ESSAYS ON ENVIRONMENTAL AND ENERGY ECONOMICS

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Dedication page

To my wife, Nancy, and my daughter, Anya, for their unwavering support, patience and encouragement over the years.

To God be the glory.

Abstract

This dissertation applies techniques from the expanding field of econometrics to the study of contemporary issues in environmental and resource economics. Three essays are offered that aim to generate meaningful policy implications through econometric analyses of the voluminous data recently becoming available to researchers. The first essay examines how overall price, quality and welfare changed as energy efficiency standards in the US became progressively more stringent between 2001-2011. A novel index-the Constant Quality Price Index (CQPI)-is developed to delineate changes in overall price and quality. Results obtained using point-of-sale data from individual clothes washers sold in the US during the period suggest that standards on washing machines have had at worst a negligible effect on consumer welfare, or at best lowered prices and improved quality for washers. The second essay analyzes the relationship between foreign acquisition and aspects of plant-level environmental performance using micro data from the Indonesian Census of Manufacturing. To establish a causal effect of ownership change, a difference-in-differences approach is combined with coarsened exact matching. A total of 264 acquisition cases between 1983-2001 are considered, where an acquired plant is observed at least a year before and three years after undergoing a change in ownership, and for which a carefully selected control plant exists. Results suggest that FDIs can have positive scale and technique effects on the environmental performance of acquired plants. These effects are especially pronounced for small firms and firms that were relatively inefficient prior to acquisition. The third essay analyzes the impact of oil price shocks on the US economy at the individual state level. The study accounts for the endogeneity of changes in crude oil price, differences among states, and spillover effects with neigh-

boring states. Results suggest that the implications of higher oil prices for a state's economic growth depend on the underlying cause of the oil price change and a state's average production of oil relative to its average consumption. The direct effect of oil price shocks can be either magnified or tempered by spillover effects, which may also explain why regional recessions may occur with certain oil price shocks.

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Chapter 1

Do Standards Hurt Consumers? Evidence from a Substantial Share of Household Appliance Sales[1]

1.1 Introduction

How do energy efficiency standards influence consumer welfare? With perfectly competitive markets and rational consumers, the standard economic model implies that standards make regulated durable goods more expensive or of lower perceived quality, which would imply harm to consumers, excluding possible external benefits from reduced pollution externalities. In reality, however, markets are imperfect and consumers may choose poorly, especially with regard to product attributes with intangible future benefits, like energy efficiency. As a result, it is difficult to determine how standards ultimately influence consumer welfare, even in the absence of external benefits.

From a regulatory perspective, it is important to consider consumer welfare implications of standards, for these are typically obscured in engineering-based estimates of costs and benefits. And though standards are not typically advocated by

[1]This essay is a result of a collaboration with Michael Roberts.

economists, who tend to favor pricing of externalities, standards for vehicle, building and appliance efficiencies are thought to be more politically feasible than Pigouvian taxes or cap-and-trade, which likely explains their prominence since oil embargo and associated price spikes in the 1970s. In recent years, the Obama administration has pushed to make some of these standards considerably more stringent, presumably because stricter standards can be implemented under existing law, making it a potentially feasible means of reducing greenhouse gas emissions and other pollutants.

Many also see energy efficiency as perhaps the lowest-cost way to reduce greenhouse gas emissions. For example, the widely-cited report by McKinsey & Company (Nauclér and Enkvist 2009) estimates that the cost of abating about a third of global GHG emissions is *negative*. LED lightbulbs, more fuel-efficient car engines, more energy-efficient appliances, and better-insulated buildings are just a few of these technologies. Based on these engineering-based estimates, which some may justifiably question (Allcott and Greenstone 2012), it appears as though, to a significant extent, reducing pollution and slowing climate change is a free lunch. The implicit cost not accounted for in these studies pertains to intangible product characteristics that consumers may value, but that engineering-based benefit-cost estimates cannot account.

Aside from externalities, standards may be justified, at least in part, by behavioral anomalies that inhibit people from taking full advantage of potential efficiency gains. The conundrum over consumers' apparent excess discounting of future energy savings dates back to early hedonic modeling (Hausman 1979) and consumer choice studies that relate purchase decisions to product prices, energy efficiency, and other product attributes (Train 1985). The phenomenon has been called the *energy paradox* (Jaffe and Stavins 1994b) or the *energy efficiency gap* (Jaffe and Stavins 1994a). Economists typically explain this phenomenon by pointing to information problems, bounded-rational behavior and/or internalities. The energy-efficiency component of a durable good purchase is typically small, so a boundedly-rational consumer will focus more on the observable and salient characteristics of the product, and less on energy efficiency (Allcott et al. 2014). There is also the *landlord-tenant* agency problem, in which imperfectly-informed renters may not be willing to pay more for

energy-efficient apartments, thus reducing the incentive for landlords to invest in energy efficiency (Davis 2011). Others point out that various search costs and high borrowing costs might explain why an energy efficiency gap exists (Parry et al. 2014).

Even if we accept that the energy efficiency gap reflects a market failure, as not all scholars are convinced that the gap is large and important (see, for example,Hassett and Metcalf 1993; Sallee et al. 2010; Allcott and Greenstone 2012; Busse et al. 2013; Allcott and Wozny 2014; Grigolon et al. 2014), existence of the gap itself does not necessarily imply that efficiency standards are an efficient means of correcting it. More pragmatic questions pertain to the consequences of the standards themselves, like how costly they are to businesses and consumers, how strict they ought to be if already selected as a policy tool, and whether and to what extent standards actually reduce energy consumption. Some have investigated the impact of more stringent standards in the context of markets with quality differentiated goods (see for example, Ronnen (1991); Crampes and Hollander (1995); and Valletti (2000)). A number of empirical studies looking at this issue can be found in the automobile market (Goldberg 1998; Jacobsen 2013; Sallee 2013). For household appliances, Chen et al. (2013) and Spurlock (2013) provided empirical evidence showing the correlation between imposing energy efficiency standards and, surprisingly, *declining prices* of durable goods. However, the mechanism through which these standards influence price, as well as broader quality and welfare effects, remain unclear.

In this study, we follow this later literature, evaluating how more stringent energy efficiency standards affect price and quality of clothes washers using panel, point-of sale data for a near population of models. We particularly exploit the relatively frequent changes in the minimum energy efficiency standard that uniquely occurred in the clothes washer market within the sample period. We also consider changes to the Energy Star® thresholds for washers, refrigerators and room air-conditioners. The timing of the policy changes differed somewhat across these appliances, which our empirical approach leverages. We add to existing literature in three ways: (1) by disentangling quality changes from price changes; (2) by developing a consumer welfare measure that accounts for changes in prices and qualities, and linking these changes to policy changes; and (3) by considering a mechanism through which energy

efficiency standards influence price, quality, and consumer welfare.

The first two contributions are anchored on formulating a Constant Quality Price Index (CQPI). Given unobserved heterogeneity of washer models sold over time, CQPI provides a more accurate measure of price changes by considering only continuing models that were sold across multiple periods. Given an index for constant-quality prices, and assuming prices increase monotonically with quality *within* a time period, we develop a quality index linked to the difference between average price and the CQPI. Changes in the CQPI implicitly account for changes in the price of quality, which facilitates estimates of the total welfare change under local (between-period) quasi-linear utility. We then examine how price, quality and total welfare change with changes in the federal minimum energy efficiency (ME) standards and Energy Star (ES) thresholds for clothes washers.

We find no evidence that more stringent standards increase prices. Rather, we find evidnece that price declines and quality improvements accelerate with stricter standards, which unambiguously improves consumer welfare, excluding external pollution-related benefits.[2] Finally, we show evidence that policy-induced changes in price, quality and welfare are connected to entry and exit of models. Specifically, we find that price changes are more closely connected to own-manufacturer product introductions (cannibalism) as opposed to entry and exit of models by competing manufacturers, findings that suggest an innovation channel rather than a competition channel for price and quality improvements.

1.2 Policy Background

The United States began regulating appliance energy efficiency with the passage of the National Appliance Energy Conservation Act (NAECA) in 1987. The law established the initial minimum energy efficiency standard for a set of appliances sold in the US and directed the Department of Energy (DOE) to periodically update

[2]Houde and Spurlock (2015) used revealed preference approach that allowed them to calculate a price-adjusted quality index. Surprisingly, our simple and transparent methodology generates similar results indicating that our findings are robust to different empirical approaches.

the standards. Subsequent legislations, such as the Energy Policy Act (EPAct) of 1992, the EPAct of 2005 and the Energy Independence and Security Act (EISA) of 2007, included additional products. Stipulations from these laws were agreed upon by manufacturers and energy efficiency advocates (Gold et al. 2011). In 2014, the DOE reported that more than 50 products representing about 90 percent of household energy use are covered under federal standards.

Clothes washers were one of the appliances that were subjected to minimum energy efficiency standards under the 1987 NAECA. The first standard took effect in 1988. DOE updated the standard in 1990 and implemented it in 1994. In 2001, DOE adopted a new standard that was implemented into two phases. The first phase revised the basis for the energy minimum efficiency standard from the traditional energy factor (EF) to the modified energy factor (MEF). While both are measured in terms of cubic feet per kilowatt-hour (kWh) cycle, the MEF includes energy required for drying. Washers with faster spin cycles remove more moisture before drying, thereby saving energy. The higher the EF or the MEF, the more efficient the product. The second phase increased the MEF by more than 20 percent from its 2004 level. In 2007, DOE updated the standard to include a maximum water factor (WF) requirement. WF measures the ratio of the quantity of water used in one cycle to the capacity of the washer. A lower WF increases MEF, mainly to account for energy saved from heating water. The updated standard was implemented in 2011.

Although DOE has the authority to impose regulations governing energy efficiency for many categories of appliances and equipment used in homes, businesses and other applications, each proposed rule must undergo a roughly three-year process of review, including a thorough consideration of impacts to consumers and businesses (US Department of Energy).[3] Evaluation of benefits and costs typically invovle engineering-based estimates. These consider the cost of specific energy-saving technologies that can be used to satisfy proposed standards as well the discounted value of energy-related savings. A common complaint is that these explicit costs and benefits do not account for intangible benefits and costs connected to the way consumers

[3]see http://energy.gov/eere/buildings/process-rule for details.

perceive and value altered product characteristics. More energy efficienty appliances may not perform as well or as desired as the less efficient appliances. By their nature, such benefits and costs are difficult to ascertain and likely impossible to evaluate before proposed standards have been implemented. In this paper we therefore develop methods to evaluate the *ex-post* net benefits of intangible consumer-related welfare impacts.

Clothes washers are also part of the Energy Star (ES) program. ES is a voluntary program that identifies and promotes energy efficiency through labeling of products that exceed minimum standards by a certain threshold. In 2001, ES certification adopted MEF as a measure of energy efficiency. The threshold was updated in 2004, increasing the required MEF level from 1.26 to 1.42. In 2007, DOE increased MEF level another 21 percent and also included the water factor (WF). In July 2009, certification requirement increased the ES threshold efficiency by 5 percent and reduced WF by more than 6 percent. In March 2008, the Department of Energy updated the July 2009 standard with additional requirements that went into effect in January 2011. The 2011 threshold improves the energy and water efficiency level by an additional 10 and 20 percent over 2009 levels, respectively. Table (1.1) summarizes the minimum energy efficiency and Energy Star standards adopted and implemented between 1991 and 2011.

1.3 Data

We use point-of-sale data for clothes washers, clothes dryers, room air conditioners, and refrigerators from the NPD Group, purchased by Lawrence Berkeley National Laboratory. The data were collected from a set of US retailers and are aggregated at the national level.[4] The data contain monthly total revenue and total quantity sold by individual model number from January 2001 to December 2011.[5] We calculated

[4]NPD group was unable to provide subnational aggregations.

[5]Our model identification is based on brand model number, which includes brand name and detailed product attributes including colors. This is distinct from SKU number, which are codes only relevant to stores using it to manage inventory.

Table 1.1: US Energy Efficiency Standards for Residential Clothes Washers, 1991-2011.

Date Adopted	Date Effective	Federal Minimum Standard	Energy Star Standard
1991	1994	EF $\geq$ 1.18	-
1997	2001	-	MEF $\geq$ 1.26
2001	2004	MEF $\geq$ 1.04	MEF $\geq$ 1.42
2001	2007	MEF $\geq$ 1.26	MEF $\geq$ 1.72
		-	WF $\leq$ 8.0
2009	2009	-	MEF $\geq$ 1.8
		-	WF $\leq$ 7.5
2007	2011	MEF $\geq$ 1.26	MEF $\geq$ 2.0
		WF $\leq$9.5	WF $\leq$ 6.0

Standards for washers are set based on the Modified Energy Factor (MEF), the Energy Factor (EF) and the Water Factor (EF). The Department of Energy defines (i) MEF as the ratio of the capacity of the washer to the energy used in one cycle; (ii) EF as the MEF excluding the energy for drying clothes; and (iii) WF as the quantity of water used in one cycle per unit capacity of the washer. The table does not include standards adopted and implemented for non-residential and compact (capacity less than 1.6 cubic feet) type of clothes washers.

Source: Department of Energy

the unit price by dividing total revenue by total units sold in each month. We can interpret this price variable as average revenue, which includes in-store discounts for an individual clothes washer, but not mail-in rebates. To check how our price variable represents the actual selling price of individual clothes washer, we randomly selected 30 models. We verified the manufacturer's suggested retail price (MSRP) of these models online and find that our price variable is 20 percent less on average, which seems reasonable given the time since NPD collected the data and the inclusion of in-store discounts.

We drop observations with prices falling below $100, as these observations are outliers and appear unrealistic. Remaining models comprise 99.9 percent of total revenue. About 35 percent of the observations have masked model numbers to preserve the anonymity of NPD Group's partner retailers. NPD assigned these models alternative codes, but it is possible that the models may in fact be the same as others in the data set. Because these masked model numbers may not be new when each is first observed in the data, we compute separate statistics with and without masked models to check the robustness of our findings.[6] Summary statistics are reported in Table (1.2).

1.4 Appliance Price and Quality Trends

We calculate average price by simply dividing total revenue in each month by total units sold (panel (a) of Figure 1.1). The trend is slightly up from 2001 through 2006, then falls slightly through 2008, and then rises again through 2010, and then falls sharply in the latter part of the data. These changes in average price include changes in the mix of models sold as well as quality changes, as models enter and exit the marketplace. Changes in mix and overall quality may be driven by technological advance, income growth or decline, standards, or other factors affecting demand, production costs, or competition.

To measure how prices for a fixed quality of washers has changed over time, we

[6]See Appendix B for the results of the robustness check.

Table 1.2: Summary Statistics

	Baseline Data	No Masked Models
	(1)	(2)
Price ($)	650.55	700.09
	(355.92)	(348.89)
Sales (units)	744.00	872.30
	(1,908.47)	(2,007.55)
Revenue ('000$)	382.40	481.45
	(966.37)	(111.02)
Share of Front Loaders	38.90	42.85
Share of Energy Star Qualified	48.53	44.28
No. of models	2,733	1,245
Observations	38,504	24,838

The table shows the monthly average price, sales and revenues generated between 2001 and 2011 for the sampled clothes washers for each of the dataset: (1) Baseline Data treats all model numbers (including masked) as unique models, and (2) No Masked drops the masked models. Standard deviations are in parentheses. Observations with prices falling below $100 were dropped as these observations are outliers and appear to be unrealistic.

Source: The NPD Group

construct a price index that holds quality constant. We call this index the constant quality price index or CQPI. The CQPI is based on the percentage changes in price, p_{it}, of a specific model i for two consecutive time periods within its shelf life, weighted by average units sold, q_{it}, in these periods. In cases where a model's lifetime overlaps with another, we take the average price change of these models and weight it by units sold (see equation 1.1). The index explicitly excludes new models and exiting models because these differences over time cannot be calculated. Panel (b) of Figure 1.1 shows the trend of the constructed monthly CQPI between 2001 and 2011. Holding quality constant, the price of an average clothes washer goes down, even in the presence of policy changes as illustrated by the solid vertical lines. Quality-adjusted price declines at an average of 0.9 percent each month, which translates to an annualized deflation of about 11.23 percent.

$$\text{CQPI}_t = \text{CQPI}_{t-1}\left(1 + \frac{2\sum_i W_{it}\left(\frac{p_{it}-p_{it-1}}{p_{it}+p_{it-1}}\right)}{\sum_i W_{it}}\right),\ \forall t > 0 \tag{1.1}$$

where

$$\text{CQPI}_0 = \frac{\sum_i q_{i0}p_{i0}}{\sum_i q_{i0}}$$

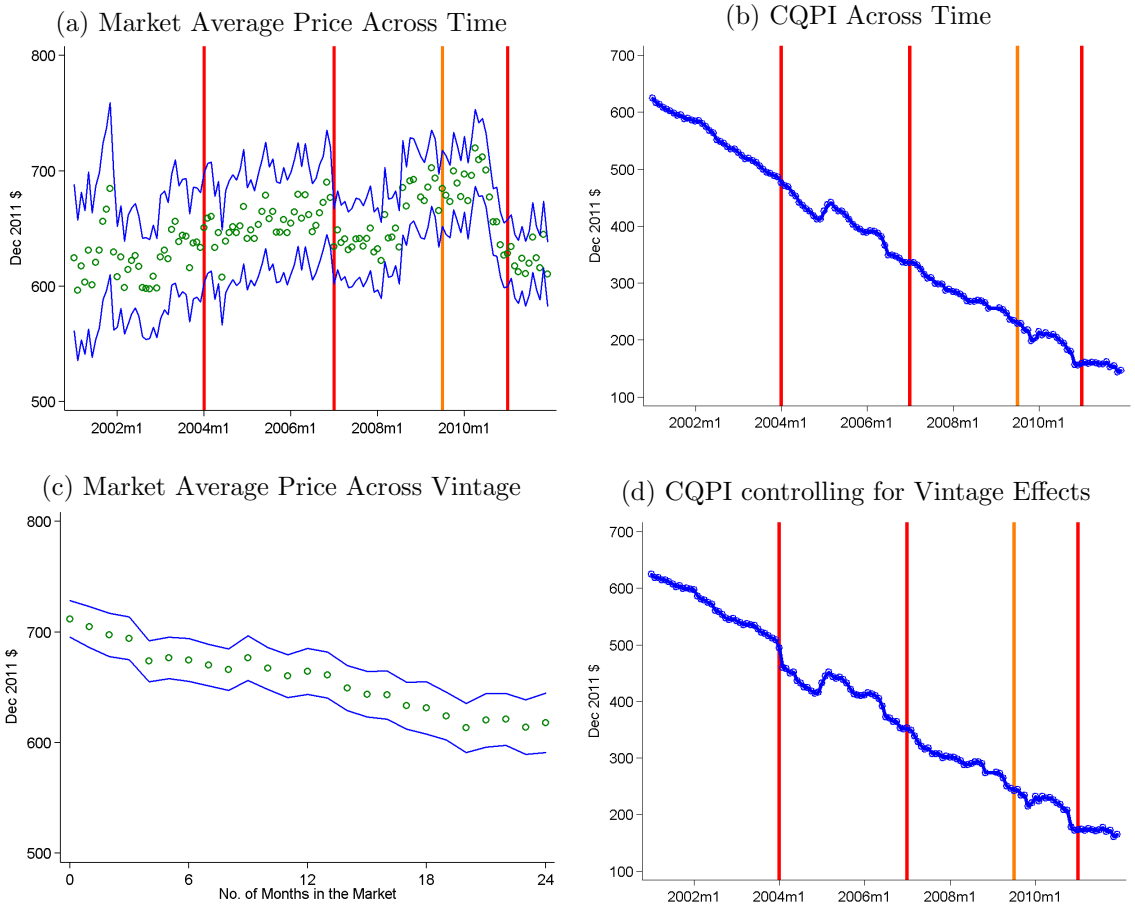
and

$$W_{it} = \frac{q_{it} + q_{it-1}}{2}, \forall i \text{ that exist in } t \ \& \ t-1.$$

One concern about the CQPI is that model weights are endogenous. Consumers may substitute toward products with larger price declines, causing a bias in the overall trend. If we weight price changes by the initial period of the difference, the bias would most likely be positive, as models discounted in the initial period would presumably rise in price and be weighted more heavily. Conversely, if we were to weight by the second period then models discounted in the second period would presumably see a larger price decline while sales increased, biasing the overall trend downward. We therefore weight the two periods equally. Note, however, that weighting by the initial or second period sales has no noticeable influence on the CQPI. Appendix A.6 reports these alternative constructions.

Panel (c) shows that average price of clothes washers declines across the product's vintage (months since first introduction). Clothes washers appear to have lower prices as the product ages, typically declining by more than 10 percent after a year. The trend of high introductory price and declining price as product ages can be due to several factors. Through learning-by-doing, the firm's costs may decline over time. Alternatively, firms may need to lower prices as newer competition products are introduced. Relatedly, firms may use intertemporal price discrimination to extract rents from consumers with different demands for the latest technology (Stokey 1979). This kind of price discrimination may be more acute for goods with status or fashion

Figure 1.1: Market Average Price and CQPI Trends



Panel (a) shows sales-weighted average prices and 95 percent confidence band in blue. Panel (b) shows the constant quality price index (CQPI). Panel (c) shows average price in relation to product vintage, defined as months since the model number first appeared in the data. Panel (d) shows the CQPI adjusted for product vintage, estimated from a fixed effects regression model. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold change that took effect in July 2009. All prices are in December 2011 US dollars.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); CQPI (Authors' calculation).

values, like cars or perhaps more visible appliances like refrigerators (Stamminger et al. 2005). Intertemporal price discrimination can occur if there is sufficiently rapid

technological advance, so that the latest models have sufficiently higher quality than earlier vintages, and different buyers have different willingness to pay for quality. And if the user value of having the appliance in a timely manner is sufficiently high, as is likely the case with clothes washers, it's easy to see why many buyers would be unwilling to wait for price to fall or quality to rise.

Unless declining production costs explain the price pattern with respect to vintage, which seems unlikely given the magnitude, the pattern itself suggests competition is imperfect. Presumably imperfectly competitive firms would strategically time product entry, staggering introduction of new products so as to maximize potential novelty. Although we don't attempt to model it formally, we expect that, in the absence of policy or other interventions, equilibrium product introductions would be spread out over time, akin to spatial models of product diversification in monopolistic competition. Many kinds of events could disrupt equilibrium timing of product entry. Because prices are influenced by vintage, and via competition are likely connected to vintages of competing models, it is plausible that changes in standards may affect pricing patterns via the rate and timing of product introductions. We return to this issue below.

For now we focus on how vintage influences CQPI. If product entries were uniform over time, the distribution of product vintages would be constant, and CQPI would be unaffected. If the distribution of vintages shifts lower or higher, this would decelerate or accelerate the decline in the CQPI, respectively. The data show this distribution does in fact shift periodically. We control for this effect by estimating a regression of model prices against vintage fixed effects, model fixed effects, and time fixed effects. The model is:

$$p_{it} = \alpha_i + v_k + \gamma_t + \varepsilon_{it}, \tag{1.2}$$

where p_{it} denotes the price of model i at time t, α_i is a model fixed effect, v_k is vintage fixed effect for vintages $k \in \{2, ..99\}$ representing periods since first introduction, γ_t is a time period fixed effect, and ε_{it} is the error. Because the CQPI excludes entering and exiting models, the regression also excludes them, so vintage

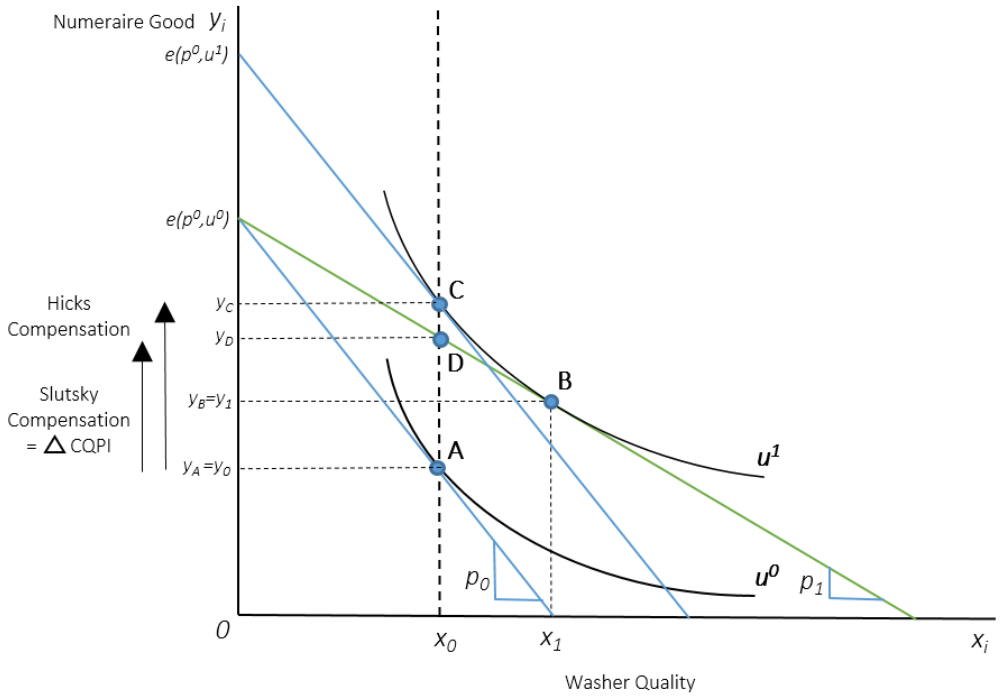
starts with a value of two instead of one. To adjust the CQPI for vintage effects, we take the sales-weighted average of the vintage fixed effect in each time period and deduct it from the CQPI. Panel (d) in Figure 1.1 shows the CQPI adjusted for the product's vintage fixed effect. While the trend generally exhibits a downward sloping pattern similar to the unadjusted CQPI, it is somewhat less smooth. Of particular interest in this figure is the visible discontinuous drop in the price of clothes washers around the policy change in the beginning of 2004. This is intuitive since, as we show below, the policy change may have induced most manufacturers to introduce new models at the same time in January 2004, which makes the effect of vintage-effect adjustment on price relatively more significant than in other periods. We discuss this in detail in succeeding sections.

1.5 Welfare Implications of the Price Change

Consumer welfare impacts are influenced by both price and quality changes. In this section we develop a simple framework that estimates the total welfare impact of these changes, assuming the *quantity* of appliances sold is unaffected by price and quality changes. Thus, we evaluate welfare effects of the quality decision. Higher quality appliances are more expensive and the price of quality is relative. Income not spent on appliance quality can be spent on other goods and services. As appliance prices fall, the budget constraint pivots out, allowing the consumer to buy a higher quality appliance while spending less (Figure 1.2). The figure shows standard constrained consumer choice, with appliance quality on the horizontal axis and the numeraire (real dollars) on the vertical axis. As appliance prices fall, the consumer's choice moves from point A to point B on the graph.

We estimate welfare changes using standard Hicksian compensation—the income needed to achieve utility u_1 had prices not fallen, represented by the vertical distance between point A to point C in Figure 1.2, which we denote ΔW. We can estimate the welfare improvement by assuming a quasi-linear form for a representative consumer's utility function u. Given total consumption of quality x and the consumption of numeraire y, utility is $u(x, y) = v(x) + y$ where $v' > 0$ and $v'' < 0$. This specification

Figure 1.2: Welfare Implications of a Price Fall of Clothes Appliances



assumes zero income elasticity of demand for x_i, an assumption that can be justifed on two counts: (1) appliance purchases account for a small share of representative buyer's lifetime income, while the changes in appliance prices are a couple orders of magnitude smaller, and (2) we recallibrate utilty between every two periods, such that small income effects, if present, will not accumulate. Moreover, the quasi-linear utility assumption underestimates Hicksian compensation when price falls, which makes our consumer welfare estimate conservative. A quadratic approximation should provide a reasonably accurate estimate of the true change in welfare that is also simple and tractable.

$$v(x) = ax - \frac{b}{2}x^2$$

Define ΔW as

$$\Delta W = e(p^0, u^1) - e(p^0, u^0) \tag{1.3}$$

where $e(p, u)$ describes the minimum amount of money the consumer needs to achieve utility level u at price p. Thus, $e(p^0, u^1)$ and $e(p^0, u^0)$ correspond to the downward sloping blue lines intersecting points C and A, respectively, in Figure 1.2. Because $e(p^0, u^0) = e(p^1, u^1)$,

$$\begin{aligned} \Delta W = &\quad e(p^0, u^1) - e(p^1, u^1) \\ = &\quad \int_{p_1}^{p_0} h(p, u^1)\, dp, \end{aligned} \tag{1.4}$$

where $h(p, u^1)$ is the Hicksian (compensated) demand curve, which comes from the consumer's cost minimization problem,

$$\begin{aligned} &\min_{x \geq 0, y \geq 0} px + y \\ \text{s.t.} \quad &ax - \frac{b}{2}x^2 + y \geq \bar{u} \end{aligned}$$

which gives,

$$x^* = \frac{a - p}{b}$$

The change in welfare is thus

$$\begin{aligned} \Delta W &= \int_{p_1}^{p_0} \frac{a - p}{b} dp \\ &= \frac{a(p_0 - p_1)}{b} - \frac{p_0^2 - p_1^2}{2b} \end{aligned} \tag{1.5}$$

Note that because utility is quasi-linear, the Marshallian demand and Hicksian compensated demand curves are identical. Demand implies $x_0 = \frac{a - p_0}{b}$ and $x_1 = \frac{a - p_1}{b}$. Given observed values for the x_i and p_i for two consecutive periods, we can solve for the parameters to give the local approximation of utility, which implies $b = \frac{(p_0 - p_1)}{(x_1 - x_0)}$. Given b, $a = bx_i + p_i$.

Estimating the welfare change requires measures for prices and quality, which we construct from the CQPI. The change in CQPI gives a lower bound for the welfare change for the representative individual. If prices fall, consumers can afford the same

average quality of appliance at a lower price. Thus, assuming no change in behavior, consumers have ($-\Delta$CQPI) more income to spend on other goods and services. This extra income measures the *Slutsky compensation*, equal to the distance between A and D in Figure 1.2, which also equals the change in the CQPI. This change also implicitly measures the shift in the price of quality: $y_D - y_A = x_0(p_0 - p_1) = \Delta\text{CQPI}$. Without loss of generality, fix $p_0 = 1$, which implies

$$p_1 = 1 - \frac{\Delta\text{CQPI}}{x_0} \tag{1.6}$$

The last needed piece is a measure of quality. Since we set the initial price of average quality to 1, x_0 is simply defined as average retail price of appliances in the initial period, which we denote $\bar{w}_0$. As appliance prices decline, consumers substitute toward higher quality, so the change in average retail price relative to the change in CQPI reflects substitution toward quality. One can scale this change in different ways, but it mainly affects the measures of a and b. We measure $x_1 = \frac{\bar{w}_1 - \text{CQPI}_1}{p_1}$. Thus, the change in the value of quality, $p_i x_i$, equals the change in average price minus the change in constant-quality price.[7]

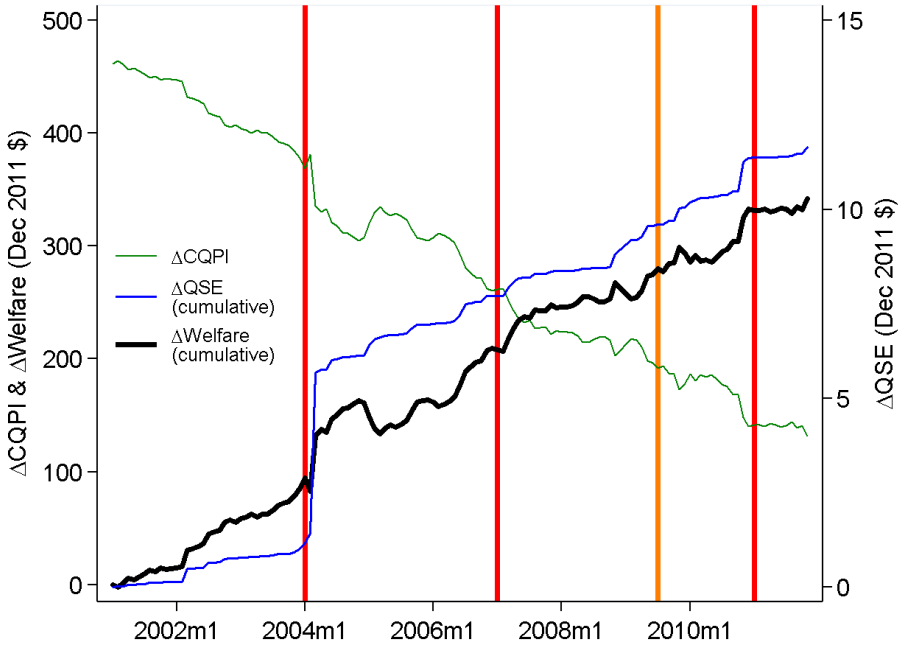
Note that if there were no substitution toward quality then the Slutsky compensation—equal to $-\Delta$CQPI—would equal the welfare change. We therefore call the difference between ΔW and ΔCQPI the Quality Substitution Effect (QSE).

Figure 1.3 summarizes the trend in the CQPI and the cumulative changes in consumer welfare and QSE between 2001 and 2011. The CQPI fell by \$330.36 over time, generating an estimated consumer welfare gain of \$342.00; the difference we attribute to the cumulative change in QSE, which denotes the additional utility from substituting to higher quality washers. A sharp drop in the CQPI occurred around the 2004 policy change, which also corresponds to the biggest jump in consumer welfare gain and QSE. There also appears to be accelerated welfare gains shortly after the 2007 policy change and a bit before the 2011 policy change, although these are less discernible.

Note that because policy changes were anticipated far in advance of implemen-

[7] In appendix **??** we show how a few specific product attributes relate to the quality index.

Figure 1.3: Change in Constructed CQPI, QSE,
and Consumer Welfare, 2001-2011



Changes in consumer welfare and quality substitution effect (ΔQSE) are cumulative. The red solid vertical lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange solid vertical line pertains to the ES policy change in July 2009. Prices are in December 2011 dollars.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); CQPI, QSE and consumer welfare measure (Authors' calculation).

tation, and affect the manufacture of washers but not their sale, there is no reason to expect a sharp discontinuity at the time of policy change. As a result, it is reasonable to model changes in quality and prices as a reflection of consumer choice. That is, policy changes may have affected costs of production by forcing production of more efficient units, or by encouraging pre-manufacture and storage of banned less-efficient products. These cost changes would presumably be reflected to some degree in prices, depending on market structure. It therefore may seem surprising that prices actually fell more rapidly around the times of the standard changes while

quality rose.

Although policy changes appear to benefit consumers, there are important caveats. First, the welfare analysis is based on a representative consumer. In reality, however, different consumers care to varying degrees about various product characteristics, an aspect of demand that the model may not fully capture. Discrete choice models like Berry et al. (1995) and McFadden and Train (2000) can account for heterogeneity of preferences and complex monopolistically competitive market structure. However, one must impose restrictive and otherwise questionable assumptions in using these models to extract certain distributions of consumer utilities (Berry et al. 2004). Different methods exist, but require data on consumer characteristics that rarely exist (Petrin 2002; Berry and Pakes 2007). Our method offers a simple and transparent way of calculating consumer welfare price changes and does not require additional data that relates characteristics of consumers to characteristics of the products they purchase.

A second caveat is that while one might reasonably attribute at least some of the consumer welfare gains to changes in energy-efficiency standards, perhaps through policy-induced innovation or intensified price competition (Ronnen 1991), it's not clear how much of the overall decline in prices and improvement in quality would have occurred in the absence of the standard changes. To consider the effects of policy, a control is neeeded, which we consider next.

1.6 Effects of Policy Changes

In this section we examine the effect of imposing more stringent standards on CQPI, quality index and welfare estimates. We estimate these effects using differences (pre/post) and difference-in-differences (DID).

Figure 1.4 plots trends in the CQPI, quality index and the cumulative change in welfare for washers and refrigerators over the study period. Table 1.3 summarizes the average change in the CQPI, quality index and welfare estimates for washers and refrigerators around the 2004, 2007 and 2011 simultaneous minimum efficiency (ME) and Energy Star (ES) policy changes, as wells as the 2009 ES policy change.

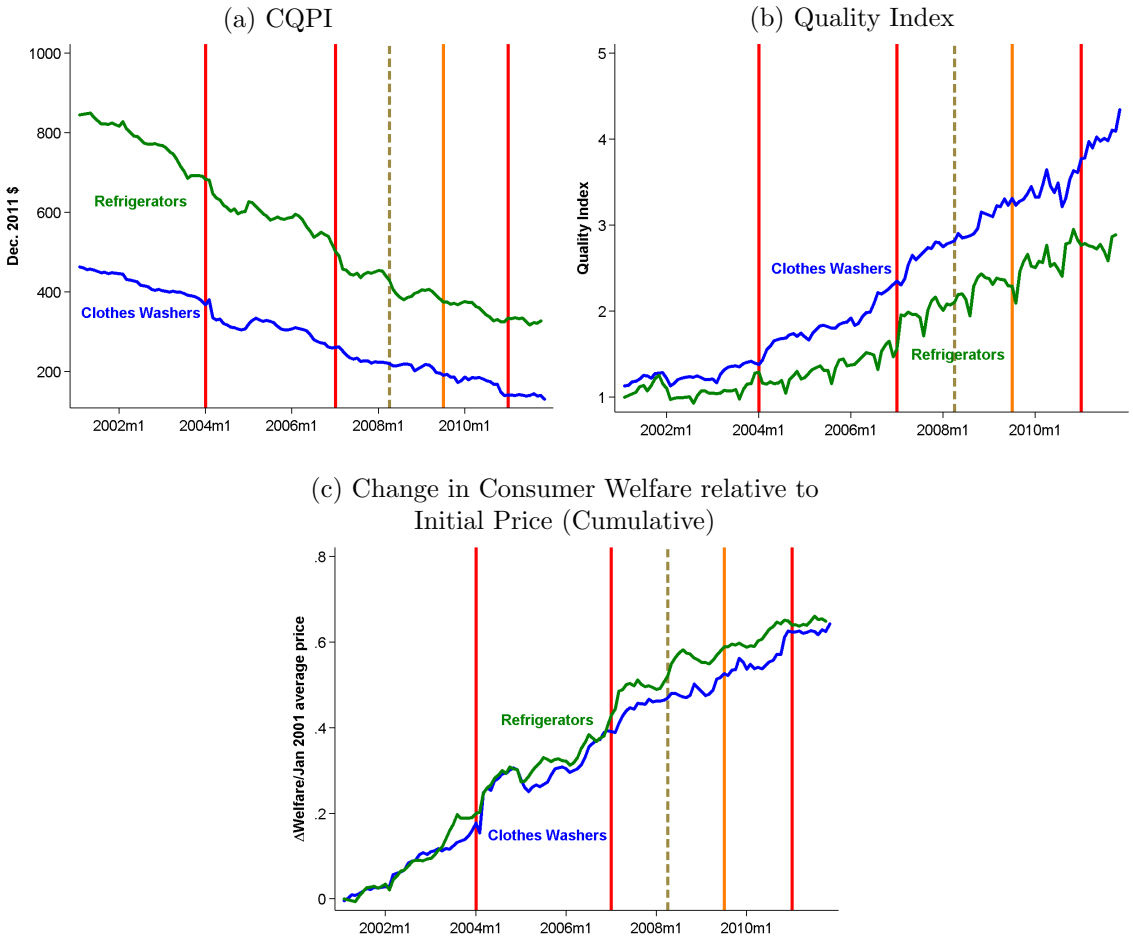
Table 1.3: Average Change in CQPI, Quality Index and Welfare
Washers vs. Refrigerators, 2001-2011.

Period	Clothes Washers			Refrigerators		
	CQPI	Quality	Welfare	CQPI	Quality	Welfare
Pre-2004	-2.147	0.011	2.173	-6.147	0.006	6.390
2004 ME & ES Policy	**-6.631**	**0.024**	**7.064**	**-8.164**	**0.007**	**8.474**
Post-2004 Policy	-0.662	0.016	-0.606	-2.267	0.012	2.427
Pre-2007 Policy	-3.006	0.012	3.050	-3.173	0.017	3.281
2007 ME & ES Policy	**-5.050**	**0.051**	**5.131**	**-9.129**	**0.038**	**9.487**
Post-2007 Policy	-1.444	0.021	1.465	-4.043	0.020	4.215
2009 ES Policy	**-2.348**	**0.028**	**2.461**	**-1.839**	**0.027**	**2.318**
2011 ME & ES Policy	**-3.545**	**0.050**	**3.362**	**-3.867**	**0.021**	**2.135**

Change in consumer welfare is measured as ΔConsumer Surplus. Except for the 2009 ES Policy that runs between January-December 2009, each period pertains to a 6-month window before and after the date of the policy change. For example, the 2004 policy change refers to the period July 2003-June 2004.

Source: Monthly sales and revenues of clothes washers and refrigerators sold in the US between 2001-2011 (The NPD Group); CQPI, QSE and consumer welfare measure (Authors' calculation).

Figure 1.4: CQPI, Quality Index and Welfare Change,
Washer vs. Refrigerator, 2001-2011



The red vertical lines indicate simultaneous ME and ES standard changes for clothes washers in January of 2004, 2007 and 2011; the orange vertical line indcates an ES standard change for clothes washers in July 2009. The brown dashed vertical line represents the ES policy change for refrigerators in April 2008. Prices are in December 2011 dollars.

Source: Monthly sales and revenues of clothes washers and refrigerators sold in the US between 2001-2011 (The NPD Group); CQPI, QSE and consumer welfare measure (Authors' calculation).

Because policy changes were announced well in advance of implementation, and may affect product introduction and pricing well before and after the change (be-

cuase standards ban the manufacture, not the sale, of appliances below the effiency threshold), we define a policy change window that includes 6 months before and after the policy change. For example, for the January 2004 policy change we assign all months from July 2003 up to June 2004 to the policy treatment. In 1.5, we report results when the window includes only three months. To the extent feasible, we compare the changes within the policy period to those in one year prior and one year after the policy period. For example, the 2004 policy change refers to the period July 2003-June 2004, and we compare changes during this period with those in July 2002-June 2003 and July 2004-June 2005.

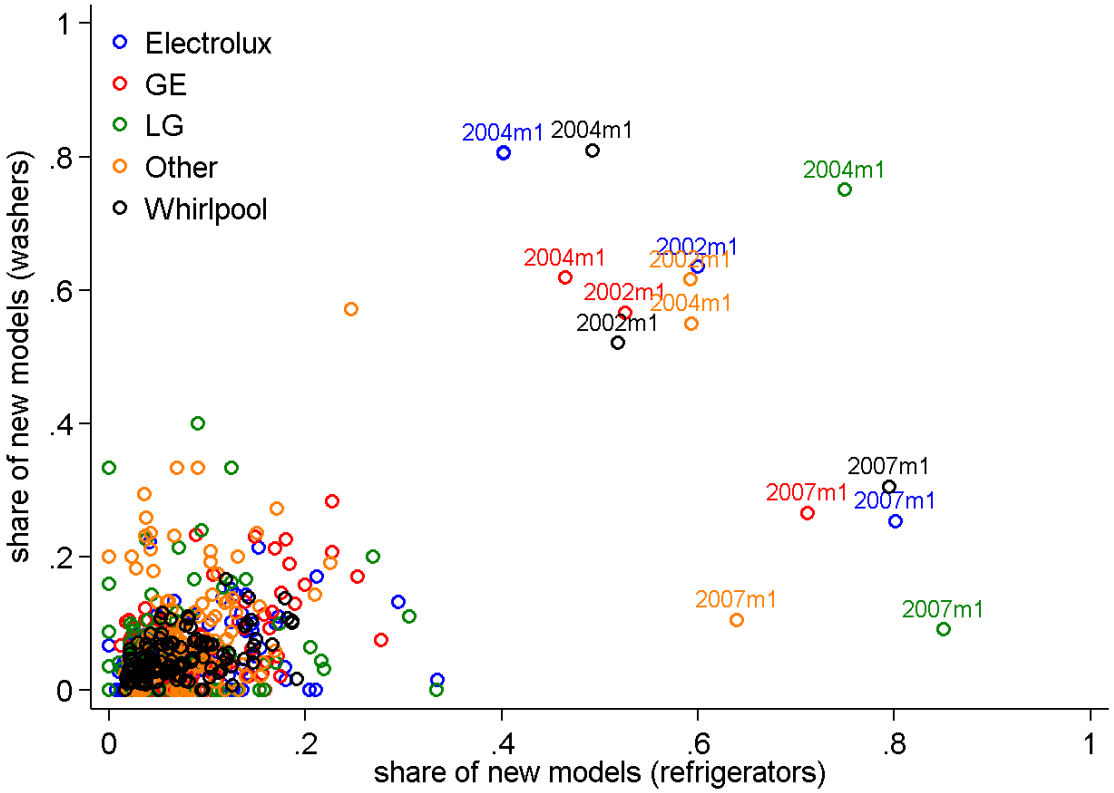
The results show that average declines in CQPI and increases in quality and welfare are larger around policy changes relative to previous and succeeding periods. For example, the average monthly drop in the CQPI for clothes washers around the 2004 ME and ES policy change was about $4.50 and $6.00 more than the pre- and post-policy periods, respectively. Interestingly, average decline is also larger for refrigerators during the 2004 and 2007 policy changes.

Statistics for the two appliances follow similar trends and fluctuations, including the significant drop around 2004 policy change. Based on the data alone, it is hard to know whether the correlated effects are due to unobserved factors, like the boom in housing, or because the policy change for washing machines also affected refrigerators, although the sharp effects right at the policy changes in 2004 and 2007 leans against the idea of a common unobserved factor. Furthermore, it is plausible that if a manufacturer of clothes washer is compelled by the policy change to introduce new models in the market, it would be spreading its overhead fixed costs (e.g. engineering and logistics) further by upgrading other appliances, like refrigerators, at the same time.

To obtain some sense of whether spillover effects are likely, we consider whether the timing of product introductions for clothes washers are correlated with those of refrigerators. At the manufacturer level, we find significant correlation in the share of new models between clothes washers and refrigerators, particularly around the policy changes in 2004 and 2007 (Figure 1.5). We performed the same exercise at the brand level and find the same significant correlation, particularly for major

brands of washers and refrigerators (see 1.6).

Figure 1.5: Correlation in the share of new models between washers and refrigerators, 2001-2011



A list of manufacturers and their subsidiary brands are presented in 1.1.

Source: The NPD Group.

Despite its potential limitations, we employ a standard difference-in-differences (DID) approach to estimate a lower bound of the effect of the standard change, using refrigerators as the control. We view these estimated effects as a lower bound due to large apparent effects from looking at differences, and potential spillover effects that we saw in Figure 1.5. The dependent variable, y_t, is the percentage change in CQPI or quality index, or level change in welfare; *Policy* is a dummy variable that turns on at the time the new standard is assumed to have effected the outcome

variables; $Treatment$ is a dummy variable equal to one for clothes washers and zero for refrigerators; and ε_t is the usual error term (equation 2.2). The coefficient of interest is β_3, which accounts for policy-affected periods of the treatment.

$$y_t = \beta_0 + \beta_1 Policy + \beta_2 Treatment + \beta_3 (Policy \cdot Treat) + \varepsilon_t \tag{1.7}$$

Regression results are reported in Table 1.4. Columns labeled (1) pertain to the standard DID; (2) includes time-period effects to control for unobserved time-varying factors; and (3) includes the intersection of month and refrigerator dummies to control for seasonality that is evident for refrigerators. We find that constant-quality prices fall while overall quality and consumer welfare increase on the average as a result of the policy change. Although the estimates are small and statistically insignificant, the estimates represent a worst-case outcome for consumers. Standards on washing machines have had at worst a negligible effect on consumer welfare, or at best lowered prices and improved quality for both washers and refrigerators.

Table 1.4: Results from Estimating the Average Effect of the Policy Change

Variables	**Dependent Variable**								
	%Δ CQPI			**%Δ Quality**			**Δ Welfare**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Treatment	0.070	0.165	0.192	0.042	-0.246	4.434*	-1.884*	-2.088*	-1.332
	(0.263)	(0.213)	(0.736)	(0.753)	(0.662)	(2.256)	(1.019)	(0.846)	(2.509)
Policy Dummy	-0.498	-1.948**	-0.745	0.324	-13.326***	-15.750***	2.176	5.957**	5.781*
	(0.305)	(0.941)	(1.167)	(1.241)	(2.031)	(3.377)	(1.627)	(2.915)	(3.271)
Treatment x Policy	**-0.774**	**-0.818***	**-0.804***	**0.311**	**0.565**	**0.441**	**0.898**	**0.869**	**0.858**
	(0.600)	**(0.485)**	**(0.425)**	**(1.355)**	**(1.372)**	**(1.026)**	**(2.157)**	**(1.549)**	**(1.420)**
Constant	-0.547***	0.298	-1.268	0.922***	13.568***	16.296***	3.428***	-0.044	2.256
	(0.167)	(0.213)	(1.000)	(0.677)	(0.662)	(3.113)	(0.888)	0.846	(3.008)
Year-month fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x ref dummy	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.052	0.707	0.785	0.003	0.560	0.800	0.039	0.744	0.817
Adj. R-squared	0.040	0.393	0.510	-0.009	0.088	0.544	0.027	0.469	0.583
Observations	254	254	254	254	254	254	254	254	254

Treatment is a dummy variable equal to one if the observation is for the appliance that is affected by the standard (i.e. clothes washer); Policy is a dummy variable that turns on at the time new standard is perceived to have effect on the key variables. We assume that the effect of the policy takes place within a 6-month period. For example, the 2004 policy change, due to its anticipatory nature, is perceived to have effect starting July 2003 up to June 2004. Columns labeled (1) pertain to the standard difference-in-differences approach; (2) include year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) include the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators. Robust standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10 percent level, respectively.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); vintage-adjusted CQPI, QSE and consumer welfare measure (Authors' calculation).

1.7 Entry, Exit and Average Vintage

We have shown evidence that prices decline with vintage, and briefly suggested that policy-driven entry and exit of models may affect average vintage and the price of washers. One hypothesis is that the vintage effect derives from competition, that entry of new models pushes manufactures to lower prices of older vintages. Thus, a natural measure for competition is average vintage. For any given model, regardless of vintage, the lower is average vintage, the more new, presumably higher-quality models with which it must compete. By forcing gradual exit and entry, standards may significantly alter the distribution of vintages and thereby affect innovation and competition. To investigate this hypothesis, we calculated average vintage, or average time since market introduction, and found that average vintage declines sharply around the times of major policy changes (Figure 1.6).

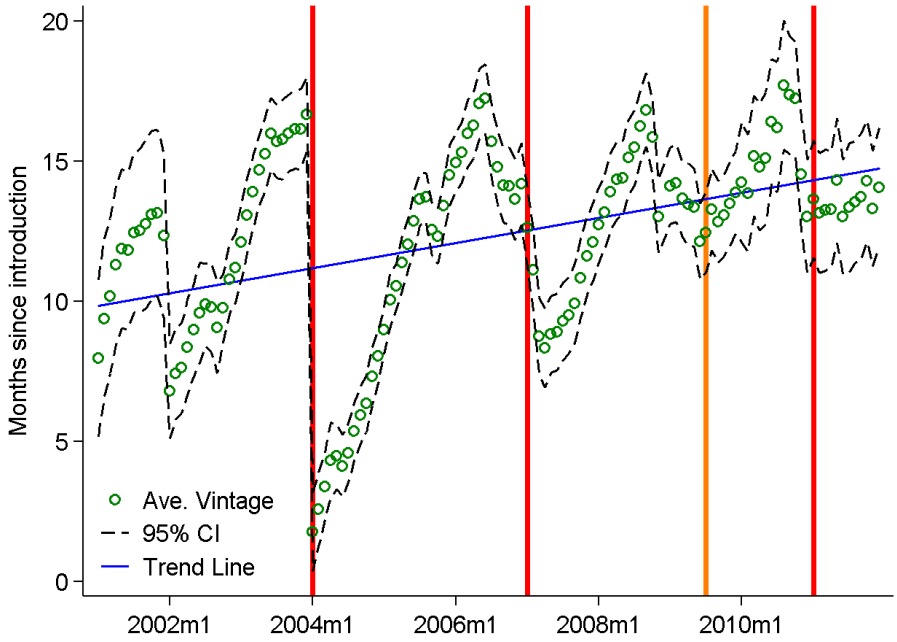
A concern with interpreting the data in Figure 1.6 is that a decline in average vintage may not be solely due to the regulatory changes. For example, average vintage also declines during early months of 2002, 2006 and 2008, when no policy changes occurred. These changes may be a result of a large firm's strategy to introduce models ahead of the others to take some revenue shares from existing yet eventually obsolete products. Nevertheless, the particularly sharp declines in 2004 and 2007 suggest energy efficiency standard changes had an important role in product entry and exit.

To examine the relationship between product entry and exit on price, we estimate the following reduced-form regression model:

$$\begin{aligned} p_{it} =& \alpha_i + \beta_0 \, \overline{vintage}_{-i,t} + f(vintage_{it}) \\ &+ g(vintage_{it}) \, \overline{vintage}_{-i,t} + month_k + \varepsilon_{it} \end{aligned} \tag{1.8}$$

where p_{it} denotes the price of model i at time t, $\overline{vintage}_{-i,t}$ is the average vintage (weighted by current sales) of all models excluding i at time t, and $f(vintage)$ and $g(vintage)$ are restricted cubic splines of model-specific vintage, representing periods since first introduction. The second spline is interacted with average vintage to

Figure 1.6: Average Vintage of Clothes Washers, 2001-2011



Vintage indicates the number of months since a product was introduced. Each point represent the sales-weighted average vintage at a particular time period. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold update that took effect in July 2009. Observations with prices falling below $100 were dropped as these observations are outliers and appear to be unrealistic.

Source: The NPD Group.

account for the possibility that prices of different vintages are more or less affected by average vintage. The spline functions allow price to change smoothly and flexibly over the life span of the product. The variable *month* denotes month dummies to account for possible seasonality in the price trend and α_i denotes the model fixed effect to account for unobserved time-invariant heterogeneity, like size and other model specifications, as well as unobserved quality attributes. ε_{it} is the usual error term.

In this model we cannot use time period fixed effects as we do in equation 1.2, because while average vintage is slightly different for different models, they are highly correlated given each excluded model is a small share of the whole market. Thus, average vintage is very nearly linearly dependent with time period fixed effects. Within models, a linear time trend is also perfectly collinear with model-specific vintage, so an overall trend is not identified either.

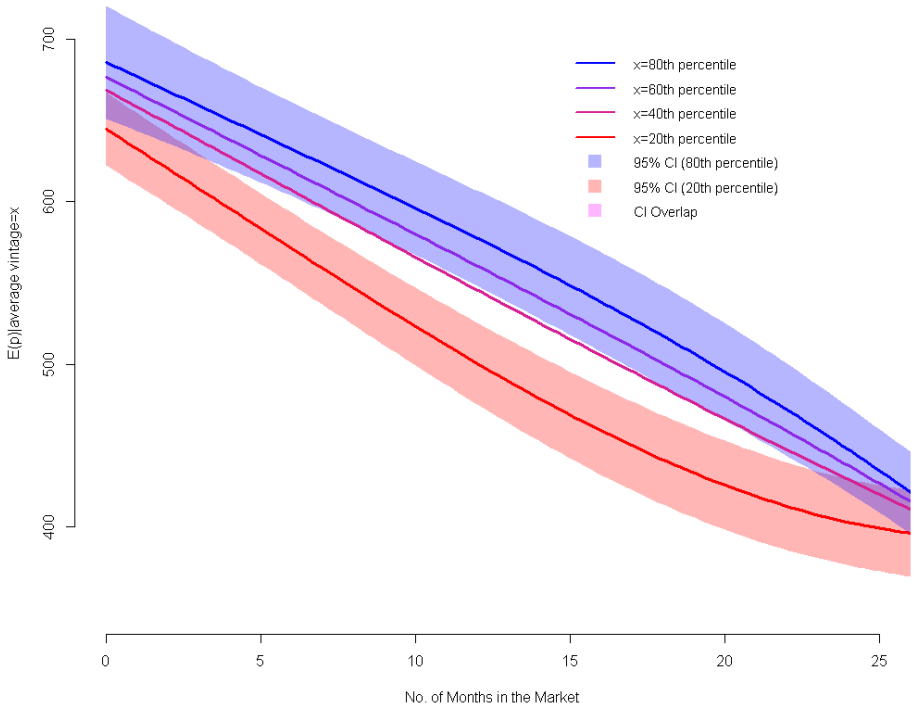
We use the estimates from equation 1.8 to predict the price trend of a typical clothes washer holding average vintage constant at different quantiles. Figure 1.7 plots this predicted price across the first two years of a clothes washer in the market, holding average vintage equivalent to about 10 months (20th percentile), 13 months (40th percentile), 14 months (60th percentile), and 15 months (80th percentile). The difference between the trend line at 10 months and at 15 months is statistically significant. Figure 1.7 shows how average vintage of clothes washers relates to the level and slope of the predicted price trend of a representative clothes washer. All else the same, increasing average vintage from 10 to 15 months is associated with a 10% price increase (see Table 1.6).

If the firm's pricing policy with respect to vintage were solely due to decreasing production cost over time, the introduction of new products in the market, which lowers average vintage but not own-model vintage, should not influence the firm's pricing policy. The data thus provide evidence of imperfect competition. Taking average vintage into account also causes the relationship between price and own-model vintage to become more strongly negative. This pattern makes sense: because own-product vintage tends to be associated with average vintage, and these two factors have opposite effects in a monopolistically competitive market, the effects confound each other if not estimated jointly. Significance tests are summarized in Table 1.5.

1.8 Within and Between Brand Competition

In this section, we look more closely at entry and exit dynamics of models within and between firms. Specifically, we examine how firms adjust prices of their own

Figure 1.7: Life-Cycle Pricing of Clothes Washers
Under Different Average Vintage



Each solid line represents a predicted price trend, given an average vintage of clothes washer, using equation 1.8 during its first two years. We estimate equation 1.8 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given an average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile correspond to 9.58, 12.63, 13.64, 14.80, respectively. The distribution of average vintage is weighted by current sales.

Source: Authors' calculation.

Table 1.5: Analysis of Variance for (real) price

Variables	d.f.	F-statistic	p-value
Average Vintage	1	41.77	<0.000
Spline Functions	4	40.73	<0.000
Interaction Terms	4	10.09	<0.000
All Variables	20	54.57	<0.000
R-sq. (within)			0.293

The table reports F-tests for the joint significance of key explanatory variables and their interactions with the vintage (number of months since introduction) of the clothes washer in the market. The model uses restricted cubic splines with 5 knots, which results in four factors in the regression equation. Key variables include the average vintage (1 degree of freedom [d.f.]) and the interactions with the four vintage factors (4 d.f.). We used STATA command *mkspline2* in estimating the spline functions.

continuing models when the firms themselves introduce new models, as well as how they adjust prices when competing firms introduce new models. In other words, we attempt to disentangle the influence of average vintage into cannibalization and external competition.

A literature on cannibalization and innovation offers mixed propositions (Nijssen et al. 2005). On the one hand, some argue that firms with some degree of market power are more likely to be the drivers of technological improvement. This is based on the idea that established firms use their market power to preempt potential entrants (Gilbert and Newbery 1982). On the other hand, some suggest that innovation comes from younger firms, since established firms may fear cannibalizing their earlier investments (Reinganum 1983).

To assess how a firm's product pricing is affected by its own and other firms' introduction (or withdrawal) of products, we break average vintage into two components, own-firm average vintage and other-firm average vintage. Specifically, denote $\overline{vintage}_{-i,c,t}$ as the average vintage (weighted by current sales) of other products within the same firm at time t but excluding the current model i and $\overline{vintage}_{-c,t}$ as the average vintage (weighted by current sales) of models manufactured by other

firms at time t. Like the model in the last section, we consider interactions between own-model vintage and average vintage measures.

$$\begin{aligned} p_{i,c,t} &= \alpha_i + \beta_1 \overline{vintage}_{-i,c,t} + \beta_2 \overline{vintage}_{-c,t} + f_c(vintage_{i,t}) + \\ &+ f_c(vintage_{i,t}) \overline{vintage}_{-i,c,t} + f_c(vintage_{i,t}) \overline{vintage}_{-c,t} + month_k + \varepsilon_{i,t} \end{aligned} \quad (1.9)$$

We use the estimates from equation 1.9 to predict the price trend of a typical clothes washer holding average vintage of models within brands constant. Panel (a) in Figure 1.8 plots this predicted price across the first two years of a clothes washer in the market, holding within-brand average vintage equivalent to about 8 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 17 months (80th percentile). We do this prediction assuming between-brand average vintage is equivalent to about 10 months (20th percentile).[8] We find no statistically significant difference between trend lines in different months. Panel (b) plots the predicted price trend of a typical clothes washer holding average vintage between brands constant at 20th, 40th, 60th and 80th percentile. The difference between the trend line at 10 months and at 15 months is statistically significant (Figure 1.8). Reducing the average vintage from 15 months to 10 months is associated with a 3% price decrease, all else the same (see Table 1.6).

Since the clothes washer market is dominated by large integrated manufacturers with several subsidiary brands, we assess whether the same pattern holds at the manufacturer level. We predict the price trend of a typical washer at different average vintage of models within the same manufacturer and between manufacturers. Panel (c) in Figure 1.8 shows the predicted price of a typical clothes washer, holding average vintage of models within the same manufacturer constant at about 9 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 16 months (80 percentile).[9] The difference between the trend line at 9 months and 16 months is

[8] 1.7 plots that assume contains plots that hold between-brand average vintage at 13 months (40th percentile), 14 months (60th percentile) and 15 months (80 percentile)

[9] We repeat this prediction for different between-manufacturer average vintages in 1.7.

Table 1.6: Regression Results: Dependent Variable - Unit Price, Clothes Washers and Dryers

	Clothes Washers		Clothes Dryers	
	(1)	(2)	(3)	(4)
β_1, average vintage within brand	2.017***		2.535***	
	(0.379)		(0.262)	
β_2, average vintage between brands	3.145***		3.580***	
	(0.630)		(0.501)	
β_1, average vintage within manufacturer		3.905***		4.657***
		(0.427)		(0.262)
β_2, average vintage between manufacturers		0.744		1.736***
		(0.462)		(0.381)
Constant	719.932***	722.204***	617.112***	612.562***
	(6.322)	(6.005)	(4.950)	(4.823)
Own Vintage Spline	yes	yes	yes	yes
Month-Fixed Effect	yes	yes	yes	yes
Model-Fixed Effect	yes	yes	yes	yes
Adj. R^2 (within group)	0.298	0.300	0.317	0.326
Observations	38,282	38,477	64,794	64,859

The table reports the results from estimating equation 1.9 without the interaction effects. Columns (1) estimates the effects of within- and between-brands average vintage, and (2) estimates the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage. ***, **, * indicate significance at the 1, 5, and 10 percent, respectively.

statistically significant. All else the same, the decline of within-manufacturer average vintage from 16 months to 9 months is associated with a 5% price decrease. We make the same prediction for different average vintage between manufacturers. We find no statistically significant difference between price trends at any given average vintage between manufacturers (Panel d). These findings imply that most and perhaps all the price declines associated with average vintage are associated with increased entry

and exit of models that occur within the same manufacturer.

A reasonable interpretation of these results is policy-induced creative destruction. The imposition of more stringent regulation forces all firms in the clothes washer market to introduce newer models at the expense of the older ones. The clothes washer market is dominated by large integrated manufacturers (e.g Whirlpool, General Electric and Electrolux) producing several brands of clothes washers and a number of relatively small independent manufacturers (e.g. Samsung and Fisher & Paykel). Firms, forced to bring new products to market meeting new standards, may find it more profitable to bundle other innovations that complement energy efficiency. Due to brand loyalty, and perhaps a general narrowing of product heterogeneity, older vintages from the same manufacturer face greater competition, inciting them to lower the price of an existing product (Padmanabhan and Bass 1993).

To see if cannibalism is unique to those appliances that had more stringent energy efficiency standards over the sample period, we use refrigerator, room AC and clothes dryer as counterfactuals. None of these appliances had adopted or implemented a simultaneous minimum energy efficiency standards and Energy Star certification change during the study period. We use the estimation strategy presented in equation 1.9 for these appliances. Table 1.6 presents the regression results using equation 1.8 for clothes dryers and Table 1.7 is for refrigerators and room ACs.

Interestingly, we also observe the same pattern in the clothes dryer market. We see that price declines in the clothes dryer market are strongly associated with cannibalism both at the brand and manufacturer level (Table 1.6). This pattern can be explained by the complementarity of the two durable goods as consumers often purchase washers and dryers simultaneously. Thus, changes in clothes washer standards may have influence on the rate of model entry and exit, and pricing in the clothes dryer market. We do not observe this strong pattern of inter-brand cannibalism in the markets for room AC and refrigerators (Table 1.7), although cannibalism tends to drive down unit price at the brand level for refrigerators. This can be explained by the seasonality of refrigerators unit sales. The bulk of sales and price discounts occur during the first and last quarter of the year when the refrigerator market has generally lower unit price but more new models.

Table 1.7: Regression Results: Dependent Variable - Unit Price, Room ACs and Refrigerators

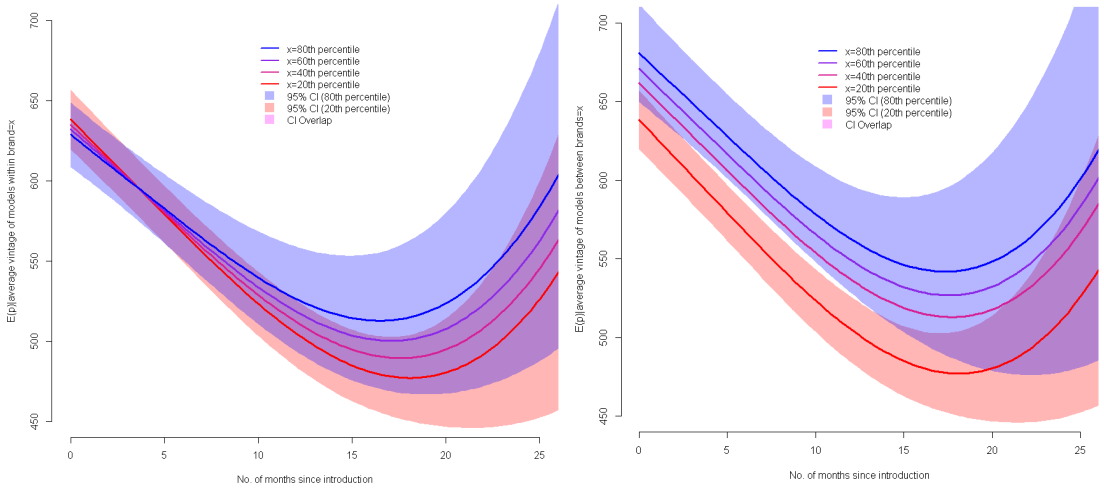
	Room AC		Refrigerator	
	(1)	(2)	(3)	(4)
β_1, average vintage within brand	0.158		4.264***	
	(0.130)		(0.411)	
β_2, average vintage between brands	0.999***		4.429***	
	(0.202)		(0.739)	
β_1, average vintage within manufacturer		0.002		0.137
		(0.003)		(0.084)
β_2, average vintage between manufacturers		1.109***		6.829***
		(0.175)		(0.706)
Constant	403.189***	403.503***	1450.485***	1465.583***
	(3.986)	(4.021)	(8.646)	(8.253)
Own Vintage Spline	yes	yes	yes	yes
Month-Fixed Effect	yes	yes	yes	yes
Model-Fixed Effect	yes	yes	yes	yes
Adj. R-Squared (within group)	0.115	0.115	0.101	0.098
Observations	45,324	45,305	181,277	181,449

The table reports the results from estimating equation 1.9 without the interaction effects for room ACs and refrigerators. Columns (1), and (3) estimate the effects of within- and between-brands average vintage, while (2) and (4) estimate the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Figure 1.8: Life Cycle Pricing of Clothes Washers

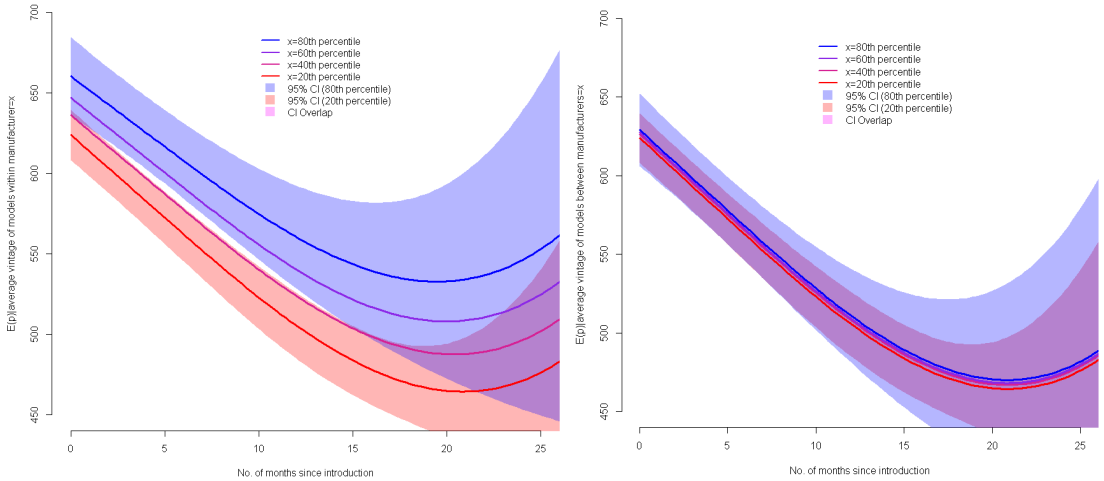
(a) Different *Within-Brand* Average Vintage

(b) Different *Between-Brands* Average Vintage



(c) Different *Within-Manufacturer* Average Vintage

(d) Different *Between-Manufacturers* Average Vintage



Each solid line represents a predicted price trend using equation 1.9 during its first two years, holding average vintage within- and between-brands (for panels a & b) or manufacturers (for panels c & d) constant. We estimate equation 1.9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 7.71, 10.67. 13.32 and 16.58, respectively. For the between-brand average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.62, 12.54, 13.67, and 14.90, respectively. For within-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 8.86, 11.14, 13.18, and 15.68, respectively; and 9.47, 12.53, 13.85, and 16.12, respectively, for between-manufacturers average vintage.

Source: Authors' calculation.

1.9 Conclusion

Recent imposition of more stringent energy efficiency standards on durable goods has spurred debate about whether such policies are in consumers' best interests. On the one hand, some argue that standards can improve environmental quality while simultaneously addressing inefficiencies that derive from consumer behavioral anomalies that cause people to underinvest in energy efficiency. Firms, recognizing consumers' unwillingness to invest in energy-saving products, produce fewer efficient products. Firms' incentives to innovate may be further attenuated by partial nonexcludability of new technologies and dynamic pricing concerns. On the other hand, some believe that standards unnecessarily constrain consumer choice and increase production costs, ultimately reducing consumer welfare. Apparent underinvestment in energy efficiency may derive from unobserved quality characteristics that are associated with energy efficiency, or perhaps because people are credit constrained, not because people overweigh more salient up-front costs compared to less salient future energy-related operating costs.

In this study we approach the issue from a different vantage point. Instead of trying to asess implicit values from consumer choices, we attempt to measure the implications of actual standard changes on market outcomes. From these outcomes we develop methods that allow us to ascertain the *ex-post* welfare implications associated with restricted product variety and changing prices, factors that heretofore have been acknowledged but difficult to assess. While standard changes provide some pre-post basis for comparison, and we construct a kind of quasi experiment using refrigerators as a control, we acknowledge that the study design is imperfect. For one, standard changes were announced and anticipated well before they were implemented, and the evidence strongly suggests that the policy affected the control.

Despite these design imperfections, the data clearly indicate that past standard changes did little to harm consumers and likely improved consumer welfare considerably. We find remarkable declines in constant-quality prices of washers and refrigerators, particularly so around the times of policy changes. The coincidence of policy changes with sharp price declines, quality increases, and product entry and

exit strongly suggest a causal link. Over a time period with a series of markedly stricter efficiency standards, we estimate consumer welfare improvement of about $342 per washer assuming quasi-linear utility, and lower bound of $330 improvement based on a constant-quality Slutsky compensation measure. Difference-in-differences estimates, which may suffer from large spillover effects, suggest that imposing more stringent energy efficiency standards will have, at worst (i.e., assuming no spillover), a negligible effect on consumer welfare.

It is difficult to square these observations with an argument that efficiency standards cause a great burden to consumers. It is important to emphasize that these estimated benefits are *in addition to* external envrionmental benefits or benefits that may arise from correcting behavioral errors associated with possible undervaluation of energy efficiency, and perhaps quite different from those that may have been intended.

What might explain these counterintuitive effect of standards on consumer welfare? One theory is that standards make heterogeneous products more homogeneous, and thereby increase competition as theorized by Ronnen (1991). Another possibility is that standards facilitate innovation (Jaffe and Palmer 1997). We find little evidence of increased competition as a mechanism, since entry of other-manufacterur products has little influence on own-manufactuer prices. But we do find evidence supporting policy-induced innovation, wherein firms lower prices of older models as they are forced to introduce new model meeting new, stricter efficiency standards. Of course, firm profits may have decline as a result of the policy changes, an aspect of the issue we cannot address in this paper.

More generally, these findings clarify that the evaluation of energy efficiency standards pertains to much more than pollution externalties and the existence, size, and causes of the energy efficiency gap. Energy-consuming durable goods markets contain multiple market failures, including pollution externalities, behavioral anomalies, imperfect competition and public-good aspects of innovation. While stricter standards may help to improve matters in some cases, it is also generally understood that efficient policy requires as many instruments as market failures. Nor does our analysis provide any indication of what an efficient standard would look like from

the vantage point of the second best.

Aside from a novel examination of energy efficiency standards, we present simple and transparent method for evaluating price and quality changes over time. This method may be useful for price indexing in other contexts, assuming availability of suitable data. For example, economists have long noted that the Consumer Price Index (CPI) may exaggerate inflation because the Bureau of Labor Statistics employs methods that cannot fully account for changes in quality (Hausman 2003). The bias resulting from not fully accounting for quality adjustments and introduction new products could be substantial. Bils (2009) estimates that the quality bias from introducing new models equals two-thirds of nominal price increases. At least for products with identifiable model numbers and overlapping lifetimes, the methods used here might help to improve construction of price indices.

Chapter 2

Can FDI Improve Plant-Level Environmental Performance? Evidence from Indonesian Manufacturing Sector[1]

2.1 Introduction

For many developing countries, foreign direct investment (FDI) has been an important source of development and growth. In addition to bringing capital and creating jobs, FDI stimulates economic growth by enhancing firm-level efficiency. It does so directly by transferring cutting-edge technologies and management practices to its affiliates (Arnold and Javorcik 2009; Javorcik and Poelhekke 2016) and by encouraging product and process innovation (Guadalupe et al. 2012) as well as indirectly through knowledge spillovers (Javorcik 2004).

The spectacular growth in FDI flows, along with the increasing importance of developing countries as host countries, has raised concerns about the potential effect of FDI on the natural environment (Zarsky 1999). On the one hand, environmentalists

[1]This essay is a result of a collaboration with Beata Javorcik and Inessa Love.

argue that highly polluting multinationals relocate to countries with weaker environmental standards in order to circumvent costly regulations in their home country and in this way increase pollution levels not only in host countries but also globally. This notion has been labelled as "pollution haven hypothesis".[2] On the other hand, supporters of globalization point out that FDI has a positive effect on natural environment because multinationals often have more efficient and cleaner technologies than their domestic counterparts. This possibility is referred to as "pollution halo hypothesis".[3] Since the existing literature (reviewed below) has produced mixed results, the issue remains controversial.

This study contributes to our understanding of the link between FDI and environmental protection by taking a novel approach. Rather than examining whether FDI flows are influenced by environmental standards in the destination countries or whether polluting industries are more likely to engage in FDI, we examine the impact of foreign acquisitions on environmental performance of acquired plants. We use plant-level panel data from the Indonesian Manufacturing Census covering the period 1983-2001. To establish a causal effect of foreign acquisitions on plant performance, we combine a difference-in-differences approach with coarsened exact matching (CEM). This allows us to account for selection on observables and to control for unobservable time-invariant plant heterogeneity. To the best of our knowledge, this study is the first to employ such an approach in determining the effect of foreign ownership on plant-level environmental performance.

Our analysis is based on 264 foreign acquisition cases where an acquired plant is observed a year before and at least three years after an ownership change and for which a carefully selected control plants exist. The results suggest that while foreign ownership increases total energy use and (CO_2) emissions of acquired plants (due to expansion of the production scale), it lowers the energy- and therefore emission-

[2]Anecdotal evidence abound. For instance, in 2013, the smoke haze from Indonesia's palm oil production, which was dominated by foreign investors, elevated to dangerous levels and caused significant health hazards not only in Indonesia, but also in Malaysia and Singapore (Chachavalpongpun 2013).

[3]Rondinelli and Berry (2000) list a number of examples showcasing how multinationals and their affiliates help improve the environmental condition of their host country.

intensity of output. Interestingly, we find that the effect of foreign acquisition on plant-level performance varies across plants; those with lower pre-acquisition size and higher pre-acquisition energy-intensity exhibit a much larger drop in the energy and emissions per unit of output after the acquisition. We also find that, in Indonesia, acquired firms rely more on electricity in expanding its production, most likely due to the relatively low unit cost of this energy source.

Our paper contributes to the literature examining how foreign ownership influences plant-level environmental performance. There are very few studies in this literature, and the evidence is still mixed. In a pioneering study, Eskeland and Harrison (2003), used plant-level data from Cote d'Ivoire, Mexico and Venezuela, and found that the energy share, i.e., the cost of energy used divided by the total value of the plants output was negatively related to foreign ownership. Using plant-level data from Ghana, Cole et al. (2008), find that foreign ownership does not influence fuel use or total energy use but is found to increase electricity use. Due to data limitations, neither of these studies was able to take into account selection into foreign ownership (the possibility that foreign investors choose to acquire local plants with better environmental performance) or unobservable plant heterogeneity, which an improvement we implement in our analysis. Unlike these studies, we are also able to measure energy use in physical units and we also have more detailed information on the types of energy used.[4]

Our study is also related to the broader literature which asks whether FDI (and particularly FDI in polluting industries) is attracted to countries or locations within countries with weaker environmental standards. The studies that consider FDI from industrialized countries to developing economies find no or very little support for the pollution haven hypothesis (Eskeland and Harrison 2003; Javorcik and Wei 2004; and Dean et al. 2009). In contrast, Keller and Levinson (2002), who study FDI inflows into the US states, conclude that abatement costs have moderate deterrent effects

[4]In a related study, Cole et al. (2011), consider per-capita emissions of pollutants in 112 major Chinese cities during the 2001-4 period. They find that the share of output of foreign-owned firms increases emissions while output of firms from Hong Kong, Macao, and Taiwan either reduces pollution or is statistically insignificant. The aggregated nature of the data (city level) makes it difficult to draw conclusions about pollution haven or halo hypothesis.

on foreign investment.

Finally, our work makes a contribution to the relatively new literature examining the effects of foreign acquisitions on the acquired plants (Arnold and Javorcik 2009; Guadalupe et al. 2012). We enhance our understanding of this issue by pointing out the positive impact of foreign ownership on environment performance, an outcome that has not been considered by the existing studies.

The rest of the paper is organized as follows. Sections 2 and 3 describe the data and empirical strategy, respectively. Section 4 discusses the results. Section 5 concludes the paper and discusses its policy implications.

2.2 Data

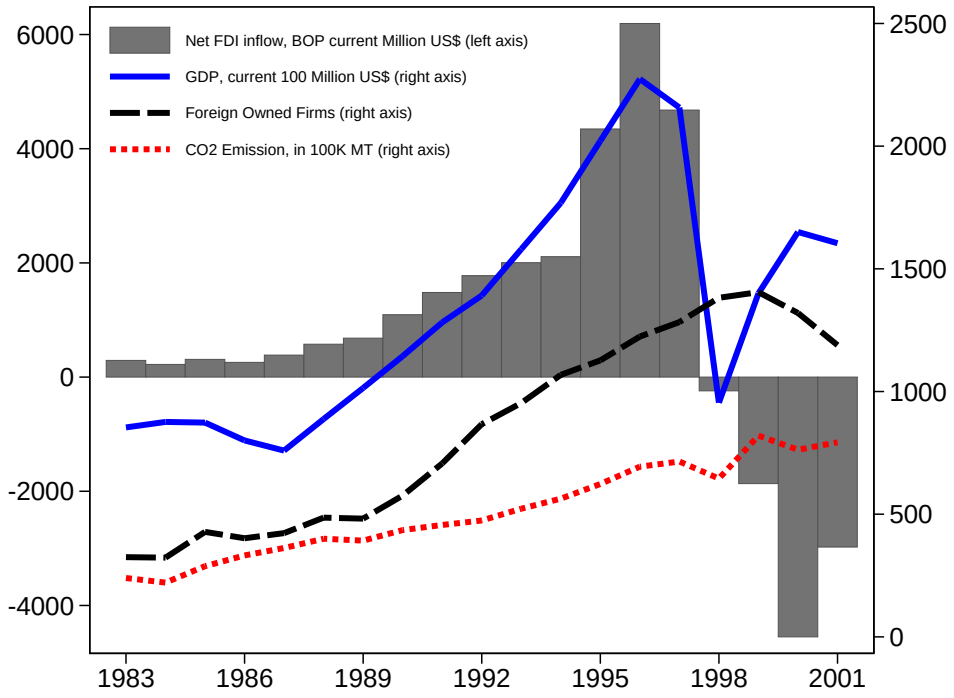
2.2.1 Background information

Indonesia is a suitable setting for studying the effects of foreign acquisitions on plant-level environmental performance for two reasons. First, the country received significant inflows of FDI, ranking as the 5^{th} largest recipient of FDI among developing countries in the mid 1990s (see Arnold and Javorcik 2009). The influx of FDI was in part driven by significant reductions in trade barriers and industrial deregulation in the early 1980s and 1990-1996. The period of high capital inflows also coincided with economic recessions in the United States, Japan and some European countries. During this period, competing FDI destinations, such as Thailand, experienced a rise in labor cost and had limited infrastructure, which may have prompted investors to reallocate their portfolios to other emerging economies, including Indonesia. Second, as pointed out by Garcia et al. (2007), environmental protection in Indonesia was generally weak and ineffective during the country's impressive industrial growth in the 1980s and 1990s. Thus the results of our analysis will not be influenced by pollution-related policies in the host country and thus will give us a cleaner picture of the impact of FDI on environmental performance.

Figure 2.1 illustrates Indonesia's net FDI inflows, Gross Domestic Product (GDP), CO_2 emissions and number of foreign-owned plants from 1983 to 2001. The vertical

bars represent the net FDI inflows from balance-of-payment statistics measured in million US$ (left axis), the solid line indicates the country's GDP in 100 million US$, the dashed line is the number of foreign-owned plants (calculated based on the Census of Manufacturing) and the dotted line is the CO_2 emission in 100K metric tons, all scaled by the right axis. The graph shows an upward trend in all the variables, with the number of foreign plants picking up in 1984, followed by GDP and net FDI flows around 1987. Interestingly, GDP increased at a much faster pace than did emissions, suggesting that emissions per dollar unit of output may have declined during the period. Both GDP and FDI inflows experienced a significant decline following the 1997-1998 Asian financial crisis.

Figure 2.1: Indonesia's Net FDI inflows, Gross Domestic Product, CO_2 Emissions and Foreign-Owned Firms, 1983-2001



Sources of Data: The World Bank, Oak Ridge National Laboratory, Indonesian Census of Manufacturing

2.2.2 Data sources

We use data from *Survei Manufaktur*, the Indonesian Census of Manufacturing conducted by the National Statistical Office (BPS). The data encompass all manufacturing plants with 20 or more employees on an annual basis since 1975. The census has detailed information on fuel and electricity use, both in terms of values and physical quantities.[5] The sample available to us spans the period from 1983 to 2001 covering about 40,000 plants with 300,893 plant-year observations, of which 11,436 observations belong to plants that are owned by foreign companies during the period.

Following (Arnold and Javorcik 2009), we define foreign acquisition as a change in the foreign ownership share from below 20% to at least 20%. The exact value of the threshold does not matter because more than 99% of the surveyed plants have foreign capital share equal to zero in the pre-acquisition period. In the same manner, 95% of the cases have foreign ownership shares of at least 25% during the year of acquisition, and more than 75% have at least 50% (Figure 2.2).

Foreign acquisitions are distributed across a wide range of industries. The main one is manufacturing of fabricated metal products, machinery and equipment which comprises 22.48% of the plants in the sample data. 22.09% of the plants are involved in textile and wearing apparel industries, while 20.08% are involved in manufacturing chemical products. For a detailed discussion on the distribution of foreign-owned plants by industry and by year, see Appendix 2.2.

Table 2.1 provides summary statistics for foreign-owned and domestic plants. Foreign-owned plants dominate domestic plants in almost all economic variables. For example, plants under foreign ownership are much bigger, have more skilled labor, rely more on international markets and are more capital intensive. In terms of environmental attributes, they spend more on energy and emit more carbon dioxide. Their production process is, however, less energy intensive and produces lower CO_2 emissions per 1000 Rps. of output.

[5]The survey questionnaires and other relevant information about the dataset can be accessed online at http://www.rand.org/labor/bps/statistik_industri.html.

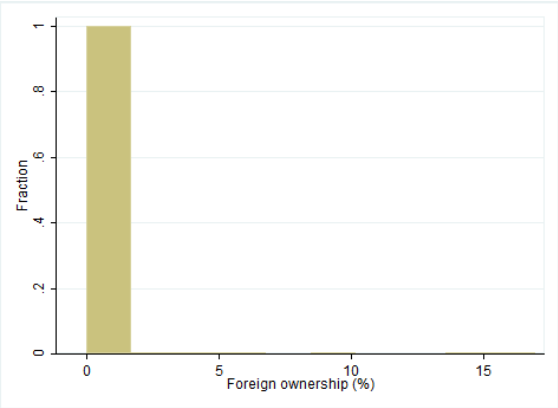
Table 2.1: Summary Statistics

Variables	Domestic plants			Foreign-owned plants		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Economic						
Output ('000 RP)	288,988	25.364	280.392	11,412	133.245	473.066
Employment (no. of workers)	288,973	150.490	572.316	11,409	433.12	787.421
Unskilled workers	238,225	119.925	472.837	8,791	342.814	655.938
Skilled workers	237,822	25.324	134.587	8,764	68.138	142.87
Capital ('000 RP)	189,156	25.624	1,773.008	7,751	111.243	1441.377
Materials ('000 RP)	288,990	13.259	135.387	11,412	67.288	249.862
Per worker wage ('000 RP)	288,990	2.587	36.978	11,412	6.335	30.769
Investment in machineries ('000 RP)	233,694	9.215	268.481	10,076	46.654	725.930
Exporter Dummy	289,266	0.082	0.274	11,436	0.234	0.423
Share of exports (%)	289,266	6.310	22.410	11,436	18.171	35.334
Share of imported materials (%)	289,266	11.698	28.639	10,076	38.231	40.522
Capital-labor ratio	189,146	117.450	7,439.627	7,751	273.878	3538.143
Share of skilled workers (%)	237,822	13.588	14.546	8,764	21.812	18.572
Public ownership dummy	289,266	0.032	0.177	11,436	0.040	0.197
Age	273,844	13.406	14.196	10,587	11.851	15.083
Environmental						
Energy Expenditure ('000 RP)	228,153	0.695	9.257	8,656	2.751	15.503
Energy Use ('000 MBTUs)	228,153	16.536	291.464	8,656	69.119	524.509
CO2 Emission (M Kg)	228,151	1.280	22.283	8,656	5.688	45.949
Energy Expenditure Intensity	228,153	0.048	0.072	8,656	0.04	0.063
Energy Use Intensity (MBTUs/RP)	228,153	0.986	1.758	8,656	0.854	2.146
Emission Intensity (KgCO2/RP)	228,151	78.428	141.848	8,656	66.814	155.304
No. of Plants		39,652			1,121	

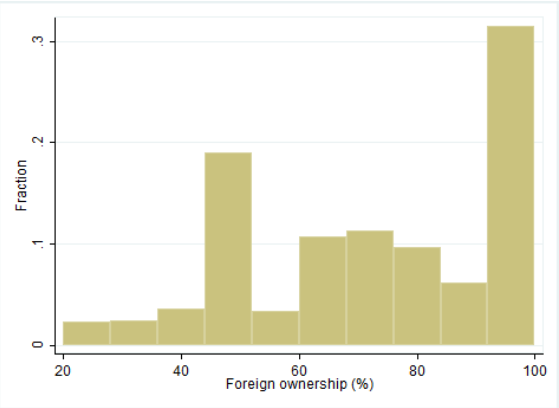
Source: Indonesian Census of Manufacturing

Figure 2.2: Distribution of Foreign Ownership, 1983-2001.

(a) Pre-Acquisition



(b) Post-Acquisition



Source: Indonesian Census of Manufacturing

2.3 Measuring Energy Usage and Emission

The data includes plant-level expenditures (in Rps) and physical usage (e.g. in metric tons or liters) of each energy input. The energy inputs consist of fuels and lubricants and electricity use. Fuels and lubricants are divided into more detailed inputs, which include gasoline, diesel, diesel oil, kerosene, lubricant, bunker oil, coal, coke, public gas, liquefied petroleum gas (LPG), firewood, and charcoal. We also have information on the amount of fuels and lubricants that are used for electricity generation, as some of the plants are generating their own electricity for their own consumption and to sell to other end users. We also have information on the amount of electricity sold and the amount bought from the state-owned power company Perusahaan Listrik Negara (PLN) and from other independent power producers (non-PLN).

The original data set includes 300,893 observations. 61,561 observations in our dataset contain positive energy expenditure on a particular energy input but missing energy use in physical units. We impute the plant-level physical energy consumption using the following equation:

$$lny_{it} = lnCost_{it}\beta + ISIC_k + PROV_l + YEAR_m + u_{it} \tag{2.1}$$

where y_{it} is the physical measure of energy inputs (e.g. gasoline, in liters) and $Cost_{it}$ is total cost of energy inputs (e.g. gasoline, in '000 Rps). $ISIC$, $PROV$ and $YEAR$ are industry, province and year fixed effects, respectively. We estimate this specification separately for each energy input (see Table 2.2 for a list). In this way, we impute the usage of each energy input in physical units. Table 2.2 reports the goodness-of-fit in estimating equation 2.1. Except kerosene, the model predicts more than 90% of the variation of energy use in physical units.[6]

The energy content of each energy input (in BTUs) is calculated using conversion factors from reliable US agencies and institutions found in Table B.1.[7] A sample calculation of the energy usage of a plant using 100 barrels of diesel fuel at a certain time period is illustrated below:

$$100 \text{ barrels diesel x } \frac{5.825 \text{ million BTUs (MBTUs)}}{1 \text{ barrel}} = 582.50 \text{ MBTUs}$$

We follow the same procedure for calculating CO_2 emission (in Kg CO_2). Using the same example above, we calculate the CO_2 emission as below:

$$582.50 \text{ MBTUs x } \frac{71.80 \text{ kg } CO_2}{1 \text{ MBTU}} = 41,845.04 \text{ kg } CO_2$$

Among the key variables of interest are energy intensity (defined in two ways), and pollution intensity. We first define energy intensity as total expenditure on energy per 1000 Rps of output, following Eskeland and Harrison (2003). Except for energy, all inputs and outputs are deflated using a set of 192 wholesale price indices for manufactured commodities published by the BPS. Energy expenditure is deflated using a CPI specific to energy (Arnold and Javorcik 2009). It is plausible that acquired firms, possibly due to greater reliance on international markets, may use technologies that utilize more expensive but cleaner and more energy-efficient

[6]There are also observations where there are physical units but total cost is missing. We regard these observations as missing in the data.

[7]British Thermal Unit (BTU) is a traditional unit of energy. The US-EIA interprets BTU as the amount of energy needed to heat one pound of water from 39 to 40 degrees Fahrenheit (EIA, 2011).

Table 2.2: Goodness-of-Fit in estimating plant-level energy use (in physical units).

	Obs.	R.sq.	Adj. R-sq.	RMSE
Fuel and Lubricant (Total)				
Gasoline	140,744	0.993	0.993	0.144
Diesel	198,309	0.992	0.992	0.208
Diesel Oil	30,279	0.966	0.966	0.564
Kerosene	104,509	0.696	0.695	1.164
Lubricant	213,705	0.944	0.944	0.520
Bunker Oil	2,049	0.999	0.999	0.102
Coal	1,370	0.975	0.973	0.640
Coke	2,912	0.942	0.940	0.633
Public Gas	9,598	0.931	0.930	0.812
LPG	11,906	0.993	0.993	0.175
Firewood	9,089	0.990	0.990	0.218
Charcoal	1,460	0.988	0.987	0.236
Fuel and Lubricant (Elec. Generation)				
Gasoline	1,435	0.983	0.982	0.303
Diesel	37,683	0.987	0.987	0.285
Diesel Oil	2,538	0.966	0.965	0.580
Kerosene	317	0.981	0.974	0.449
Lubricant	22,606	0.972	0.972	0.357
Bunker Oil	179	0.996	0.995	0.258
Coal	29	0.997	0.988	0.401
Coke	6	1.000	.	-
Public Gas	93	0.991	0.983	0.402
LPG	110	0.985	0.969	0.488
Firewood	44	0.983	0.945	0.760
Charcoal	16	1.000	.	-
Electricity Use				
Sold	702	0.978	0.974	0.489
PLN	216,193	0.979	0.979	0.349
Non-PLN	5,022	0.974	0.974	0.465

Note: The table reports the goodness-of-fit in estimating equation 2.1. Each variable is expressed in log. LPG denotes liquefied petroleum gas. PLN refers to amount of electricity bought form Indonesia's state-owned power company *Perusahaan Listrik Negar*, while non-PLN refers to those that are bought from independent power producers. Source: Indonesian Census of Manufacturing

energy inputs. Thus, energy expenditure per unit of output may remain constant (or even increase) but actual energy use (in BTUs) per unit of output may decline. In

order to address this issue, we also express energy intensity as total physical energy (in MBTUs) per currency unit of output. We replicate the same process to calculate a plant's pollution intensity, which is defined as total carbon dioxide emissions (in kg CO_2) per currency unit of output. See Table 2.1 for summary statistics.

2.4 Empirical Strategy

The empirical strategy used to identify the causal effect of foreign ownership on plant-level environmental performance is anchored on three foundations. First, the study focuses on the changes from domestic to foreign ownership taking place within the same plant. In particular, we consider plants that are observed for at least four consecutive years with initially less than 20% foreign equity and at least 20% of equity belonging to foreign owners thereafter. By focusing on ownership change we are able to take into account the selection bias that would plague a comparison of domestic plants to all foreign plants, due to the possibility that foreign affiliates may choose the most energy-efficient domestic plants. This approach, however, dramatically reduces the number of observations that can be considered. Fortunately, thanks to large FDI inflows into Indonesia during the sample period, we are able to observe 264 acquisition cases, which is in our view a large enough number to allow us to generalize the results with confidence.

Second, we use a difference-in-differences approach to compare the performance of foreign-acquired plants with the performance of plants remaining in domestic hands. This approach eliminates the influence of all unobservable non-random elements of the acquisition decision that are constant or strongly persistent over time.

A key challenge is how to develop a reasonable estimate of the counterfactual, that is, the change in the variables of interest that would have been observed had the acquisition case not occurred. We employ a one-to-one coarsened exact matching (CEM) procedure following Iacus et al. (2009) and Iacus et al. (2011) to identify a control plant for each plant acquired by foreign investors. We choose CEM over methods that rely on estimating a propensity score matching because CEM guarantees balance on all higher order moments and interactions on all variables. This is

appropriate for the analysis because we are also particularly concerned with nonlinear effects of foreign acquisition on plant-level environmental performance.[8]

We ensure that each acquired plant is paired with a domestic plant that is operating in the same sector and year and has very similar pre-acquisition output, energy use, emission level, and trends of energy consumption and emissions (see Table 2.3 for a list o variables used in matching samples). With these similarities in characteristics, we assume that the two plants would have performed in a similar way in the absence of ownership change and thus any divergence in their paths of performance is attributed to the change in ownership.

We assess how our matching performs by comparing the sample means between the treatment group (acquired plants) and the control group (plants remaining in Indonesian hands). As evident from (Table 2.3), there is no statistically significant difference in the means of pre-acquisition characteristics between the treatment and the control group. The same is true even for the plant characteristics that were not used in the matching procedure.[9] This is in contrast to the unmatched sample, shown in the left panel of Table 2.3, where the potentially acquired plants are statistically different in almost all aspects, including their energy consumption levels.

After obtaining the matched pairs, we examine the effect of foreign acquisitions on outcomes of interest using a difference-in-difference approach. More specifically, we estimate the following equation on the matched sample which is observed in the pre-acquisition period and in one of the post-acquisition periods:

$$y_{it} = \alpha_i + \gamma Post_t + \beta(Post_t * Acquired_i) + \varepsilon_{it} \tag{2.2}$$

where i denotes a plant and t the time period. *Acquired* is an indicator variable

[8]The application of CEM is not without precedence. For example, Wang et al. (2010) use CEM to estimate the magnitude of spillovers generated by academic "superstars" to their collaborators' publication rates. Singh and Agrawal (2011) use the same matching technique to determine how firms are making use of their recruits' prior stock of ideas. Beatty and Tuttle (2015) employ CEM in studying the effect of the unprecedented increase in Supplemental Nutrition Assistance Program on participants' expenditure on food.

[9]The share of imported inputs is an exception, though this variable is neither used in matching nor considered as an outcome.

denoting plants that undergo a foreign acquisition. *Post* is an indicator variable that takes on the value of unity in the year of foreign acquisition (or a subsequent year), and equals zero otherwise. Each plant is observed twice: once in the pre-acquisition and once in the post-acquisition period. We consider three post-acquisition years (the year when the transaction takes place and two subsequent years). Each of these years is considered in a separate estimation to produce cumulative effects. The coefficient of interest *beta* captures the effect of acquisition on the acquired plants, the average treatment effect on the treated (ATT).

Table 2.3: Balancing Test.

Variables	Unmatched sample (pre-acquisition period, N=293,549)				Matched sample (pre-acquisition period, N=524)			
	Foreign Owned	Control	Diff.	p-value	Acquired Plants	Control	Diff.	p-value
Used in matching								
Log (real output)	7.665	9.492	-1.827	0.000	9.298	9.311	-0.013	0.932
Log (energy expenditure)	3.854	5.542	-1.689	0.000	5.378	5.396	-0.018	0.914
Log (energy use)	6.785	8.470	-1.685	0.000	8.286	8.314	-0.028	0.874
Log (CO2 emission)	11.169	12.866	-1.697	0.000	12.674	12.713	-0.040	0.818
Log (energy expenditure) Trend	0.046	0.075	-0.029	0.008	0.120	0.093	0.026	0.637
Log (energy use) Trend	0.048	0.073	-0.024	0.037	0.105	0.088	0.017	0.769
Log (CO2 emission) Trend	0.050	0.075	-0.025	0.032	0.102	0.087	0.016	0.780
Unused in matching								
Log (energy expenditure/output)	-3.828	-3.905	0.077	0.000	-3.928	-3.924	-0.004	0.971
Log(energy use/output)	-0.896	-0.977	0.081	0.000	-1.019	-1.006	-0.014	0.904
Log(CO2 emission/output)	3.487	3.418	0.069	0.000	3.368	3.393	-0.025	0.818
Log(energy exp./materials exp.)	-2.993	-3.034	0.041	0.042	-3.169	-3.069	-0.100	0.419
Log (employment)	4.063	5.027	-0.964	0.000	4.840	4.991	-0.151	0.133
Exporter dummy	0.082	0.175	-0.093	0.000	0.212	0.212	0.000	1.000
Share of imported materials	0.116	0.245	-0.129	0.000	0.169	0.241	-0.072	0.018
Share of skilled workers	0.136	0.196	-0.060	0.000	0.196	0.193	0.003	0.860
Log(investment in machineries)	5.358	7.376	-2.018	0.000	7.225	7.344	-0.120	0.652
Log (real output) Trend	0.051	0.066	-0.015	0.051	0.125	0.094	0.031	0.609
Log (energy expenditure/output) Trend	-0.003	-0.003	0.000	0.986	-0.007	0.002	-0.009	0.878
Log(energy use/output) Trend	0.000	-0.005	0.005	0.686	-0.021	-0.003	-0.019	0.769
Log(CO2 emission/output) Trend	0.001	-0.003	0.004	0.735	-0.024	-0.005	-0.019	0.758
Log(energy exp./materials exp.) Trend	-0.009	-0.009	0.000	0.987	-0.003	-0.005	0.002	0.970

Source: Indonesian Census of Manufacturing

2.5 Results from the Difference-in-Differences Analysis on the Matched Sample

2.5.1 Output, Energy Consumption and CO_2 Emissions

We start by presenting the results capturing the *scale effect* of foreign acquisitions. This set of outcomes includes: output, energy use, energy expenditure and emission levels. The result suggest an increase in the scale of operations of the acquired plants, which is consistent with the existing findings (Arnold and Javorcik 2009).[10] This is visible in Figure 2.3 which graphs the trajectories of these variables for the treated (acquired) plants and the control group. Both groups display very similar paths two years prior to the ownership change. The paths start to diverge already in the acquisition year and the gap between the groups increases over the two subsequent years.

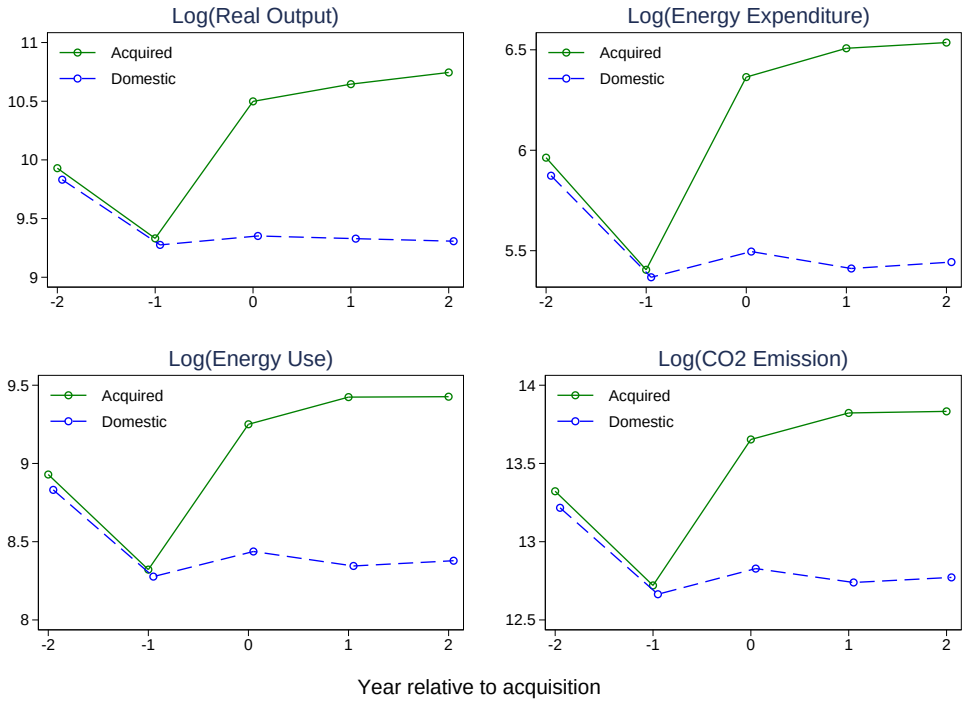
The effect of foreign acquisitions is formally tested by estimating equation 2.2 whose results are presented in Table 2.4. We find that acquired plants experience a statistically significant increase in output of 1.098 log points (or about 200%) relative to the control group already during the acquisition year. The difference between the two groups continues to increase to more than 1.374 log points (or more than 290%) in the subsequent two years. This expansion in plant-level output is accompanied by higher energy use and CO_2 emissions. Energy consumption, either measured in terms of value or in units of physical energy, more than doubles in the year of ownership change, and the increase persists in the two subsequent years. We also observe the same pattern for CO_2 emissions, indicating a significant positive scale effect.

To check the robustness of our findings, we consider a longer time horizon (5 years after the ownership change) and restrict our sample to plants for which the outcome of interest can be observed throughout this period (as well as during the two pre-acquisition years). This means that compare the changes over time within the same sample of plants. As illustrated in (see Appendix 2.3, our results are robust to this change. The estimated coefficients are significant in all specifications, and

[10] Of the three outcomes considered here, (Arnold and Javorcik 2009) examined only output.

their magnitudes are slightly larger.

Figure 2.3: Trajectories of acquired and domestic plants: output, energy expenditure and use, and CO_2 emission.



The figure illustrates the average value of each variable of interest in a given time period for the treated and the control group. The horizontal axes indicate the year relative to the period a treated plant is acquired, where the year of acquisition is denoted with 0.

Next we focus on energy and emission intensities as measures of the *technique effect* of foreign acquisitions. These intensities are obtained by dividing energy consumption (measured either in monetary terms on in BTUs) and emissions by the total value of output. As illustrated in Fig 2.4, acquired plants experience a substantial decrease in their energy consumption and emissions per unit of output relative to the plants that remain in domestic hands.

We statistically validate these findings by estimating equation 2.2 and summarizing the results in Table 2.5. The estimated coefficient of interest is statistically

Table 2.4: Regression results on output, energy and pollution levels.

	Acquisition Year	One Year Later	Two Years Later
Panel A	Log(Output, in Rps)		
Acquired	1.098***	1.263***	1.374***
	(0.119)	(0.123)	(0.128)
Adj. R^2	0.696	0.678	0.661
No. of Obs.	1056	1056	1056
Panel B	Log (Energy Expenditure, in Rps)		
Acquired	0.815***	1.011***	0.998***
	(0.129)	(0.145)	(0.187)
Adj. R^2	0.735	0.717	0.623
No. of Obs.	1005	951	902
Panel C	Log (Energy Use, in MTBUs)		
Acquired	0.750***	0.995***	0.948***
	(0.134)	(0.152)	(0.191)
Adj. R^2	0.738	0.716	0.635
No. of Obs.	1005	951	902
Panel D	Log (CO2 Emission, in $KgCO_2$)		
Acquired	0.749***	0.984***	0.950***
	(0.133)	(0.150)	(0.190)
Adj. R^2	0.738	0.717	0.631
No. of Obs.	1005	951	902

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

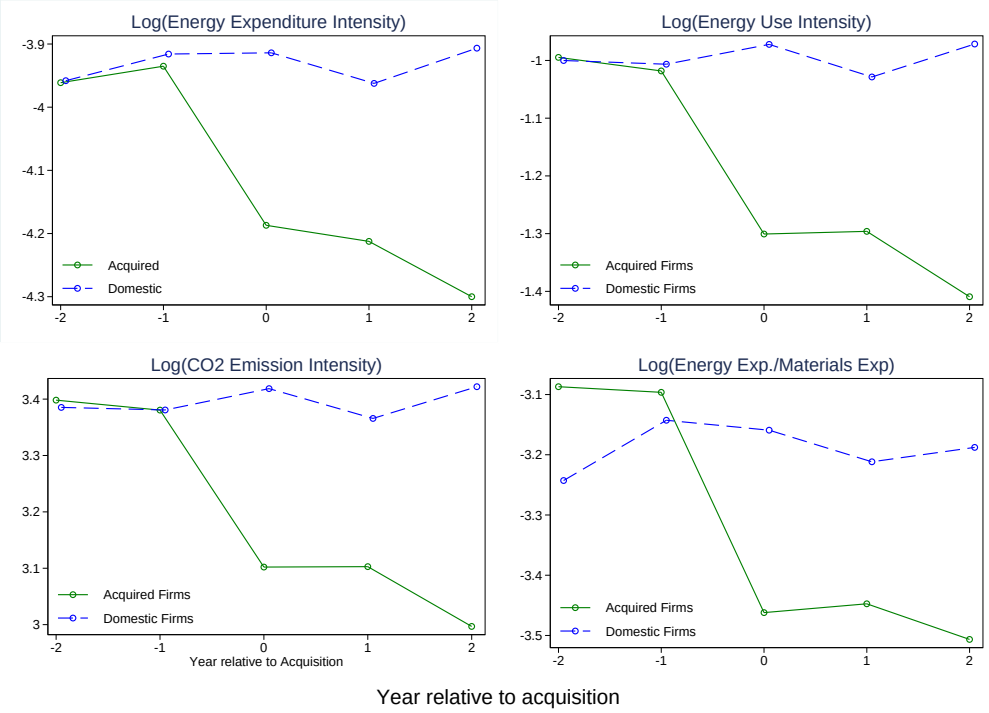
Source of Data: Indonesian Census of Manufacturing

significant in all specifications. The estimated magnitudes are also economically meaningful. They suggest that the share of energy cost to the total value of output falls in acquired plants (relative to the control group) by 22% during the acquisition year, and further declines to 32% after two years. The decline in physical energy and carbon dioxide content of output is larger than the decline in the share of energy cost

to total output. In terms of physical energy use, acquired plants reduce their energy intensity by 27% during the acquisition and by more than 35% two years after. We find a similar pattern for emission intensity, which may indicate that acquired plants tend to use less energy intensive and cleaner production techniques.

In Appendix 2.3, we show that the results are robust when we focus on plants observed for 5 years after the acquisition that report values of the variables of interest in each year.

Figure 2.4: Trajectories of acquired and domestic plants: intensities in energy expenditure, energy use, and CO_2 emission.



The figure illustrates the average of the variable of interest at a particular time period for matched acquired and domestic plants. The horizontal axes indicate the year relative to the period a treated plant is acquired (i.e. 0 is the year of acquisition and -1 is a year before the acquisition.)

As another test of the persistence of the estimated effects, we estimate the equa-

Table 2.5: Regression results for plant-level energy and CO_2 intensities.

	Acquisition Year	One Year Later	Two Years Later
Panel A	Log(Energy Expenditure/Output)		
Acquired	-0.253**	-0.239*	-0.382**
	(0.111)	(0.126)	(0.153)
Adj.R^2	0.543	0.483	0.407
No. of Obs.	1005	951	902
Panel B	Log(Energy Use/Output)		
Acquired	-0.318***	-0.255*	-0.432***
	(0.115)	(0.134)	(0.157)
Adj. R^2	0.567	0.487	0.438
No. of Obs.	1005	951	902
Panel C	Log(CO2 Emissions/Output)		
Acquired	-0.319***	-0.266**	-0.430***
	(0.115)	(0.133)	(0.157)
Adj. R^2	0.553	0.477	0.419
No. of Obs.	1005	951	902

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

tion of interest focusing in the third, fourth and fifth year under foreign ownership (i.e., t+3, t+4, t+5). Naturally, the number of observations falls as the number of plants observed over a longer horizon falls. The results, as presented in Table 2.6, confirm our hypothesis. We find statistically significant evidence of a widening difference between the energy use and emission intensities of plants acquired by foreign investors and domestic plants.

One drawback on normalizing energy use and CO_2 emissions by output is the potential increase in mark-up or premiums for products produced by plants which undergo foreign acquisitions. Thanks to gaining greater access to international mar-

Table 2.6: Regression results for plant-level energy and CO_2 intensities, three to five years after the acquisition.

	3 Years Later	4 Years Later	5 Years Later
Panel A	Log(Energy Expenditure/Output)		
Acquired	-0.493***	-0.640***	-0.614**
	(0.178)	(0.220)	(0.251)
Adj. R^2	0.387	0.294	0.335
No. of Obs.	835	792	744
Panel B	Log(Energy Use/Output)		
Acquired	-0.491***	-0.628***	-0.593**
	(0.185)	(0.232)	(0.257)
Adj. R^2	0.418	0.325	0.380
No. of Obs.	835	792	744
Panel C	Log(CO2 Emissions/Output)		
Acquired	-0.499***	-0.616***	-0.608**
	(0.185)	(0.233)	(0.255)
Adj. R^2	0.401	0.295	0.369
No. of Obs.	835	792	744

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

kets acquired plants may enjoy an increase in mark-ups (Javorcik and Poelhekke 2016). Thus, it is possible that the value of their output may increase, even if the total physical quantity of output remains unchanged. If this is true, then energy and emission intensities may fall, even if energy use and emissions per physical unit of output remain constant. To address this issue, we normalize energy expenditure, physical energy use and emission level by the value of expenditures on materials. The lower right panel in Figure 2.4 shows the decline in energy intensity experienced by the treated plants relative to the control group is also found for this alternative normalization. The regression estimates, presented in Table 2.7, confirm this mes-

sage. They show that acquired plants reduce energy cost, energy physical use and emission level per unit cost of materials relative to domestic plants.

Table 2.7: Regression results for plant-level energy use and CO_2 emission per unit cost of materials

Panel A	Acquisition Year	One Year Later	Two Years Later
	Log(Energy Expenditure/Materials)		
Acquired	-0.370***	-0.330**	-0.408**
	(0.123)	(0.134)	(0.175)
Adj. R^2	0.604	0.603	0.475
No. of Obs.	972	923	875
Panel B	Log(Energy Use/Materials)		
Acquired	-0.443***	-0.360**	-0.473***
	(0.124)	(0.140)	(0.179)
Adj. R^2	0.631	0.602	0.485
No. of Obs.	972	923	875
Panel C	Log(CO_2 Emission/Materials)		
Acquired	-0.442***	-0.370***	-0.470***
	(0.124)	(0.139)	(0.179)
Adj. R^2	0.625	0.599	0.474
No. of Obs.	972	923	875

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

We also test whether the results remain the same if we control for the potential increase in the share of exported output by the acquired plants. We add export share as an explanatory variable in equation 2.2. The results are summarized in Table 2.8. As before, we find that the acquired plants decrease their emissions and energy use per unit of materials used and the difference between the two groups widens over time. In particular, acquired plants reduce their energy expenditure intensity by about 23% in the year of acquisition and by 31% two years after. More

interestingly, the magnitude of decline in intensity is greater in terms of physical energy use and CO_2 emission, ranging from 28% in the year of acquisition to 34% two years after the ownership change. The effects are statistically significant in all (but one) specification.[11].

2.5.2 Does Foreign Acquisition Influence Plants Uniformly?

The evidence presented so far suggests that foreign acquisitions lower energy consumption and emission levels per unit of output. Nonetheless, it is not obvious whether these effects are similar across all plants. It could be that the effect of a change in ownership on plant-level environmental performance is stronger for plants that were initially smaller and less energy efficient. In other words, the improvement in the production technique may be larger for plants that were initially further from the technological frontier.

To test this hypothesis, we estimate equation 2.2 augmented with an interaction term between the foreign acquisition dummy and the plant's output level in the pre-acquisition year. The estimated results are presented in Appendix Table B.5, and they are also plotted in Figure 2.5. In the figure, the solid line corresponds to point estimates, while the dashed lines denote the 95% confidence interval. On average, about 83% of all acquired plants experience a reduction in the cost of energy in total output, and about 90% of the acquired firms reduce the energy and CO_2 emission content of their products. We observe that the decline in the cost of energy per unit of output is much larger at low levels of pre-acquisition output. This effect is also statistically significant. These results indicate that smaller and perhaps less efficient plants tend to benefit more in terms of reducing energy use and emission intensities from foreign acquisitions.

We also estimate equation 2.2 augmented with an interaction term between the foreign acquisition dummy and the plant's pre-acquisition energy expenditure per unit of output. The idea is to test whether domestic plants that were more energy

[11]We also estimate a specification that includes the share of exported output and its interaction with the Foreign Acquisition dummy variable. We find that the estimates our robust to this change (see Appendix 2.4)

Table 2.8: Regression results for plant-level energy use and CO_2 emission intensities after controlling for share of exported output.

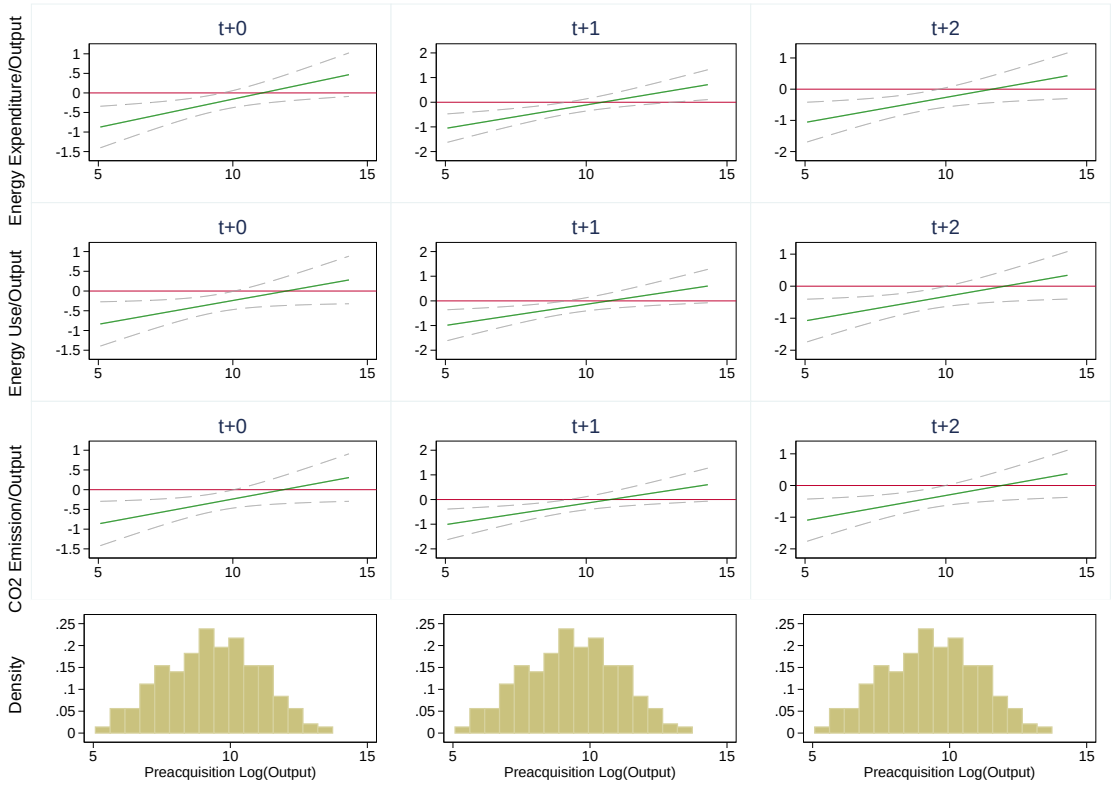
	Acquisition	1 Year Later	2 Years Later
	Energy Expenditure Intensity		
Foreign Acquisition	-0.258**	-0.228*	-0.370**
	(0.111)	(0.128)	(0.153)
Export Share	0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)
Adj. R^2	0.542	0.482	0.406
No. of Obs.	1005	951	902
	Energy Use Intensity		
Foreign Acquisition	-0.327***	-0.241*	-0.420***
	(0.116)	(0.137)	(0.158)
Export Share	0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)
Adj. R^2	0.566	0.486	0.438
No. of Obs.	1005	951	902
	CO2 Emission Intensity		
Foreign Acquisition	-0.326***	-0.251*	-0.417***
	(0.116)	(0.136)	(0.158)
Export Share	0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Adj. R^2	0.552	0.477	0.418
No. of Obs.	1005	951	902

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

intensive tend to reduce their energy intensity more when acquired by foreign firms. The estimation results are presented in Appendix Table B.6. Figure 2.6 illustrates the point estimates at varying levels of pre-acquisition energy expenditure per unit output. The results indicate that 70% of acquired plants experience a reduction in

Figure 2.5: Effect of foreign acquisition on the outcome variables at varying pre-acquisition output level.



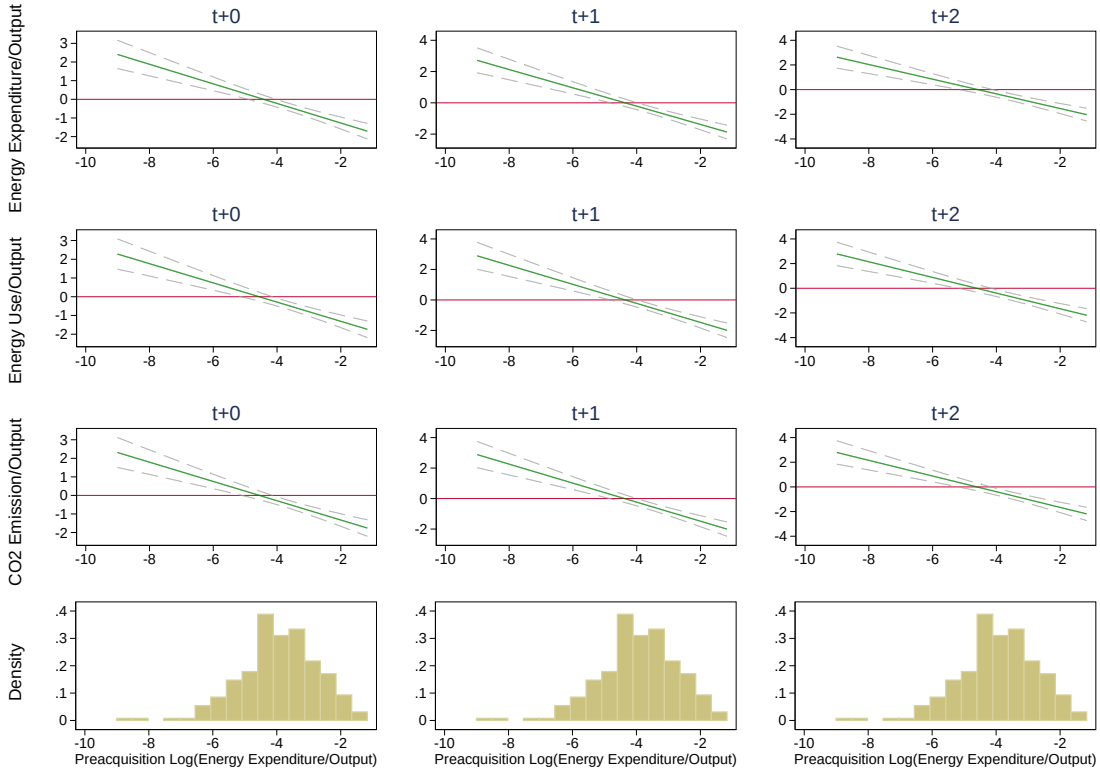
Note: The plots at the top three panels of the figure illustrates the point estimates generated from the difference-in-differences approach at varying preacquisition output level. Each plot reflects a separate estimation procedure, covering a particular outcome variable (left vertical axis) and time period (t pertains to the year of acquisition). The solid lines in these plots are the estimated coefficients and the dashed lines denote 95% confidence interval. Plots in the bottom panel reflects the distribution of acquired firms, in terms of their preacquisition log(output) level, in each time period.

Source: Indonesian Census of Manufacturing

their energy and CO_2 emission intensities. Plants that were initially more energy intensive are the ones experiencing a greater decline in energy intensity. Somewhat surprisingly, 30% of the acquired plants that were less energy intensive to begin with seem to have increased their energy and emission intensities. We observe the same results when changing the measure of pre-acquisition energy intensity to physical

units of energy (in BTUs) per unit of output (see Table B.7 and Figure B.4 in Appendix 2.5.).

Figure 2.6: Effect of foreign acquisition on the outcome variables at varying pre-acquisition energy expenditure/output.



In order to determine why less energy intensive plants become more energy intensive when they are acquired, we focus on plants that are below the median pre-acquisition energy intensity and consider the impact of foreign acquisitions on several other outcome variables. The goal is to determine whether foreign acquisition induces a restructuring in acquired plants that may explain the above results. Table 2.9 illustrates the results of the difference-in-differences approach on matched samples that

had below-median pre-acquisition energy intensity. The results show that for plants that had relatively low energy intensity initially, foreign acquisition brings significant expansion in employment and capital, with the proportional magnitude of capital increase being greater. However, except for the acquisition year, there is no statistically significant evidence of an increase in capital intensity. The acquired plants experience an increase in investment in machinery and its share in total capital. 50% of these plants belong to the textile industry, which reportedly has undergone dramatic industrial upgrading through increased investment in machinery, particularly in the spinning industry, and improving the quality of machinery in the weaving industry (Szirmai et al. 2002). Thus, plants that use low-energy intensive technology prior to acquisition use more energy after the ownership change due to mechanization of their production processes.

2.5.3 Do Acquired Plants Reallocate Across Energy Inputs?

The final question of interest is whether acquired plants change their mix of energy inputs. We investigate this question in Table 2.10 which considers as outcome variables the plants' expenditures on major energy sources; fuel and lubricants, electricity (net of own generation), and their respective intensities. The results indicate that foreign ownership affects the plant's mix of energy sources. During the acquisition year, expenditures on fuel and lubricants in acquired plants increase by 46% relative to the control group with the gap increasing to 50% two years after. Meanwhile, consumption of electricity in acquired plants increases at a much higher rate, beginning at 63% during the acquisition period, rising to 72% a year after and then remaining at this level a year later. All of these changes are statistically significant.

As for energy intensity, we observe a significant reduction in the cost of fuel and lubricants per unit of output during the acquisition period. The acquired plants' fuel intensity declines to 36% during the acquisition period to about 80% two years after. Surprisingly, we do not observe any significant reduction in the electricity cost per unit of output due to foreign acquisition, which might suggest that expansion in production is mostly driven by increased consumption of electricity.

Table 2.9: Regression results for select outcome variables on matched plants below median pre-acquisition energy intensity

	Acquisition Year	One Year Later	Two Years Later
Panel A		Log(Capital)	
Acquired	0.749***	0.808***	0.577*
	(0.257)	(0.272)	(0.330)
Adj. R^2	0.061	0.059	0.024
No. of Obs	426	426	415
Panel B		Log(Employment)	
Acquired	0.306***	0.356***	0.408***
	(0.071)	(0.076)	(0.082)
Adj.R^2	0.177	0.206	0.187
No. of Obs	548	548	548
Panel C		Log(Machinery stock)	
Acquired	1.244***	1.304***	1.090***
	(0.264)	(0.295)	(0.356)
Adj. R^2	0.163	0.145	0.104
No. of Obs	418	419	404
Panel D		Log(Machinery-Capital Ratio)	
Acquired	0.490***	0.467**	0.458**
	(0.187)	(0.198)	(0.212)
Adj. R^2	0.064	0.056	0.068
No. of Obs	418	419	404
Panel E		Log(Capital-Labor Ratio)	
Acquired	0.461*	0.369	0.074
	(0.256)	(0.273)	(0.334)
Adj. R^2	0.013	0.005	-0.003
No. of Obs	426	426	415

Note: The table reflects the result of estimating equation 2.2 on the matched sample with below-median preacquisition energy intensity. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

We conjecture that expansion of acquired firms is fueled mostly by electricity

Table 2.10: Regression results for select energy sources

	Acquisition Year	One Year Later	Two Years Later
Panel A	Total Fuel & Lubricants Expenditure		
Acquired	0.611***	0.686***	0.691***
	(0.167)	(0.186)	(0.230)
Adj. R2	0.694	0.663	0.586
No. of Obs.	974	924	873
Panel B	Net Electricity Expenditure		
Acquired	0.991***	1.263***	1.292***
	(0.191)	(0.225)	(0.267)
Adj. R2	0.703	0.638	0.605
No. of Obs.	826	782	745
Panel C	Fuel & Lubricants Exp./Output		
Acquired	-0.422***	-0.478***	-0.586***
	(0.142)	(0.166)	(0.187)
Adj. R2	0.603	0.534	0.504
No. of Obs.	974	924	873
Panel D	Net Electricity Expenditure/Output		
Acquired	-0.087	-0.029	-0.168
	(0.161)	(0.199)	(0.238)
Adj. R2	0.567	0.424	0.359
No. of Obs.	826	782	745

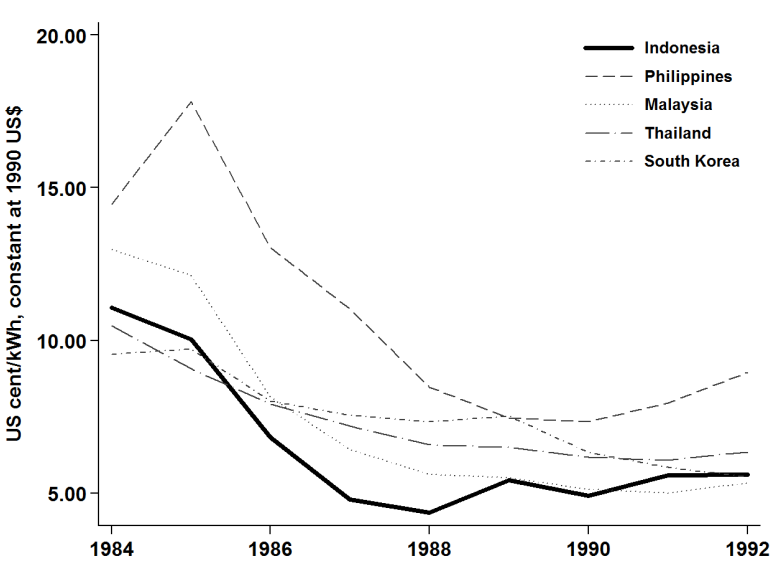
Note: The table reflects the result of estimating equation 2.2 on the matched sample with below-median preacquisition energy intensity. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

because of the relatively low electricity rates prevailing in Indonesia. This conjecture is consistent with the findings of other studies suggesting that the kind of technology a firm will use to reduce emission (either through pollution abatement or increasing energy efficiency) may be effectively influenced by policies that directly affect factor prices (see, for example, Harrison et al. 2015; Khanna and Zilberman 2001). Figure 2.7 shows that Indonesia's industrial electricity tariffs are much lower when

compared to its neighboring countries, which might explain why a lot of FDI that flowed into the country during the sample period is found in generally electricity-intensive industries. The low electricity tariffs are due to the country's generous subsidies (Mourougane 2010).

Figure 2.7: Industrial Electricity Rates for Select ASEAN Counties, 1984-1992.



Source: Malhotra, et al. 1994.

2.6 Conclusion

Rising concerns about the potential effect of FDI inflows on natural environment, along with the growing importance of developing countries, have engulfed the literature with studies trying to validate the pollution haven hypothesis. Some argue that highly polluting multinationals relocate to countries with weaker environmental standards (pollution havens) in order to circumvent costly regulations in their home country. Those voices view FDI as a vehicle for moving pollution from developed to developing countries. Others, in contrast, point out that FDI has positive (pollution

halo) effects because multinationals often have more efficient and cleaner technology.

This study contributes to the nascent literature on the causal effect of FDI on plant-level environmental performance by examining how foreign acquisitions influence plant-level energy and CO_2 emission intensities using data from the Census of Indonesian Manufacturing covering the period 1983-2001. Our analysis improves on the previous literature in three important respects. First, we estimate physical consumption of energy and carbon dioxide emissions, an information that is hardly available for most developing countries. Second, we examine the changes in ownership taking place within the same plant. This allows us to focus on changes in plant-level environmental performance introduced by foreign ownership. Third, rather than focusing on the narrow question of energy expenditure, we consider a wider range of outcomes which can potentially explain the changes in energy consumption and emission patterns of acquired firms.

Our measure of pollution externalities is far from perfect. The analysis is limited to global pollution (i.e. CO2 emission) and completely ignores the impact of FDI on local pollutants, which may be of greater interest when analyzing the impact of cross-country differences in local environmental regulations. Devising a close approximation of plant-level emission of local pollutants is extremely challenging as it requires information on plant-level pollution abatement that our data does not have. Moreover, the analysis does not address the potential spillover effect of FDI on domestic plants, potentially through agglomeration or supplier-buyer linkages. It is possible that domestic plants are catching up in terms of using cleaner technologies, which partly explains why the trajectory of energy and emission levels of domestic plants slightly goes up. To the extent that spillover effects are large and significant, completely ignoring this may bring in downward bias in our initial ATT estimates.

Despite these methodological imperfections, the data show remarkable plant-level operational changes associated with ownership changes, which we decompose into scale and technique effects. We see significant positive scale effect of acquisition, which increases the output of the plant, and consequently, its levels of energy use and CO_2 emissions. The technique effect, which usually is beneficial to the environment, refers to the improvement in the efficiency of using energy inputs due to FDI-induced

innovations and investments. We see indications of falling energy and intensities, which implies that each additional unit of output is produced with lower energy and CO_2 content. We also find that the improvement in energy and emission intensity brought about by foreign acquisition is larger in magnitude when the acquired plant is smaller and had relatively higher energy intensity prior to acquisition. The results suggest that potential improvement in energy use per unit of output is probably higher when plants are relatively further from the innovation frontier.

Our results lend credence to many of the concerns raised by environmentalists. Figure B.5 shows that despite the reduction in energy intensity due to FDI inflows, Indonesia's energy intensity remains to be higher than most FDI-source countries like the US, UK and Japan. At the global scale, there is indication that pollution may have been lower had production of FDIs remained in developed countries. However, this hypothesis does not take into account the potential technological and management spillover effect to local firms located in developing countries receiving FDIs. The complexity of measuring spillovers from FDIs to local firms illustrates a need for further research in this area.

Chapter 3

Not All States Are Alike: Evaluating The Effect of Oil Price Shocks on US State-Level Economies[1]

3.1 Introduction

Due to the recent drop in oil and gasoline prices, US households saved an average of $700 in 2015. Although consumers spent half of these savings on other goods and services (Farell and Greig 2015), the resulting stimulus to the US economy was less than many expected (Hamilton 2016). Meanwhile, oil producers were severely harmed by the price drop, resulting in a loss of about 35,000 jobs from October 2014 to April 2015 (US EIA, 2015) and decline in capital expenditure by about half a percent of GDP (Hamilton 2016). A similar pattern was observed during the 1986 oil price collapse, which had no significant effect on the US macroeconomy but brought regional recession to major oil-producing states (Hamilton and Owyang 2012). The oil price declines in 1986 and 2014 show how the aggregate effect of oil

[1]This essay is a result of a collaboration with Michael Roberts.

price shocks can obscure more prominent, opposing effects at the state level.

Clearly, states differ in their responses to oil prices because they are endowed with different resources and specialize in different economic activities (Melichar 2013). The oil- and gas-rich states in the Gulf Coast area largely rely on energy and petrochemical industry, while the Great Lakes region is home to large manufacturing industries, making imported oil integral to the region. Thus, an unanticipated increase in the price of oil can stimulate the economies of the Gulf Coast region while stunting growth in the Great Lakes area.

Through trade and migration, an economic shock to one state will also have spillover effects on other states. Carlino and Inman (2013) find that a state's own deficits stimulates neighboring economies in addition to its own economy. They estimate a considerable spillover effect, averaging about two-thirds of each state's direct impact. In aggregate, we should probably expect that exogenous oil price spikes are bad for the U.S. economy because we still import oil. At the same time, it would be useful to unpack these regional differences and spillover effects.

While a number of empirical studies consider how oil price shocks influence the aggregate US economy (see, for example, Hamilton 1983; Bernanke et al. 1997; Barsky and Kilian 2004; Kilian 2008, 2009), surprisingly few studies, consider oil price-macroeconomy relationships at the state-level. Two important exceptions are Brown and Yucel (1995) and Melichar (2013).[2] A limitation of these earlier studies is that they take oil price shocks as exogenous, an assumption that more recent aggregate studies no longer make. The modern literature recognizes that price shocks are symptoms of more fundamental economic developments that drive demand and supply of oil (Barsky and Kilian 2002, 2004; Kilian 2009), with different drivers having different effects. It is also likely that different kinds of shocks have different effects on different states, depending on how much oil and related commodities each typically produces and consumes.

In this study we build upon Kilian (2009)'s work that disentangles the underlying

[2]There are also studies that use industry-level data to analyze the influence of oil price shocks to the economy. See, for example, Davis and Haltiwanger 2001; Lee and Ni 2002; Kilian and Park 2009.

demand and supply shocks in the global crude oil market, but extend it to account for varying responses of shocks on different local economies, as well as economic spillovers across neighboring states. We find that oil price shocks have substantially different impact on different states. For example, an exogenous (supply-driven) 10 percent decline in the growth of oil price causes an estimated 0.40 percentage point decrease to growth in Wyoming and an estimated 0.12 percentage point increase in New York. However, the direct effects are attenuated or magnified via spillover effects, such that within one year, the total effect for Wyoming diminishes to about 0.3 percentage point decline in growth while the effect in New York increases to 0.45 percentage point. These two states see the most extreme effects; others states lie in between these two.

Results from this study may have implications for how governments address macroeconomic fluctuations that derive from oil price shocks in the US. Monetary policy can be a crude tool in this context, given the heterogeneity of effects across states and regionally-varying need for stimulus. For example, a sufficient "rainy day fund"—reserves to use for state-level stimulus when unanticipated state revenue shortfalls occur—could provide each state the capability to weather the adverse effects of oil price shocks on their own. The federal government might also provide targeted fiscal stimulus to states that were severely harmed by oil price shocks.

The remainder of the paper is as follows. Section 3.2 discusses how we estimate the impact of each underlying oil price shock to different states in the US. In this section, we update Kilian (2009)'s work to cover the oil price drop in 2008. The section also characterizes different states based on their relative oil consumption and production and presents evidence of spatial correlation of economic growth amongst neighboring states. Section 3.3 presents the impact of oil price shocks to states' economic growth. We conclude in section 3.4 with a discussion of implications for local fiscal stimulus.

3.2 Empirical Strategy

3.2.1 Accounting for the Endogeneity of Oil Price Changes

Historically, researchers consider oil price shocks as exogenous, possibly because most of these shocks concurred with war-driven oil production shortfalls and geopolitical uncertainties in oil-exporting countries (Hamilton 1983; Guo et al. 2005; Melichar 2013; Rahman and Serletis 2010). However, there is an increasing recognition that oil price shocks are associated not only with shocks to the current physical availability of oil, but also with unanticipated changes in the aggregate demand, and with shocks driven by uncertainties about the expected supply relative to the demand for oil (Barsky and Kilian 2004; Kilian 2009; Kilian and Murphy 2014). There is also evidence that exogenous changes in oil production are significantly less important in influencing global oil price since the late 1970s, compared to changes in precautionary demand for oil and global demand fluctuations (Kilian 2008). Macro aggregates may also have influence on oil prices. One channel is through monetary conditions, which may result in changes in the demand for oil and eventually in oil price (Barsky and Kilian 2002).

The endogeneity of oil price changes has implications on how researchers evaluate the influence of crude oil price changes to macroeconomic aggregates. Identifying the underlying demand and supply shocks in the global crude oil market helps us understand what is driving oil price changes and determine how macroeconomic aggregates are affected by different shocks influencing oil price changes (Kilian 2009). For our purpose, it is important to recognize the extent to which oil price changes are driven by one shock or another because it is plausible that different oil price shocks may have different effect on individual state economies.

In order to account for the potential endogeneity of crude oil prices, we use Kilian (2009)'s vector autoregression (VAR) model to extract the underlying structural innovations behind each oil price shock. We updated the sample period up to 2015 to cover the most recent oil price changes. The model uses monthly data of $z_t = (prod_t, rea_t, rpo_t)'$, where $prod_t$ refers to global crude oil production from the Energy

Information Administration (EIA), rea_t denotes the index of real economic activity derived from the bulk dry cargo shipping rate index developed in Kilian (2009), and rpo_t is the refiner's acquisition cost of imported crude oil provided by EIA, which serves as proxy to global crude oil price. Except for rea_t that is stationary by construction, all of the series are period-to-period log-transformed differences. The sample period is 1974.1 - 2015.10. We remove seasonal variation by including monthly dummies.

Following Kilian (2009), the following exclusion restrictions are imposed to the reduced form errors, e_t:

$$e_t = \begin{pmatrix} e_t^{prod} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil\text{-}specific\ demand\ shock} \end{pmatrix}$$

where ε_t^k denotes the serially and mutually uncorrelated structural shocks in each VAR equation $k = 1, 2, 3$. The exclusion restriction implies the following: *Oil supply shocks* denote unanticipated innovations in global crude oil production and is assumed not to respond to any innovation in the demand for oil within the same month. The assumption reflects the slow response of global crude oil production to demand shocks because of costly adjustment in production and uncertainties in the future state of the crude oil market. Shocks to global real economic activity are referred to as *aggregate demand shocks*[3]. The exclusion restriction implies that oil-specific demand shocks, which increases oil price, will not lower real economic activity within the same month but only with a delay of at least one month. This exclusion restriction is consistent with the sluggish response of the macroeconomy to major oil price increases observed in the sample period. Finally, unanticipated oil price changes, here referred to as *oil-specific demand shocks*, denote shocks to changes in demand for crude oil not already captured by instantaneous shifts in aggregate demand for industrial commodities and supply of oil. These shocks include changes

[3]Kilian (2009) clearly distinguishes aggregate demand for industrial commodities in this context as opposed to aggregate demand for overall goods and services

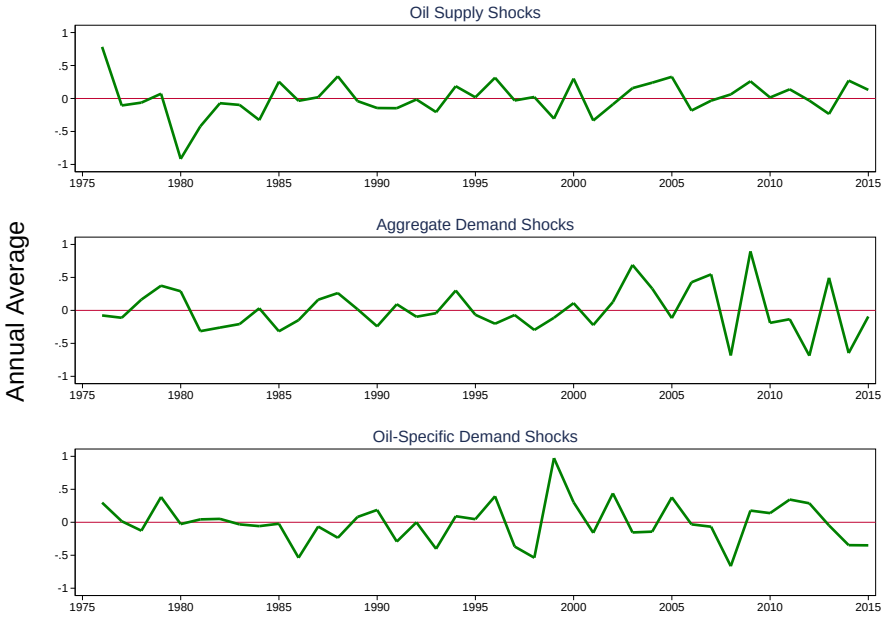
in precautionary demand for oil due to shifts in expectations about future demand relative supply of oil. For example, crude oil price started to escalate in 1979, even though there was no significant disruption in the global crude oil production. The increase in crude oil price in 1979 is associated to the outbreak of the Iran-Iraq War in 1980 (Kilian 2009).[4] While the residual shocks in the model may also include other shocks such as unexpected weather patterns and changes in preferences, there is evidence to support that the residual shock largely represents exogenous shifts in precautionary demand for oil.[5]

Figure 3.1 plots the historical evolution of the structural shocks implied by the VAR model. The shocks are expressed as annual averages for better readability. A key point that this figure emphasizes is that the spikes and drops capture the important oil price shocks in history as documented by Kilian (2009) and Hamilton (2013), and recorded US recessions from the National Bureau of Economic Research (NBER). For example, there was a global oil supply disruption in 1980 associated with the outbreak of the Iran-Iraq war. Meanwhile, the years 1978, 1979, and 1980 experienced large positive economic shocks attributed to the growing global economy. There is also an unanticipated increase in oil-specific demand in 1979, consistent with the increased uncertainties the future supply of oil attributed to the geopolitical conflicts in the Middle East. The estimated structural shocks also captures the 2008 unanticipated fall in aggregate demand following the Great Recession, which also coincides with a drop in oil-specific demand due to low expectation on future demand for oil. Meanwhile, the US oil production increased in 2014, causing a slight unexpected uptake in oil global production.

[4]The 1978-1979 Iranian revolution brought insignificant change in the global production of oil as Iranian cutbacks were more than offset by increased production elsewhere (Kilian 2009; Hamilton 2013).

[5]For detailed discussion, see (Kilian 2009).

Figure 3.1: The Historical Evolution of the Structural Shocks, 1976-2015.



Notes: The figure illustrates that estimated structural residuals from the VAR model, averaged to annual frequency. A figure showing the historical trend of the variables used in the VAR is presented in Table C.1.
Source: State Energy Data System (SEDS), EIA.

3.2.2 Accounting for the Heterogeneity of States

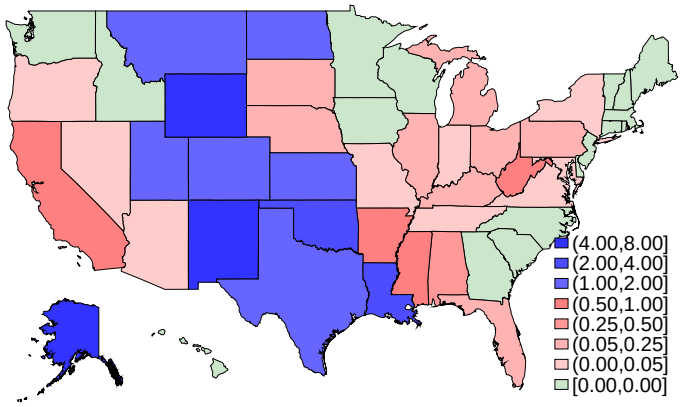
We characterize diversity through the states' oil production relative to their consumption.[6] The ratio is calculated by taking the sum of the energy content (in British Thermal Units) of crude oil and natural gas produced by the state from 1963-2013 divided by the sum of energy consumed from crude oil and petroleum at end-use level. The idea is to get a sense of how each state depends on its oil endowments in meeting local demand. A ratio greater than 1 implies that the state is a net

[6]Another way to characterize diversity is through relative shares of industry gross value added to total Gross State Product (GSP). However, the industry classification changed from SIC to NAICS in 1997 and created discontinuity in the series, making comparison across years difficult.

producer of oil, and a net importer if otherwise. We recognize that this measure is imperfect, primarily because a state may increase production in response to changing oil demand. Nonetheless, we argue that this ratio is a long run average, and any transitory change to consumption or production will average out in the long-run. We also recognize that data on crude oil production do not include Federal Offshore production from 1981 forward. Petroleum Administration for Defense District (PADD) 5 makes up about 10-percent of California's production over time, and will not make significant change in California's long-run production-consumption ratio. Meanwhile, the states in PADD 3 that have the most of offshore production (i.e. Texas and Louisiana) are already net producers and adding the offshore production will not make the states net importers. Figure 3.2 illustrates the diversity of the US economy based on state-level average oil production-consumption ratios from 1963 to 2013. Major net oil producers include Alaska, Wyoming and New Mexico. Large economies (i.e. California and New York) are both net consumers, while a number states (e.g. Hawaii and Washington) do not have any production of oil and natural gas over the sample period.

Since states are diverse, the response of each state to oil price shocks may also be different, depending on their oil endowment relative to their local requirement. In order to test this hypothesis, we observe the trend of average Gross State Product (GSP) growth rates of net oil-producing and -consuming states in periods of major oil price changes. Figure 3.3 summarizes the result. From around 1975-1986, considerable divergence of GSP growth paths were observed between net producers and net consumers. For example, the oil price hike in 1980 is associated with high positive GSP growth of net oil-producers, and negative GSO growth of net oil-consumers. When real oil price plunged to about \$30/barrel in 1986, net producing states experienced negative GSP growth rates while net consumers experienced positive growth. In the 1990s up to 2002, the growth path of the two groups follow a somewhat similar pattern. Significant differences in the pattern start to appear in 2003. During the Great Recession in 2007-2008, when real oil price drops from \$100 to about \$60 per barrel, all states experienced negative GSP growth, with net oil-producing states suffering disproportionately more.

Figure 3.2: Oil-based energy production-consumption ratio, by state



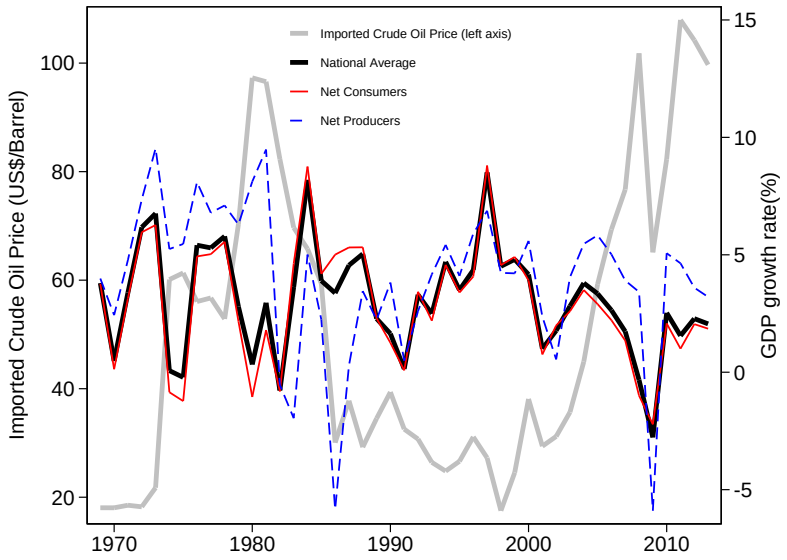
Notes: The figure illustrates that calculated energy production-consumption ratio of each state in the US. The ratio is generated by taking the sum of all energy produced within the state from 1960-2013 (in British Thermal Units or BTUs) divided by the sum of all energy consumed (end-use). Oil based sources include crude oil, and natural gas.

Source: State Energy Data System (SEDS), EIA.

3.2.3 Accounting for Economic Spillovers Across Neighbors

Another hypothesis is that state economies are related to one another through factor mobility and trade of goods. For example, the sharp increase in shale extraction in North Dakota resulted in rapid population increase from 2010 to 2013, largely due to influx of young adults from other states seeking employment in the oil fields. There is also evidence suggesting that state-specific policies, including welfare spending, have significant positive spillover effect on neighboring states (Baicker 2005; Figlio et al. 1999). In order to test the hypothesis, we look at the spatial patterns of growth during periods of major oil price changes. Figure 3.4 shows the GSP growth rate of different states in the US during the oil price surge in 1980 and the 1986 oil price collapse. In 1980, we see patterns of regional recessions in the Great Lakes region while remarkable regional growth around the Gulf Coast area. We see the opposite pattern in 1986. Overall, there is an indication that clusters of negatively-

Figure 3.3: Gross state product growth rate (average, net importers, net producers) and crude oil price.



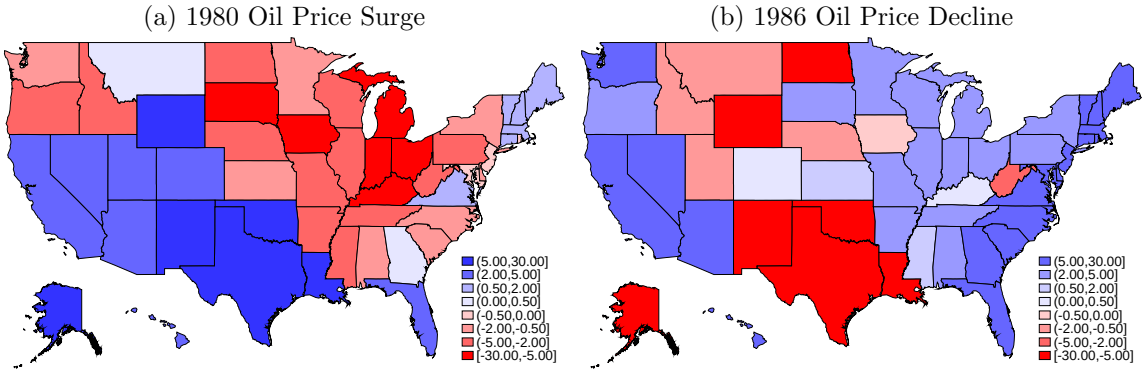
Imported crude oil price (solid gray line) denote refiners' acquisition cost (in 1981 US$). Net producers are those with average energy production/consumption≥1 from 1960 to 2013.

Source: (Energy Production-Consumption) SEDS, EIA; (Crude Oil Price) EIA, (GSP) BEA.

or positively-affected states emerge during periods of major oil price changes. This is consistent with the findings of Hamilton and Owyang (2012) supporting the existence of regional groupings based on comovement of state employment growth rates during periods of economic recession.

In order to determine if there is a strong statistical evidence of spatial correlation, we look at the Moran scatter plot during the oil price surge in 1980 and the price decline in 1986 (left panel of Figure 3.5). The Moran scatter plot shows the relation between the individual state's GSP growth rate (in standardized form) in the horizontal axis and the average growth rates of neighboring states weighted by the spatial lag vector W in the vertical axis. W assumes that the spillover effect of state's neighbor is inversely related to the geographic distance between the two states

Figure 3.4: Gross State Product Growth Rates, 1980 and 1986



Source: BEA.

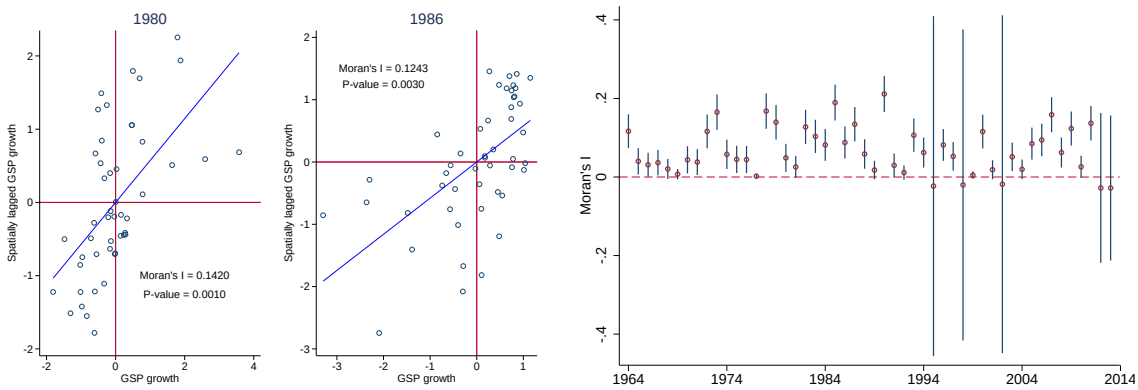
and positively related to the economic size of the neighboring state. We provide a more detailed discussion on this spatial lag vector in the next section. The scatter plot is centered around zero becuase of standardization. The upper right quadrant shows the states that have GSP growth rates above the cross-sectional mean, where the average of neighboring states are also above the mean. The lower left quadrant shows the states and its neighboring states' GSP growth rates that are both below mean. The scatter plot indicates a positive correlation between states' GSP growth rate and that of their neighboring states in both periods. Indeed, the Moran's I statistic, a metric often used to formally test for spatial dependence is positive and statistically significant (the alternative in this test is that the slope is zero, indicating no spatial dependence). We also calculate the Moran's I statistic for all time periods and they are generally positive and statistically significant (right panel of Figure 3.5), which suggests that there is positive comovement in GSP among neighboring states.

3.2.4 A Model of Oil Price Shocks with Inter-State Spillovers

After estimating the monthly structural shocks in the crude oil market in Section 3.2.1, we take the annual average of the shocks in order to have the same fre-

Figure 3.5: Moran scatter plot and Moran's I-statistic

(a) Moran Scatter Plot, 1980, 1986 (b) Moran's I-statistic, 1963-2013.



The left panel shows the Moran scatter plot during the oil price surge in 1980 and the price collapse in 1986. The right panel presents that calculated Moran's I-statistic from 1963 - 2013. The whiskers denote 95 percent confidence interval.

Source: (GSP) BEA, (Moran's I-statistic) Authors' calculation.

quency with the annual GSP estimates provided by the Bureau of Economic Analysis (BEA), as follows:

$$\hat{\zeta_{jt}} = \frac{1}{12}\sum_{i=1}^{12} v_{j,i,t}, \quad j = 1, 2, 3 \tag{3.1}$$

where $v_{j,i,t}$ refers to the estimated residual in the j^{th} equation in the VAR model in the i^{th} month of the t^{th} year of the sample. We can examine the influence of these stuctural shocks on US state-level economies based on the specification:

$$y_t = \tau y_{t-1} + \lambda W y_t + \rho W y_{t-1} + X_t\beta + \alpha I_N + u_t \tag{3.2}$$

where y_t is a nx1 vector denoting GSP growth rate for each state at period t, X_t is a mx(nt) matrix of m-explanatory variables containing our estimated structural shocks $\hat{\zeta_{kt}}$ and their interaction with states' long-run average oil production-consumption ratio, α is nx1 vector of state fixed effects, and u_t is the usual error term. We include

a spatial lag variable Wy_t and Wy_{t-1} to capture the spatial relationships amongst states in the sample. We define the spatial lag variable, W, as

$$W = \begin{pmatrix} 0 & w_{1,2} & w_{1,3} & \dots & w_{1,n} \\ w_{2,1} & 0 & w_{2,3} & \dots & w_{2,n} \\ w_{3,1} & w_{3,2} & 0 & \dots & w_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{n,1} & w_{n,2} & w_{n,3} & \dots & 0 \end{pmatrix} \tag{3.3}$$

$$w_{i,j} = \frac{M_i M_j}{d_{ij}^2} \tag{3.4}$$

where M denotes the economic size of states i & j (measured as average GSP from 1960-2014, in 2014 US$), and d is the distance (measured in terms of geographic and economic distance) between the most populous urban areas of states i and j. For economic distance, we take the average value of inbound and outbound zone-based cargo freight rates from FedEx in 2015 to approximate shipping costs from and to different states. The shipping cost is based on a hypothetical 15,000-lb cargo. We also use spatial contiguity as a measure of W to test for the robustness of our estimates. This kind of spatial lag matrix takes the value of 1 for $w_{i,j}$ if two states share a common border and 0 otherwise. The sum of each row takes the value of 1 (row standardization), which implies that the spillover effect for each state is the weighted average effect of all other states.

Equation 3.2 implicitly assumes that there is no reverse causality between the estimated oil price shocks and the states' GSP growth rates. We validate this assumption by eliminating large state economies such as California, New York and Texas, which may influence crude oil price through changes in state-level demand. Our results are robust even after eliminating these states in the sample.[7]

We estimate equation 3.2 via generalized method of moments (GMM) following Lee and Yu (2014). The procedure involves eliminating state fixed-effects through forward orthogonal deviation (FOD) transformation or creating the deviations of a

[7]See Table A.C.1 in Appendix for the robustness check of the results.

variable for its forward mean. Thus, equation 3.2 becomes

$$y_t^* = \sum_{k=1}^{3} \phi_k \hat{\zeta}_{kt}^* + \tau y_{t-1}^* + \lambda W y_t^* + \rho W y_{t-1}^* + X_t^* \beta + v_t^* \tag{3.5}$$

where y_t^*, $\hat{\zeta}_{kt}^*$, y_{t-1}^*, Wy_t^*, Wy_{t-1}^*, X_t^* and v_t^* are FOD-transformed variables. We estimate equation 3.5 using all strictly exogenous variables X_s for $s = 1, \ldots T-1$ and the time lag variables as instrumental variables (IV) for y_{t-1}^* and WX_s for $s = 1, \ldots T-1$ and Wy for $s = 0, \ldots t-1$ as IVs for Wy_{t-1}^*.

3.3 Empirical Results

Table 3.1 summarizes the result of estimating equation 3.5. Each column is a separate regression evaluating the first difference in log-transformed GSP. We use different spatial weight matrices for spatial autoregression (SAR) models in order to check for the robustness of our results. Coefficients of spatial lags (λ and ρ) are significant, suggesting the presence of economic spillovers across neighboring states. The coefficients of structural shocks using OLS are generally larger in magnitude suggesting the potential upward bias of the estimates, because variations from spatial dependence are being attributed to individual shocks. Estimates from the SAR models are fairly robust and the qualitative results remain regardless of the spatial lag matrix we use. Based on stability condition following LeSage (2008) (i.e. $\lambda < 1$ in the short run), we choose SAR using spatial contiguity weight matrix as our preferred model.

Table 3.1: Dependent variable: first difference in log-transformed Gross State Product

Variables	OLS		SAR					
	50 states	48 states	Economic Distance		Geographic Distance		Spatial Contiguity	
Oil Supply	0.030***	0.030***	0.005*	0.007**	0.005*	0.007**	0.007**	0.008**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
REA	0.005***	0.005**	0.001	0.003	0.000	0.002	0.001	0.004
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Oil-Specific Demand	-0.011***	-0.009***	-0.004**	-0.007***	-0.003*	-0.007***	-0.004*	-0.006***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Oil Supply* Prod/Cap	-0.015***	-0.012***	-0.010***	-0.008***	-0.011***	-0.009***	-0.008***	-0.007***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
REA*Prod/Cap	-0.003*	-0.004	-0.002	-0.002	-0.002	-0.002	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Oil-Specific*Prod/Cap	0.013***	0.009***	0.007***	0.005***	0.007***	0.006***	0.006**	0.005***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
GSP growth$_{t-1}$ (τ)	0.228***	0.268***	0.175***	0.616***	0.169***	0.573***	0.148***	0.700***
	(0.047)	(0.038)	(0.036)	(0.105)	(0.035)	(0.095)	(0.035)	(0.111)
Spatial lag (λ)			1.026***	1.056***	1.036***	1.072***	0.786***	0.934***
			(0.032)	(0.040)	(0.031)	(0.041)	(0.040)	(0.063)
Spatial lag$_{t-1}$ (ρ)				-1.038***		-0.985***		-1.066***
				(0.269)		(0.234)		(0.212)
Observations	1,850	1,776	1,776	1,776	1,776	1,776	1,776	1,776
Time Period (years)	37	37	37	37	37	37	37	37
No. of Panels	50	48	48	48	48	48	48	48
GMM-AIC	0.000	0.000	-1.573	-8.111	-3.772	-8.685	-0.093	-9.465
GMM-BIC	0.000	0.000	-34.466	-35.522	-36.665	-36.096	-32.985	-36.875
Pseudo-Adj. R.sq	0.109	0.112	0.454	0.454	0.446	0.446	0.465	0.464
Hansen J-statistic	0.000	0.000	10.427	1.888	8.228	1.315	11.907	0.535
p-value of J-statistic	-	-	0.108	0.864	0.222	0.933	0.064	0.991

Oil Supply, Real Economic Activity (REA) and Oil Specific Demand are structural shocks mentioned in the text. Prod/Cap is the state-level long-run ratio of energy (BTUs) produced and consumed from crude oil and petroleum form 1963-2013. The 48 states refer to 48 contiguous states in the US. Regression results are derived using GMM following Lee and Yu (2014). GMM-AIC and GMM-BIC are calculated following Andrews (1999). Standard errors clustered by state are in parentheses. ***, **, * denote statistical significance at 1, 5 and 10 percent respectively.

We can derive the marginal effects of each underlying shock controlling for the characteristic of each individual state by rewriting the spatial econometric model:

$$Y_t = (I - \lambda W)^{-1}(\tau I + \rho W)(Y_{t-1}) + (I - \lambda W)^{-1}(\sum_{k=1}^{3} \phi_k \hat{\zeta_{kt}} + X_t\beta) + R \qquad (3.6)$$

where R is a rest term containing state fixed effects and error term. To simplify the analysis, let us first assume that there is no spillover effect (i.e. $\lambda = \rho = 0$) and that we are only concerned with the direct impact of each oil price shock to state level economic growth in the short term and long term.[8] Thus, the matrix of partial derivatives with respect the k^{th} explanatory variable –the measure of marginal impact– is illustrated below. Each partial derivative denotes the effect of a unit change of a particular oil price shock in a particular state. We express the direct effects both in short-term and long-term horizon.

$$\left[\frac{\partial Y}{\partial \hat{\zeta}_{1k}} \cdots \frac{\partial Y}{\partial \hat{\zeta}_{Nk}}\right]_t = \phi_k I_N \qquad \text{(short term)}$$

$$\left[\frac{\partial E[Y]}{\partial \hat{\zeta}_{1k}} \cdots \frac{\partial E[Y]}{\partial \hat{\zeta}_{Nk}}\right] = (I_N - \tau I)^{-1}\phi_k I_N \qquad \text{(long term term)}$$

Figure 3.6 illustrates the short-run and long-run impact of a unit increase in each underlying oil price shock to state-level economic growth. The estimation results are very much similar to Kilian (2009). Unanticipated oil supply disruptions are found to decrease state-level economic growth for non-producers but increase growth for major oil producers in the short run. For example, a 10 percent decline in the growth of oil price causes an estimated 0.40 percentage point decrease to growth in Wyoming and an estimated 0.12 percentage point increase in New York. The same result holds for unanticipated increases in oil-market specific demand. These results are intuitive since both shocks increases oil price, translating to revenue gains for producers, while increasing costs for non-oil producers. Unanticipated increases in

[8] Our definition of direct effects here (i.e. no spatial dependence) is different from LeSage (2008)'s direct effects, which are the diagonal elements of the matrices $(I - \lambda W)^{-1}[\phi_k I_N]$.

real economic activity do not have any significant result on economic growth of all states, regardless if they are producing crude oil or not. Kilian (2009) postulates that increases in aggregate demand have two opposing pressures on GSP growth: a positive income-growth effect and a negative effect due to inflationary pressures. For net importing states, this intuition makes sense. For net-producing states, this explanation would only make sense if the coincidental price adjustment of all other goods and services in these states are sufficiently big enough to absorb the positive effect of increased oil revenues. It is also possible the most increased oil revenues do not stay at the state and are being remitted to the headquarters located in other states. At the moment, we cannot find any empirical evidence that sheds light on this issue. Finally, while there seems to be asymmetric effect between net oil-producing and net-oil consuming states, none of the shocks has statistically significant long-term effect on GSP growth.

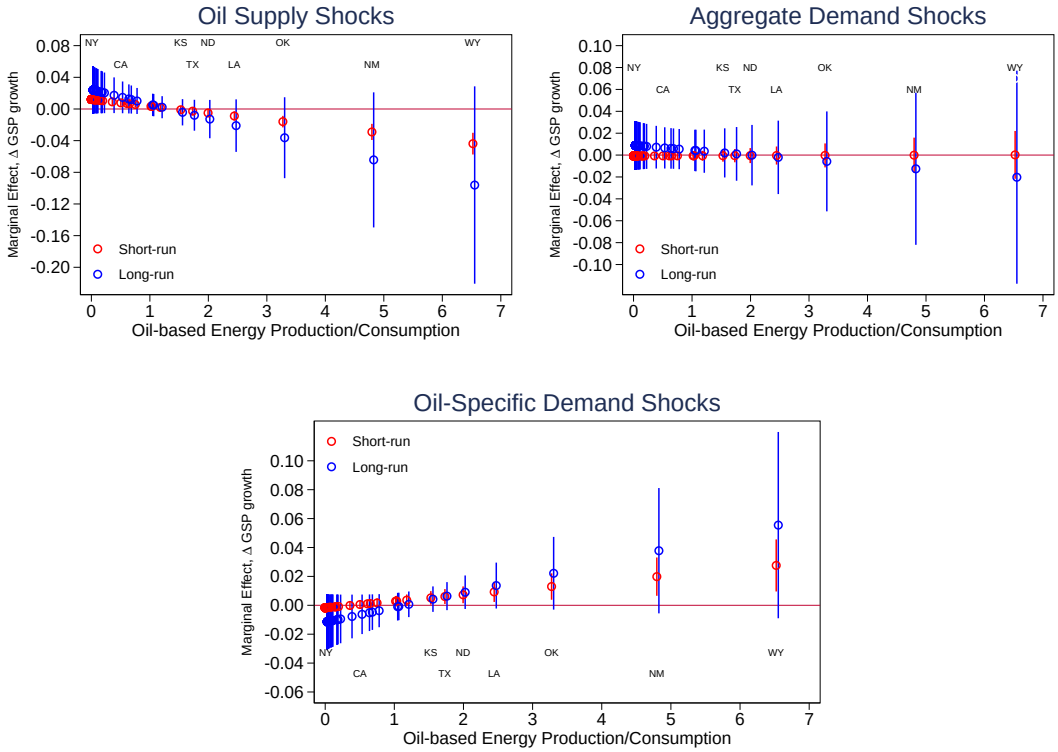
We now consider the effect of oil price shocks on GSP growth rate while taking into account the spillovers across states (i.e. assume that $\lambda \neq 0; \quad \rho \neq 0$). The matrix of partial derivatives with respect the k^{th} explanatory variable is expressed below. The partial derivatives denote the effect of a unit change in each underlying oil price shock in a particular state on the economic growth of all other states in the short term.

$$\left[\frac{\partial Y}{\partial \hat{\zeta}_{1k}} \dots \frac{\partial Y}{\partial \hat{\zeta}_{Nk}}\right]_t = (I - \lambda W)^{-1}[\phi_k I_N] \qquad \text{(short term)}$$

$$\left[\frac{\partial E[Y]}{\partial \hat{\zeta}_{1k}} \dots \frac{\partial E[Y]}{\partial \hat{\zeta}_{Nk}}\right] = [(1-\tau)I - (\lambda+\rho)W)]^{-1}[\phi_k I_N] \qquad \text{(long term)}$$

For simplicity, we focus on the short run effects (since stability conditions imply the effect of the shock will dissipate in the long run). Figure (3.7) illustrates the short-run impact of a unit increase in each underlying oil price shock to state-level economic growth while considering non-zero spillover effects. For positive oil supply shocks, we find that neighboring net-oil-consuming states get significantly positive gains through spillovers. For example, the direct effect of the supply shock to New York is amplified from 0.12 to 0.45 percentage point increase within the year. Texas

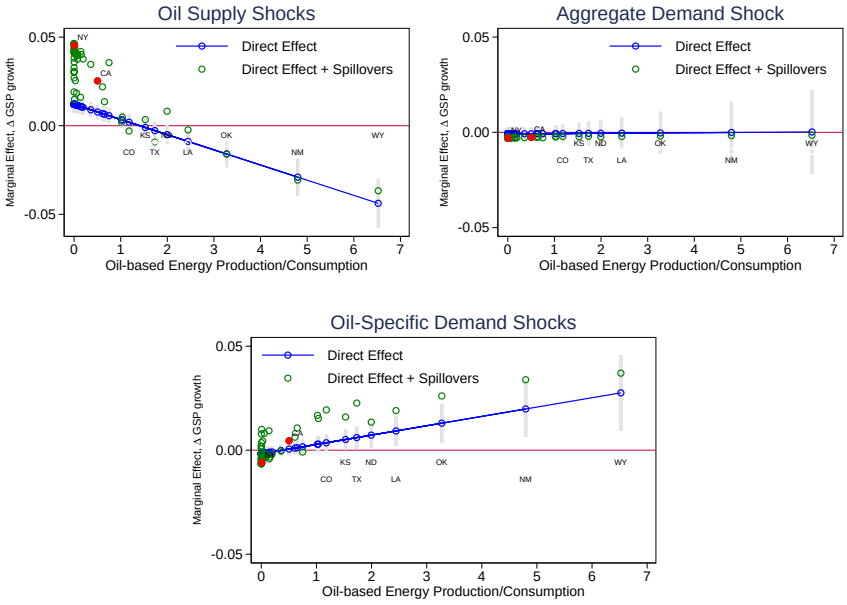
Figure 3.6: Effect of underlying oil price shocks on state economies in the US (direct effect only)



Note: Each figure illustrates the marginal effect of a unit increase in each underlying oil price shock given each state long-run average energy production/consumption from crude oil and petroleum. The vertical spikes represent 95 percent confidence interval.

and New Mexico, in contrast, do not gain any benefit from spillovers because they are surrounded by other net oil-producing states. Meanwhile, the direct impact of the supply shock on Wyoming's growth is attenuated by the spillovers from neighboring net oil consuming states, from 0.40 to about 0.30 percentage point decline. We observe a similar pattern for unanticipated increase in the precautionary or speculative demand for oil, although the spillover effect is more pronounced for major oil-producing states. Aggregate demand shocks do not have any significant on states' GSP growth, even if we account for spillover effects between neighboring states.

Figure 3.7: Effect of underlying oil price shocks on state economies in the US (direct effect and spillovers)

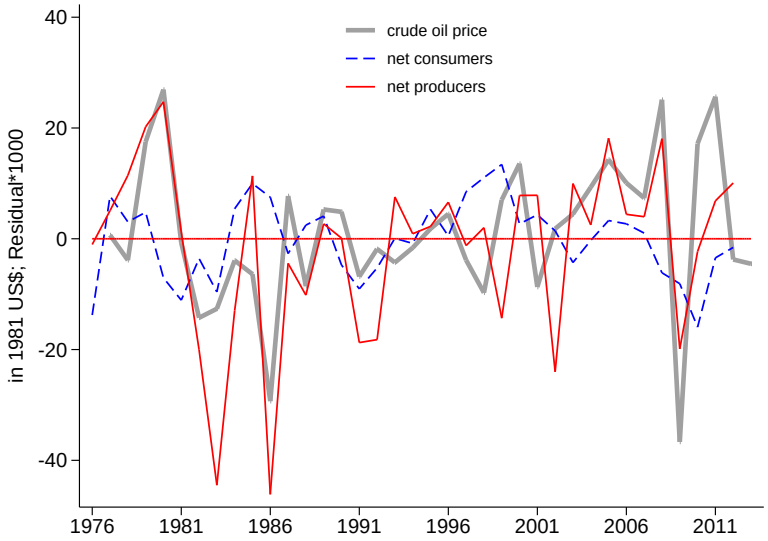


Each figure illustrates the marginal effect of a unit increase in each underlying oil price shock given each state long-run average energy production/consumption from crude oil and petroleum. The vertical spikes represent 95 percent confidence interval.

We also look at the average residuals from estimating equation 3.2 for net-producing and net-consuming states during periods of major oil price changes. By construction, residuals capture the effects of other factors influencing growth that are not captured by any of the underlying oil price shocks and the spillover effects between states. These factors may include, for example, increased uncertainties arising from plunging oil prices which may lead to lower capital expenditures on oil-extraction industries or more precautionary savings of households in oil-producing states. Figure 3.8 illustrates that net producers have more pronounced volatility of residuals compared to net consumers, particularly around periods of major oil price drops. During the 1986 oil price collapse, for example, growth for net-oil producing states is slower compared to what would have been predicted from the historical relation between GSP growth and oil price shocks. The disproportionately larger

volatility in residuals implies that net producing states are more vulnerable to oil price shocks not only in terms of predictable effects but also in form of increased uncertainties.

Figure 3.8: Average residuals from estimating equation 3.2 for net oil producing and net consuming states, and changes in imported crude oil price.



The solid and dash lines show the residuals from estimating equation 3.2 for net-producing and net-consuming states, respectively, and changes in the real price of imported crude oil (in 1981 US$). The residuals are multiplied by 1000 for better visibility.

3.4 Conclusion

The literature is replete with theoretical, empirical and policy research looking at the effects of higher oil prices on the US aggregate economy. While a few studies attempt to look at the differential effect of oil price changes to state-level economies, we deviate from the literature by recognizing that (1) changes in oil prices may be endogenous, (2) differences in states may come from their dependence on oil, and (3) state economies are inter-connected potentially due to factor mobility and cross-

border trade.

The main point of this paper is that not all states are alike, and thus, their responses to various demand and supply shocks underlying oil price changes are also not alike. For example, an unanticipated increase in global production of crude oil, which reduces oil price, increases economic growth of net-consuming states while reducing growth of net-producing states in the short run. Aggregate demand shocks, on the other hand, do not have direct significant effect on growth of state-economies, regardless of their oil production-consumption ratios. Net oil producing states have also more pronounced cycles of positive and negative economic growth as opposed to net oil consuming states, which have more stable growth paths and are more in line with the aggregate US economy. Moreover, we find that the direct effect of oil price shocks may be amplified depending on direction and magnitude of the economic spillovers from neighboring states.

Results of this study raise considerations on how the states and federal government address fluctuations in state-level economies associated with oil price shocks. In general, the results at the state-level economies reaffirm the need for monetary policy response that focuses on underlying determinants of oil price changes. However, results of this study also suggest that a sophisticated model of monetary policy response, which may account for the endogeneity of the price of oil, may still be inadequate in that it postulates the same response of all states to oil price changes regardless of their dependence and vulnerability on oil price shocks. There may be a need for a policy that takes into account the differences in the response of the states, and the potential of certain areas or regions to deviate from the growth path of the US macroeconomy.

In particular, the empirical results presented in this study raise the potential for a state-level fiscal policy that addresses the fluctuations in growth associated with changes in oil prices over time. A sufficient "rainy day fund"– budget reserves for use when unanticipated revenue shortfall occurs– could provide states the capability to weather the adverse effect of oil price shocks on their respective economies. Funds such as this is particularly crucial to states that are more vulnerable to oil price shocks, such as Wyoming and New Mexico (and more recently North Dakota) because

of their heavy reliance on oil and natural gas production. Not only that the presence of rainy days fund should be present but the cap should be either remove or raise to more adequate levels (McNichol 2014).

As some unanticipated shocks can cause severe revenue shortfalls, the rainy day funds may able to fill in only a modest share of states' budget gaps. The recent oil price collapse starting in 2014, for example, led North Dakota to use almost all of its $572 million rainy day fund due to lower-than-expected tax collections. Yet, the state government still struggles to revive the economy with the continuously dwindling oil prices. Potentially, the central government can provide fiscal stimulus to help adversely affected states. Whether a centralized fiscal stimulus is warranted will depend on the persistence of an underlying oil price shock and how fast a fiscal stimulus could influence a state's economy. Kilian (2009) postulates that different demand and supply shocks in the crude oil market have different level of persistence. For example, supply shocks have negative effects on GDP that last up to 2 years, while unanticipated oil-specific demand shocks have negative effect on GDP up to 3 years. Meanwhile, there is an indication that fiscal stimulus can have immediate influence on growth. A case in point is the recent 2009 Car Allowance Rebate System (CARS) which significantly increased auto purchases during the first two months of the program (Mian and Sufi 2012). If indeed the effect of fiscal stimulus is fast enough to address the persistent effect of oil price shocks, then there may a role for a centralized and coordinated fiscal policy to stabilize the economy in periods of major oil price changes.

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Appendix A

Chapter 1 Appendices

1.1 List of Manufacturers and Brands in the NPD Data

Table A.1: List of Manufacturers and their Respective Brand

Manufacturer	Brands	
Whirlpool	Amana	Magic Chef
	Estate	Maytag
	Inglis	Roper
	KitchenAid	Whirlpool
General Electric	Ariston	
	GE	
	GE Profile	
	Hotpoint	
Electrolux	Electrolux	
	Frigidaire	
	Westinghouse	
	White Westinghouse	
LG	LG	
Others	Asko	Fagor
	Avanti Pro	Fisher & Paykel
	Bosch	Haier
	Danby	Miele
	Electro Brand	Speed Queen
	Equator Appliances	Summit
	Eurotec	

The table lists the four major clothes washer manufacturers in the US (based on their market share) and their respective brands and subsidiaries. Three of the major manufacturers sell clothes washers under four or more brands.
Source: Spurlock (2013).

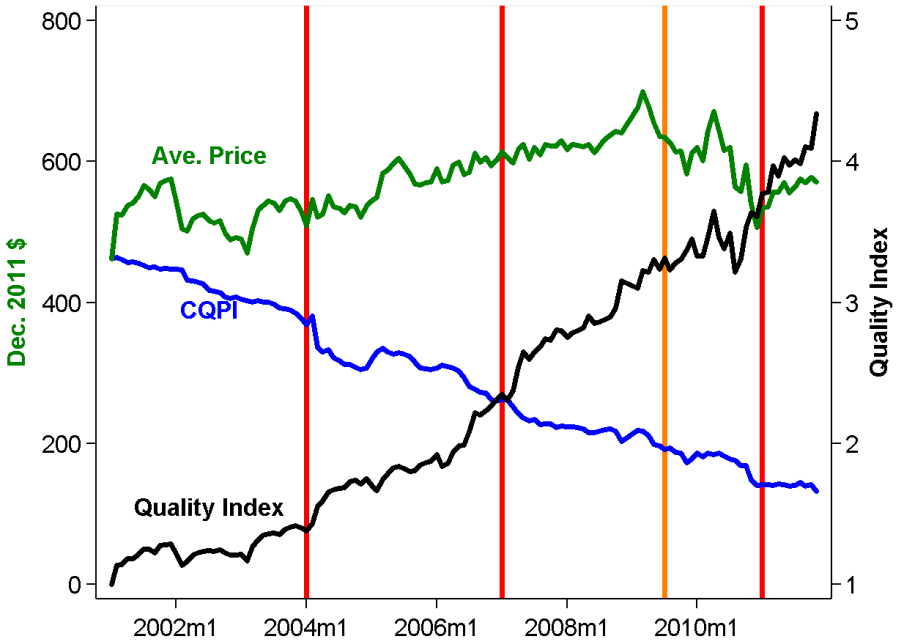
1.2 Quality Trend of Clothes Washers Over Time

Given a measure of constant-quality price, and assuming quality is increasing in price within any given month, we construct a measure of quality using the difference between observed average market price and the CQPI. We measure this difference by the ratio between average price and CQPI, excluding entering and exiting models and adjusting for vintage effects as described above for the CQPI. Because average price is relatively flat, and CQPI declines sharply, the quality index must be increasing, as shown in Figure A.1. Interestingly, the index increases more quickly around the times of policy changes. Note that acceleration in quality increases around policy changes is *not* due to vintage effects (e.g., a large introduction of new models), as these have been excluded. Instead, it comes from substitution toward higher-quality continuing models as prices generally fall.

To validate price-based estimates of overall quality, it helps to identify whether particular attributes, like energy efficiency, are associated with it. Two observable characteristics directly contribute to measures energy efficiency metrics for clothes washers: spin speed (measured by the number of revolutions per minute or RPMS) and capacity (measured in cubic feet). Clothes washers with higher spin speeds extract more water from clothes, which reduces time and energy spent on drying. Models with higher capacity thereby reduce the number of loads for laundry for a typical household. Over time, we can see that more clothes washers have higher spin speed and capacity (Figure A.2). More importantly, we see market's inclination towards washers with higher spin speed and capacity right around the imposition of more stringent ME and ES standards. For example, the shares of clothes washers that have spin speed of 649 rpms and lower fell around January 2004 and 2007. Meanwhile, clothes washers that have 1000-1299 and 1300-1599 rpms significantly increased around 2004 and 2007 policy changes, respectively. Conversely, the share of lower-capacity clothes washers fell more rapidly around the policy changes, while those that have higher capacity (i.e. 3.5-3.9 and more than 4.5 cu. ft.) grew around January 2004 and 2007.

While energy efficiency improves over time, we also observe improvements in the

Figure A.1: Trend in Average Price, CQPI and Quality Index, Jan. 2001-Dec.2011



Masked models and the models introduced at a particular time period were dropped in calculating the ratio. Both average price and CQPI are net of vintage-fixed effect to control for any potential effect of introducing new models at a specific time period. The red solid vertical lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange solid vertical line pertains to the ES policy change in July 2009. All prices are in December 2011 US dollars.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); CQPI and Quality Index (Authors' calculation).

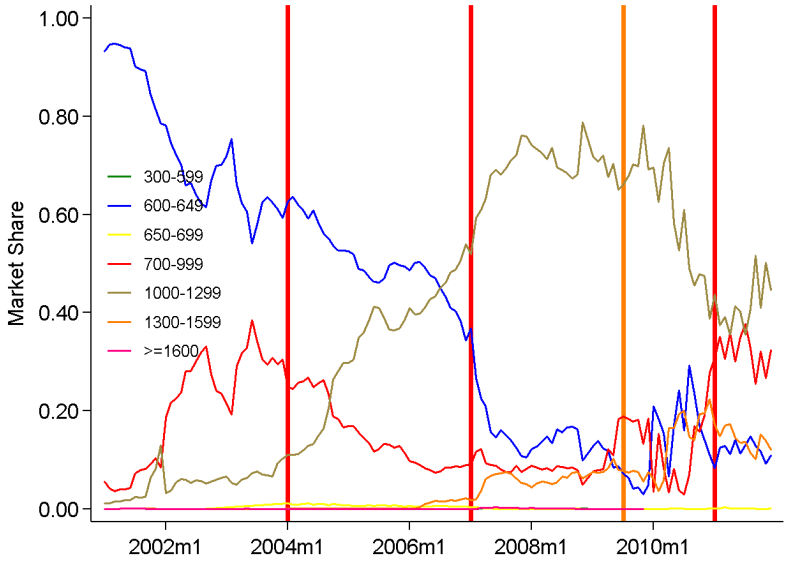
quality of each model that do not necessarily contribute to the energy efficiency metric for clothes washers. Figures A.3 to A.4 illustrate the trend of market share of characteristics that affect the cleanliness of clothes (number of wash cycles options); convenience (i.e. whether controls are mechanical or electronic); and space requirement (i.e. whether the model is regular or portable and within each category, if the model is side-by-side, stackable, pre-stacked, or combined washer/dryer). Panels (a) & (b) in Figure A.3 illustrate how sales shifted toward more space-saving front-loading and portable models starting with the policy change in 2004. There were also shifts towards stackable models starting in 2004, both in regular and portable types of clothes washers.

Over time, more models also have more wash cycle options with electronic controls (Figure A.4). Particularly around 2004, washers that have 11-15 wash cycle options increased significantly, taking more than 20 percent of the share of the dominant low-wash-cycles models. The share of models with a larger number of wash cycles continues to rise and becomes dominant around the 2011 policy change. The share of models with more than 16 wash cycle options also increased significantly around the 2009 Energy-Star threshold update.

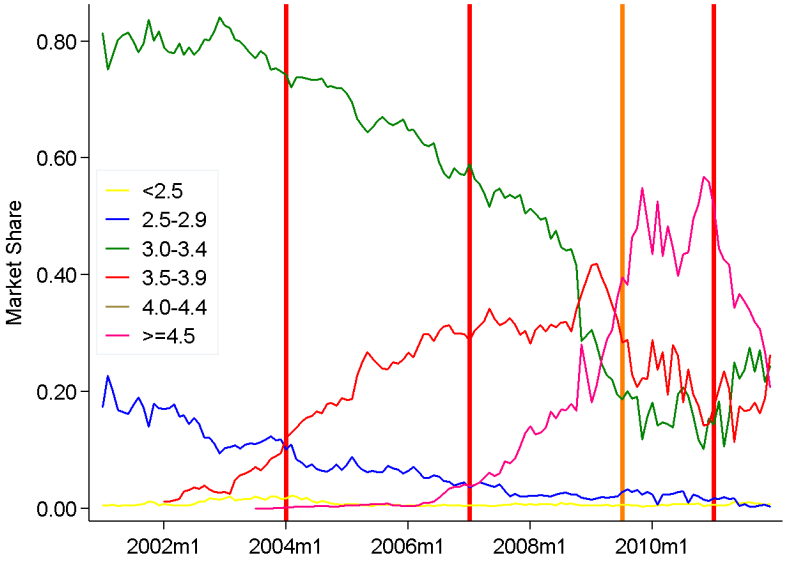
The 2011 policy change had minimal or counter-intuitive effect on most characteristics for which we have information on. Newer features appeared during this period about which are not observed in our data. These include steam wash technology and direct drive technology that is reportedly quieter than traditional belt and pulley mechanisms.

Figure A.2: Market share by product category, energy-efficiency characteristics, Jan. 2001-Dec. 2011

(a) Revolutions per minute



(b) Volume/Capacity



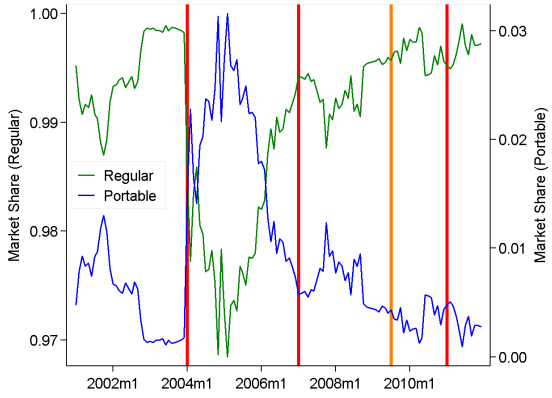
Capacity/volume is in cubic feet. The red vertical solid lines mark simultaneous minimum efficiency and Energy Star policy changes in January of 2004, 2007 and 2011; the orange vertical solid line marks the Energy Star policy change in July 2009.

Source: The NPD Group.

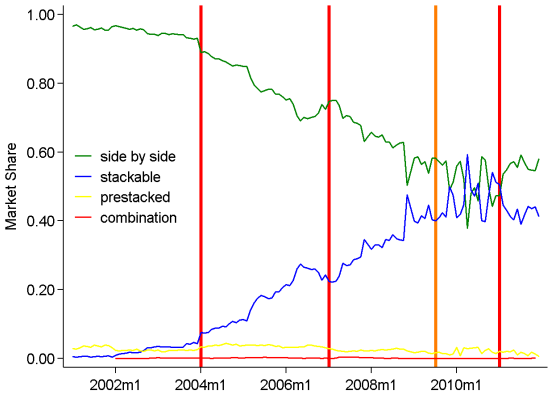
Figure A.3: Market share by product category,
space-saving characteristics, Jan. 2001-Dec. 2011

(a) Front-loaders vs. Top Loaders

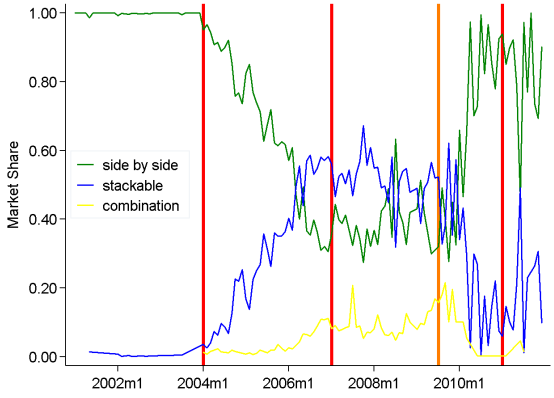
(b) Regular vs. Portable



(c) Regular Clothes Washers



(d) Portable Clothes Washers

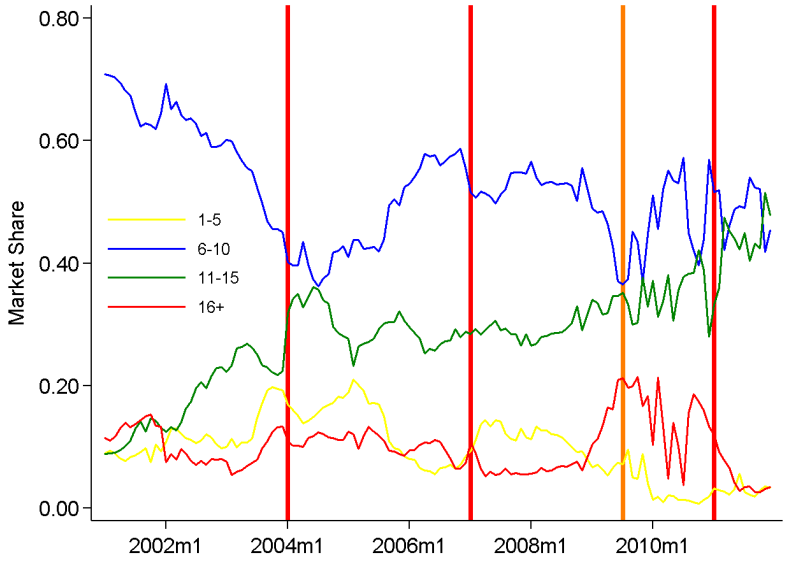


The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertains to the ES policy change in July 2009.

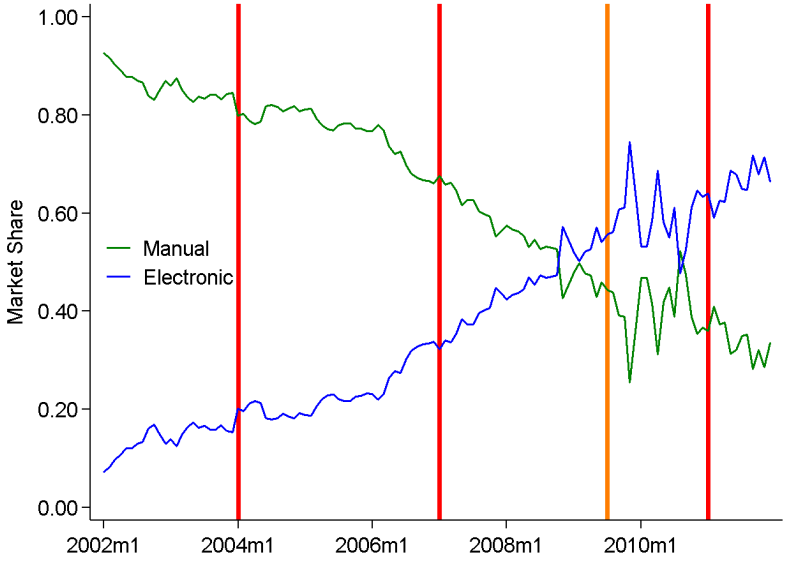
Source: The NPD Group.

Figure A.4: Market share by no. of wash cycle options and panel control type, Jan. 2001-Dec. 2011

(a) No. of wash cycles options



(b) Type of controls



The red vertical solid lines pertain to the simultaneous ME and ES policy changes in January of 2004, 2007 and 2011; while the orange vertical solid line pertain to the ES policy change in July 2009.

Source: The NPD Group.

1.3 Exclusion of Masked Models in the Analysis

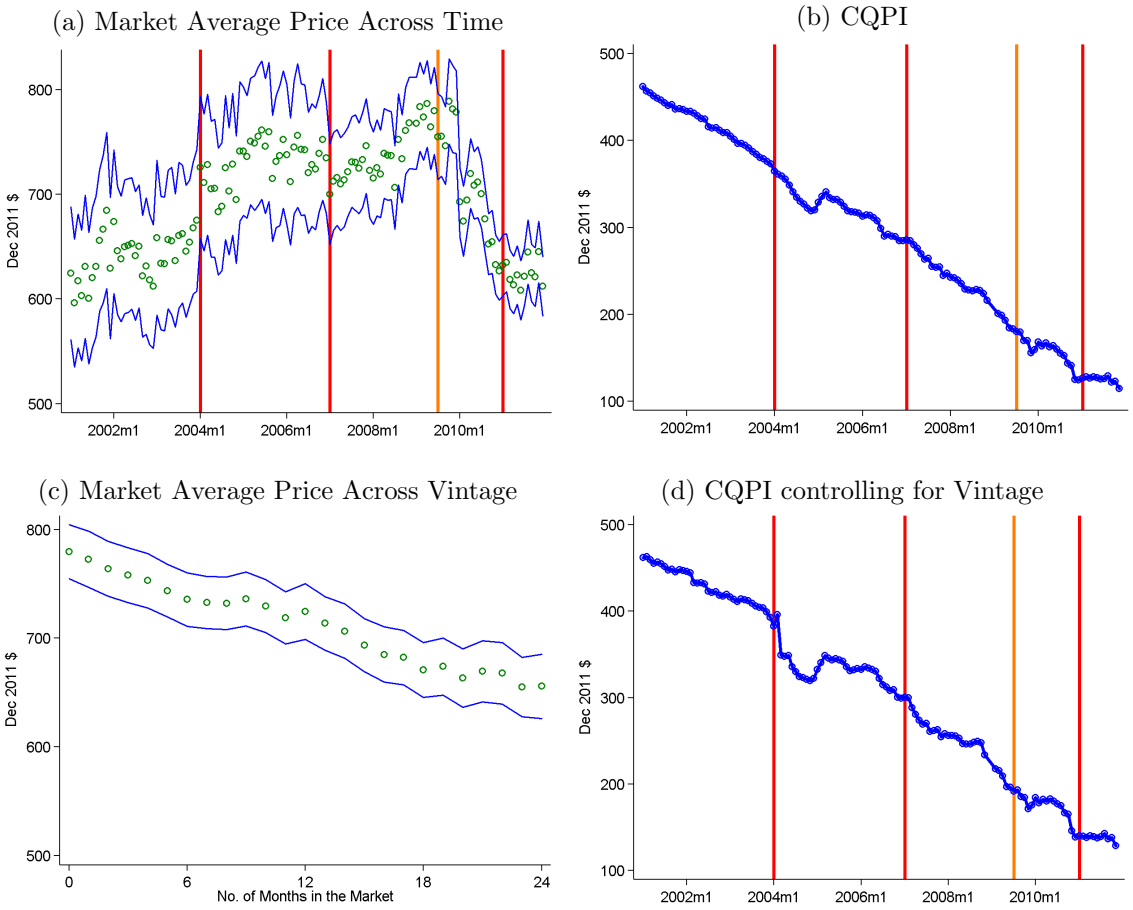
To address the potential bias introduced by including the 35 percent masked models in the data, we conduct a series of robustness checks. This include repeating all the important figures in the analysis and the regressions of price against the average vintage within and between firms, both at the brand and manufacturer levels (equation 1.8). The results from estimating equation 1.8 without masked models are presented in Table A.2. We find the our qualitative results remain the same. Meanwhile, the figure representing the average and constant-quality price trends without masked models is presented in Figure A.5. We also find no significant influence of excluding masked models on the price trends, both the market average price and the constructed CQPI.

Table A.2: Regression Results: Dependent Variable – Unit Price, Clothes Washers (Unmasked Models only)

	(1)	(2)
β_1, average vintage *within brand*	2.007***	
	(0.456)	
β_2, average vintage *between brands*	4.011***	
	(0.775)	
β_1, average vintage *within manufacturer*		3.817***
		(0.468)
β_2, average vintage *between manufacturers*		1.083*
		(0.561)
Constant	700.737***	664.264
	(142.630)	(140.270)
Own Vintage Spline	yes	yes
Month-Fixed Effect	yes	yes
Model-Fixed Effect	yes	yes
Adj. R^2 (within group)	0.373	0.372
Observations	22,445	22,755

The table reports the results from estimating equation 1.9 without the interaction effects *using unmasked models only*. Column (1) estimates the effects of within- and between-brands average vintage, and column (2) estimates the effects of within- and between-manufacturer average vintage on price. Clustered standard errors are in parentheses. We use restricted cubic splines with 5 knots in estimating the spline function of vintage.

Figure A.5: Market Average Price and CQPI Trends,
Clothes Washers (Unmasked Models Only)



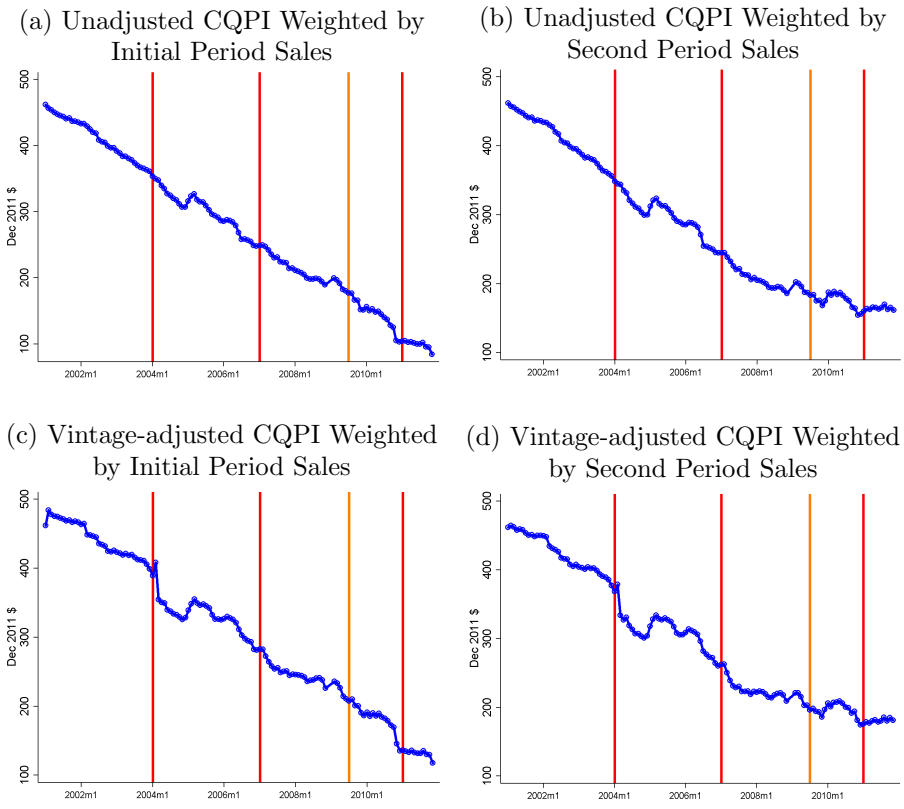
The figure shows the average market price and CQPI trends *using unmasked models only*. Panel (a) shows sales-weighted average prices and 95 percent confidence band in blue. Panel (b) shows the constant quality price index (CQPI). Panel (c) shows average price in relation to product vintage, defined as months since the model number first appeared in the data. Panel (d) shows the CQPI adjusted for product vintage, estimated from a fixed effects regression model. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold change that took effect in July 2009. All prices are in December 2011 US dollars.

Source: Monthly sales and revenues of clothes washers sold in the US between 2001-2011 (The NPD Group); CQPI (Authors' calculation).

1.4 The CQPI With Different Weights

One concern about the CQPI is that the weights are endogenous. Consumers may substitute toward products with lower prices, causing a bias in the overall trend. If we were to weight price changes by the initial period of the difference, the bias would most likely be positive, as models discounted in the initial period would presumably rise in price and be weighted more heavily. Conversely, if we were to weight by the second period then models discounted in the second period would presumably see a larger price decline while sales increased, biasing the overall trend downward. We therefore weight the two periods equally. In this section, we weight the CQPI by the initial and second period sales. We find no noticeable influence on the CQPI under different weighting schemes (see Figure A.6).

Figure A.6: CQPI Trends Under Different Weights



Panels (a) & (b) show the unadjusted CQPI weighted by initial and second period sales, respectively. Panel (c) & (d) show the CQPI adjusted for product vintage, estimated from a fixed effects regression model, and weighted by initial and second period sales, respectively. The solid red vertical line represents the effective date of simultaneous policy changes in the federal minimum energy efficiency standard and Energy Star certification threshold, while the orange vertical line is for the Energy Star threshold change that took effect in July 2009. All prices are in December 2011 US dollars.

*Source:*Authors' calculation.

1.5 Average Effect of Policy Change (3-month Period)

To check the robustness of the estimated average effect of a policy change, we estimate equation 2.2 with an assumption that the effect of the policy change occurs within a 3-month pre- and post-policy change. For example, for 2004 policy change, we believe that the effect of the announcement started to take place in October 2003 up to March 2004. We then compare this with the observations starting from April 2002 (i.e. two-year period). Table A.3 summarizes the results of the regression for the percentage change in the CQPI, quality index and level change in estimated welfare. Column (1) pertains to the standard DID; (2) includes year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) includes the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators in each of the key variable. Results are qualitatively similar with what we find using the 6-month pre- and post-implementation period.

Table A.3: Results from Estimating the Average Effect of the Policy Change

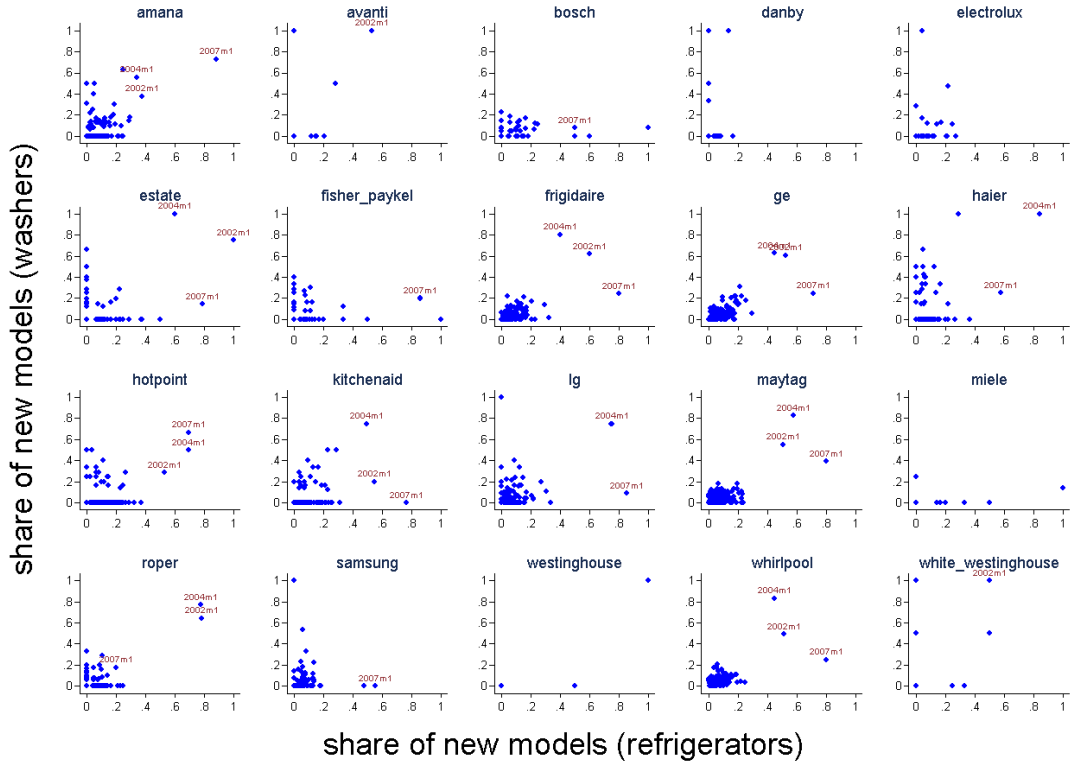
Variables	**Dependent Variable**								
	%Δ CQPI			**%Δ Quality**			**Δ Welfare**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Treatment	-0.045	0.042	0.132	0.182	-0.048	4.656**	-1.610*	-1.841**	-0.757
	(0.251)	(0.206)	(0.697)	(0.672)	(0.622)	(2.181)	(0.906)	(0.741)	(2.435)
Policy Dummy	-0.724*	-0.028	1.417	0.704	-11.431***	-15.769**	3.705	0.332	0.227
	(0.437)	(0.574)	(1.392)	(1.719)	(3.220)	(3.113)	(2.351)	(3.038)	(6.300)
Treatment x Policy	**-0.876**	**-0.963**	**-0.892**	**-0.148**	**0.082**	**-0.076**	**0.193**	**0.424**	**-0.581**
	(0.880)	**(0.707)**	**(0.635)**	**(1.828)**	**(1.934)**	**(1.625)**	**(3.305)**	**(2.207)**	**(2.058)**
Constant	-0.599***	0.422**	-1.214	0.911	13.370***	16.097	3.551***	-0.291	1.738
	(0.145)	(0.206)	(1.002)	(0.603)	(0.622)	(3.010)	(0.766)	(0.741)	(2.932)
Year-month fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month x ref dummy	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.056	0.707	0.783	0.003	0.560	0.799	0.048	0.743	0.816
Adj. R-squared	0.044	0.391	0.506	-0.009	0.087	0.543	0.037	0.468	0.581
Observations	254	254	254	254	254	254	254	254	254

The table presents the results from estimating equation 2.2, which yields the average effect of the policy change on trend in CQPI, Quality Index and estimated welfare change. Treatment is a dummy variable equal to one if the observation is for the appliance that is affected by the standard (i.e. clothes washer); Policy is a dummy variable that turns on at the time the new standard is perceived to have effect on our key variables. We assume that the effect of the policy took place *within the 3-month pre- and post-policy change*. For example, the 2004 policy change, due to its anticipatory nature, is perceived to have effect starting October 2003 up to March 2004. We then compare this with the observations starting from April 2002 (i.e. two-year period). Column (1) pertains to the standard difference-in-differences approach; (2) includes year-month fixed effect to control for potential idiosyncratic shocks in each time period; and (3) includes the intersection of month and refrigerator dummies to control for the fairly robust seasonality that we observed for refrigerators in each of the key variable. Robust standard errors are in parentheses. ***, **, * represent statistical significance at 1, 5, and 10 percent level, respectively.

1.6 Correlation in the introduction of new models between clothes washers and refrigerators at the brand level

We observe that unit price (holding quality constant), quality and consumer welfare gains for clothes washers and refrigerators follow similar trends and fluctuations, including the significant drop around 2004 policy change. In order to get a sense of the potential factor that might influence the correlated effect, we look at the correlation in the share of new models to the total stock of units in a particular time period between clothes washers and refrigerators. At the manufacturer level, we find significant correlation in introducing new models between clothes washers and refrigerators right around the policy change in 2004 and 2007. We did the same exercise at the brand level and find the same significant correlation particularly for major brands of washers and refrigerators like GE, LG, Maytag, and Whirlpool (Figure A.7).

Figure A.7: Correlation in the share of new models to total stock units between washers and refrigerators, brand level, monthly, 2001-2011



Source: The NPD Group

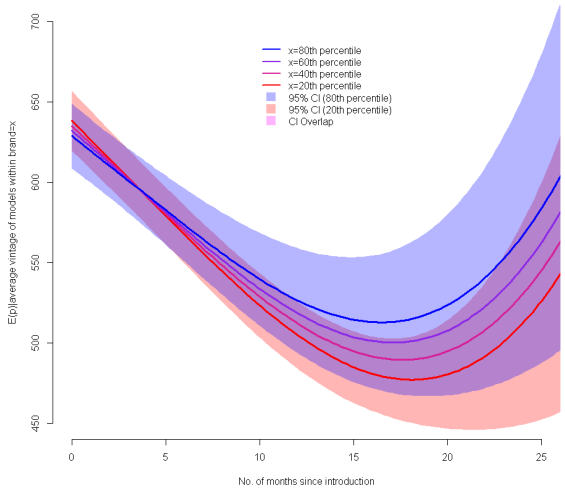
1.7 Within and Between Brands Competition and Price Trends for Clothes Washers

We use the estimates from equation 1.9 to predict the price trend of typical clothes washer holding average vintage of models within brands constant. Figure A.8 plots this predicted price across the first two years of a clothes washer in the market, holding *within-brand* average vintage equivalent to about 8 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 17 months (80th percentile), while Figure A.9 plots the predicted price holding average vintage of models *between brands* constant at about 10 months (20th percentile), 12 months (40th percentile), 14 months (60th percentile), and 15 months (80th percentile).

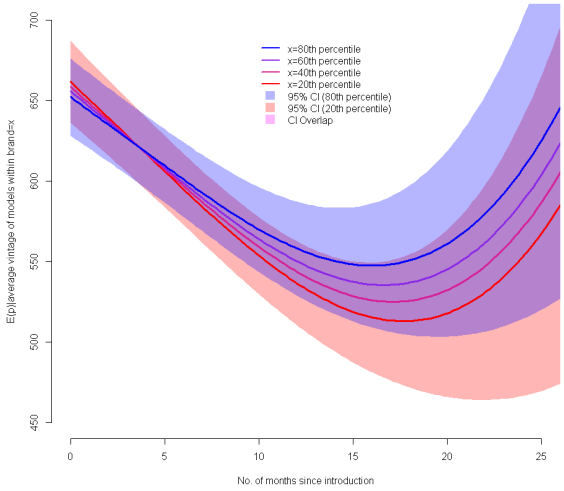
We also predict the price trend of a typical washer at different average vintage *within the same manufacturer* and *between manufacturers*. Figure A.10 shows the predicted price of a typical clothes washer, holding average vintage of models *within the same manufacturer* constant at about 9 months (20th percentile), 11 months (40th percentile), 13 months (60th percentile) and 16 months (80 percentile). Figure A.11 plots the predicted price at *between-manufacturers* average vintage equivalent to 9 months (20th percentile), 13 months (40th percentile), 16 months (60th percentile) and 19 months (80 percentile).

Figure A.8: Life Cycle Pricing of Clothes Washers
Under Different Within-Brand Average Vintage

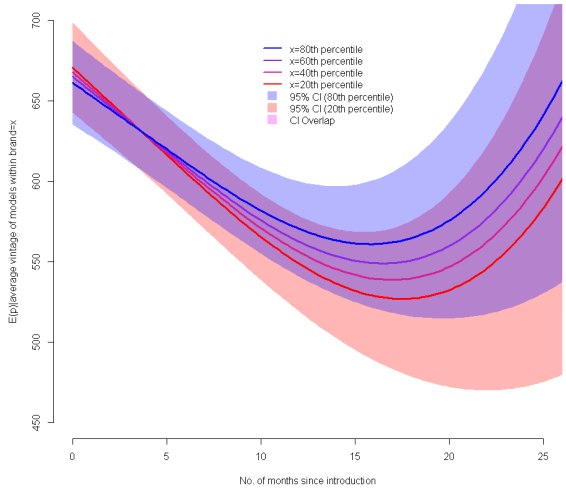
(a) Between Brands Average Vintage = 20^{th} percentile



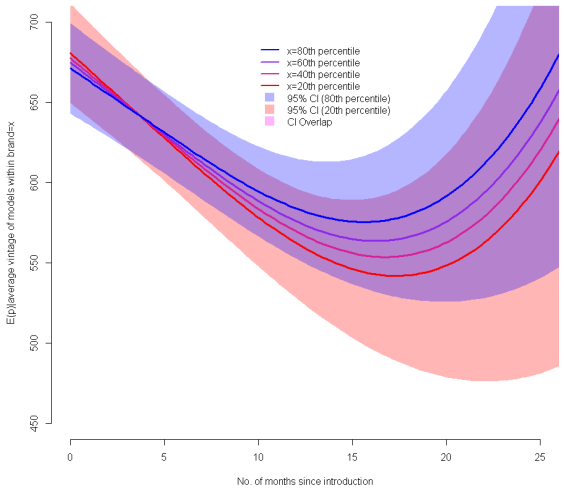
(b)Between Brands Average Vintage = 40^{th} percentile



(c) Between Brands Average Vintage = 60^{th} percentile



(d) Between Brands Average Vintage = 80^{th} percentile

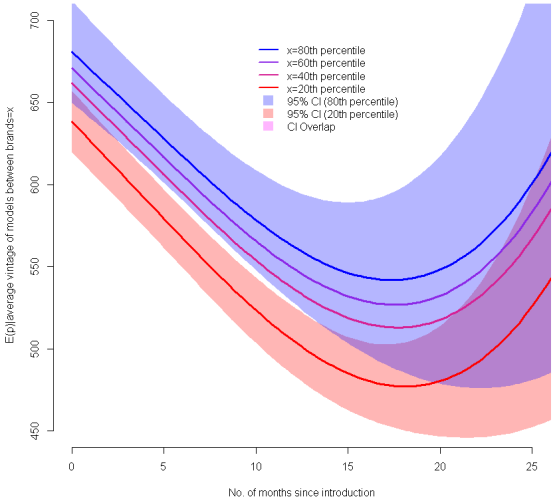


The figure shows that trend in the predicted price of a representative clothes washer using equation 1.9 during its first two years. We estimate equation 1.9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-brand average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 7.71, 10.67. 13.32 and 16.58, respectively. For the between-brands average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.62, 12.54, 13.67, and 14.90, respectively.

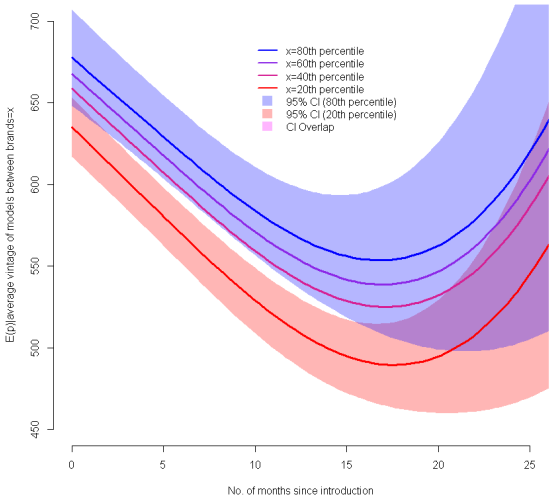
Source: Authors' calculations.

Figure A.9: Life Cycle Pricing of Clothes Washers
Under Different Between-Brands Average Vintage

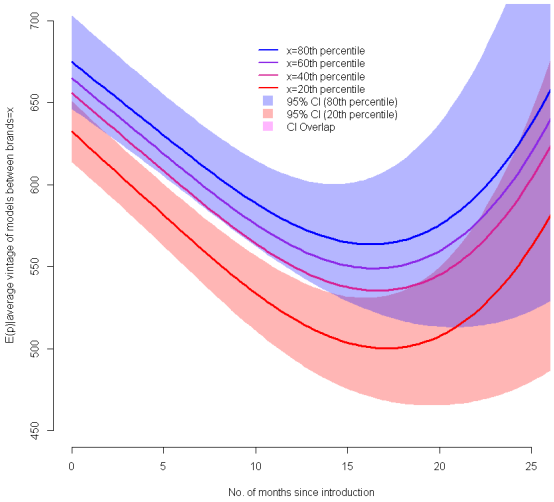
(a) Within Brand Average Vintage = 20^{th} percentile



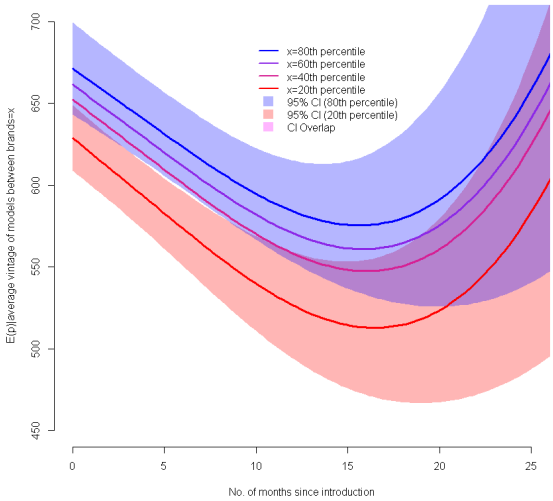
(b)Within Brand Average Vintage = 40^{th} percentile



(c) Within Brand Average Vintage = 60^{th} percentile



(d) Within Brand Average Vintage = 80^{th} percentile

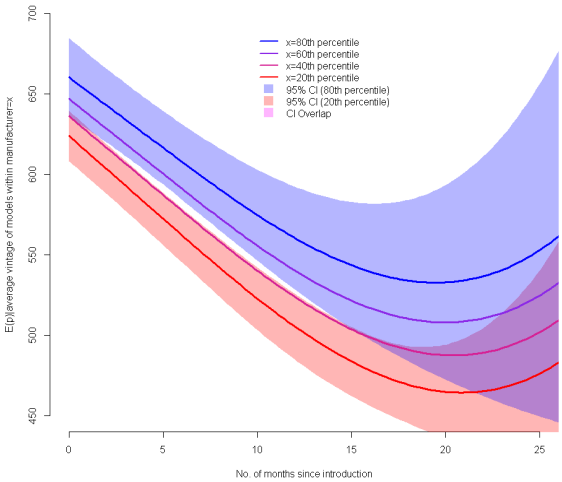


The figure shows that trend in the predicted price of a representative clothes washer using equation 1.9 during its first two years. We estimate equation 1.9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-brands average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-brand average vintage correspond to 9.62, 12.54, 13.67, and 14.90, respectively. For the between-brands average vintage, the 20th, 40th, 60th and 80th percentile correspond to 7.71, 10.67. 13.32 and 16.58, respectively.

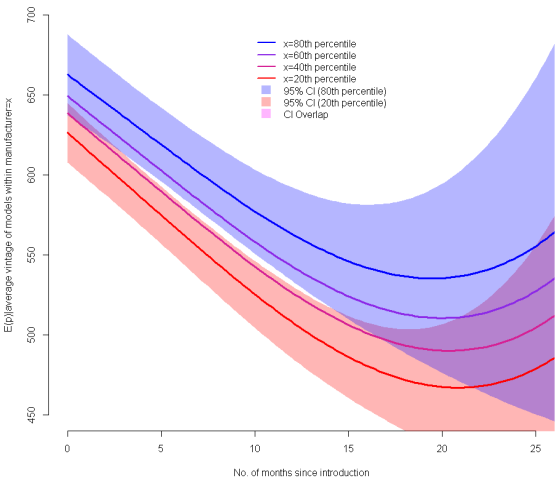
Source: Authors' calculations.

Figure A.10: Life Cycle Pricing of Clothes Washers
Under Different Within-Manufacturer Average Vintage

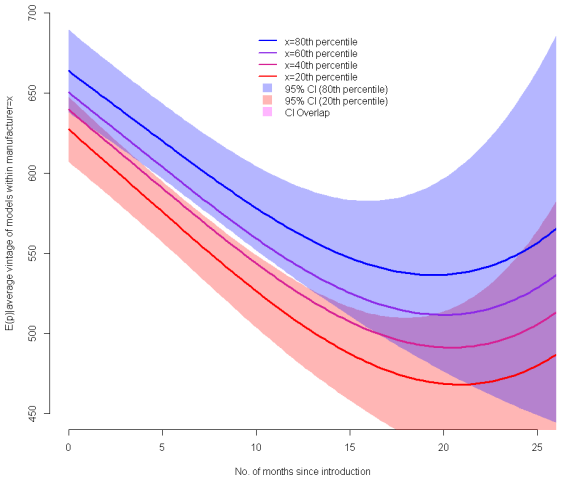
(a) Between Manufacturers Average Vintage = 20^{th} percentile



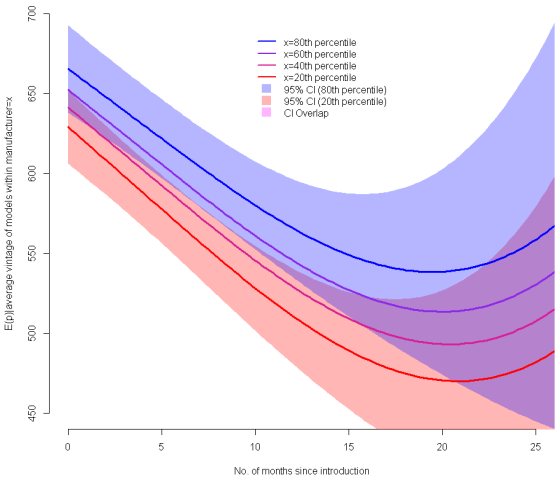
(b)Between Manufacturers Average Vintage = 40^{th} percentile



(c) Between Manufacturers Average Vintage = 60^{th} percentile



(d) Between Manufacturers Average Vintage = 80^{th} percentile



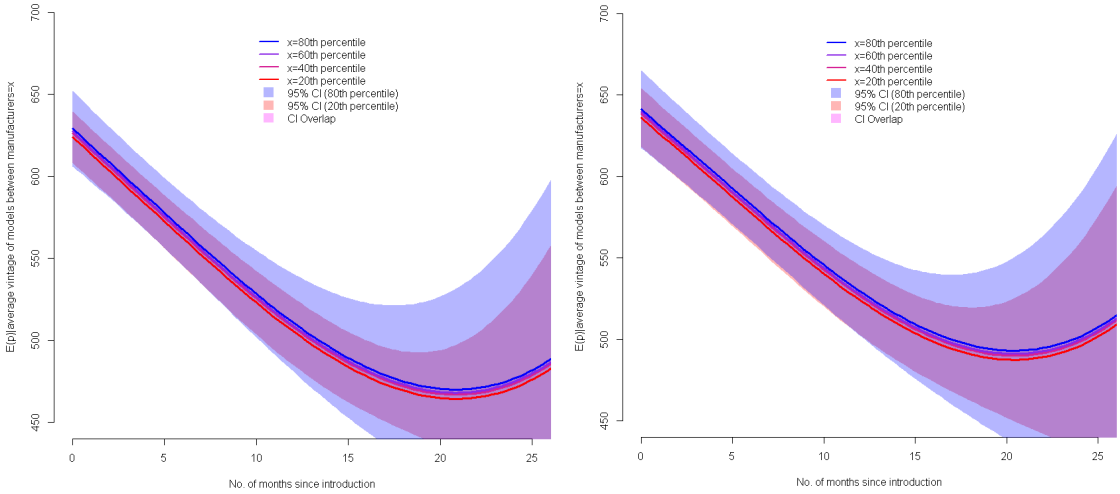
The figure shows that trend in the predicted price of a representative clothes washer using equation 1.9 during its first two years. We estimate equation 1.9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a within-manufacturer average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of within-manufacturer average vintage correspond to 8.86, 11.14, 13.18, and 15.68, respectively. For the between-manufacturers average vintage, the 20th, 40th, 60th and 80th percentile correspond to 9.47, 12.53, 13.85, and 16.12, respectively.

Source: Authors' calculations.

Figure A.11: Life Cycle Pricing of Clothes Washers
Under Different Between-Manufacturers Average Vintage

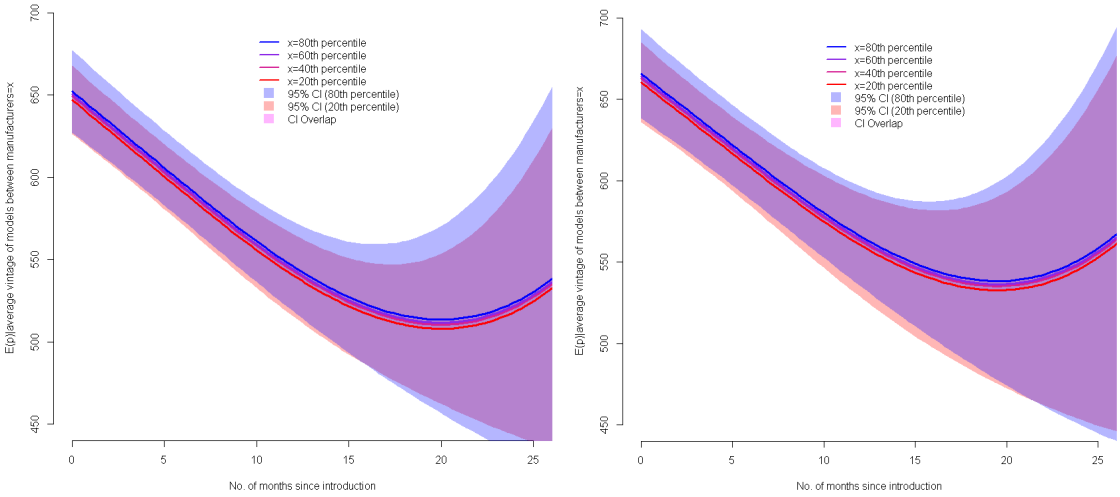
(a) Within Manufacturer Average Vintage = 20^{th} percentile

(b) Within Manufacturer Average Vintage = 40^{th} percentile



(c) Within Manufacturer Average Vintage = 60^{th} percentile

(d) Within Manufacturer Average Vintage = 80^{th} percentile



The figure shows that trend in the predicted price of a representative clothes washer using equation 1.9 during its first two years. We estimate equation 1.9 using a spline function of vintage with 5 knots. Each solid line represents a predicted price trend, given a between-manufacturer average vintage of clothes washer. The 20th, 40th, 60th and 80th percentile of between-manufacturer average vintage correspond to 9.47, 12.53, 13.85, and 16.12, respectively. For the within-manufacturer average vintage, the 20th, 40th, 60th and 80th percentile correspond to 8.86, 11.14, 13.18, and 15.68, respectively.

Source: Authors' calculations.

Appendix B

Chapter 2 Appendices

2.1 Sources of Conversion Factors

Table B.1: Sources of Conversion Factors

Conversion to Energy (in MBTUs)	
Gasoline	Silverman, D. (Univ. of California, Irvine)
Diesel	US Energy Information Administration
Fuel Oil/Bunker Oil	US Energy Information Administration
Kerosene	US Energy Information Administration
Lubricants	US Energy Information Administration
Coal	US Environmental Protection Agency
Coke	US Energy Information Administration
Public Gas	US Bureau of Mines
Liquefied Petroleum Gas	US Environmental Protection Agency
Firewood	Silverman, D. (Univ. of California, Irvine)
Charcoal	Oak Ridge National Laboratory
Electricity	US Energy Information Administration
Conversion to Carbon Dioxide (in Kg/C)	
Gasoline	US Energy Information Administration
Diesel	US Environmental Protection Agency
Fuel Oil/Bunker Oil	US Environmental Protection Agency
Kerosene	US Environmental Protection Agency
Lubricants	US Energy Information Administration
Coal	US Energy Information Administration
Coke	US Energy Information Administration
Public Gas	US Energy Information Administration
Liquefied Petroluem Gas	US Energy Information Administration
Firewood	Partnership for Policy Integrity
Charcoal	Akagi et al. (2011)
Electricity	US Environmental Protection Agency

2.2 Distribution of Foreign Ownership

Figure B.1: Distribution of foreign ownership share after acquisition, 1980-2000.

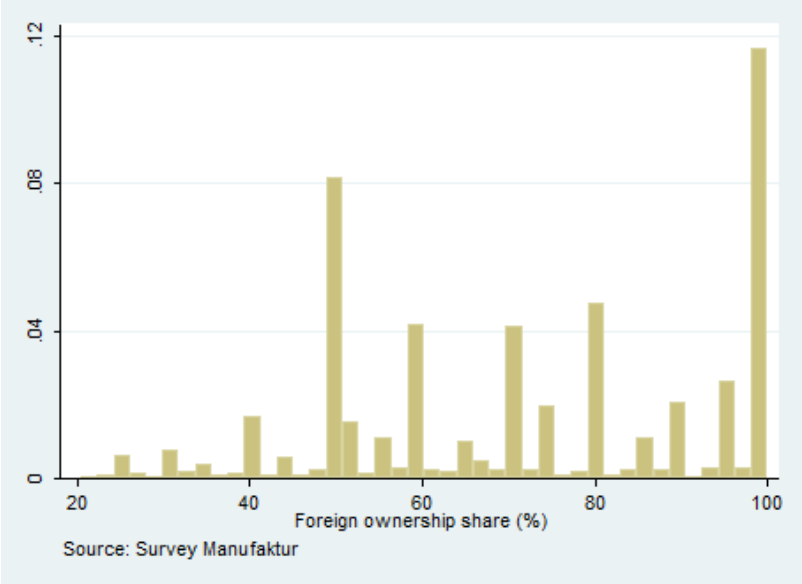


Figure B.2: Distribution of foreign-owned plants, 1980-2000.

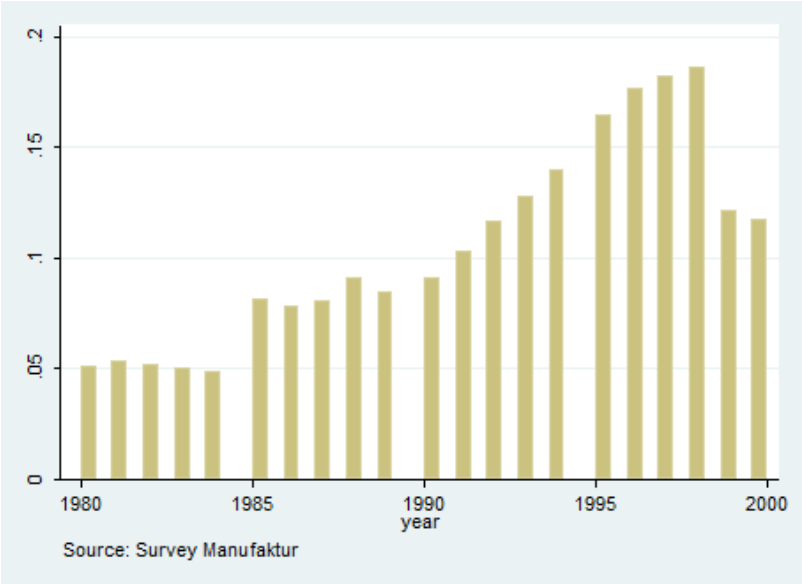
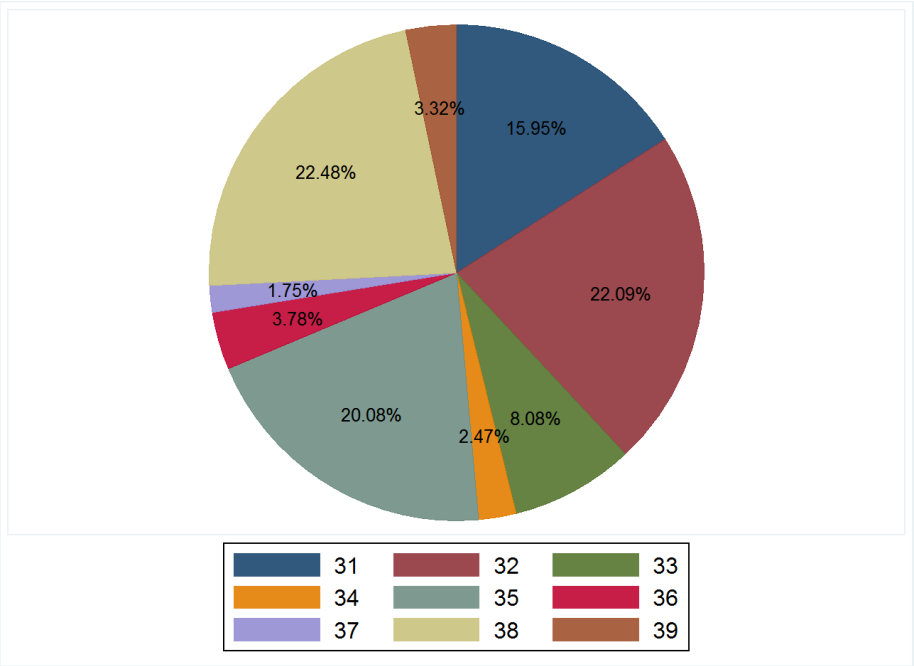


Figure B.3: Distribution of foreign-owned plants by industry



31	Food, Beverages and Tobacco
32	Textile, Wearing Apparel and Leather Industries
33	Wood and Wood Products, Including Furniture
34	Paper and Paper Products, Printing and Publishing
35	Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products
36	Non-Metallic Mineral Products, except Products of Petroleum and Coal
37	Basic Metal Industries
38	Fabricated Metal Products, Machinery and Equipment
39	Other Manufacturing Industries

2.3 Robustness Check: Truncated Sample

This section presents the results from estimating equation 2.2 on matched sample but focusing on firms with non-missing observations for each outcome variable between preacquisition year and six years after. Table B.2 summarizes the results for output, energy consumption, and emission levels; while Table B.3 summarizes results for energy and emission intensities.

Table B.2: Regression results on output, energy and pollution levels.

	Acquisition Year	1 Year Later	2 Years Later	3 Years Later	4 Years Later	5 Years Later
Panel A			Log(Output)			
Acquired	1.116***	1.320***	1.435***	1.485***	1.512***	1.469***
	(0.156)	(0.159)	(0.170)	(0.181)	(0.188)	(0.193)
Adj. R^2	0.676	0.669	0.645	0.618	0.610	0.597
No. of Obs.	634	634	634	634	634	634
Panel B			Log (Energy Expenditure)			
Acquired	0.560***	0.734***	0.838***	0.804***	0.833***	0.951***
	(0.186)	(0.196)	(0.222)	(0.226)	(0.242)	(0.242)
Adj. R^2	0.725	0.700	0.625	0.636	0.591	0.601
No. of Obs.	424	424	424	424	424	424
Panel C			Log (Energy Use)			
Acquired	0.524***	0.727***	0.833***	0.844***	0.890***	0.973***
	(0.196)	(0.203)	(0.234)	(0.234)	(0.254)	(0.252)
Adj. R^2	0.718	0.698	0.623	0.645	0.602	0.602
No. of Obs.	424	424	424	424	424	424
Panel D			Log (CO2 Emission)			
Acquired	0.523***	0.708***	0.826***	0.820***	0.883***	0.956***
	(0.192)	(0.199)	(0.231)	(0.233)	(0.253)	(0.250)
Adj. R^2	0.723	0.706	0.624	0.643	0.597	0.603
No. of Obs.	424	424	424	424	424	424

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

Table B.3: Regression results on energy and emission intensities.

	Acquisition Year	1 Year Later	2 Years Later	3 Years Later	4 Years Later	5 Years Later
Panel A			Log (Energy Expenditure Intensity)			
Acquired	-0.491***	-0.581***	-0.623***	-0.605***	-0.697***	-0.597***
	(0.155)	(0.172)	(0.192)	(0.186)	(0.202)	(0.196)
Adj. R^2	0.615	0.525	0.443	0.465	0.389	0.443
No. of Obs.	424	424	424	424	424	424
Panel B			Log (Energy Use Intensity)			
Acquired	-0.528***	-0.588***	-0.629***	-0.565***	-0.640***	-0.576***
	(0.162)	(0.181)	(0.197)	(0.192)	(0.214)	(0.201)
Adj. R^2	0.627	0.526	0.467	0.494	0.410	0.470
No. of Obs.	424	424	424	424	424	424
Panel C			Log (CO2 Emission Intensity)			
Acquired	-0.528***	-0.607***	-0.635***	-0.589***	-0.647***	-0.593***
	(0.162)	(0.179)	(0.197)	(0.192)	(0.214)	(0.200)
Adj. R^2	0.610	0.519	0.446	0.477	0.383	0.458
No. of Obs.	424	424	424	424	424	424

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

2.4 Robustness Check: Controlling for Share of Exports to Total Output

This section presents the results from estimating equation 2.2 on matched sample while controlling for any change in acquired firm's share of exports. Table B.4 summarizes the results. Columns 2-4 estimates equation 2.2 with export share as another control variable, while columns 5-7 include an interaction between the acquisition dummy varaible and export share.

Table B.4: Regression results on energy and emission intensities, controlling for export share.

	Acquisition Year	1 Year Later	2 Years Later	Acquisition Year	1 Year Later	2 Years Later
Panel A	Energy Expenditure Intensity			Energy Expenditure Intensity		
Acquired	-0.258**	-0.228*	-0.370**	-0.275**	-0.202	-0.424**
	(0.111)	(0.128)	(0.153)	(0.131)	(0.154)	(0.174)
Export Share	0.001	-0.001	-0.001	0.000	-0.000	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Acquired*Export Share				0.001	-0.001	0.003
				(0.003)	(0.003)	(0.003)
Adj. R2	0.542	0.482	0.406	0.542	0.481	0.406
No. of Obs.	1005	951	902	1005	951	902
Panel B	Energy Use Intensity			Energy Use Intensity		
Acquired	-0.327***	-0.241*	-0.420***	-0.351**	-0.186	-0.477***
	(0.116)	(0.137)	(0.158)	(0.138)	(0.164)	(0.179)
Export Share	0.001	-0.001	-0.001	0.000	-0.000	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Acquired*Export Share				0.001	-0.002	0.003
				(0.003)	(0.003)	(0.003)
Adj. R2	0.566	0.486	0.438	0.565	0.486	0.437
No. of Obs.	1005	951	902	1005	951	902
Panel C	CO2 Emission Intensity			CO2 Emission Intensity		
Acquired	-0.326***	-0.251*	-0.417***	-0.353**	-0.206	-0.479***
	(0.116)	(0.136)	(0.158)	(0.138)	(0.163)	(0.179)
Export Share	0.001	-0.001	-0.001	0.000	-0.000	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Acquired*Export Share				0.001	-0.002	0.003
				(0.003)	(0.003)	(0.003)
Adj. R2	0.552	0.477	0.418	0.552	0.476	0.418
No. of Obs.	1005	951	902	1005	951	902

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. Columns 2-4 estimates equation 2.2 with export share as another control variable, while columns 5-7 include an interaction between the acquisition dummy varaible and export share. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

2.5 DD Estimation With Interaction Term Between Foreign Acquisition Dummy and Pre-Acquisition Characteristics

Figure B.4: Effect of foreign acquisition on the outcome variables at varying pre-acquisition energy use/output.

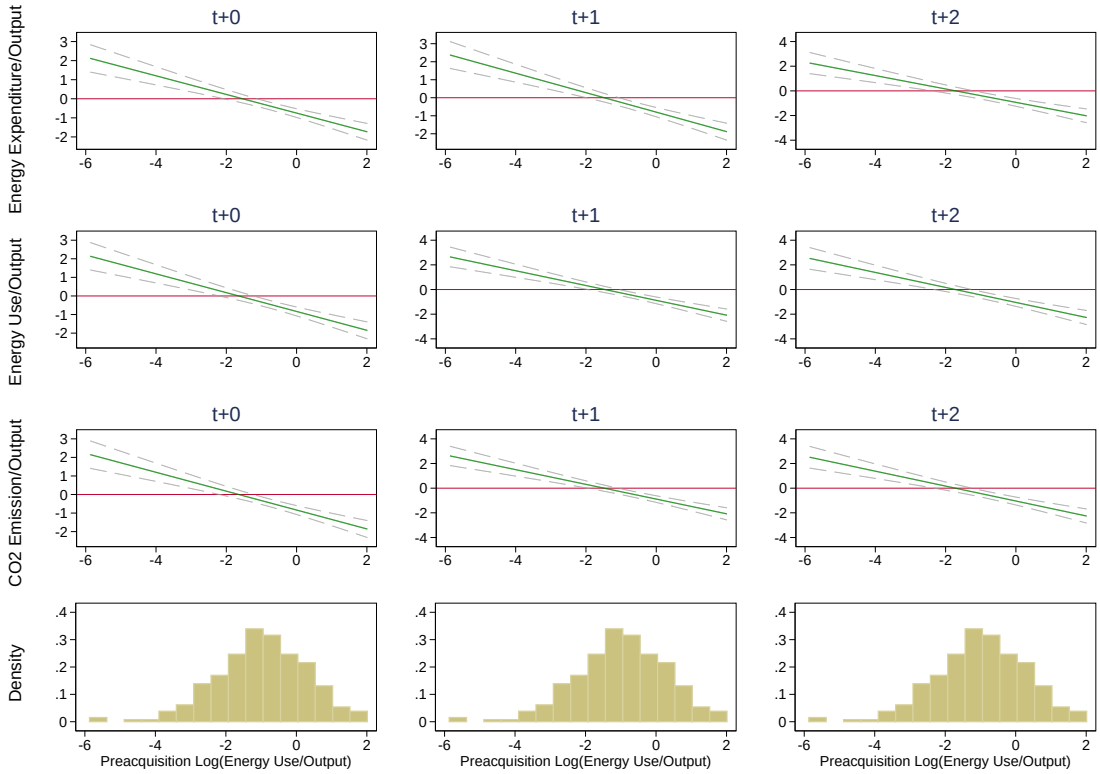
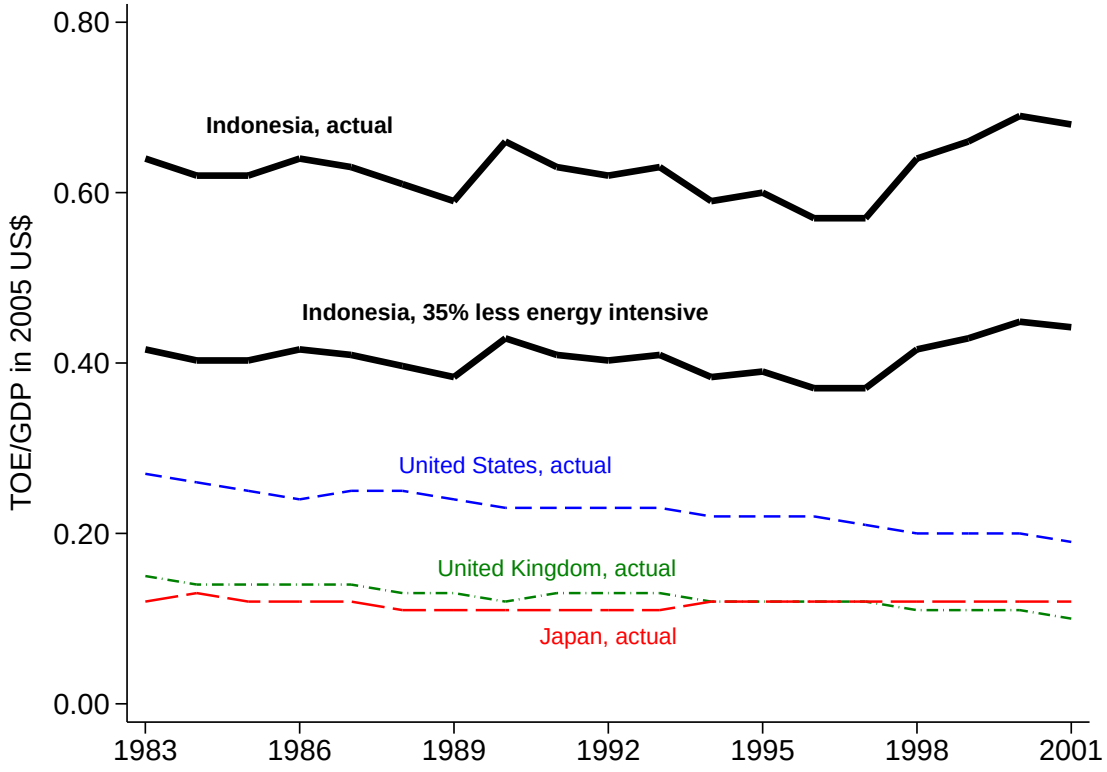


Figure B.5: Energy Intensity of Indonesia and select developed countries, 1983-2001



Note: Energy intensity is expressed as Ton of Oil Equivalent (TOE) per dollar unit of GDP (in 2005 US$). The 35% less energy intensity is due to foreign acquisition as described in the text.

Source of Data: International Energy Agency (IEA).

Table B.5: DD estimation with interaction between pre-acquisition log(output) and foreign acquisition dummy.

	Acquisition Year	1 Year Later	2 Years Later
Panel A	Energy Expenditure Intensity		
Acquired*Log(Output)$_{t-1}$	0.145***	0.190***	0.161**
	(0.055)	(0.059)	(0.068)
Acquired	-1.607***	-2.013***	-1.870***
	(0.540)	(0.582)	(0.651)
Adj. R^2	0.553	0.501	0.419
No. of Obs	1005	951	902
Panel B	Energy Use Intensity		
Acquired*Log(Output)$_{t-1}$	0.121**	0.172***	0.153**
	(0.059)	(0.066)	(0.070)
Acquired	-1.446**	-1.854***	-1.847***
	(0.575)	(0.639)	(0.676)
Adj. R^2	0.572	0.499	0.448
No. of Obs	1005	951	902
Panel C	CO2 Emission Intensity		
Acquired*Log(Output)$_{t-1}$	0.126**	0.174***	0.158**
	(0.059)	(0.065)	(0.070)
Acquired	-1.496***	-1.887***	-1.897***
	(0.575)	(0.632)	(0.676)
Adj. R^2	0.559	0.490	0.430
No. of Obs	1005	951	902
Implied Level of Pre-Acquisition Log(Output) for the ATT to be zero.			
Energy Exp. Intensity	11.08	10.59	11.61
Share of firms below threshold	*0.83*	*0.77*	*0.91*
Energy Use Intensity	11.95	10.78	12.07
Share of firms below threshold	*0.94*	*0.79*	*0.95*
Emission Intensity	11.87	10.84	12.01
Share of firms below threshold	*0.94*	*0.80*	*0.95*

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4, with an interaction term between the acquisition dummy (*Acquired*) and preacquisition log-transformed output (*Log(Output)*$_{t-1}$). The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. The bottom panel illustrates the level of preacquisition period for the estimated average treatment effect on the treated (ATT) to be zero. Firms that fall below this level ar expected to have significant reduction in energy consumption and emissions per unit of output. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

Table B.6: DD estimation with interaction between pre-acquisition log($\frac{\text{Energy Expenditure}}{\text{Output}}$) and foreign acquisition dummy.

	Acquisition Year	1 Year Later	2 Years Later
Panel A	Energy Expenditure Intensity		
Acquired*Log(Energy Exp./Output)$_{t-1}$	-0.525***	-0.585***	-0.595***
	(0.072)	(0.074)	(0.084)
Acquired	-2.320***	-2.551***	-2.721***
	(0.289)	(0.303)	(0.352)
Adj. R^2	0.605	0.569	0.498
No. of Obs	1003	949	900
Panel B	Energy Use Intensity		
Acquired*Log(Energy Exp./Output)$_{t-1}$	-0.513***	-0.623***	-0.635***
	(0.076)	(0.082)	(0.089)
Acquired	-2.338***	-2.718***	-2.929***
	(0.307)	(0.331)	(0.369)
Adj. R^2	0.618	0.572	0.532
No. of Obs	1003	949	900
Panel C	CO2 Emission Intensity		
Acquired*Log(Energy Exp./Output)$_{t-1}$	-0.520***	-0.624***	-0.636***
	(0.076)	(0.080)	(0.089)
Acquired	-2.366***	-2.730***	-2.931***
	(0.307)	(0.324)	(0.368)
Adj. R2	0.607	0.566	0.516
No. of Obs	1003	949	900
Implied Level of Pre-Acquisition Log(Energy Expenditure/Output) for the ATT to be zero.			
Energy Exp. Intensity	-4.42	-4.36	-4.57
Share of firms above threshold	*0.68*	*0.65*	*0.74*
Energy Use Intensity	-4.56	-4.36	-4.61
Share of firms above threshold	*0.73*	*0.65*	*0.76*
Emission Intensity	-4.55	-4.38	-4.61
Share of firms above threshold	*0.73*	*0.66*	*0.76*

Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4, with an interaction term between the acquisition dummy (*Acquired*) and preacquisition log-transformed energy expenditure per unit of output (*Log(Energy Exp./Output)*$_{t-1}$). The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. The bottom panel illustrates the level of preacquisition period for the estimated average treatment effect on the treated (ATT) to be zero. Firms that fall below this level ar expected to have significant reduction in energy consumption and emissions per unit of output. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

Table B.7: DD estimation with interaction between pre-acquisition $\log(\frac{\text{Energy Use}}{\text{Output}})$ and foreign acquisition dummy.

	Acquisition Year	1 Year Later	2 Years Later
Panel A	Energy Expenditure Intensity		
Acquired*Log(Energy Use/Output)$_{t-1}$	-0.489***	-0.541***	-0.543***
	(0.070)	(0.073)	(0.084)
Foreign Acquisition	-0.750***	-0.798***	-0.930***
	(0.117)	(0.132)	(0.162)
Adj. R^2	0.603	0.565	0.491
No. of Obs	1003	949	900
Panel B	Energy Use Intensity		
Acquired*Log(Energy Use/Output)$_{t-1}$	-0.506***	-0.600***	-0.608***
	(0.072)	(0.078)	(0.086)
Foreign Acquisition	-0.833***	-0.876***	-1.046***
	(0.122)	(0.139)	(0.164)
Adj. R^2	0.624	0.576	0.534
No. of Obs	1003	949	900
Panel C	CO2 Emission Intensity		
Acquired*Log(Energy Use/Output)$_{t-1}$	-0.509***	-0.596***	-0.605***
	(0.072)	(0.076)	(0.086)
Foreign Acquisition	-0.836***	-0.883***	-1.040***
	(0.122)	(0.137)	(0.164)
Adj. R^2	0.612	0.568	0.517
No. of Obs	1003	949	900
Implied Level of Pre-Acquisition Log(Energy Use/Output) for the ATT to be zero.			
Energy Exp. Intensity	-1.53	-1.46	-1.71
Share of firms below threshold	*0.69*	*0.67*	*0.73*
Energy Use Intensity	-1.65	-1.46	-1.72
Share of firms below threshold	*0.71*	*0.67*	*0.73*
Emission Intensity	-1.64	-1.48	-1.72
Share of firms below threshold	*0.71*	*0.67*	*0.73*

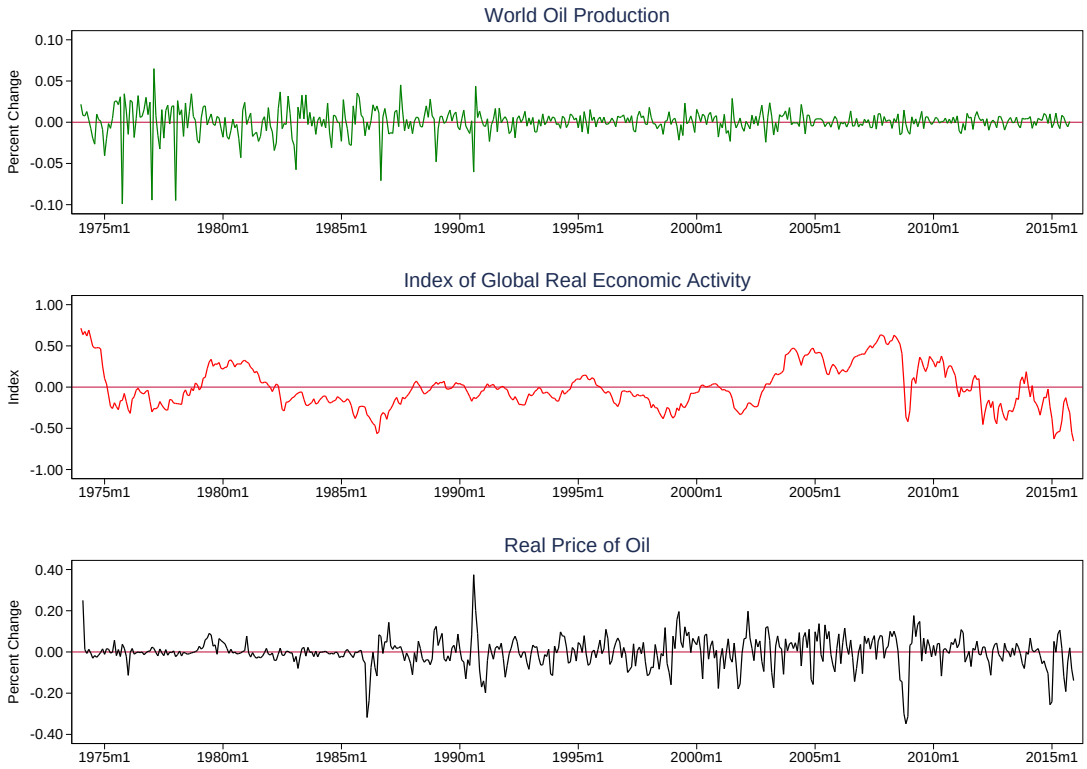
Note: The table reflects the result of estimating equation 2.2 on the matched sample described in Section 2.4, with an interaction term between the acquisition dummy (*Acquired*) and preacquisition log-transformed energy use per unit of output (*Log(Energy Use /Output)*$_{t-1}$). The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Acquired is a dummy taking the value of 1 for foreign-owned plants after the acquisition, and zero otherwise. The bottom panel illustrates the level of preacquisition period for the estimated average treatment effect on the treated (ATT) to be zero. Firms that fall below this level ar expected to have significant reduction in energy consumption and emissions per unit of output. Heteroskedasticity-robust standard errors are in parentheses. A constant is included in all specifications, but not reported. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Source of Data: Indonesian Census of Manufacturing

Appendix C

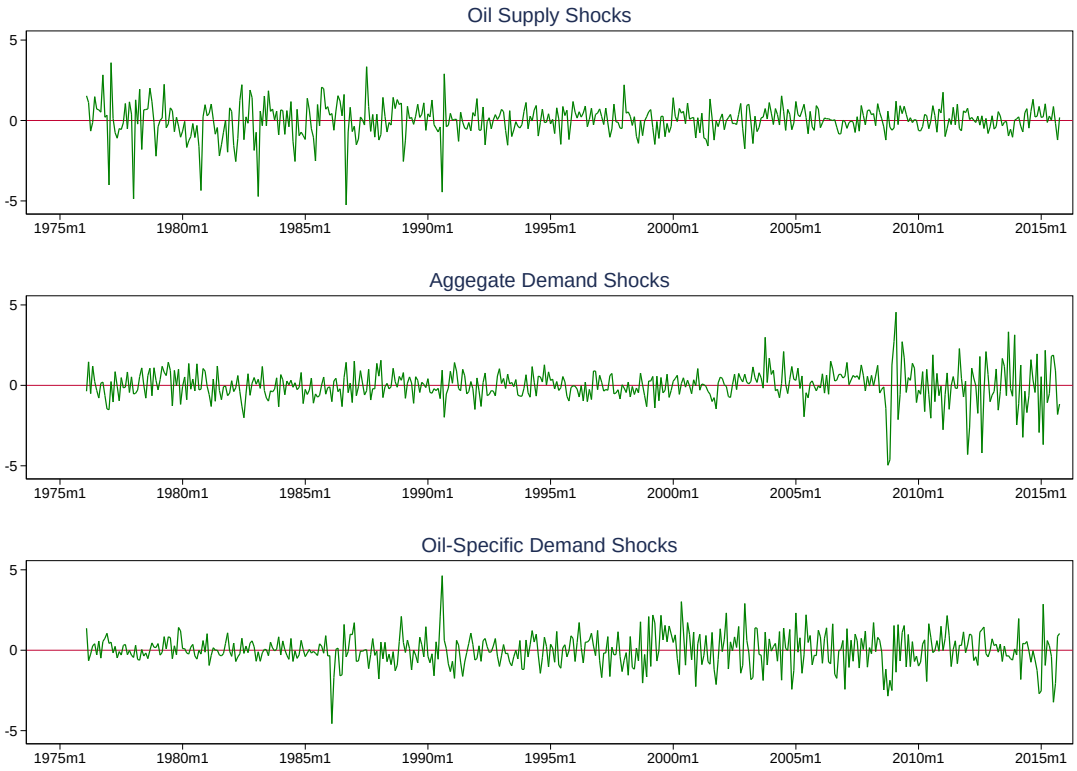
Chapter 3 Appendices

Figure C.1: Evolution of VAR Variables, 1976-2015.



Source: World Oil Production (EIA); Index of Global Real Economic Activity (Kilian 2009); Real Price of Oil (EIA).

Figure C.2: Evolution of VAR Residuals (Monthly), 1976-2015.



Source: World Oil Production (EIA); Index of Global Real Economic Activity (Kilian 2009); Real Price of Oil (EIA).

Table C.1: Dependent variable: first difference in log-transformed Gross State Product (Robustness Check)

Variables	SAR (Binary Weights)									
	48 States		No CA		No NY		No TX		No CA,NY,TX	
Oil Supply	0.007**	0.008**	0.012***	0.008**	0.012***	0.008**	0.011***	0.007**	0.012***	0.008**
	(0.0025)	(0.0026)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
REA	0.001	0.004	-0.001	0.003	-0.001	0.003	-0.001	0.003	-0.001	0.003
	(0.0014)	(0.0024)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Oil Price	-0.004*	-0.006***	-0.002	-0.004*	-0.002	-0.003*	-0.001	-0.003*	-0.002	-0.003*
	(0.0016)	(0.0016)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Oil Supply* Prod/Cap	-0.008***	-0.007***	-0.009***	-0.006***	-0.009***	-0.006***	-0.009***	-0.006***	-0.009***	-0.006***
	(0.0014)	(0.0016)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
REA*Prod/Cap	-0.001	-0.003	0.000	-0.001	0.000	-0.001	-0.000	-0.002	-0.000	-0.002
	(0.0019)	(0.0025)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Oil Price*Prod/Cap	0.006**	0.005***	0.005**	0.003***	0.004**	0.003***	0.004**	0.004***	0.004**	0.004***
	(0.0020)	(0.0011)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged GDP growth	0.148***	0.700***	0.161***	0.656**	0.173***	0.678**	0.176***	0.655**	0.171***	0.630**
	(0.0347)	(0.1112)	(0.037)	(0.200)	(0.037)	(0.217)	(0.037)	(0.202)	(0.038)	(0.197)
Spatial lag (Lambda)	0.786***	0.934***	0.751***	0.908***	0.733***	0.901***	0.752***	0.898***	0.750***	0.889***
	(0.0397)	(0.0634)	(0.040)	(0.074)	(0.042)	(0.080)	(0.042)	(0.078)	(0.042)	(0.078)
Spatial lag (t-1) (Rho)		-1.066***		-0.937*		-0.961*		-0.932*		-0.891*
		(0.2123)		(0.375)		(0.405)		(0.390)		(0.384)
Observations	1,776	1,776	1,776	1,776	1,776	1,776	1,776	1,776	1,665	1,665
Time Period (years)	37	37	37	37	37	37	37	37	37	37
No. of Panels	48	48	47	47	47	47	47	47	45	45
GMM-AIC	-0.093	-9.465	1.039	-5.908	3.306	-4.642	1.934	-5.614	-0.601	-6.372
GMM-BIC	-32.985	-36.875	-31.727	-33.214	-29.460	-31.947	-30.833	-32.919	-33.107	-33.460
Pseudo-Adj. R.sq	0.465	0.464	0.456	0.456	0.452	0.452	0.437	0.437	0.435	0.434
Hansen J-statistic	11.907	0.535	13.039	4.092	15.306	5.358	13.934	4.386	11.399	3.628
p-value of J-statistic	0.064	0.991	0.042	0.536	0.018	0.374	0.030	0.495	0.077	0.604

Oil Supply, Real Economic Activity (REA) and Oil Specific Demand are structural shocks mentioned in the text. Prod/Cap is the state-level long-run ratio of energy (BTUs) produced and consumed from crude oil and petroleum form 1963-2013. The 48 states refer to 48 contiguous states in the US. Regression results are derived using GMM following Lee and Yu (2014). GMM-AIC and GMM-BIC are calculated following Andrews (1999). Clustered standard errors are in parenthnses. ***, **, * denote statistical significance at 1, 5 and 10 percent respectively.