *Mind the Gap: Quantifying Principal-Agent Problems in Energy Efficiency*. International Energy Agency (IEA), Organization for Economic Cooperation and Development (OECD), 2007.

(Dinar *et al.* 1992) A. Dinar, M.B. Campbell, and D. Zilberman. Adoption of improved irrigation and drainage reduction technologies under limiting environmental conditions. *Environmental and Resource Economics*, 2(4):373–398, 1992.

(EPA 2008) EPA. Epa and doe spread a bright idea: Energy star light bulbs are helping to change the world. yosemite.epa.gov, 2008.

(Farrell and Klemperer 2009) J. Farrell and P. Klemperer. *Coordination and Lock-In: Competition with Switching Costs and Network Effects*, volume 3, chapter 31, pages 1967–2072. Amsterdam: Elsevier, 2009.

(Frankel and Rose 2005) Jeffrey A. Frankel and Andrew K. Rose. Is trade good or bad for the environment? sorting out the causality. *The Review of Economics and Statistics*, 87(1):pp. 85–91, 2005.

(Goldberg *et al.* 2010) P.K. Goldberg, A.K. Khandelwal, N. Pavcnik, and P. Topalova. Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly Journal of Economics*, 125(4):1727, 2010.

(Gordon forthcoming) Brett Gordon. A dynamic model of consumer replacement cycles in the pc processor industry. *Marketing Science*, forthcoming.

(Gowrisankaran and Rysman 2009) Gautam Gowrisankaran and Marc Rysman. Dynamics of consumer demand for new durable goods. *Econometrica*, in revisions, 2009.

(Grossman and Krueger 1991) G.M. Grossman and A.B. Krueger. Environmental impacts of a north american free trade agreement, 1991.

(Harrison *et al.* 2011) Ann E. Harrison, Leslie A. Martin, and Shanthi Nataraj. Learning versus stealing: How important are market-share reallocations to india's productivity growth? Working Paper 16733, National Bureau of Economic Research, January 2011.

(Hassett and Metcalf 1993) K.A. Hassett and G.E. Metcalf. Energy conservation investment. *Energy Policy*, 21(6):710–716, 1993.

(Hausman 1979) J.A. Hausman. Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 10(1):33–54, 1979.

(Hendel and Nevo 2006) I. Hendel and A. Nevo. Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673, 2006.

(Itron 2007) Itron. 2004-2005 statewide residential retrofit single-family energy efficiency rebate evaluation. Technical Report CPUC-ID:1115-04, Itron and KEMA, 2007.

(Jaffe and Stavins 1995) A.B. Jaffe and R.N. Stavins. Dynamic incentives of environmental regulations: The effects of alternative policy instruments on technology diffusion. *Journal of Environmental Economics and Management*, 29(3):43, 1995.

(Jaffe *et al.* 2002) A.B. Jaffe, R.G. Newell, and R.N. Stavins. Environmental policy and technological change. *Environmental and Resource Economics*, 22(1):41–70, 2002.

(Jaffe *et al.* 2005) A.B. Jaffe, R.G. Newell, and R.N. Stavins. A tale of two market failures: Technology and environmental policy. *Ecological Economics*, 54(2):164–174, 2005.

(Kahn 2007) M.E. Kahn. Do greens drive hummers or hybrids? environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management*, 54(2):129–145, 2007.

(Karp 2011) Larry Karp. The environment and trade. *Annual Review of Resource Economics*, 3(1):397–417, 2011.

(Levine *et al.* 1995) MD Levine, JG Koomey, JE McMahon, AH Sanstad, and E. Hirst. Energy efficiency policy and market failures. *Annual Review of Energy and the Environment*, 20(1):535–555, 1995.

(Levinson 2009) Arik Levinson. Technology, international trade, and pollution from us manufacturing. *American Economic Review*, 99(5):2177–92, 2009.

(Levinson 2010) A. Levinson. Offshoring pollution: is the united states increasingly importing polluting goods? *Review of Environmental Economics and Policy*, 4(1):63–83, 2010.

(Linn 2008) J. Linn. Energy prices and the adoption of energy-saving technology. *The Economic Journal*, 118(533):1986–2012, 2008.

(McMillan and Rodrik 2011) Margaret S. McMillan and Dani Rodrik. Globalization, structural change and productivity growth. Working Paper 17143, National Bureau of Economic Research, June 2011.

(Melitz 2003) Marc J. Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725, November 2003.

(Mongia *et al.* 2001) Puran Mongia, Katja Schumacher, and Jayant Sathaye. Policy reforms and productivity growth in india's energy intensive industries. *Energy Policy*, 29(9):715 – 724, 2001.

(Nevo 2000) A. Nevo. A practitioner's guide to estimation of random-coefficients logit models of demand. *Journal of Economics and Management Strategy*, 9(4):513–548, 2000.

(NRC 2010) NRC. *Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use*. The National Academies Press, 2010.

(Pavcnik 2002) Nina Pavcnik. Trade liberalization, exit, and productivity improvements: Evidence from chilean plants. *The Review of Economic Studies*, 69(1):pp. 245–276, 2002.

(Philibert 2006) C. Philibert. Technology penetration and capital stock turnover: Lessons from iea scenario analysis, 2006.

(Popp 2002) D. Popp. Induced innovation and energy prices. *American Economic Review*, pages 160–180, 2002.

(Prince 2009) J.T. Prince. How do households choose quality and time to replacement for a rapidly improving durable good? *International Journal of Industrial Organization*, 27(2):302–311, 2009.

(Pulliam 2006) Richard Pulliam. California residential efficiency market share tracking: Lamps 2005. Technical report, Itron, Inc, 2006.

(Rosen 1974) S. Rosen. Hedonic prices and implicit markets: Product differentiation in pure competition. *The Journal of Political Economy*, 82(1):34–55, 1974.

(Rud 2011) J.P. Rud. Infrastructure regulation and reallocations within industry: Theory and evidence from indian firms. *Journal of Development Economics*, forthcoming, 2011.

(Rust 1987) J. Rust. Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica*, pages 999–1033, 1987.

(Sanstad *et al.* 1995) Alan H Sanstad, Carl Blumstein, and Steven E Stoft. How high are option values in energy-efficiency investments? *Energy Policy*, 23(9):739 – 743, 1995.

(Schiraldi and Street 2008) P. Schiraldi and H. Street. Automobile replacement: a dynamic structural approach. *working paper*, 2008.

(Shafik and Bandyopadhyay 1992) N. Shafik and S. Bandyopadhyay. Economic growth and environmental quality: time series and cross section evidence. *World Bank Policy Research Working Paper WPS 904. Washington, DC: The World Bank*, 1992.

(Sivadasan 2009) J. Sivadasan. Barriers to competition and productivity: evidence from india. *The BE Journal of Economic Analysis & Policy*, 9(1):42, 2009.

(Sunding and Zilberman 2001) D. Sunding and D. Zilberman. The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbooks in Economics*, 18(1A):207–262, 2001.

(Suri and Chapman 1998) V. Suri and D. Chapman. Economic growth, trade and energy: implications for the environmental kuznets curve. *Ecological Economics*, 25(2):195–208, 1998.

(Topalova and Khandelwal 2011) P. Topalova and A. Khandelwal. Trade liberalization and firm productivity: The case of india. *The Review of Economics and Statistics*, 93(3):995–1009, 2011.

(Train 1985) K. Train. Discount rates in consumers' energy-related decisions: A review of the literature. *Energy*, 10(12):1243–1253, 1985.

(Train 2003) K.E. Train. *Discrete Choice Methods with Simulation*. Cambridge University Press, 2003.

(Unruh 2000) G.C. Unruh. Understanding carbon lock-in. *Energy Policy*, 28(12):817–830, 2000.

(Villas-Boas and Winer 1999) J.M. Villas-Boas and R.S. Winer. Endogeneity in brand choice models. *Management Science*, 45(10):1324–1338, 1999.