ESSAYS ON ENERGY AND REGULATORY COMPLIANCE

A Dissertation

by

CESAR ALFREDO THEODORO CANCHO DIEZ

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2012

Major Subject: Economics

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Approved by:

Chair of Committee,	Steven L. Puller
Committee Members,	Steven N. Wiggins
	Stephanie A. Houghton
	Lori L. Taylor
Head of Department,	Timothy J. Gronberg

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ABSTRACT

Essays on Energy and Regulatory Compliance. (August 2012)

Cesar Alfredo Theodoro Cancho Diez, B.S., Pontificia Universidad Catolica del Peru

Chair of Advisory Committee: Dr. Steven L. Puller

This dissertation contains two essays on the analysis of market imperfections. In the first essay, I empirically test whether in a three-level hierarchy more competition among intermediaries leads to more deception against the principal. In this setting, intermediaries supervise agents by delegation of the principal, and compete among themselves to provide supervision services to the agents. They cannot be perfectly monitored, therefore allowing them to manipulate supervision results in favor of the agents, and potentially leading to less than optimal outcomes for the principal. Using inspection-level data from the vehicular inspection program in Atlanta, I test for the existence of inspection deception (false positives), and whether this incidence is a function of the number of local competitors by station. I estimate the incidence of the most common form of false positives (clean piping) to be 9% of the passing inspections during the sample period. Moreover, the incidence of clean piping – passing results of a different vehicle fraudulently applied to a failing vehicle – per station increases by 0.7% with one more competitor within a 0.5 mile radius. These results are consistent with the presence of more competitors exacerbating the perverse incentives introduced by competition under this setting.

In the second essay, we test whether electricity consumption by industrial and commercial customers responds to real-time prices after these firms sign-up for prices linked to the electricity wholesale market price. In principle, time-varying prices (TVP) can mitigate market power in wholesale markets and promote the integration of intermittent generation sources such as wind and solar power. However, little is known about the prevalence of TVP, especially in deregulated retail markets where customers can choose whether to adopt TVP, and how these firms change their consumption after signing up for this type of tariff. We study firm-level data on commercial and industrial customers in Texas, and estimate the magnitude of demand responsiveness using demand equations that consider the restrictions imposed by the microeconomic theory. We find a meaningful level of take-up of TVP – in some sectors more than one-quarter of customers signed up for TVP. Nevertheless, the estimated price responsiveness of consumption is still small. Estimations by size and by type of industry show that own price elasticities are in most cases below 0.01 in absolute value. In the only cases that own price elasticities reach 0.02 in absolute value, the magnitude of demand response compared to the aggregate demand is negligible.

To my father, Alfredo Cancho Garayar.

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CHAPTER I

INTRODUCTION

This dissertation contains two essays on the analysis of market imperfections. In the first essay, I analyze the effect that the market structure may have over the behavior of market participants. The setting I study is a three-level hierarchy, with a principal that delegates the supervision of agents to intermediary firms. These intermediaries compete among themselves to provide the supervision service to agents. They have an informational advantage over the principal, and they can collude with the agents to deceive the principal by obtaining false positive results from the supervision. Considering a setting as the described, I study whether collusion exists and how extended is it by testing for the existence of one form of test manipulation in a vehicular emission inspection program (Atlanta, GA) designed as a three-level hierarchy. I am also interested in answering the question of whether the incidence of deception by station is affected by the number of local competitors, which constitutes a metric of the intensity of competition. The results will provide empirical evidence about the strength of perverse incentives in settings where competition is introduced to improve the outcomes from the provision of government services, as is the case of outsourcing of certification and supervision capacity.

In Chapter III, I test whether the patterns of electricity consumption vary after customers decide to sign-up for real-time prices. In the setting I study, industrial and commercial customers have the option to sign-up for prices linked to the electricity wholesale market price, which varies every 15 minutes. Time-varying prices (TVP) have the potential to make total demand for electricity more elastic and thus reduce

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This dissertation follows the style of the *American Economic Review.*

market power in wholesale electricity markets. In addition, TVP can promote the integration of intermittent generation sources such as wind and solar power, by introducing incentives to curtail demand when unexpected changes in the production of electricity from these sources occur. However, little is known about the prevalence of TVP, especially in deregulated retail markets where customers can choose whether to adopt TVP, and how these firms change their consumption after signing up for this type of tariff. Using firm-level data on commercial and industrial customers in Texas, we are interested in studying how meaningful is the level of take-up of TVP, and what the magnitude of the response to electricity prices is for signed-up firms. The results will contribute to a growing literature about the effect of real-time prices on electricity consumption by residential, industrial and commercial firms, and provide some guidance to policy makers about the potential of sign-up programs to induce demand responsiveness.

CHAPTER II

FRAUD AND MARKET COMPETITION IN THE EMISSION INSPECTION MARKET

A. Introduction

Governmental entities often outsource the provision of public services, such as garbage and recyclable materials collection, fire protection, and prison management to commercial contractors. Vehicle emission certification capacity delegated to private inspection stations is one of this cases. After passage of the Clean Air Act of 1990, vehicle inspection stations tested vehicle tailpipe emissions as one facet of a multi-pronged approach to curbinng air pollution. A number of states adopted decentralized, privately operated inspection and maintenance (I/M) programs affording car owners the freedom of choice of inspection stations. Under this model, competition would keep the cost of the inspections as low as possible, and the wide availability of stations across a city would also save costs for car owners in terms of distance and time. Texas, New York, New Jersey, Nevada, and Georgia were among the states implementing this decentralized format. The alternative centralized format, where a single entity performs all the inspections was adopted by Arizona, Illinois, Wisconsin and the District of Columbia, among others.

Unfortunately, the potential welfare gains expected from outsourcing the vehicular emission inspections to private firms were not guaranteed, since some of the necessary assumptions for perfect competition were not satisfied. First, the service transacted is not an homogeneous good. Test results can be manipulated in many different ways by the inspectors to obtain a false result, given that they cannot be perfectly supervised. Moreover, the risk of losing customers to other competitors and with that, the future stream of income coming from those interactions, create a misalignment of incentives between the inspectors and the state air quality regulators, potentially leading to adverse outcomes. Stations seek to maximize profits, while the regulator wants to reduce pollution. With costly and imperfect supervision, stations can alter the results of the tests without being discovered if such practices are profitable.

There are other markets where this misalignment of incentives between supervisors and principal may occur. For instance, auditing firms act as supervisor for the shareholders of a company that want to know the real situation of the firm where their money is invested. However, audit firms offer other services directly to the firms, creating a conflict of interest. Another example is the case of environmental impact assessments, in which independent firms are hired to evaluate the possible effects of mining projects. These firms act as supervisors for the government, whose motivation is sustainable development of the mining projects. As many of these firms, however, offer other services to the mining companies, there also exists a misaligment of incentives.

This paper's contribution is to identify the effect that market structure can have over fraudulent behavior in the emission inspection market in a major I/M program. I focus on a particular form of test manipulation that is arguably one of the most common forms of vehicular emissions inspection fraud in the United States: clean piping. Clean piping is the practice of using a clean car to obtain a passing result for a car that would otherwise not pass emissions inspection. Specifically, I focus on cases in which one car that has already passed the inspection is used a second consecutive time for a new reading, this time the reading being assigned to a different vehicle. This way, a nonpassing vehicle can obtain a passing result without any need to perform repairs. This form of test manipulation has been documented by Oliva (2012) for the Mexico City I/M program to account for 14% of all passing vehicles. Other studies have analyzed how per-station failure rates in the United States are affected by the station internal and vertical organization, as shown by Hubbard (1998), for the California program, or Pierce and Toffel (2012) for a northeastern state.

In this paper I develop a new methodology for detecting cheating in the form of clean piping. This methodology generates data for a decision process on where to focus supervision to improve the efficacy of I/M programs, especially in developing countries. In this study, the test technology used for the inspections analyzed is based on direct tailpipe measurements. This testing technology has been replaced in recent years by a technology based on readings of the information stored in the vehicles' on-board computers, installed in cars 1996 and newer. In time, inspections based on tailpipe measurements will be used only a small fraction of the market inspection in most developed countries. In developing countries, however, lower income levels induce car makers to produce cars at the lowest possible cost, which, in many cases, means producing cars without standard on-board computers. More importantly, cars remain in service for many more years than in developed countries. Low labor costs for repair and low income result in car owners keeping their cars many more years, and often operating at less than optimal conditions. Many developing countries are now using or are planning to use tailpipe emissions inspections to reduce the pollution from the vehicular fleet. For instance, in Latin America, many cities have implemented emissions inspection programs, including Mexico City, Sao Paulo, Rio de Janeiro, Santiago, Buenos Aires, and Bogota; other locations are considering the implementation of such programs.

The empirical strategy used in this paper to detect fraud compares how well the gas readings obtained from each inspection fit to any of two possible distributions based on observable variables. For the first distribution, the gas readings are explained by the observable characteristics of the vehicle. For the second distribution, the gas readings from two consecutive inspections are assumed to come from the same vehicle. Then, the difference between two consecutive readings is attributed only to differences in inspection-specific variables, such as temperature or humidity. The estimated prevalence of clean piping fraud was 9% for the sample analyzed. To check that results are not a mechanical artifact arising from a natural correlation between samples from the same distribution, I performed falsification tests re-ordering randomly the arrival of vehicles to the stations. Results of this analysis show that the results are not an artifact of pure statistical correlation.

Based on the fit of gas readings with one or another distribution, I obtained probabilities of incidences of clean piping for each inspection in my sample. Then I performed ordinary least square (OLS) regressions of these probabilities on car and station characteristics, including the number of competitors. I expect to observe fraud only if stations in a vicinity are perceived as close substitutes. At the same time, I expect an effect on incidents of fraud by station only if customers are not extremely loyal to a particular station. If this were the case, stations will have no incentive to change the results of the inspections in their customers' favor, since a loyal customer base would return to the station regardless of result.

The presence of one additional station in the local market can affect incidence of fraud in either direction. With customers without loyalty to a particular station, inspectors will have little incentive to help them pass, since return customers are unlikely. In this case, the more local competitors that exist, the more uncertain will be customer loyalty, and the number of competitors will have a negative effect on the incidence of cheating per station. If inspection stations perceive a negative reaction to a failing result in the test, then inspectors have an incentive to achieve passing scores on emissions testing. Otherwise, with more local competitors, it would be easier for customers to switch to a different station.

There are two other effects that can be correlated with the number of stations. First, it may be the case that the number of inspection stations is associated with characteristics (such as propensity to fail an emissions test) of the vehicles owned by local clientele. I control this effect by incorporating vehicle characteristics in the estimation. Second, it is possible that the number of stations is associated with the reputation of certain stations or certain inspectors to have an enabling relationship with their customers. In this case, the parameter of the number of stations would be identifying the location of these stations or inspectors (dense clusters or isolated) rather than the effect of competition. I control this effect by using fixed effects per inspector, so that the parameter of the number of competitors captures deviations with respect to the mean probability per inspector. OLS estimation results show that with one more competitor in a radius of 0.5 mile, the chances of clean piping fraud increases by 0.7%. This result is consistent with the hypothesis of loyal customers reacting negatively to past experiences.

This paper is organized into eight more sections. The next section reviews the related literature. Section C describes the vehicular emission inspection program in Atlanta. Section D presents the strategies used to detect clean piping in the sample. Section E describes data used for the estimation. Section F presents the results of the estimation, and performs falsification tests to check that results are not spurious. Section G presents the results of the effect of competition on the probabilities of clean piping, and section H concludes.

B. Literature Review

Asymmetries of information have been studied in the economic literature mostly within the principal–agent framework. Typically, the agent has an informational advantage or has the ability to perform activities that the principal cannot verify without a considerable cost. To encourage agents to reveal their private information, the principal offers contracts where the more productive agent receives a premium compared to the first-best solution.[1] Several studies have found empirical evidence that principals cannot always insure themselves against agents taking advantage of their private information. For instance, Afendulis and Kessler (2007) found that for patients with coronary artery disease, the chances of receiving a surgical treatment are higher when the diagnosing cardiologist also performs surgical operations, compared with the cardiologist that performs only drug treatments. Another example is the case of real estate agents studied in Levitt and Syverson (2008). They found that despite having contracts rewarding effort as measured by a commission on the price paid for the houses for sale, when the house for sale is owned by the agents, houses stay longer on the market and sell for higher prices than when the house is owned by a third party. Jacob and Levitt (2003) analyzed teacher cheating behavior using data from standarized test scores in Chicago. They developed an algorithm that detects unusual patterns in the answers, and obtained evidence of cheating in around $4\% - 5\%$ of the classrooms. More importantly, they found that the probabilities of cheating behavior increase when schools are in danger of being closed, or when students are required to pass the standard examination to progress to the next grade. These studies highlight the fact that agents may have different incentives than their principals, and the final

[1] See Holmstrom (1979), Tirole (1988), Baron-Myerson (1982), Markin-Riley (1984), Laffont-Tirole(1986) for a more formal treatment of this relationship.

outcome can be inefficient from the point of view of the principal.

The vehicle emission inspection market differs from a conventional principal–agent framework in that there is an intermediary in the relationship between car owners and regulator. It can be better described as a three-level hierarchy: principal–supervisor–agent. The salient feature of this setting is that collusion between supervisors and agents against the principal is possible.[2] Principals try to discourage this behavior by offering contracts with premiums to the supervisor. In two seminal papers studying this setting, Tirole (1986, 1992) offers a stylized model of a three-level firm where the owner (principal) has to hire a supervisor to collect information about a productive agent. The supervisor can conceal what he learns and can engage in a collusive side-contract with the agent when doing so favors his own interests.[3] Most theoretical studies have focused on transactions occurring inside a single firm.

Several empirical studies have analyzed the emission inspection markets, focusing on the station-car owner relationship. Oliva (2012) studies the emission inspection market in Mexico City. Using a structural model of car owner retesting and cheating decisions, she found that at least 14% of owners of older vehicles paid bribes of $20 to circumvent test failure. Hubbard (1998), using a sample of inspections from

[2] As mentioned in Tirole (1986), other cases of three-level hierarchies are restaurant owner/maitre d'/waiter or voter/government agency/defense contractor (or regulated firm), brass/colonel/regiment, economic profession/Ph.D. advisor/Ph.D. student, investor/broker/firm, Department of Defense/contractor/subcontractor, train company/ticket inspector/passenger.

[3] Other related paper are Kofman and Lawarree (1993), who develop a model with internal and external supervisors, and show that the optimal contract may specify random external audits; Faure-Grimaud, Laffont and Martimort (1999, 2002), who show that the cost of collusion between supervisor and agent depends upon the collusion stake, the accuracy of the supervisor technology and the supervisor's degree of risk aversion; and Khalil and Lawarree (2006), who show that the supervisor can be totally useless if the supervisor's independence can be compromised with relative ease and derive a demand for independent external supervisors, for whom the cost of collusion is given by the risk of future detection.

California. tested whether passing results are affected by the organization of the firm, and found results consistent with agency theory. In particular, he found less incidence of collusion between stations when the station is a chain shop (e.g. Sears, Pep Boys) than an independent firm. In chain shops, usually the manager receives a salary that it is not attached to the number of customers, reducing the incentive to promote repeated business. In independent garages, the manager is often the owner of the station, so any gains from returning customers will benefit him directly. He also found that the probabilities of failing tests increases with the number of inspectors in the station. When inspectors are paid by the number of customers they service, in stations with several inspectors, the chances of one single customer coming back to the same inspector are small, even considering other types of services the stations can provide. Consequently, as the number of inspectors increases, the incentives to induce a customer to return by offering a high-quality service are smaller compared with the case of a station with a single inspector. In a related work, Hubbard (2002) found that consumers are 30 percent more likely to return to a station at which they previously passed compared to one at which they failed. This result is consistent with customers incomplete information about a station's trustiness, and with weak priors about a station's type. At the same time, however, Hubbard finds that demand is sensitive to a firm's overall failure rate, which indicates that customers are actually not completely uninformed about a station's type either. Otherwise, after controlling for station-observable characteristics (from the point of view of the car owner), there should be no relationship between the failure rate and the choice of station. This finding constitutes evidence that the information from inspection outcomes diffuses significantly across consumers in the market. Customers create an incentive to the station to be friendly to encourage repeat business. Pierce and Toffel (2012) analyzed the emission inspection market in a northeastern state and tested if monitoring leniency is associated with the internal organization of the firm. They found that opportunities of selling other products or services to the cars inspected, especially for stations that can sell high-margin products (e.g., parts) and services (e.g., repairs), increases leniency. They also found more leniency from independent stations than from branded or subsidiary facilities, which is consistent with the hypotheses that certain governance structures inside the firm increase the cost of failing to enforce regulations.

C. Emission Inspections in Atlanta

The inspection and maintenance Program in Atlanta started in 1995. By 2002, most cars registered in the metropolitan area were required to pass an annual emission inspection.[4] This mandate included gasoline-powered passenger cars and light-duty trucks up to 8,500 pounds. Vehicles up to two years old and older than 25 years are exempted from this obligation. If a car fails an inspection, and after having performed corrective repairs equivalent to a certain amount[5], fails a re-inspection, the owner can apply for a waiver and obtain a sticker for that year. Any business in the area can apply for and, after some mandatory training, obtain a license to perform inspections. The state agency charged with running the program is the Georgia's Clean Air Force (GCAF), which has granted licenses to repair stations, gas stations, car wash businesses, and some firms dedicated exclusively to emission inspections. By the end of 2003, there were more than 700 testing stations in the Atlanta metropolitan area performing the type of inspections analyzed in this paper. The price stations charge for the inspections is regulated by the GCAF. For the period covered in the data available (2002–2003), the price cap was $25 per inspection, and the vast majority

[4]Counties of Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, and Rockdale.

[5]Equivalent to $787 in 2009.

of stations charged this price. This fee allows for one free re-inspection at the same station. If a car fails the inspection and is taken to a different station, the inspector is not required to waive the fee. The average failure rate for the sample period is 13.5

The inspection method applied to a vehicle varies with the age of the vehicle. For this paper, I will use only the data from the acceleration simulated mode (ASM) test. This test methodology is used for cars with make year 1995 or older. This test is based on direct readings of gases from the tailpipe of the vehicles. In the sample period considered in my data, about half the fleet of vehicles in Atlanta were inspected using this method. For cars 1996 or newer, the test performed is the on-board diagnosis (OBD), based on readings of the information stored on the on-board computer. For cars that cannot be inspected with either of the previous methodologies, the two-speed idle (TSI) test is applied. Table 1 presents the number of cars inspected in the period analyzed and the results of the inspection by type of test. As can be noticed, cars inspected under ASM tend to fail more often, since they are older vehicles.

The mechanics of the ASM test work as follows. The inspector scans or types the vehicle identification number (VIN) of the vehicle into the gas analyzer (a computer with gas sensors to perform the inspection). This computer downloads the vehicle's information from a centralized database. The inspector places a probe inside the tailpipe. To obtain a realistic and representative sample of the vehicle's emissions, the car is parked over a treadmill-like dynamometer. To pass the test, the 10-second moving average readings for the three regulated gases (hydrocarbons, nitric oxide, and carbon monoxide) must be below the applicable test standard, which varies by vehicle, vehicle year and weight. The test takes 90 seconds, though a 15 second "warm-up period" is excluded from the result. Complementing the gas test is a visual check of the catalytic converter and the gas cap.

There are many ways in which a station can help their customers pass. Hubbard

Table 1—Inspections by Type of Test

Test Type		Test Result: Pass	Failure	Abort	Total
ASM	*Inspections*	1,523,655	328,436	1,924	1,854,015
	Percentage	82.3	17.7	0.1	100.0
OBD		1,666,376	173,591	102	1,840,069
		90.6	9.4	0.0	100.0
TSI		58,925	3,818	128	62,871
		93.9	6.1	0.2	100.0
Total		3,248,956	505,845	2,154	3,756,955
		86.5	13.5	0.1	100.0

Notes: Reported statistics referred to all the inspections performed between May 2002 and December 2003 in the 13 counties of the Atlanta Metropolitan Area under the I/M program. ASM stands for Acceleration Simulated Mode, OBD stands for On-Board Diagnosis, and TSI stands for Two-Speed Idle.

(1998) describes legal options such as warming-up the vehicle before the inspection, or being more lenient in the visual inspection. Pierce and Toffel (2012) describe other methods to manipulate the test, like introducing fuel additives (e.g., denatured alcohol), adjusting the tailpipe probe, diverting exhaust before it reaches the tailpipe, or inducing the car to run at fewer revolutions per minute. To the extent that the complementary information about the inspection, like oxygen reading, or revolutions per minute are recorded, I believe that those forms of test manipulation are not prevalent. Oliva (2012) documents in detail a form of test manipulation employed in the

Mexico City emission inspection program. This consists of using a clean car to obtain a passing reading for the next car in the line. The great advantage of this form of test manipulation is that once the second gas reading was obtained and the passing result recorded, it is very difficult to verify *ex post* that the actual car was inspected.

In the United States, states with emission inspection programs are aware of the higher failure rates in centralized programs compared with their decentralized counterparts. State regulators and the Environmental Protection Agency try to discourage test manipulation by applying severe sanctions to violators. These types of illegal activities persist, however, as reported in the media.[6] As can be noticed on the news reported, and according to conversations with state officials, the most common type of manipulation is clean piping (or clean scanning for newer cars). However, most of these cases are detected not by routine audits but by unusual patterns in the reported data or by anonymous tips. Most states make undercover visits to the stations, but they are expensive and performed on a limited scale. Chances of detecting misbehavior this way are limited.[7]

D. Methodology

To detect clean piping I developed a methodology based on a switching regression model that assigns probabilities to each inspection of being a clean piping case. Before proceeding with this estimation, I applied the reduced-form methodology developed

[6] See news reports from Nevada (http://www.justice.gov/opa/pr/2010/January/10-enrd-015.html), California (http://business-video.tmcnet.com/news/2007/01/15/2245227.htm, http://www.almanacnews.com/news/show_story.php?id=6626), Georgia (http://www.bizjournals.com/atlanta/news/2011/02/28/3-locals-indicted-on-emissions-fraud.html).

[7] In Georgia, during the year 2003, 2,139 undercover visits were performed for more than 1 million inspections performed across 683 stations. In 766 of these visits, the cars were emitting pollutants over the permitted limit. Only in 10 (1.3%) of these 766 visits obtained a passing result, leading to an investigation to the station.

by Oliva (2012) to detect the existence of clean piping cases in the sample, and explain the obstacles obtaining an unbiased mean incidence estimator. The details of both methodologies are explained next.

1. Linear Estimations

When a clean car is used to obtain a passing result for the next car in line, two consecutive readings will be very similar, after controlling for differences in the inspection conditions like temperature or humidity. Following this intuition, Oliva (2012) suggests the use of linear regressions for testing for the existence of manipulation, using as dependent variables the gas readings, and as explanatory variables, the reading of the preceding car and observable characteristics of the car supposedly tested. If the recorded emissions from the car tested inmmediately before has explanatory power, then we can claim that there is evidence of clean piping.

More formally, for the general case of an honest inspection, the gas readings can be modeled according to the following linear specification:

$$r_i^h = X_i\beta + Z_i\gamma + e_i^h \tag{2.1}$$

where index i corresponds to the car inspected. r_i^h is the true gas reading that would be obtained if the car were inspected, X_i is car characteristics that determine the gas readings (e.g., odometer, displacement, body type). Z_i include two type of variables that are specific to the inspection: environmental factors that can affect the reading (e.g., temperature, humidity) and car characteristics that determine the resistance of the dynamometer when the car is tested (e.g., displacement, weight). The variables contained in Z_i are a subset of the ones in X_i, so the γ parameters for this subset of variables will not be separately identifiable from β. e_i^h is the error term associated which each honest inspection. The error term e_i^h is assumed to be *i.i.d.*, which means that the linear specification is appropiate to capture the relationship between X, Z, and r^h. At the same time, we assume that there is no serial correlation that cannot be captured by the observable characteristics, nor by fixed effects per analyzer/month. This implies that the variables observed by the econometrician are good enough to characterize the readings.

When the inspection is a clean piping case, the reading comes from the following specification:

$$r_i^c = X_{i-1}\beta + Z_i\gamma + e_i^c \tag{2.2}$$

which means that the reading is generated by the observable characteristics of the car ahead in line, inspection-specific variables, and an error term. The superindex c in the error term is used to distinguish this error term from the generated when is an honest case. r_i^c can also be expressed in terms of the gas reading of the car ahead in line. In this case, we would have that:

$$\begin{aligned} r_i^c &= X_{i-1}\beta + Z_i\gamma + e_i^c + \left(r_{i-1}^h - X_{i-1}\beta - Z_{i-1}\gamma - e_i^h\right) \\ &= r_{i-1}^h + \left(Z_i - Z_{i-1}\right)\gamma + \left(e_i^c - e_{i-1}^h\right) \end{aligned} \tag{2.3}$$

Given these specification for r_i^h and r_i^c, each observed gas reading can be characterized as:

$$r_i = m_i \left[r_i^c\right] + (1 - m_i) \left[r_i^h\right] \tag{2.4}$$

where m_i is an index variable equal to one for the clean piping cases. After replacing both r_i^c and r_i^h by their observed components, we obtain:

$$r_i = m_i \left[r_{i-1}^h + (Z_i - Z_{i-1})\,\gamma + e_i^c - e_{i-1}^h\right] + (1 - m_i) \left[X_i\beta + Z_i\gamma + e_i^h\right] \tag{2.5}$$

I prefer replacing r_i^c with the specification based on the reading of the car ahead in line, instead of just plugging the observables of the car ahead in line, because the actual reading contains more information (i.e., the error term) than the specification based on observables. Also, the error term is smaller since the error term included $(e_i^c - e_{i-1}^h)$ is only the difference between readings coming from the same car. Finally, using r_{i-1}^h allows to obtain an intuitive direct parameter that can be used for testing for the existence of clean piping cases in the sample.

Based on (2.5), we can estimate the following linear specification:

$$r_i = \tilde{\varphi} r_{i-1} + (Z_i - Z_i)\,\tilde{\gamma} + X_i\tilde{\beta} + Z_i\hat{\gamma} + u_i \tag{2.6}$$

where

$$u_i = m_i \left[e_i^c - e_{i-1}^h\right] + (1 - m_i) \left[e_i^h\right] \tag{2.7}$$

This specification collapses to the following specification when all m_i are equal to zero:

$$r_i = X_i\beta + Z_i\gamma + e_i^h \tag{2.8}$$

Hence, to test whether all the m_i in the sample are equal to zero, we can estimate (2.6) by OLS and analyze the individual significance test of $\tilde{\varphi}$. Alternatively, we could also evaluate the test for individual significance of $\tilde{\gamma}$, or on a test of joint significance for $\tilde{\varphi}$ and $\tilde{\gamma}$, under the assumption that $\gamma \neq 0$. I will prefer to test directly for the significance of $\tilde{\varphi}$ rather to the other two tests because these other tests rest on the additional assumption of the differences in environmental variables having an effect on the readings ($\gamma \neq 0$), while the individual significance of $\tilde{\varphi}$ depends entirely on the existence of clean piping cases in the sample.

In case some of the observations in the sample are clean piping cases, then $\tilde{\varphi}$ will be different from zero. If this is the case, using matrix notation we can express the OLS estimator for $\tilde{\varphi}$ in (2.6) as:

$$\hat{\varphi}_m^{OLS} = (r'_{-1}(I - P_V)r_{-1})^{-1} r'_{-1}(I - P_V)r \tag{2.9}$$

where $r_{-1}$is the vector of readings of the car ahead in line, P_V is the projection matrix of the matrix V that contains all the other right-hand side variables in (2.6), and r is the vector of readings of the car inspected. Formally I will define the test for the existence of clean piping cases as[8]:

$$H_0 : plim(\tilde{\varphi}) = 0 \qquad if \ \ \forall m_i = 0 \tag{2.10}$$

[8]The asymptotic properties of this test can be found in Appendix A.

$$H_1 : plim(\tilde{\varphi}) \neq 0 \qquad if \;\; \exists m_i \neq 0 \tag{2.11}$$

The results of the estimation of (2.6) under different linear specifications are presented in Table 2. The table reports only the parameter $\tilde{\varphi}$. For all the specifications considered the parameter $\tilde{\varphi}$ is statistically different from zero, rejecting the null hypothesis of no clean piping cases. Hence, I conclude that there is evidence that at least a sub sample of the observations are cases of clean piping, where two consecutive readings come from the same vehicle.

2. Mean Incidence Estimation Limitations

A natural extension of the methodology developed in the preceding section would be its use to estimate the mean incidence of clean piping. We can estimate (2.6), and ideally, we would like $\tilde{\varphi}$ to be equal to an estimator of the incidence of clean piping:

$$\hat{m}_0 = \frac{\sum_i^N m_i}{N} \tag{2.12}$$

Imposing temporarily the additional assumption in (2.9) that r_{-1} is orthogonal to all the variables contained in V, we obtain the following expression for $\hat{\varphi}_m^{OLS}$:

$$\hat{\varphi}_m^{OLS} = (r_{-1}' r_{-1})^{-1} r_{-1}' r \tag{2.13}$$

After replacing r by its observable components, as defined in (2.5), we obtain an explicit form for $\hat{\varphi}_m^{OLS}$:

Table 2—Gas Readings SUR Estimates

	(1)	(2)	(3)	(4)
Hydrocarbon	0.0177	0.0102	0.0086	0.0091
(*z-test*)	65.53	39.60	34.19	35.99
Carbon monoxide	0.0056	0.0028	0.0029	0.0031
	23.61	12.19	13.03	13.77
Nitric oxide	0.0240	0.0107	0.0112	0.0118
	33.71	15.30	16.37	17.12
Carbon dioxide	0.3109	0.1605	0.0466	0.0475
	329.70	183.25	85.62	72.25
Fixed effects by station/month		X	X	X
Vehicle and inspection controls			X	X
Differences between consecutive inspections				X
Chi2 test joint significance	110,000.00	34,827.28	8,678.16	6,697.59
p-value	0.00	0.00	0.00	0.00
Observations	675,522	675,119	675,119	675,119

Notes: Table reports the parameter $\tilde{\varphi}$ from (2.6) from four SUR especifications. $\tilde{\varphi}$ is the effect of the gas reading of the preceding car over the gas reading of the next car in line. Vehicle and inspection controles are vehicle age, engine size (cc), odometer reading, weight, transmission type, temperature, humidity and dilution factors, previous repairs performed (dummy), and trial number. Differences between consecutive inspections are differences in temperature, humidity and dilution factors. All the continuos variables were included as polynomial of third degree.

$$\hat{\varphi}_m^{OLS} = \frac{\sum_{i=1}^{N} m_i r_{i-1}^2}{\sum_{i=1}^{N} r_{i-1}^2} + \frac{\sum_{i=1}^{N} \left\{ r_{i-1} m_i \left[\left(Z_i - Z_{i-1}\right)\gamma + e_i^c - e_{i-1}^h \right] + r_{i-1}\left(1 - m_i\right)\left[X_i\beta + Z_i\gamma + e_i^h\right] \right\}}{\sum_{i=1}^{N} r_{i-1}^2} \tag{2.14}$$

$$= \frac{\sum_{i=1,m_i=1}^{N} r_{i-1}^2}{\sum_{i=1}^{N} r_{i-1}^2} + \frac{\sum_{i=1,m_i=1}^{N} r_{i-1}\left[\left(Z_i - Z_{i-1}\right)\gamma + e_i^c - e_{i-1}^h\right]}{\sum_{i=1}^{N} r_{i-1}^2} + \frac{\sum_{i=1,m_i=0}^{N} r_{i-1}\left[r_i^h\right]}{\sum_{i=1}^{N} r_{i-1}^2} \tag{2.15}$$

The first term of the right hand side can work as an estimator for the mean incidence, given that the r_{i-1} terms included in the numerator have the same magnitude, on average, than the r_{i-1} not included. Actually, since the readings included in the numerator will most likely be readings well under the permitted maximum, the estimator will be biased downward. However, there is an important source of bias in the second term. In that term, e_{i-1}^h is present by itself and as part of r_{i-1}. Then, even if r_{i-1} is orthogonal to the difference in inspection specific variables $(Z_i - Z_{i-1})$ and the error term of the clean piping reading (e_i^c), the correlation between r_{i-1} and e_{i-1}^h for the clean piping cases will not be different from zero. Hence, that term will not cancel out. The third term will vanish since for the honest cases we can assume that the consecutive readings are not correlated. Lifting the assumption of orthogonality between r_{-1} and V will add more complexity to the expression, making more difficult its interpretation.[9]

3. Switching Regression Model

To avoid this problem and obtain an unbiased estimator for the mean incidence I propose a switching regression model estimated using the E-M algorithm. This methodology has the advantage of obtaining unbiased estimates, under distributional assumptions of the error terms, and assigning a probability of clean piping to each inspection.

To understand the methodology, let's start by considering the case of one particular station in one given month in the sample. We define, for each inspection in the station/month, the probability of clean piping, m_i, as coming from a Bernoulli distribution, with probabilities λ_j of m_i being equal to one and $(1-\lambda_j)$ of m_i being equal to zero. This parameter is different for each station, and within a single station it will take different values for each month of the year. For simplicity, consider the case of one particular gas.[10] Define the probability of observing jointly u_i from (2.7) and m_i as coming from a mixture of normal distributions as follows:

$$\begin{aligned} f\left(u_i, m_i | r_{i-1}, V, \theta\right) &= f_m\left(u_i | m_i, r_{i-1}, V, \theta\right) f\left(m_i | r_{i-1}, V, \theta\right) \\ &= f_m\left(u_i | m_i = 1, r_{i-1}, V, \theta\right) \lambda_j + \\ &\quad f_m\left(u_i | m_i = 0, r_{i-1}, V, \theta\right)\left(1-\lambda_j\right) \end{aligned} \tag{2.16}$$

According to (2.2) and (2.3), u_i will come from different linear specifications depend-

[9] A more detailed discussion of the existence of bias can be found in the Appendix B.

[10] For the rest of the section, I use only one gas as dependent variable. In the actual estimation, I use the 4 gases recorded, allowing the error terms to be correlated.

ing on the value of m_i.Then, under the assumption of the error terms of both (2.2) and (2.3) being normal $i.i.d.$ with mean zero and constant variance, we can express the probability of realization of each observation as:

$$\begin{aligned} f\left(u_i, m_i | r_{i-1}, V, \theta\right) = & \frac{1}{\sqrt{2\pi\sigma_1^2}} exp\left[-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right]\left(\lambda_j\right) \\ & + \frac{1}{\sqrt{2\pi\sigma_2^2}} exp\left[-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right]\left(1-\lambda_j\right) \end{aligned} \tag{2.17}$$

From here we can derive the following log-likelihood function:

$$\begin{aligned} \mathcal{L} = & \sum_{j=1}^{J}\sum_{i=1}^{N_j} - \frac{1}{2} ln\left(2N\right) + \sum_{j=1}^{J}\sum_{i=1}^{N_j} ln\{\frac{\lambda_j}{\sigma_1} exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right) \\ & + \frac{1-\lambda_j}{\sigma_2} exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\} \end{aligned} \tag{2.18}$$

By maximizing directly (2.18) we can obtain the parameters λ_j, γ , β ,σ_1, and σ_2. The explicit solution for expression for the estimator of the mean incidence of clean piping per station/month (λ_j) can be explicitly obtained from the FOC with respect to λ_j. After some manipulation, the FOC can be expressed as

$$\frac{\partial \mathcal{L}}{\partial \lambda_j} = \sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)}{\frac{\lambda}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} = 0 \tag{2.19}$$

where μ_i^1 and μ_i^2 are respectively $\left(\varepsilon_i - e_{i-1}\right)$ and e_i from (2.7). $\phi\left(.\right)$ is the normal standard density function. Then, (2.19) implies:

$$\sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right)}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} = \sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} \tag{2.20}$$

To gain some intuition about the interpretration of (2.20), consider the case where for a subset of observations (N_{j1}) the probability of being a clean piping case is positive ($\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) > 0$) and the probability of being an honest case is very small ($\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right) \to 0$). For the other observations (N_{j2}), consider the opposite situation, the probabilities of being clean piping are very remote ($\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) \to 0$), and the probabilities of being honest are at least positive ($\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right) > 0$). To have this case, we would need each observation to be clearly assigned to only one of the possible cases. Then (2.20) will collapse to

$$\begin{aligned} \sum_{i=1;i\in N_{j1}}^{N_j} \frac{1}{\lambda_j} &= \sum_{i=1;i\in N_{j2}}^{N_j} \frac{1}{1-\lambda_j} \\ \frac{N_{j1}}{\lambda_j} &= \frac{N_{j2}}{1-\lambda_j} \\ \lambda_j &= \frac{N_{j1}}{N_{j1}+N_{j2}} \end{aligned} \tag{2.21}$$

Then, the incidence parameter will represent the share of observations that are clean piping within the station/month. In case the specifications assign the same probabilities to each observation, then (2.20) will collapse to the equality $N_j = N_j$, which implies that any value for λ_j will satisfy the FOC, and the parameter will not be identifiable.

To obtain consistent parameters from the maximum likelihood estimation (MLE), the FOC coming from the log-likelihood function need to hold. These FOC are required as regularity conditions in order to apply the usual properties of MLE estimators, including consistency and asymptotic normality. These necessary conditions are that the error terms from the second specification (honest cases) have be orthogonal to X_i, and the error terms from each specification have to be orthogonal to the variables $(Z_t - Z_{t-1})$ for the manipulation cases, and to X_i for the honest cases. The necessary assumptions for these conditions to hold are presented in Appendix C.

4. E-M Algorithm

The empirical estimation by maximum likelihood of (2.18) would require the estimation of one individual incidence parameter per station/month, which would make the estimation intractable given the high number of parameters. To avoid this problem, I use the E-M algorithm, in a similar way as used in Porter (1983). As shown in Kiefer (1980), the solutions to this algorithm maximize also the likelihood equation. The sequence of the algorithm is as follows.

First, I obtain initial values m_i^0. Kiefer (1980) does not indicates any particular form to obtain initial values, so I decided on a strategy that initially identifies as clean piping cases those for which the error term under the honest specification is quite large. For this, I estimate linear regressions of the gas readings against observables, as if all the cases were honest. Since I expect to have a small share of clean piping cases, I expect the value of the parameters to be driven mostly by the honest cases and, hence, to have a small bias. With these parameters, I obtain initial error terms for both specifications (clean piping and honest). These error terms are then transformed into normal standard distributions, and the probability density function for each standardized error term is obtained. Then, I compare values coming from similar distribution functions[11]. More formally, m_i^0 is obtained as:

$$m_i^0 = \frac{\frac{1}{\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\hat{\xi}_i^{OLS}\right)^2\right]}{\frac{1}{\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\hat{\xi}_i^{OLS}\right)^2\right] + \frac{1}{\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\hat{\epsilon}_i^{OLS}\right)^2\right]} \tag{2.22}$$

where $\hat{\xi}_i^{OLS}$ and $\hat{\epsilon}_i^{OLS}$ are the standardized error terms coming from the clean piping and honest specifications. In the next step, I estimate the other parameters of the log-likelihood function, substituting λ_j for m_i^0, and obtaining $\widehat{\theta}^0 = \left(\widehat{\gamma}^0, \widehat{\beta}^0, \widehat{\sigma_1^2}^0, \widehat{\sigma_2^2}^0\right)$:

$$\mathcal{L}\left(\widehat{\theta}^0\right) = \sum_{j=1}^{J}\sum_{i=1}^{N_j} ln\{\frac{m_i^0}{\widehat{\sigma_1}^0} exp\left(-\frac{1}{2\widehat{\sigma_1^2}^0}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\widehat{\gamma}^0\right)^2\right) \tag{2.23}$$

$$+ \frac{1 - m_i^0}{\widehat{\sigma_2}^0} exp\left(-\frac{1}{2\widehat{\sigma_2^2}^0}\left(r_i - X_i\widehat{\beta}^0 - Z_i\widehat{\gamma}^0\right)^2\right)\} \tag{2.24}$$

with $\widehat{\theta}^0$, I update m_i^0 applying Bayes' rule and replacing λ_j by an initial estimator λ_j^0 based on the initial values for m_i^0 as follows:

$$\lambda_j^0 = \frac{\sum_{i=1}^{N_j} m_i^0}{N_j} \tag{2.25}$$

Hence, the updated value m_i^1 is obtained as:

$$m_i^1 = \frac{\lambda_j^0\left[\frac{1}{\widehat{\sigma}_1^0}\phi\left(\frac{r_i - r_{i-1} - (Z_i - Z_{i-1})\widehat{\gamma}^0}{\widehat{\sigma}_1^0}\right)\right]}{\lambda_j^0\left[\frac{1}{\widehat{\sigma}_1^0}\phi\left(\frac{r_i - r_{i-1} - (Z_i - Z_{i-1})\widehat{\gamma}^0}{\widehat{\sigma}_1^0}\right)\right] + \left(1 - \lambda_j^0\right)\left[\frac{1}{\widehat{\sigma}_2^0}\phi\left(\frac{r_i - X_i\widehat{\beta}^0 - Z\widehat{\gamma}^0}{\widehat{\sigma}_2^0}\right)\right]} \tag{2.26}$$

[11] They will not be exactly equal since the error terms for the 4 gases present are correlated.

with these new values m_t^1 I estimate λ_j^1as the average of m_t^1 per station/month, and maximize again the log-likelihood function, obtaining $\widehat{\theta}^1$. This procedure is repeated until the correlation between the series m_i^k and m_i^{k+1} is higher than 0.99.

5. Identification

The identification of the switching regression model arises from how well the readings of the four gases fit simultaneously the linear specifications, compared with how well they fit the clean piping specification. A drawback is that inspections with large error terms under the honest specification can be identified as clean piping cases, if the clean piping specification has a smaller error term, even when they are not. In these cases, the clean piping specification does not fit well, just not as badly as the honest specification. This can lead to identify as clean piping cases that are actually honest readings.

At the same time, in stations/month with lower incidence (λ_j), the clean piping specification has to fit much better than the honest specification for a case to be detected as clean piping. This is because in the predicted probability as defined in (2.26), the parameter of the incidence (λ_j) weighs the value of the density function under clean piping, so that the error term has to be very close to zero for the density function be high and the predicted probability high, as well. This may cause some cases not to be detected if the incidence is low for the station/month. In an analogous manner, station/months with high incidence may end up mis-classify some inspections in stations/months with high λ_j.

6. Linear Regressions on Predicted Probabilities

From the switching regressions we obtain the probabilities for each inspection to belong to one specific type, honest or manipulated. To determine how this incidence is associated with the characteristics of the station and the local market where it is located, I perform OLS regressions of these probabilities against the characteristics of the vehicle inspected, characteristics of the market where the station is located and fixed effects by inspector. I prefer to use disaggregated data rather than station-level aggregations to take the maximum advantage of the information available. The specification to be estimated is then:

$$\widehat{m}_i = \Theta Competitors_j + W_i\tau + Inspector_k\psi + \zeta_i \tag{2.27}$$

where $\widehat{m}_i$ is the predicted probability, $Competitors_j$ is the number of competitors within 0.1, 0.25, 0.5, 1.0, 2.0 and 5 miles. W_i represents the control variables used, which vary station and by vehicle inspected. $Inspector_k$ are inspectors fixed effects, and ζ_i is the error term.

E. Data

Data available correspond to all ASM inspections performed in Atlanta from April 2002 to December 2003. The information was provided by Georgia Clean Air Force, and contains the recorded gas readings and vehicle characteristics, such as make, model, and odometer reading. The data provided also contains information about the address of the station where the inspection was performed, and the inspector identification. The address information was used to estimate the number of local competitors, defined as the number of other stations performing also ASM inspections in the same month within a defined radius of the station.

For the estimation, I used data on the four gases recorded during the inspection. Many stations perform more than one type of inspection, and the sequence of recorded readings can contain different types of inspections. I consider in the sample only cases where two or more ASM tests were performed consecutively, and the second one obtained a passing result. In addition, I normalized the variables subtracting the mean and dividing the difference by the standard deviation of the variables. Additionally, to avoid estimating a high number of parameters in the switching regression model, I demeaned the variables by station/analyzer/month. Finally, I did not consider the first inspection per day in every station/analyzer, since the previous recorded inspection in the data corresponds to the last inspection performed the day before.

From the 2000 Census, I obtained the number of vehicles and median household income per census tract, which I used as controls for demand potential for every station. The number of competitors was obtained using the address of the stations. Tables 3 and 4 present the summary statistics for the variables available at the inspection level and at the station/month and market level.

F. Estimation Results

1. Switching Regression Results

The results from the estimation of the switching regression model show that the average probability of being a clean piping case is 8.8%, for the sample used in the estimation[12]. Moreover, when analyzing the distribution of the estimated probabilities, we observe that they are very close either to one or zero. (see Figure 1) This

[12] The parameters obtained from the estimation can be found at Appendix D.

Table 3—Variables Available by Inspection

Variable Type	Name	Mean	Std. Dev.
Gas Readings	Hydrocarbons (ppm)	59.07	45.6
	Carbon monoxide (%)	0.20	0.3
	Nitric oxide (ppm)	444.75	388.8
	Carbon dioxide (%)	14.50	1.3
Car characteristics	Weight (lb)	3,480.50	598.0
	Displacement (cc)	3,171.19	1,218.9
	Manual transmission	0.20	–
	Odometer reading	127,705.70	64,119.0
	Vehicle age	11.17	3.5
	Repairs performed	0.11	–
Inspection characteristics	Temperature	79.99	14.2
	Humidity factor	0.96	0.1
	Dilution factor	1.08	0.1
	First trial	0.89	–
	Second trial	0.09	–
	Third or later trial	0.02	–
Observations		675,119	

Notes: Gas readings correspond to the 25/25 section of the test. Standard deviation omitted for discrete variables that represent shares of the sample.

Table 4—Variables Available at Station and Market Level

Variables		Mean	Std. Dev.
Active stations by month		496.1	12.4
Inspectors by station/month		3.6	1.9
Inspections by station/month		68.0	86.0
Competitors by market	0.10 miles	0.14	0.37
	0.25 miles	0.44	0.74
	0.50 miles	0.97	1.16
	1.0 miles	2.12	1.90
	2.0 miles	5.98	4.19
	5 miles	25.93	16.06
Inspections by market	0.10 miles	211.38	202.08
	0.25 miles	258.61	233.22
	0.50 miles	348.72	302.24
	1.0 miles	526.27	392.70
	2.0 miles	1,133.97	665.71
	5 miles	4,444.48	2,646.50
Census Tract Information	Number of vehicles	4,902.4	2,680.1
	Median household income	52,095.6	17,650.3

Notes: Information at the station/month level represents the average across stations and months. There are 9,922 combinations of station and month with at least one inspection performed. Information by market represent the average across markets and months. Markets are defined by a circle with the indicated raduis centered at each station. Census tract information obtained from the 2000 Census.

means that the model assign each inspection to one particular type (clean piping or honest) very clearly. The average incidence by station/month have a decent amount of variation, having a standard deviation of 0.144 and with few cases going over 20% of incidence. The incidence by station/month falls on average when there are more competitors in a circle of 1/2 mile, which is a preliminary indication that that more competition leads to less cheating. The average incidence falls only marginally when the size of the station increase, as can be seen on the results by quartile of the station by number of inspection performed per month. All these results are summarized in the Table 5.

To check the characteristics of the vehicles of the inspections identified as clean piping and honest, I compared means of both groups by the most important observable characteristics. The results are shown in Table 6. As can be seen, clean piping cases are older, slightly heavier, have bigger engine size and a slight bigger share of manual transmission. Surprisingly, they have slightly lower odometer reading. Except by this last result, all the other characteristics fits what intuitively can be expected for cars with manipulated results compared to honestly inspected cars.

2. Falsification Tests

To check whether the results are actually coming from the data and are not purely statistically driven, I re estimate the SUR regressions presented in the Table 2, but re assorting randomly the arrival order to the station within month. The results are shown in Table 7. They show that all parameters, with the exception of two, are non significant at standard levels of statistical significance. Moreover, for all cases, the value of the parameters is much smaller than the values obtained in Table 2. For the only two significant parameters, the estimated values are negative and very close to zero, which is very different to the parameters obtained with the actual arrival order.

Table 5—Predicted Probabilities of Clean Piping by Inspection

		Mean
All sample		0.088
Number of competitors (0.5 miles)	0	0.103
	1	0.074
	2	0.088
	3	0.065
	4	0.065
	5	0.044
Station size (quartiles based on inspections)	Smallest	0.109
	2	0.110
	3	0.081
	Biggest	0.088
Average incidence of clean piping by station/month		0.089
Std. Dev.		*0.144*

Notes: Results obtained using a 10% random sample of inspections to reduce estimation time. Quartiles were obtained independently for each month, considering the number of test performed by each station. One station can be in different quartiles in different months. Incidence represents the average of the percentage of inspections that obtained a predicted probability higher than 0.50 by station/month.

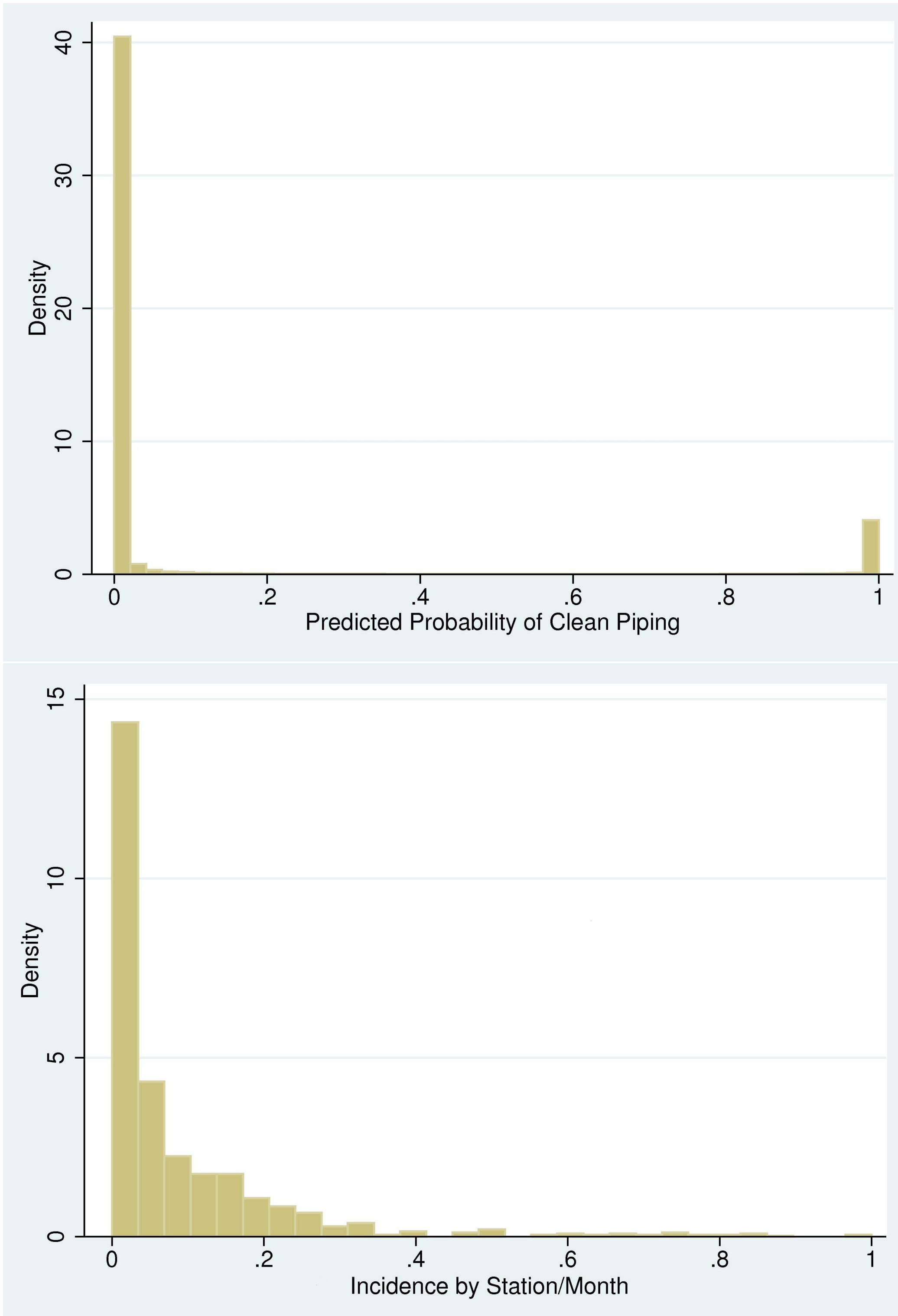


Figure 1. Histograms of Predicted Probabilities by Inspection and Estimated Incidence of Clean Piping by Station/Month

Table 6—Vehicle Characteristics by Predicted Status

	Honest	Clean Piping	All Sample
Age (years)	11.0	13.7	11.2
Weight (lb.)	3,474.0	3,571.9	3,482.6
Displacement (cc)	3,143.2	3,668.1	3,189.6
Odometer (miles)	127,839.1	121,585.0	127,286.1
Manual transmission (share)	0.20	0.23	0.20

However, the joint significance test for the four parameters cannot be rejected at 5% of significance level for two of the models presented. Most of these results support the claim that the results presented in Table 2 are not coming from purely statistical association between consecutive readings. Otherwise, the estimated parameters would be very similar, and as we have seen, they differ drastically from the ones previously presented.

Regarding the results from the switching regression model, I obtained the mean probability of being clean piping by the trial number per inspection cycle. As can be seen in Table 8, the average probability increases from 8.2% to 14% when passing from the first trial to the second one, which is an expected result since the pressure to obtain a passing result for a customer would be higher in each retrial than in the first one. The average probability increases up to 14.8% for the fourth or later trial.

Table 7—Gas Readings SUR Estimates (Re-assorted)

	(1)	(2)	(3)	(4)
Hydrocarbon	0.00821	0.00017	0.00036	0.00036
(*z-test*)	29.67	0.64	1.43	1.40
Carbon monoxide	0.00444	-0.00022	-0.00010	-0.00014
	14.79	-0.93	-0.43	-0.61
Nitric oxide	0.01207	-0.00132	-0.00114	-0.00115
	16.45	-1.84	-1.63	-1.62
Carbon dioxide	0.14479	-0.00187	-0.00079	-0.00183
	140.16	-2.02	-1.42	-2.68
Fixed effects by station/month		X	X	X
Vehicle and inspection controls			X	X
Differences between inspections				X
Chi2 test joint significance	20453.5	9.1	7.3	12.4
p-value	0.000	0.059	0.122	0.015
Observations	625,895	625,403	625,403	625,403

Notes: Table reports the parameter $\tilde{\varphi}$ from (2.6) from four SUR especifications. $\tilde{\varphi}$ is the effect of the gas reading of a car tested over the gas reading of another car tested in the same station and month, selected randomly. Vehicle and inspection controles are vehicle age, engine size (cc), odometer reading, weight, transmission type, temperature, humidity and dilution factors, previous repairs performed (dummy), and trial number. Differences between inspections are differences in temperature, humidity and dilution factors. All the continuos variables were included as polynomial of third degree.

Table 8—Incidence by Trial Number

Trial Number	Mean Incidence	Number of Inspections
1	0.082	58,764
2	0.140	5,988
3	0.122	1,388
4 or later	0.148	559
Total	0.088	66,699

3. Competition and Clean Piping Probabilities

The final step consisted of the regression of the predicted probabilities on the characteristics by station, including the number of competitors. The parameters for the number of competitors obtained from these regressions are reported in Table 9, where each row considered a different size of local market by changing the size of the radius from the station. The results show two different qualitative results for the leftmost two columns, and the rightmost columns. In the first two columns, the probability of being a clean piping case decreases with the number of local competitors, varying from -0.8% to -0.2% depending on the size of the local market selected. Only in once case this effect is positive, and all cases are significant. However, in the last two columns the effect of local competitors is positive, with the exception of the biggest local market defined. This difference between these two set of results is explained by the inclusion of fixed effects per inspector in the last two columns. If the test manipulation depends more on a bad inspector performing the inspection rather than on the market characteristics, then is the location of these bad inspectors that explains the effect of the number of competitors. In this case, the inclusion of fixed effects by inspector will capture this relationship and the number of competitors will turn not significant. If this is not the case, then including fixed effect by inspector should not affect the results. As the results show, after including these fixed effects, and after controlling by all the observable inspection, car and market characteristics available, the effect of the number of competitors becomes positive and significant. This means that regardless of being a good or bad inspector performing the inspection, the probabilities of being a clean piping case increases with the number of local competitors. The effect of the number of competitors falls as we increase the size of the radius from the station to define the local market, until becoming negative and nonsignificant. This result is explained by the closest station driving the effect. As more stations are added to the market, the effect is diluted among more stations, so the parameters becomes smaller. According informal interviews performed to mechanics and inspectors, 0.5 miles is the distance considered by the industry as the definition for local market.

G. Conclusion

Using data from the vehicular inspection program in Atlanta, I tested for the existence of inspection manipulation (false positives) in the program. I estimated the incidence of the most common form of test fraud (clean piping) to be 9% of the passing inspections during the sample period. Moreover, the incidence of clean piping – passing results of a different vehicle frauduently applied to a failing vehicle – per station increased by 0.7% with one more competitor within a 0.5 mile radius, after control-

Table 9—OLS Regressions on Predicted Probability

	(1)	(2)	(3)	(4)
0.10 miles	-0.00840**	0.0100***	0.0391***	0.0350***
	-2.73	3.33	4.42	3.99
0.25 miles	-0.00914***	-0.00452**	0.00807	0.0130*
	-5.53	-2.80	1.58	2.53
0.50 miles	-0.0133***	-0.00889***	0.00100	0.00724*
	-12.41	-8.43	0.29	2.03
1.0 miles	-0.00981***	-0.00878***	0.00473*	0.00609**
	-15.00	-13.52	2.32	2.82
5 miles	-0.00229***	-0.00171***	-0.00005	-0.00046
	-31.47	-22.73	-0.12	-1.05
Vehicle, station, and census-tract controls		X		X
Inspector fixed effects			X	X
Observations	66,699	63,492	66,699	63,492

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable is the predicted probability of being clean piping. The parameter reported is Θ from (2.27), that represents the effect of one additional competitor over the predicted probability of being clean piping. Car characteristics include weight, displacement (cc), transmission type, odometer, vehicle age, dual exhaust, repairs performed before the inspection, car body type (sedan, station wagon, pickup, SUV, minivan, full-size van), dummies for car make, and number of trials before obtaining a passing result. Stations characteristics include the number of inspectors in the station. Census-tract variables are the number of vehicles, and the median household income in the census tract where the station is located.

ling by car, station and inspector characteristics. These results show that increased competition can lead to outcomes detrimental to society when there are asymmetries of information and the incentives are not properly aligned for all the participants in the market. These effects must also be considered when designing new markets, as it was the case for the vehicular emission inspection market. Even when the question is empirical as to whether these negative effects counterweigh the positive effects from competition, such as lower prices, better quality and more convenience for the customers, the potential for a suboptimal outcome should be considered, especially in cases where supervision is costly or unrealiable, as in developing countries.

CHAPTER III

DEMAND RESPONSE BY LARGE ELECTRICITY CUSTOMERS IN TEXAS

A. Introduction

In this chapter, we study the adoption and effect of time-varying prices using unique, new data on commercial and industrial electricity customers in Texas. Policymakers and academics have recognized the benefits of time-varying prices in electricity markets for several decades, but the potential gains have been largely unrealized. The social cost of generating electricity can more than double during the course of a day, yet retail consumers generally pay the same flat rate regardless of whether the wholesale costs are large or small.

Time-varying pricing (TVP), which in some forms is called real-time pricing, can promote multiple goals of energy policy. First, TVP provides an efficient means to curtail demand when electricity is scarce. In addition, TVP have the potential to make total demand for electricity more elastic and thus reduce market power in wholesale electricity markets. In the longer run, TVP could provide a low cost means to address the intermittency problem of renewable generation. Renewable portfolio standards and feed-in-tariffs are targeting ambitious quantities of electricity generation from renewable sources, and many of these renewable technologies such as wind and solar provide power intermittently.[1] As a result, electricity systems must either procure potentially expensive quick start generation, or alternatively, can exploit the quick stop capability of demand response induced by TVP.[2] TVP has the potential

[1] As of May 2011, twenty-nine U.S. states and the District of Columbia have enacted renewable portfolio standard (RPS) policies. (Schmalensee, 2012)

[2] See Gowriskaran, Reynolds, and Samano (2011) for an analysis that quantifies the costs of intermittency, and Joskow (2011) for a discussion of the relative costs of intermittent and dispatchable generators. For a good summary of policies that

to reduce the intermittency problem that is sometimes cited as an impediment to increased penetration of renewable generation sources. Despite the potential for TVP to make electricity systems more efficient, only a relatively small amount of TVP-induced demand response exists for a variety of regulatory, consumer, and technological reasons. In some settings, the barrier to time-varying prices was technological. Some customers, particularly residential customers did not have meters that recorded consumption over short time intervals. However, the increased installation of smart meters and home area network technologies has reduced this hurdle. In other settings, the barrier is that customers do not want to face prices that are not predictable, and as a result, regulators have been reluctant to impose time-varying prices on various classes of customers (Faruqui and Sergici, 2010).

This study uses new data on the use of time-varying prices in Texas to estimate the amount of demand response capability. In Texas, commercial and industrial electricity customers contract bilaterally with retail electric providers. The terms of these contracts are not regulated by a commission but rather arise from bilateral deals between customers and retailers. We have assembled unique, customer-level data on whether the terms of the contracts include time-varying prices. In addition, we have customer-level data on the consumption during each 15-minute interval that can be matched to real-time wholesale prices.

This study makes two novel contributions to the literature on time-varying prices. First, we summarize the characteristics of commercial and industrial customers that chose to voluntarily use time-varying prices. Much of the literature has estimated the effect of randomly assigning customers to time-varying prices. [3] In future retail

promote renewable sources of electricity generation, see Schmalensee (2012).

[3]Although often the customers on TVP are random conditional on volunteering for a pilot program.

electricity markets, many customers are very likely to have the choice to choose their pricing structure whether it be in regulated or deregulated retail markets. We have data for nearly all big commercial and industrial customers in a market that has allowed retail choice for some time. This is the first study of which we are aware that studies the types of customers likely to choose TVP. Although external validity is still uncertain, we believe that this paper provides insights into the types of customers more likely to opt for TVP. It is important to understand the types of firms that are likely to opt for time-varying prices as more states provide options for dynamic pricing either via regulated tariffs or via deregulated retail markets. Second, we estimate how much customers on time-varying prices reduce consumption in periods with high prices. This information on demand response is an important input for understanding the extent to which TVP can assist system operators in addressing intermittency problems of renewable generation.

This study also contributes to a growing literature on the effect of time-varying pricing and demand responsiveness in electricity markets. Recent years have seen an increasing attention to investigating residential customers because the installation of smart meters in some jurisdictions clears the infrastructure hurdle to charging time-varying prices. Recent contributions to this literature include Allcott's (2011) analysis of real-time pricing in Chicago and Wolak's (2010) analysis of Washington DC's critical peak and hourly pricing. The literature studying commercial and industrial customers is more extensive because the metering infrastructure has been in place for much longer, including Boisvert et al. (2007), Herriges et al. (1993), Taylor et al. (2005) and Patrick and Wolak (2001).

We find a meaningful level of take-up of TVP – in some sectors more than one-quarter of customers signed up for TVP. The empirical estimation of the own price elasticities show values smaller than 0.01 in absolute value for most intervals during the day. Only for big firms and during peak time (4 p.m. to 6 p.m.) the own price elasticity reaches -0.02. This implies a very small responsiveness of demand in absolute value, accounting for a reduction of 9MWh by hour in response to an increase of 10 cents in the price of electricity per kWH. This represents only 0.016% of the aggregate consumption during an hour. An analysis by industry shows a similar qualitative result.

The rest of this chapter is structured as follows. The next section presents the institutional setting of the electricity market in Texas. Section C presents the data used for the empirical estimation. Section D describes the methodology used for the elasticities estimation. Section E presents the results, from the data available and from the empirical estimation. Section F concludes.

B. Electricity Procurement by Commercial and Industrial Customers in Texas

Texas is one of several U.S. states to allow retail competition in electricity. Retail firms procure power from generation owners and sell to commercial, industrial, and residential end-users. Since 2002, commercial and industrial (C&I) customers served by the Electric Reliability Council of Texas (ERCOT) have been able to purchase power from a competitive retailer rather than the former vertically integrated utility.[4] Individual C&I customers and electric retailers bilaterally negotiate power contracts.

The agreements can vary along a variety of dimensions including how risk is shared and how much the customer is exposed to the wholesale spot price of power. For example, a contract could simply specify a fixed rate for all consumption, a so-called requirements contract. Other possible contracts could specify a price that varies

[4]Small parts of Texas are served by other reliability councils (Southeastern Electric Reliability Council in the southeast, the Southwest Power Pool in the northeast and northwest, and the Western Electricity Coordinating Countil in the far west), but the vast majority of Texas consumers are served by ERCOT.

in the time of day, week, or season of usage, and is often referred to as a time-of-use price. For these two types of contracts, the retail price is not directly tied to the wholesale spot price and thus does not reflect the short-run variation in supply and demand conditions of the system.[5] Besides electric consumption, customers also have to pay for transmission charges, a fee for the use of the electric grid. The design of transmission charges is based upon the consumer's contribution to demand during four peak times in summer months (Four Coincidental Peaks, 4 CP), thus providing consumers with an incentive to reduce their power purchases during the summer peaks. (Zarnikau, 2010) This transmission charge introduces a complication for the empirical work since reductions in consumption during summer peak time may be partially driven by consumers trying to avoid the transmission fee. These reductions will not be distinguishable from reductions driven purely by a high wholesale market price. Then, we may end up obtaining overestimated demand responsiveness to prices.

TVP typically take one of two forms. Critical peak pricing (CPP) allows prices to vary with short-run system conditions. Under CPP, the retailer/utility can declare a day or hour to be a critical peak period, and the price is contracted to be substantially higher during those episodes. In some cases, the critical peak price may be the wholesale spot price for that period. CPP contracts typically limit the number of times that the retailer/utility can declare critical peak periods. Real-time pricing (RTP) passes the wholesale spot price along to customers. Either of the time-varying contracts could hedge a customer against price risk for a portion of the consumption but still expose the customer to the spot price on the margin. The existing literature has detailed descriptions of the types of retail pricing schemes (for example, see Borenstein (2005)). Retail prices under such bilaterally negotiated contracts will

[5]For a description of demand response in ERCOT, see Zarnikau (2010).

reflect factors such as wholesale prices, premia paid to avoid risk, and transmission and distribution charges by the distribution utility. For instance, a retailer offering a time-varying price contract to a particular customer will pass the risk involved in having unexpectedly high wholesale prices. At the same time, a customer entering into a time-varying price contract will have the opportunity to save costs by curtailing demand at peak times, or reallocating consumption within the day.

The Texas wholesale market consists of bilateral trades between generators and end users in addition to a small balancing market run by the grid operator. Bilateral transactions are conducted in over-the-counter markets such as the Intercontinental Exchange (ICE) and then physically scheduled with the grid operator about one day before production and consumption. In order to ensure that supply and demand balance in real-time, ERCOT operators an hourly bid-based auction for "balancing power" with prices formed every 15 minutes. We will use this balancing price as our measure of the wholesale spot price for each 15-minute interval. At times, the transmission system becomes congested, and wholesale prices differ by location to ensure system balance. During our sample period, the electric grid was divided into zones which could have different prices during congested intervals. Figure 2 illustrates the four zones in 2008. The zonal boundaries were largely determined by the topology of the grid, and these boundaries would change slightly from year to year as the location of demand and generators changed.[6] An advantage of this institutional setting is that provides an additional source of variation for price for the identification of the demand response parameters.

Wholesale prices change substantially over time – even over the course of a single day – reflecting changes in demand that require more expensive generators to come

[6]For a detailed description of the operation of the Texas wholesale market, see Kiesling and Kleit (2009).

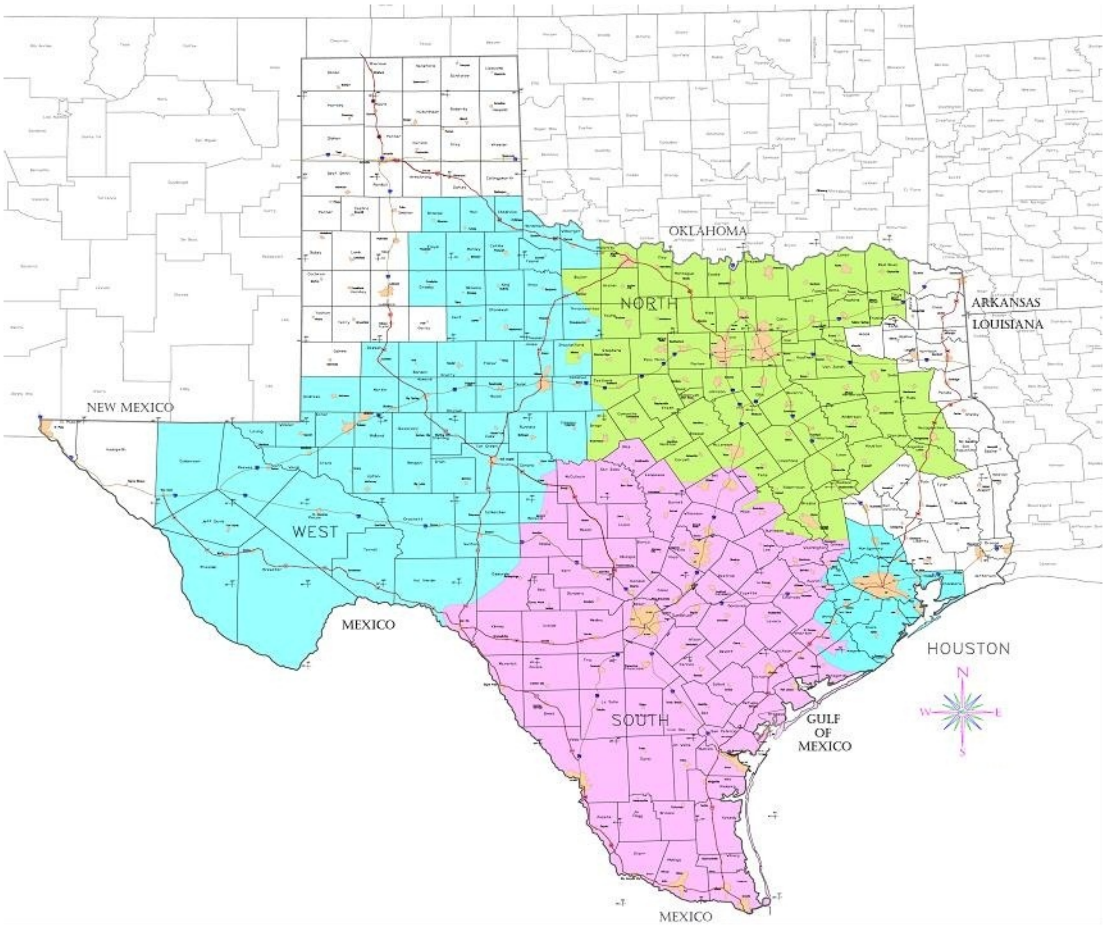


Figure 2. Transmission Congestion Zones in 2008

Source: Electric Reliability Council of Texas (2010).

on-line. Figure 2 shows different quantiles of the wholesale price over the course of the year and a day. The top panel of Figure 3 plots the 5th, 50th, and 95th percentile of interval-level prices for each week of 2008 in the Houston zone. During the high demand summer months, the 95th percentile price can be up to five times larger than the 5th percentile price. But even during the relatively low demand non-summer months, upper quantiles of prices are over twice as large as lower quantile prices. The bottom panel of Figure 3 plots quantiles of prices for each of the 96 15-minute intervals of the day. Prices vary considerably over the course of a typical day with prices in the afternoon and evening hours often exceeding $100/MWh (or 10 cents per kwh).

C. Data

We use a unique dataset of individual customer-level data for virtually all commercial and industrial (C&I) customers with interval data recorders (IDR) during the sample period.[7] ERCOT provided us with data on the electricity consumption for 8,537 C&I customers that are metered with interval data recorders that allow the distribution utility to record consumption every 15 minute interval. These customers represent approximately 20% of the total energy load in ERCOT[8] and the 33% of the C&I energy consumption in Texas.[9] For each of these customers, our data includes consumption for each 15 minute interval from October 2007 to September 2008.

For each customer, ERCOT provided us with information about the contract between the customer and its retailer. ERCOT requested that each retailer identify for each of the retailer's customers whether the contract provided "a financial incentive or requirement to reduce consumption in response to high wholesale spot prices." In particular, the retailers were asked to provide an indicator of whether the contract included either real-time pricing, critical peak pricing, or any other pricing structure

[7]During the sample period, all customers with a peak demand higher than 700 kW were required by ERCOT to have an interval data recorder installed. The compliance rate for this requirement was almost universal. Customers were also allowed to request voluntarily the installation of these devices.

[8]In the year 2008, total ERCOT energy load was 312,401,085 MWh. The total consumption of the C&I customers considered in the sample from October 2007 to September 2008 is 72,157,498 MWh (ERCOT).

[9]The total electric industry retail sales in Texas were 347,059,000 MWh in the year 2008 (Energy Information Administration). This includes some areas outside ERCOT. The 63% of these sales went to C&I customers, which account for 219,279,000 MWh. The total consumption of firms in the sample represent 33% of this number.

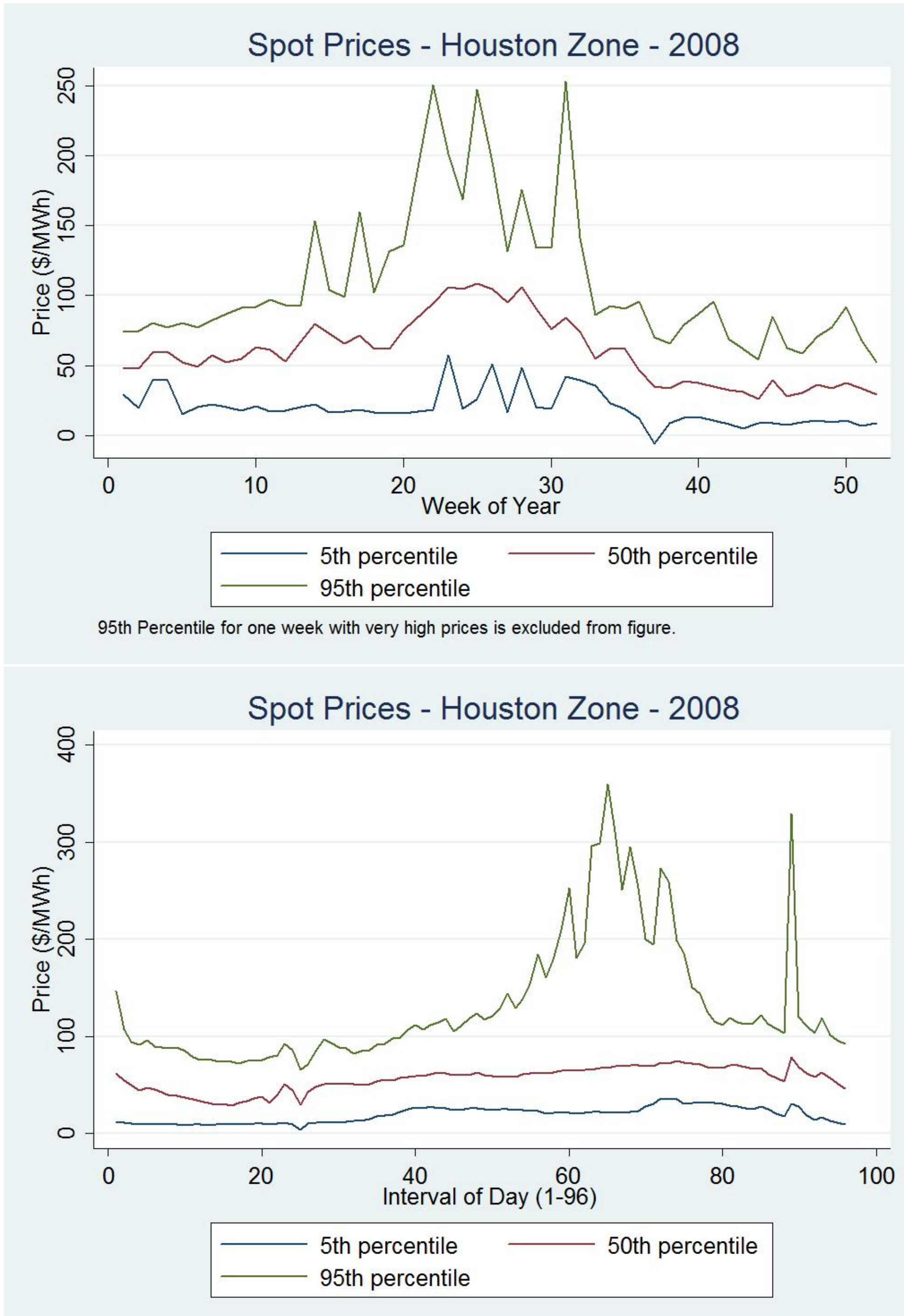


Figure 3. Patterns in Annual and Daily Wholesale Spot Prices

that created incentives to reduce demand when balancing market prices rose. [10] This measure of exposure to time-varying prices is for a single snapshot in time – the survey response was due to ERCOT on April 1, 2009. We assume that the contract in place when the retailer responded to the survey had similar properties as the contracts governing our sample period of October 2007 – September 2008. According to this metric, approximately 15% of customers were on time-varying prices. However large customers are more likely to face time-varying prices; 30% of C&I load faces time-varying prices.

This information on exposure to wholesale spot prices suggests that these customers may respond to spot prices, but it does not provide sufficient information to suggest the functional form of the response. To see this, consider a customer with a critical peak pricing contract. This customer has incentives to reduce demand in periods defined by the retailer to be a critical peak period, but we have no information on when those periods occur. To state the problem slightly differently, the customer faces a highly non-linear tariff and we do not know the form of that tariff. For customers with a real-time pricing contract, this issue is less of a concern. As long as the customer is paying the spot price for marginal sales and the customer responds to marginal prices, one would expect customers to face increasing incentives to reduce demand for any price increase.[11] Absent any additional information on the function form of tariffs, our empirical specification below uses an assumed smooth consumption response to wholesale spot price.

Customers may also sell curtailing capacity though agreements known as Loads Acting as Resources (LaaRs), either to ERCOT or directly to load-serving entities.

[10]The full text of the survey instrument is included in the Appendix E.

[11]See Ito (2012) for an analysis suggesting that residential customers may respond more to average prices than marginal prices.

As of the end of 2008, 144 firms were qualified to provide load curtailment capacity, with 5 of them concentrating about one-half of the total curtail capacity (more than 100MW). (Zarnikau, 2010) Typically, LaaRS are called to reduce load three times a year. Another alternative for selling curtailment capacity is the Emergency Interruptible Load Service (EILS). Under EILS, interruptible loads which are not providing an operating reserve receive a payment for curtailing consumption within a 30-minute of ERCOT declaring an emergency. (Zarnikau, 2010) Both programs introduce a challenge for the empirical estimation, since during high-prices episodes non TVP firms can reduce consumption because of their participation in these programs, and TVP firms could not reduce consumption or do it only marginally in order to preserve their curtailment capacity already under contract. Unfortunately, we do not have information on which firms participate in EILS. The days when LaaRs episodes occurred were excluded from the sample.

Our data also include each customer's street address that we match to firm characteristics using ReferenceUSA. This matching process was individually time consuming, so we chose to focus on matching only the biggest customers to maximize the matching ratio. Our sample consists of 1700 customers with the largest annual consumption. They represent around 75% of the total consumption recorded in the sample. This matching provides us with customer-level measures of industry type (NAICS code), number of employees, the square footage of the establishment, and latitude/longitude. We were able to successfully match address to firm characteristics for approximately 950 (55%) of the biggest 1,700 C&I customers. Table 10 presents the distribution of firms by type of tariff, for the whole and the selected sample.

Finally, we also used temperature data, obtained from the National Climatic Data Center. We used data collected from 63 different stations across the ERCOT region, assigning to each customer the information from the closest station. The

Table 10—Whole Sample and Selected Sample for Firm Information Matching

		ESIID		Total Consumption (GWh)	
Whole Sample		8,590		72,157	
	TVP	1,255	15%	21,768	30%
	Non TVP	7,335	85%	50,389	70%
Selected Sample		1,690		54,011	
	TVP	340	20%	18,749	35%
	Non TVP	1,350	80%	35,262	65%

frequency of these data is per minute. We opted for considering for each interval the "central" minute. (minutes 7, 23, 37, and 53, respectively)

The total amount of C&I consumption (metered with IDRs) subject to time-varying prices has a flatter daily load profile that the C&I consumption not facing TVP. This is illustrated in Figure 4 which shows the average daily aggregate consumption profile for customers on TVP and those not on TVP. Customers not facing TVP have a daily load shape that peaks later in the day and exhibits a higher peak to trough ratio than TVP customers.

D. Methodology

1. Generalized Mc Fadden Cost Function

To obtain the effect of prices on electricity consumption we estimate jointly the conditional input demands (CID) for the 96 intervals of the day, following and modifying

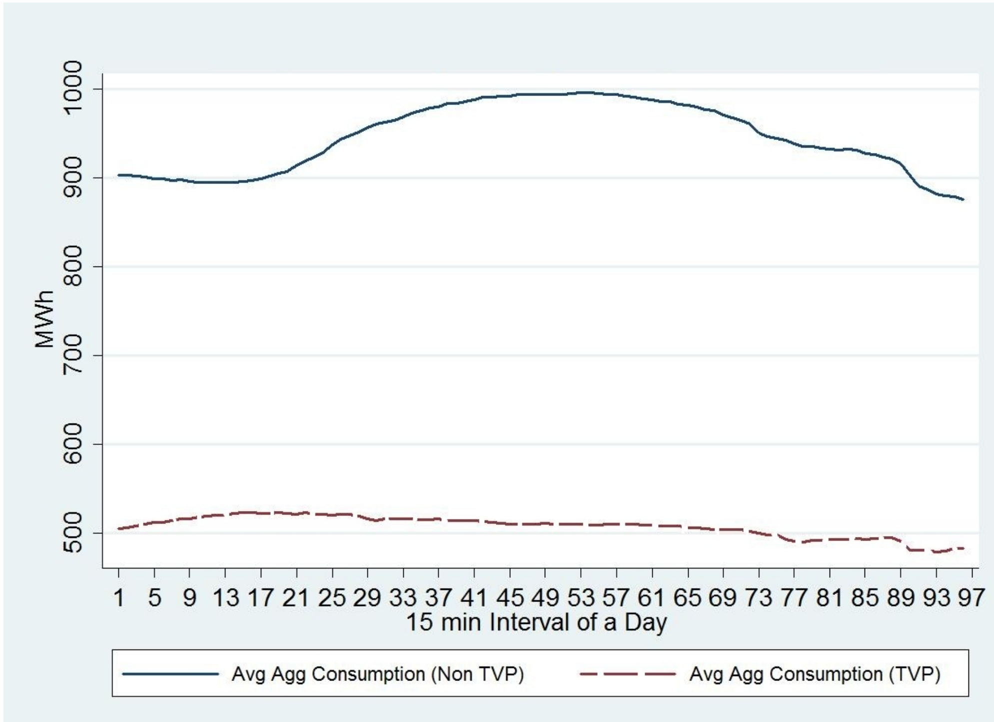


Figure 4. Average Daily Aggregate Consumption Profile for TVP and Non-TVP Customers

Patrick and Wolak's (2001) methodology. The CID used for the estimation are derived from a Generalized Mc Fadden (GMF) cost function. We opt for this cost function among many other used in the literature because of its consistency with the conditions imposed by the microeconomic theory. In addition to satisfy homogeneity of degree one in input prices, this specification can satisify the concavity in input prices, which can not be guaranteed using other common cost functions, like the Trans-log or Generalized Leontief functions.[12] In intuitive terms, homegeneity of degree one implies that if all input prices increase in certain proportion, total cost will increase

[12]See Diewert and Wales (1987) for a more detailed discussion.

by the same proportion as well. Concavity in input prices imply that if the price of one particular input increases, total cost will increase, but less than proportionally. In this case, the firm can substitute the use of that input for other cheaper ones. This second condition is particularly relevant in this study, since we want to allow firms to shift consumption across intervals within the day.

A general specification of the GMF cost function, as defined in Diewert and Wales (1987), is as follows:

$$C^1(p, y) = \left[\frac{1}{2}\left(p_1^{-1}\right)\sum_{i=1}^{k}\sum_{j=1}^{k} c_{ij}p_ip_j\right]y + \sum_{i=1}^{k} b_{ii}p_iy + \sum_{i=1}^{k} b_ip_i \tag{3.1}$$

where p_l is the price of input l, y is the level of production of the firm, and $c_.$, and $b_.$ are parameters to be obtained from the empirical estimation. Homogeneity of degree one in input prices can be easily proven, by multiplying by the same scalar all the input prices. To guarantee concavity in prices, however, we have to impose certain constraints. To do this, we define a matrix C as a symmetric matrix composed by the c_{ij} terms, placed in the respective row and column according to its subindex. Concavity in input prices can then be imposed by constraining this matrix C to be negative semi-definite. To do this, we follow the strategy developed by Lau (1978) to impose positive semi-definitiveness in symmetric matrices. This strategy consists in obtaining C as a function of two other matrices: a lower triangular matrix (B) with ones in the main diagonal, and a nonnegative diagonal matrix (D). As far as the symmetric matrix can be expressed as a function of these two other matrices, positive semi-definitiveness is guaranteed. In our particular case, since we want to impose negative semi-definitiveness, we add a negative sign at the front of the function. Then, C has be obtained as:

$$C = -\left(BD\right)\left(BD\right)' \tag{3.2}$$

Under this specification, C will always satisfy negative semi-definitiveness, and the values off the main diagonal of C may take positive or negative values, meaning that we are allowing for substitutability or complementarity between inputs.

For the actual estimation, as in Patrick and Wolak (2001), we assume that managers seek to minimize total costs of production for the next day, given the expectation of electricity prices for the 96 intervals. We use a modified GMF cost function, which can be expressed as follows (for firm k in day d):

$$\begin{aligned} C_{kd}\left(p, y\right) = &\left[\frac{1}{2}\sum_{i=1}^{96}\sum_{j=1}^{96} c_{ij} p_{id} p_{jd}\right] y_d + \sum_{i=1}^{96} b_{ii} p_{id} y_d + \\ &\sum_{i=1}^{96} b_i p_{id} + \sum_{i=1}^{96}\left[d_i f\left(W_{id}\right) + \theta F_k + U_{ikd}\right] p_{id} \end{aligned} \tag{3.3}$$

The first three terms on the right-hand side come from the general GMF specification stated lines above. The first term differs from the general specification in that there is not an input price dividing the expression. This is equivalent to lifting the condition of degree one in input prices, or to assume that the aggregate price index of the other inputs of production is constant during the sample period. We prefer to continue using this specification and lifting the degree one condition because the most important condition in this study is the concavity in input prices. We do this also because the alternatives to address this issue did not result in satisfactory outcomes. We could include one of the input prices as denominator, but there is no reason *a priori* to select a particular one among the 96 intervals. Moreover, including different ones may result in different estimates. A solution to this problem is using the Symmetric Generalized Mc Fadden function, as suggested in Diewert and Wales (1987), but the results obtained were not satisfactory.

The last term is included to capture unobserved determinants of customer-level demand that may be correlated with prices. Its inclusion does not affect the compliance with the conditions imposed by the microeconomic theory. We can see more clearly the reason for its inclusion after obtaining the CID. From Shephard's Lemma we know that the partial derivative of the cost function with respect to each input price will result in the CID:

$$\frac{\partial C_{kd}\left(p,y\right)}{\partial p_{id}} = E_{ikd}\left(p,y\right) \tag{3.4}$$

Given the defined cost function, we obtain the following CID for input i:

$$E_{ikd}\left(p,y\right) = \left[\frac{1}{2}\sum_{j=1}^{96} c_{ij} p_{jd} + b_{ii}\right] y_d + b_i + d_i f\left(W_{id}\right) + \theta F_k + U_{ikd} \tag{3.5}$$

This is the specification we use for the estimation of the 96 CID. The term inside the brackets, which comes from the GMF general specification, is a linear function of prices, scaled up or down according to the level of production of the day. (y_d) Given the characteristics of electricity consumption, however, we should be concerned that unobserved determinants of customer-level demand are correlated with prices. An ideal setting would be one in which prices are randomized for those customers subject to TVP. In our setting, wholesale spot prices arise from hourly multi-unit auctions in which supply and demand bids determine the market price. To deal with this problem and capture this unobserved determinants is that we include the third and fourth terms, aimed to control for unobserved shocks that come from weather and firm idiosyncrasies.

While this strategy will not necessarily eliminate any confounding unobservables, we expect bias to be substantially reduced. Even with a rich set of temperature controls and customer fixed effects, there still could be remaining sources of bias in our estimates of price response. For example, firms in a large industry respond to daily industry-specific demand shocks by increasing production and this industry's consumption is large enough to affect system prices, then system price could be correlated with these consumption shocks. As one potential test of this strategy, we estimate the same model on customers not subject to TVP. Non-TVP customers are likely to respond to their retail price (which is "fixed") but not to respond to the wholesale spot price. If unobservable shocks were correlated with spot prices, then one could obtain a non-zero coefficient on price despite the fact that non-TVP customers do not (or should not) respond to wholesale spot prices. However, if a specification yields a statistically zero coefficient on price, this finding is consistent with (but does not necessarily imply) that unobservables are uncorrelated with prices.

In this same specification, y_d represents the level of production, and in this context, is the level of production per day by firm. Unfortunately, we do not have information about firm production. The strategy we use instead to incorporate this variable in the estimation is to use dummy variables per day. In an ideal setting, we should include one variable per day by firm, but this implies estimating a very high number of parameters. The alternative we follow is to use dummy variables per day, common to all firms. This way, we expect to capture the variations in the cycle of production during the year for all firms, and jointly with the dummy variables by firm, approximate the level of production of the firm per day.

The actual estimation consists on estimating the system of 96 CID, where one observation of the system corresponds to one firm in one day. The total number of systems we use for the estimation is equal to the number of firms multiplied by the number of days in the sample. Along the firm dimension, prices vary when there are congestion episodes and firms are located in different zones. Along the day dimension, prices vary according to the pattern of variation during the year. The first source of variation is more likely to be uncorrelated to unobserved factors, while the second one is more likely to be endogenous.

We should note also that firms may be reducing consumption to avoid the transmission fee, which is calculated based on the peak consumption for each month during the summer months. Then, we may have that our price parameters may not only be capturing the effect of higher prices, but also the effect of the possibility of being charged the transmission fee. In this case, both effects point in the same direction, and our estimated may be biased upward, in absolute value. This would be also the case if emergency curtailment episodes called by the system (EILS) are correlated with prices. For the case of LaaRs episodes discussed above, we know when they occurred, so we decided to exclude those days from the sample.

The error term from the system of equations is very likely be correlated across CID and across firms. The first form of correlation comes from the fact that unobserved factors can induce firms to consume more or less electricity during certain blocks of time, or during whole days. For instance, firms producing mainly based on orders, or that concentrate production during certain periods of the day due to idiosyncracies of the industry, will have increases in consumption for blocks that cannot be explained by the observable variables. This problem is identical to the one addressed by the seemingly unrelated equations (SUR) framework. Patrick and Wolak (2001) addressed this issue by estimating the equations under the assumption of error terms coming from a multivariate normal distributions. Zarnikau and Hallet (2008) used a feasible generalized least squared estimator for SUR models.

The second form of error correlation (across firms) has not been addressed in the literature. This correlation comes from the fact that it may exist system-wide or regional shocks that make consumption vary across all firms in the system or region for specific intervals, or blocks of intervals. For instance, if at the beginning or the end of the work day firms across the state turn on or turn off machinery, then there is an unobservable component correlated across firms at specific intervals. In practice, this implies a more general form for the error term that needs to be modeled to obtain consistent estimators. The results presented below are obtained by minimizing squared errors assuming independent CID.

We should note also that our measure of price is the realized price that arises from the balancing market auction for bids that can be submitted up to 15 minutes before the interval. As a result, this price is not perfectly forecastable within an hour before and certainly not several days before the interval. If firms require a large lead time to adjust demand to price, then a more appropriate measure of price is the firm's forecast of price at the time when demand adjustment decisions are made. Unfortunately, we do not have information about the timing of firms' adjustment decisions. Thus, in this paper, we use the realized price.

Finally, we recognize that there are factors, like measurement errors, bounded rationality, rigidities, and transaction costs, that may introduce noise in the relationships we are trying to identify empirically, especially after imposing restrictions in the possible values parameters can take.

2. Reducing the Number of Parameters

A challenge we face for the empirical estimation is the high number of parameters to be obtained. Estimating the system of 96 CID implies obtaining 4,656 c_{ij} parameters, one estimate of b_{ii}, b_i, and d_i by each of the 96 equations, and the fixed effect by firm. Estimating directly all these parameters is too complicated. To circumvent this problem, we opted to reduce the number of parameters to be obtained in the estimation, following the strategy used by Patrick and Wolak (2001). This strategy consist in using Fourier series to estimate indirectly series of parameters, reducing considerably the necessary number of parameters to be obtained from the estimation. To see this strategy in detail, remember that as defined in (3.2):

$$C = [c_{ij}] = -\left(LD\right)\left(LD\right)' \tag{3.6}$$

where L is a lower triangular matrix and D is a diagonal matrix. Then, in order to reduce the number of parameter to be estimated, we can define each term of the 96 terms of main diagonal of D as:

$$\delta_i = \alpha_0 + \sum_{m=1}^{5} \alpha_m cos\left(m\frac{2\pi}{96}i\right) + \sum_{m=1}^{5} \alpha_{m+5} sin\left(m\frac{2\pi}{96}i\right) \tag{3.7}$$

In this case, we do not have to obtain directly all the parameters in the estimation, but we only need to obtain the α's. Once we identify them, we can reconstruct the δ parameters. An assumption behind this procedure is that the series of δ parameters $(\{\delta_1, \delta_2, ..., \delta_{96}\})$ is smooth enough as to be captured by a weighted combination of waves of different magnitude (sinus and cosinus functions).

In a similar fashion, for the matrix L we define each term below the main diagonal of L ($\frac{95\times 94}{2}$ terms) as:

$$l_{ij} = \lambda_i^1 * \lambda_j^2 \tag{3.8}$$

where each of the λ terms is defined as:

$$\lambda_i^1 = \beta_0 + \sum_{m=1}^{5} \beta_m cos\left(m\frac{2\pi}{95}i\right) + \sum_{m=1}^{5} \beta_{m+5} sin\left(m\frac{2\pi}{95}i\right) \tag{3.9}$$

$$\lambda_j^2 = \gamma_0 + \sum_{m=1}^{5} \gamma_m cos\left(m\frac{2\pi}{95}i\right) + \sum_{m=1}^{5} \gamma_{m+5} sin\left(m\frac{2\pi}{95}i\right) \tag{3.10}$$

This way we need to estimate only the α, β and γ parameters, and recover the the matrix C using only 33 parameters. We use the same approach for b_{ii}, b_i and d_i', where a generic term η_i, such that $\eta_i = \{b_{ii}, b_i, d_i'\}$, is defined as:

$$\eta_i = \rho_0 + \sum_{m=1}^{5} \rho_m cos\left(m\frac{2\pi}{96}i\right) + \sum_{m=1}^{5} \rho_{m+5} sin\left(m\frac{2\pi}{96}i\right) \tag{3.11}$$

We use this same approach for reducing the number of parameters necesary to estimate y_d when we used the whole year of information avaiable, as it will be described in detail below. In this case, our strategy is to estimate these parameters as the components of a Fourier series defined as follows:

$$y_d = 1 + \sum_{m=1}^{20} \phi_m cos\left(m\frac{2\pi}{\#days}d\right) + \sum_{m=1}^{20} \phi_{m+5} sin\left(m\frac{2\pi}{\#days}d\right) \tag{3.12}$$

3. Elasticities

Once the parameters have been obtained from the estimation of the system of 96 equations, we can obtain the price elasticities as:

$$
\begin{aligned}
e_{ikd} &= \frac{\partial E_{ikd}\left(p,y\right)}{\partial p_{id}} \times \frac{p_{id}}{E_{ikd}} \\
&= c_{ij} y_d \times \frac{p_{id}}{E_{ikd}}
\end{aligned}
\tag{3.13}
$$

This means that we obtain one price elasticity estimate by each firm and day of the year combination. At the same time, intervals where firms had zero consumption cannot be considered to recover the elasticities.

E. Results

1. Take-up of Contracts with TVP

The take-up of contracts with time-varying prices in our sample is summarized in Table 11. In our sample of the 1700 largest customers, 20% of C&I customers face time-varying prices. However those customers are concentrated among large users – slightly over one-third of customers are subject to TVP when weighted by consumption. There is a modest variation in the geographic take-up of TVP. If customers are not weighted by consumption, the West zone – the zone with the most wind generation – has slightly higher take-up than other zones. However, when weighting by consumption to account for the fact that larger customers are more likely to choose TVP, the zones with the largest number of TVP customers are the Houston and South zones.

Table 12 summarizes take-up rates by industry. We summarize industry using two digit NAICS codes. Industries vary widely in the use of TVP. Approximately half of firms in transportation sectors of air, rail, water, truck, ground passenger, pipeline, and sightseeing choose contracts with TVP. About a quarter to a third of

Table 11—TVP Take Up by Congestion Zone

	Unweighted	Consumption Weighted
All	20%	35%
Houston	20%	41%
North	18%	25%
South	25%	39%
West	26%	31%

Notes: Zones are defined as the 2008 congestion management zones.

firms have TVP contracts in Manufacturing, certain types of retail stores, and postal and warehousing services. At the other extreme, take-up of TVP is very small in sectors such as Mining, Construction, Real Estate, and Professional Services.

2. Own Price Elasticities by Firm Size

To obtain the price elasticities we decided to focus on the moments when there was a solid incentive to curtail electricity consumption. Hence, we analyzed only the days during the summer of 2008 when unusually high prices occurred. The criteria used for defining an unusually high price was 1.5 times the standard deviation above the mean price for the interval and congestion zone (Houston, North, West, South). Using this criteria, 50 days out of the 91 days were selected. The number of days selected by congestion zone can be seen at Table 13. [13]

[13] The detail of the days selected by congestion zone and interval can be found at the Appendix F.

Table 12—TVP Take Up by Industry

	Unweighted	Consumption Weighted
Agriculture, Forestry, Fishing and Hunting	*	*
Mining, Quarrying, and Oil and Gas Extr.	8%	4%
Utilities	20%	4%
Construction	13%	6%
Manufacturing- Food, Bev, Textile, Apparel, Leather	34%	40%
Manufacturing- Wood, Paper, Printing, Petroleum/Coal, Chemical, Plastic, Nonmetallic	26%	50%
Manufacturing- Primary/Fabricated Metals, Machinery, Computer Electronics, Elec. Equip, Transp., Furniture	15%	52%
Wholesale Trade	21%	37%
Retail Trade- Stores: Auto Parts, Furniture, Electronics, Building Materials, Food/Bev, Health, Gas Stations, Clothing	18%	12%
Retail Trade- Stores: Sporting Goods, Books, Merchandise, Misc. Retailers, Non-store retailers	40%	62%

Table 12—Continued

	Unweighted	Cons. Weighted
Transportation and Warehousing: Air, Rail, Water, Truck, Ground Passenger, Pipeline, Sightseeing, Support	52%	67%
Transportation and Warehousing: Postal, Courier, Warehousing and Storage	25%	20%
Information	*	*
Finance and Insurance	22%	18%
Real Estate and Rental and Leasing	12%	8%
Professional, Scientific, and Technical Services	12%	7%
Management of Companies and Enterprises	*	*
Administrative & Support & Waste Mgmt & Remediation Svcs	20%	38%
Educational Services	*	*
Health Care and Social Assistance	9%	10%
Arts, Entertainment, and Recreation	*	*
Accommodation and Food Services	17%	13%
Other Services (except Public Administration)	29%	12%
Public Administration	*	*
Unclassified	10%	18%

Notes: This table contains the fraction of customers that are exposed to time-varying prices for each category among the largest 1700 C&I customers.
* Omitted for confidentiality.

Table 13—Days Selected for Empirical Estimation

	Whole Sample			Selected Sample		
Interval	Days	Mean Price	Std. Dev.	Days	Mean Price	Std. Dev.
Houston	91	0.0971	0.0421	43	0.1214	0.0491
North	91	0.0900	0.0346	42	0.1082	0.0423
South	91	0.1019	0.0535	44	0.1304	0.0644
West	91	0.0821	0.0405	34	0.1071	0.0478
Total	91	0.0928	0.0437	50	0.1175	0.0523

Note: Price expressed as dollars per kilo-Watt hour. ($/kWH)

Next, we used the firm's electricity consumption data from June 2008 to August 2008 to construct 4 quartiles based on total electricity consumption during this period. By doing this, we divided the firms in our sample in four groups by size, using electricity consumption as a metric. This way we gain more homogeneity in the sample of firms used for the estimation, which may facilitate the estimation of the parameters. Table 14 shows the characteristics of the quartiles obtained from the sample.

We added the temperature information collected from 63 weather stations spread over Texas. In order to reduce the estimation time, we used a random sample of 100 firms for each quartile and type of tariff (TVP or non TVP). After obtaining the system parameters, we recovered the elasticities, one by each firm and day considered in the sample. Figure 5 shows the median value of the own-price elasticities obtained, by quartile and type of tariff.[14]

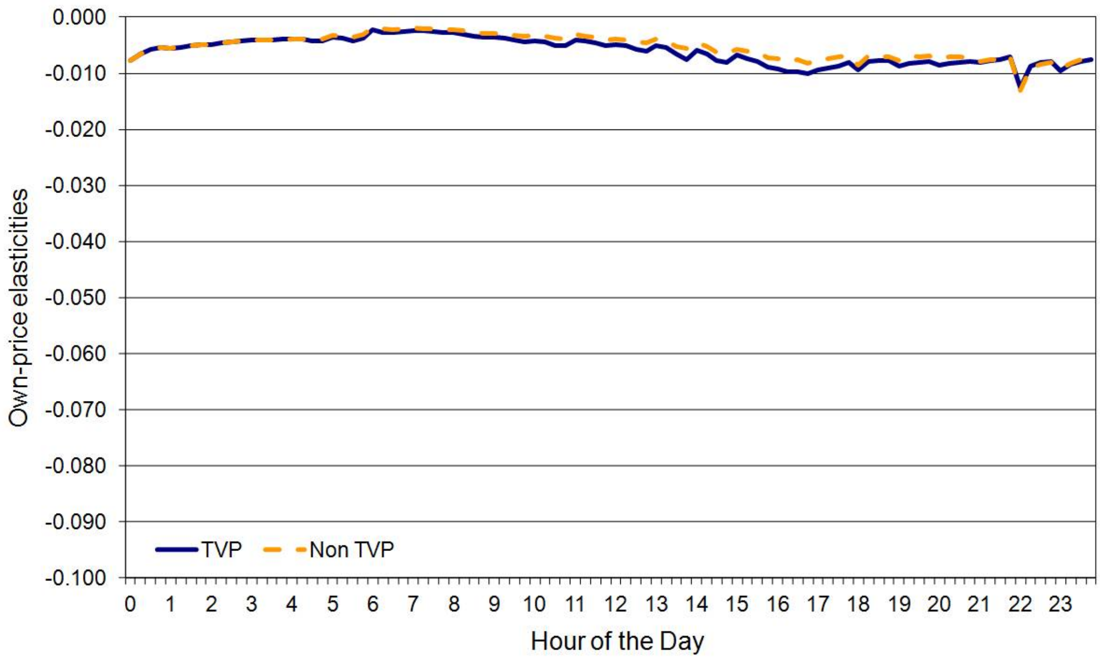
[14] The estimation did not include the estimation of standard errors.

Table 14—Total kWH Consumption per Day by Firm Size

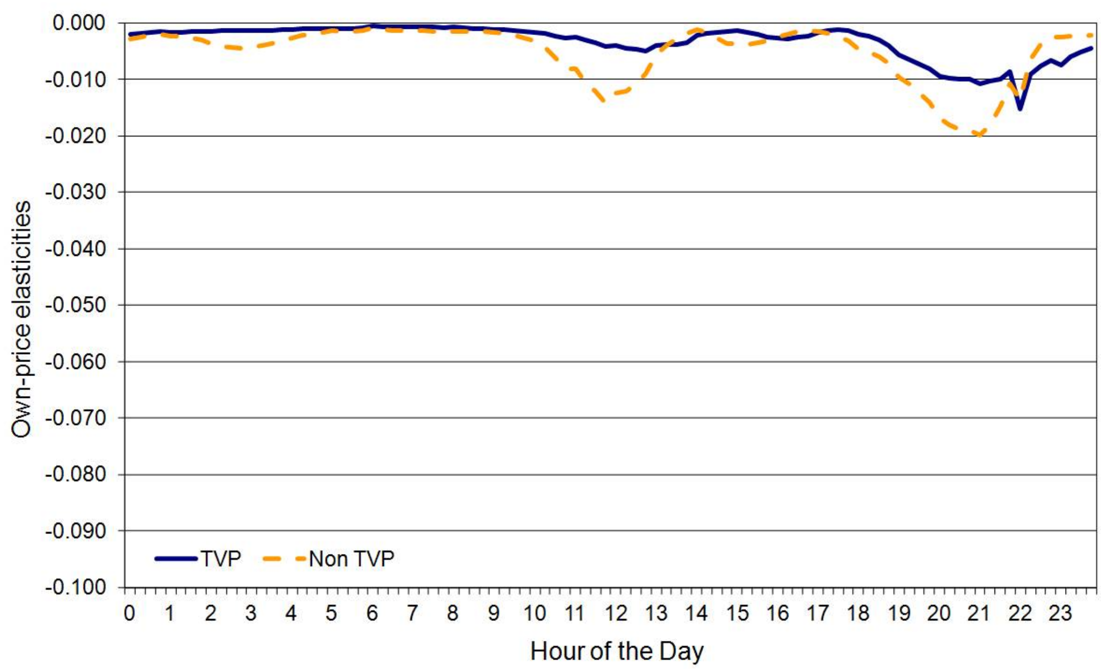
Quartile	Firms	Mean	Std. Dev.	Min.	Median	Max.
Smallest	2,137	179.1	123.2	0.0	171.3	400.0
2	2,136	644.0	142.8	400.1	643.3	892.1
3	2,136	1,195.7	200.0	892.5	1,169.2	1,608.1
Biggest	2,136	7,106.5	19,529.3	1,610.5	2,804.2	496,423.1
Total	8,545	2,281.1	10,159.4	0.0	892.1	496,423.1

We can obtain some important conclusions from these results. First, the estimated magnitudes of elasticity are modest. All the reported median values are below 0.02 in absolute value, with most of them being below 0.01. This result is consistent with previous results in the literature. For instance, Zarnikau & Hallet (2008) find that aggregate own-price elasticity of demand in ERCOT is -0.000008, while Zarnikau et al. (2007) find that the 20 largest customers in Houston have no significant response to prices.

The only sizeable own-price elasticities are observed in the second quartile for non TVP firms, and in the biggest quartile for TVP firms. In the first case, firms are more elastic around noon and 9 p.m. However, it is difficult to explain why the non TVP firms are showing some elasticity. This result may be an indication that unobservable factors correlated with prices are particularly strong in this subsample. The second group that shows a sizeable elasticity is the group of biggest firms, where firms show to be more elastic during the late afternoon, which coincides with peak electricity prices. Back of the envelope estimations indicate, however, that the absolute magnitude of

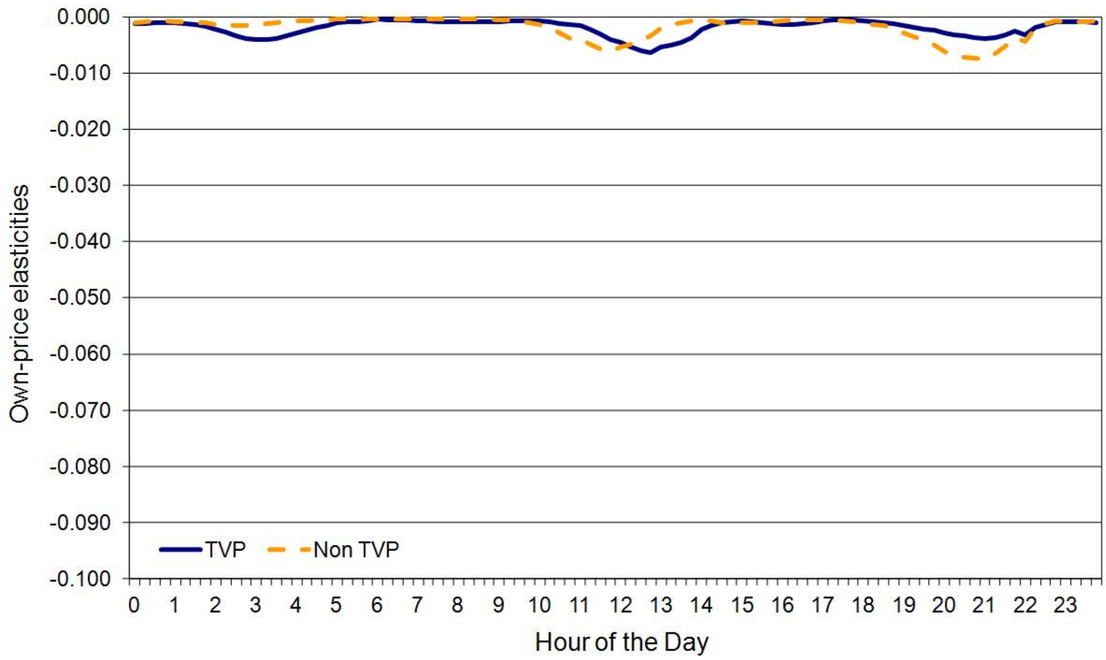


(a) First Quartile (Smallest Firms)

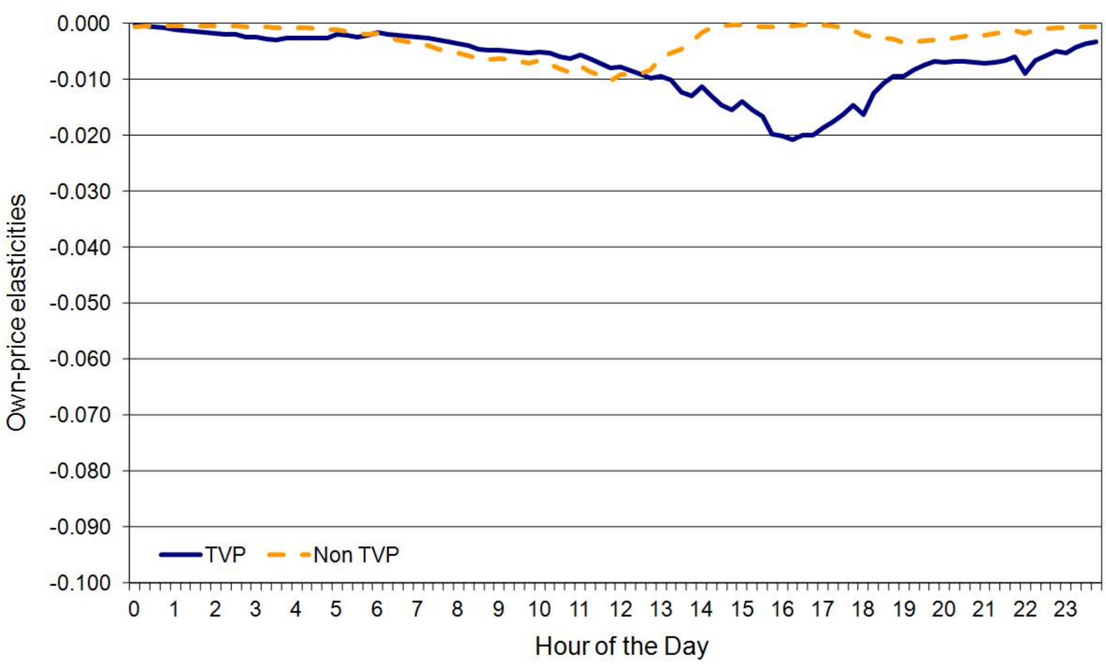


(b) Second Quartile

Figure 5. Median Own Price Elasticity of Electricity by Firm Size



(c) Third Quartile



(d) Fourth Quartile (Biggest Firms)

Figure 5. Continued

consumption reduction is very small. An increment of 10 cents in the price per kWH, will lead to a reduction in total demand in the interval between 4pm and 5pm of 9MWh. Compared to the average total sytem demand for that same time period during high prices episodes (around 56 GWH), the reduction obtained is very small, being only 0.016% of the aggregate.[15]

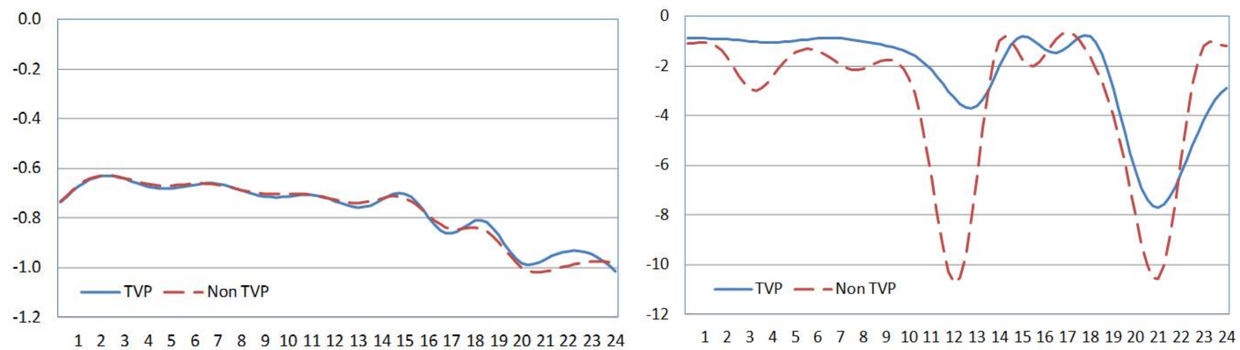
As a check that these results are driven by the parameters obtained from the estimation and not by the price/quantity ratio or the values of the dummies per day (y_d), we reported the values of the main diagonal of C in Figure 6. They all are different from zero, and show different patterns. Their magnitude increases from the lowest to the highest quartile, which is consistent with the size of firms increasing across quartiles. If these parameters were close to zero, that would indicate the functional form cannot capture adequately the relationship between prices and quantities.

3. Own Price Elasticities by Industry

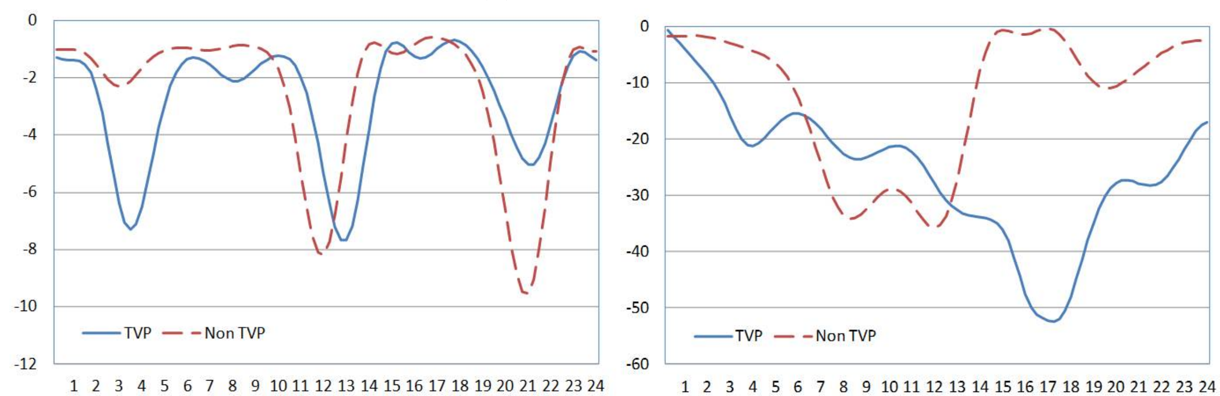
Next, we were interested to see if, even when magnitudes obtained are small, some industries are more responsive to electricity prices than others. We would expect capital-intensive industries which use energy-intensive machinery to be more responsive, granted that they have enough flexibility to curtail electricity consumption when necessary.

For this section we had to restrict our analysis to the firms for which we obtained the characteristics of the firm, including the NAICS code. This reduced the number of observations considerably, so we decided to extend the time interval to the whole year, instead of the price peak times during the summer. Then, we restricted our analysis

[15]We assumed an average consumption by firm in the quartile of 3.76 MWh from 4pm to 5pm, and an average mean price of US$1.8 per kWH. The intervals considered to obtain this values are only the high price episodes, defined as at least 1.5 times the standard deviation above the mean.



(a) Quartiles 1 and 2



(b) Quartiles 3 and 4

Figure 6. c_{ij} Estimated Parameters from C Main Diagonal

to the industries for which we had at least five firms in each tariff regime. We decided to work at the 3-digit level NAICS code because we wanted to ensure homogeneity of the firms within each selected industry, but have also a decent number of firms in the sample[16]. The sample of industries analyzed and the type of tariff participation is described in Table 15. The median elasticities obtained are presented in the Figure 7.

The graphs where scaled from 0 to -0.10, when possible. A first reading shows that for the selected sample of industries, the non TVP firms have in all cases null responsiveness to electricity prices. We double checked that the elasticity estimates were driven by the c_{ij} parameters and not by the other terms of the elasticity estimate.

Analyzing each graph obtained we see that for most of them the magnitude of the elasticity obtained is very small, consistent with the results obtained by quartile. In two industries, the elasticities obtained were positive, but this result was driven by the y_d parameters. Two of the industries (331 and 423) show an increase in the magnitude of the elasticity by the end of the day, a result that is difficult to interpret in intuitive terms. Overall, the size of the obtained elasticities are very small in absolue value.

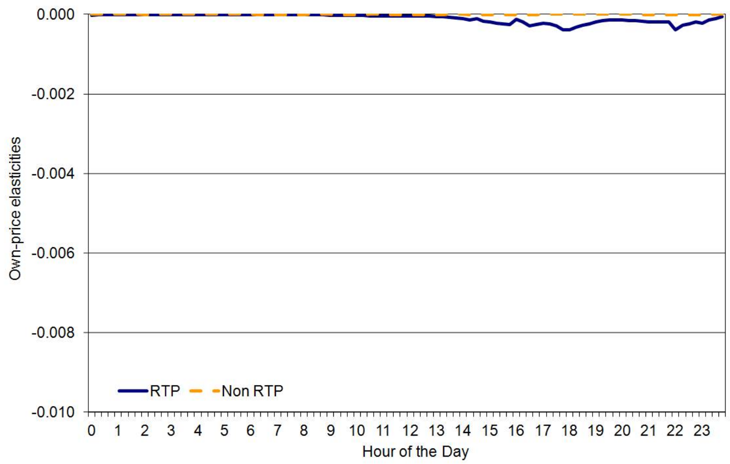
F. Conclusions

We impose a functional form derived from microeconomic theory to estimate the responsiveness of demand for electricity in a sample of commercial and industrial customer in Texas. The results show, first, that an opt-in type of program can reach a considerable share of participation for real-time pricing tariffs. 20% of customers with more than 700 kW peak load during the day signed for this program, which increases to 35% when weighted by consumption during the year.

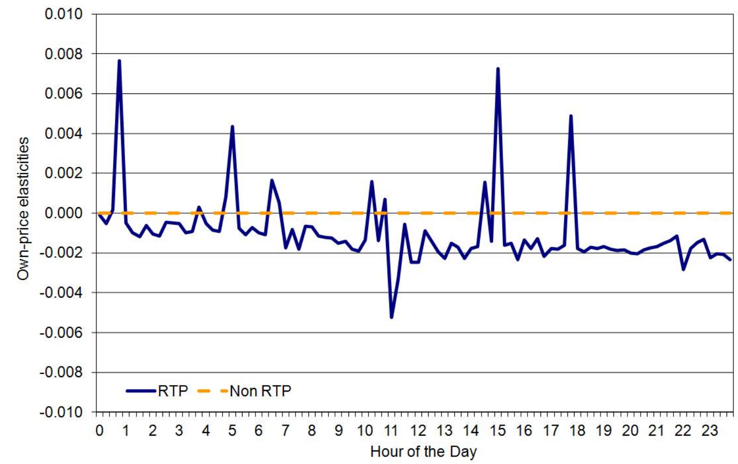
[16]The defintion of each NAICS category selected can be found at the Appendix G.

Table 15—Industries Selected for Elasticity Estimation

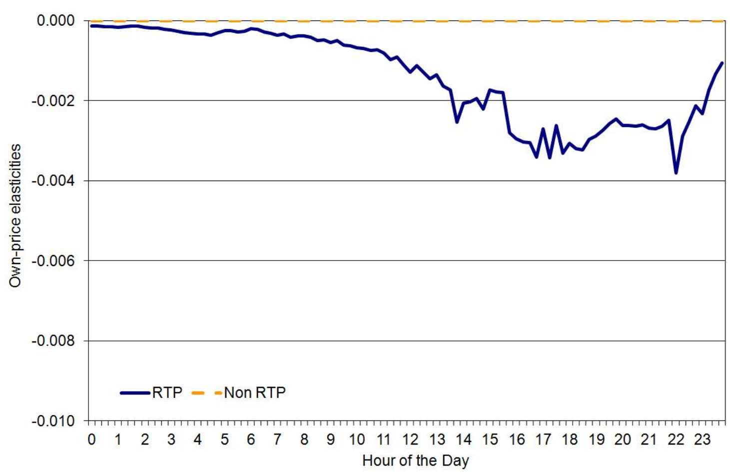
NAICS	Description	Number of Firms			
3-digit code		Total	Non TVP	TVP	Share TVP
812	Personal and Laundry Services	13	7	6	46
325	Chemical Manufacturing	32	20	12	38
311	Food Manufacturing	34	22	12	35
331	Primary Metal Manufacturing	16	11	5	31
522	Credit Intermediation and Related Activities	35	26	9	26
326	Plastic and Rubber Products Manufacturing	24	18	6	25
722	Food Services and Drinking Places	23	18	5	22
423	Merchant Wholesalers, Durable Goods	43	35	8	19
541	Professional, Scientific and Technical Services	100	88	12	12



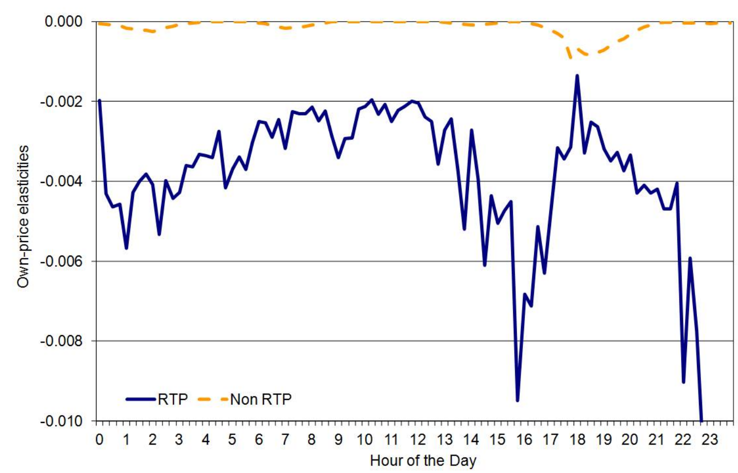
(a) NAICS 812: Personal and Laundry Services



(b) NAICS 325: Chemical Manufacturing

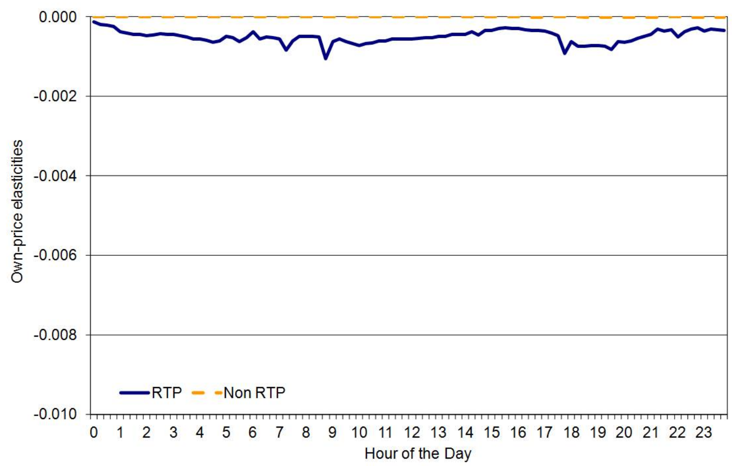


(c) NAICS 311: Food Manufacturing

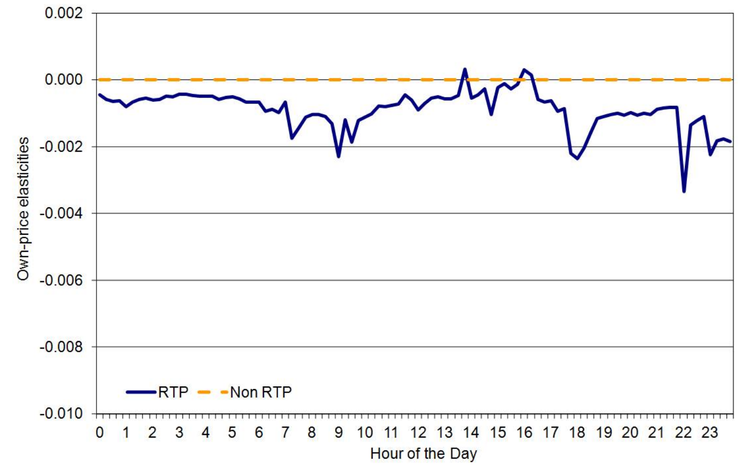


(d) NAICS 331: Primary Metal Manufacturing

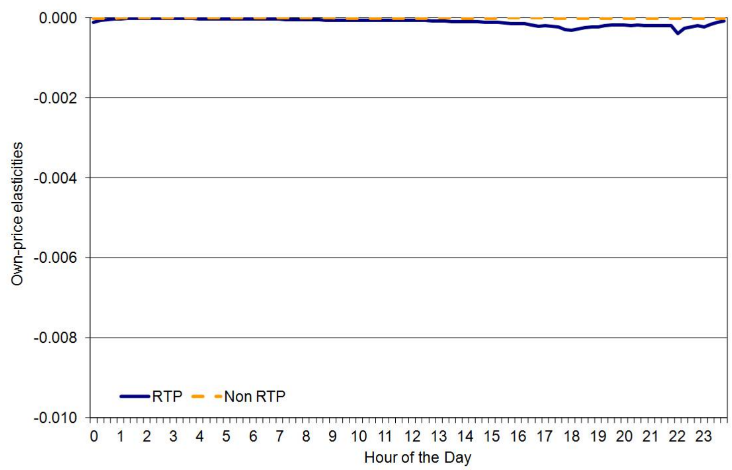
Figure 7. Median Own Price Elasticity of Electricity by Industry



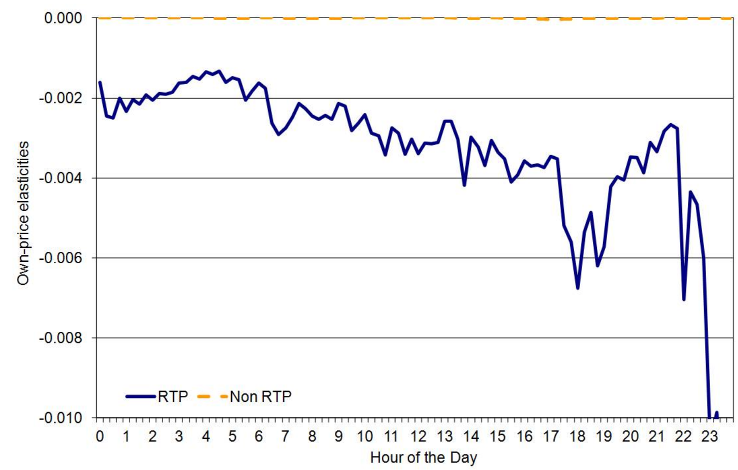
(e) NAICS 522: Credit Intermediation



(f) NAICS 326: Plastic Products Manufacturing

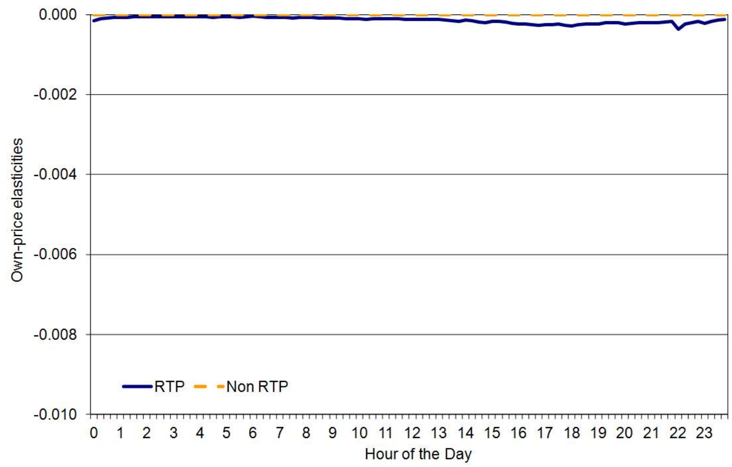


(g) NAICS 722: Food Services and Drinking Places



(h) NAICS 423: Merchant Wholesalers, Durable Goods

Figure 7. Continued



(i) NAICS 541: Professional, Scientific and Technical Services

Figure 7. Continued

Secondly, we found that the magnitude of the own price elasticities of demand are not significant in economic terms. Estimations performed by firm size and by industry showed that the magnitude was only in few cases bigger than 0.01 in absolute value. A back of the envelope estimation showed that for the group where the elasticity reaches -0.02, the reduction in consumption for an increase of 10 cents in the price of electricity per kWH is negligible. The industry-level estimations also showed very small response, and consistently demonstrated that customers under non TVP do not react to electricity prices. All these results show that the expected potential of real-time pricing for inducing reductions in consumption in the short-run is still not realized.

CHAPTER IV

SUMMARY

In Chapter II, I test for the existence of false positives among inspections from the Atlanta vehicular emission inspection program between April 2002 and December 2003. I also test whether this incidence is a function of the number of local competitors for each station. The specific form of test manipulation tested consists of using a satisfactory vehicle to obtain a passing result for another vehicle. I used two approaches to detect test manipulations: a reduced-form approach following the methodology developed by Oliva(2010), and a switching regression model approach, aimed to assign probabilities of clean-piping to each inspection performed. I estimate the incidence of test fraud (clean piping) to be 9% of the passing inspections during the sample period. Moreover, a linear regression of the predicted probabilities of clean-piping per inspection against the number of competitors for the inspecting station demonstrates that the incidence of clean piping per station increases by 0.7% with one more competitor within a 0.5 mile radius. These results show that increased competition can lead to outcomes detrimental to society when there are asymmetries of information and the incentives are not properly aligned for all the participants in the market. These effects must also be considered when designing new markets, as was the case for the vehicular emission inspection market.

In Chapter III, we test whether electricity consumption by industrial and commercial customers responds to real-time prices after these firms sign-up for prices linked to the electricity wholesale market price. As in Patrick and Wolak (2001), we impose a functional form derived from microeconomic theory in order to estimate the responsiveness of demand for electricity in a sample of commercial and industrial customers in Texas. The results show, first, that an opt-in type of program can reach a considerable share of participation for real-time pricing tariffs. 20% of customers with more than 700 kW peak load during the day signed up for this program. This share increases to 35% when weighted by consumption during the year.

Secondly, we found that the magnitude of the elasticities of demand are not significant in economic terms. Estimations performed by firm size and by industry showed that the magnitude was only in few cases larger than 0.01 in absolute value. A back of the envelope estimation showed that for the group where the own price elasticity reaches -0.02, the reduction in consumption for an increase of 10 cents in the price of electricity per kWH is negligible. The industry-level estimations also showed very small response, but also consistently demonstrated that customers under non TVP do not react to electricity prices. All these results show that the expected potential of real-time pricing for inducing reductions in consumption in the short-run is still not realized.

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APPENDIX A

PROOF OF THE ASYMPTOTIC PROPERTIES OF $\tilde{\varphi}$

To proof the asymptotic properties of $\tilde{\varphi}$, we start from (2.5):

$$r_i = m_i \left[r_{i-1} + (Z_i - Z_{i-1}) \gamma \right] + (1 - m_i) \left[X_i \beta + Z_i \gamma \right] + u_i$$

where

$$u_i = m_i \left[\varepsilon_i - e_{i-1} \right] + (1 - m_i) \left[e_i \right]$$

we re-express (2.5) in matrix form. Define the matrix M as an nxn matrix such that $M = I * m$, where m is a vector containing all the $m_i$terms. Define also the matrices r, r_{-1}, X, Z, Z^d, and u as the matrices resulting from stacking each observation from r_i , r_{i-1}, X_i , Z_i, $(Z_i - Z_{i-1})$, and u_i. The resulting expression is:

$$r = Mr_{-1} + MZ^d\gamma + (I - M)X\beta + (I - M)Z\gamma + u \tag{A.1}$$

where I is the nxn identity matrix. If we estimate (A.1) by OLS, the resulting expression, using matrix notation is:

$$\begin{aligned} r &= \tilde{\varphi} r_{-1} + Z^d \tilde{\gamma} + X\tilde{\beta} + Z\hat{\gamma} \\ &= \tilde{\varphi} r_{-1} + V\tilde{\theta} \end{aligned}$$

Then, the OLS estimator for $\tilde{\varphi}$ can be expressed as:

$$\tilde{\varphi}^{OLS} = (r'_{-1}(I - P_V)r_{-1})^{-1} r'_{-1}(I - P_V)r$$

where $P_v = V \left(V'V \right)^{-1} V'$. Replacing r by its components according to (A.1), we have that:

$$\begin{aligned}
\tilde{\varphi}^{OLS} &= (r'_{-1}(I-P_V)r_{-1})^{-1}r'_{-1}(I-P_V)Mr_{-1} \\
&+ (r_{-1}(I-P_V)r'_{-1})^{-1}r_{-1}(I-P_V)MZ^d\tilde{\gamma} \\
&+ (r_{-1}(I-P_V)r'_{-1})^{-1}r_{-1}(I-P_V)\left(I-M\right)X\tilde{\beta} \\
&+ (r_{-1}(I-P_V)r'_{-1})^{-1}r_{-1}(I-P_V)\left(I-M\right)Z\hat{\gamma} \\
&+ (r_{-1}(I-P_V)r'_{-1})^{-1}r_{-1}(I-P_V)u
\end{aligned}$$

Under H_0 all the elements of M are equal to zero, and $u = e$. Also, remember that X and Z are components of V, so they belong to the span of V. Hence, we have that:

$$\tilde{\varphi}^{OLS} \overset{H_0}{=} (r_{-1}(I-P_V)r'_{-1})^{-1}r_{-1}(I-P_V)e$$

Then, to have $\tilde{\varphi}_{OLS}$ equal to zero in expectation under the null hypothesis, we need each component of V to be orthogonal to e. In other words, we need the following sufficient conditions to be satisfied:

Condition 1 $E\left[r'_{-1}e\right] = 0$

Condition 2 $E\left[Z^{d'}e\right] = 0$

Condition 3 $E\left[X'e\right] = 0$

Condition 4 $E\left[Z'e\right] = 0$

Regarding condition 1, since the null hypothesis holds, we can replace r_{-1} by its components, according to 2.8. Condition 1 will be satisfied then if the following conditions are satisfied: Condition 1.1 $E\left[X_{i-1}e_i\right] = 0$ Condition 1.2 $E\left[Z_{i-1}e_i\right] = 0$ Condition 1.3 $E\left[e_{i-1}e_i\right] = 0$ Conditions 1.1 and 1.3 are the same that the assumptions (A1) and (A2) discussed by Oliva (2010). To have condition 1.1 not to hold, an observable characteristic of the car ahead in line (X_{i-1}) should create a systematic noise in the honest reading of the next inspection. For instance, a big engine or a high odometer reading from a vehicle creating an effect on the next gas reading that cannot be explained by the observable characteristics of the next vehicle. For condition 1.3 not to hold, consecutive honest inspections should have a common systematic deviation from the predicted value from observable characteristics. If this deviation were common to all the vehicles in a single station, this effect will be captured by station fixed effects. If it is not common to all the vehicles, but to a subset of them, and it is not correlated with any of the observable variables, it can potentially be a problem. I assume that none of these cases occur, so that conditions 1.1 and 1.3 hold.

Condition 1.2 will be satisfied if the error term is not related with the contextual variables that affect the readings of the car ahead in line. Z_{i-1} is composed of two set of variables, environmental (Z_{i-1}^{env}) and dynamometer-resistance determinants (Z_{i-1}^{dyn}). Since the null hypothesis holds, dynamometer-resistance determinants (Z_{i-1}^{dyn}) are a subset of X_{i-1}, and they are non correlated with the e_{it} if condition 1.1 holds. Then, condition 1.2 will not be satisfied for Z_{i-1}^{env} if temperature or humidity have a systematic effect on the readings of the next car in line. For instance, if extremely hot weather makes the inspectors position the gas reader in some way that affects the result of the inspection of the next vehicle in line. It can also be the case that environmental variables do not vary considerably from inspection to inspection. In this case, the error term from the honest reading must be independent from these variables. This is, humid or hot days should not induce a systematic error in the reading, I assume that none of these cases occur, so condition 1.2 holds. Then, under the assumptions described, condition1 holds.

Condition 2 will be satisfied if the difference between inspection-specific variables and the error term is not correlated. For this to happen, it is necessary that every inspection performed after an change in temperature or humidity contain a systematic error. The same should happen every time a small-engine car is followed by a big-engine car. Conditions 3 and 4 are satisfied if e is orthogonal to X and Z, which will be satisfied if the linear specification, and the variables included are good enough as to explain the readings, and leave an independent error term. I assume that all these conditions are satisfied, so that under the null hypothesis, the expectations of $\tilde{\varphi}_{OLS}$ is equal to zero.

Under the alternative hypothesis, at least some of the elements of the main diagonal of M are equal to one. This implies that the first term in the definition of $\tilde{\varphi}_{OLS}$ is different from zero:

$$(r'_{-1}(I - P_V)r_{-1})^{-1}r'_{-1}(I - P_V)Mr_{-1} \neq 0$$

so that, regardless of the value of the other terms in the expression, we have that:

$$E\left[\tilde{\varphi}^{OLS}\right] \overset{H_1}{\neq} 0$$

Then, the individual significance test for the parameter φ will provide information about the existence of "clean piping" cases in the sample.

APPENDIX B

PROOF OF BIAS OF $\tilde{\varphi}^{OLS}$

We want to obtain an unbiased estimator for (2.12):

$$\hat{m}_0 = \frac{\sum_t^N m_t}{N}$$

To see why $\tilde{\varphi}^{OLS}$ is a biased estimator of this mean incidence, remember that it is obtained from the OLS estimation of (2.6):

$$r_i = \tilde{\varphi} r_{i-1} + (Z_i - Z_i)\,\tilde{\gamma} + X_i \tilde{\beta} + Z_t \hat{\gamma} + u_i$$

As mentioned in Oliva(2010), remember that the expression $[r_{i-1} + (Z_i - Z_i)\,\gamma]$ is actually a proxy for r_i^{cp} in (2.5). Even if this approximation can be very accurate, there is still some random error not captured by the observable variables. Hence, we have a case of a variable measured with error, which causes the estimation of $\tilde{\varphi}^{OLS}$ being biased toward zero (attenuation).

However, an even more important problem is the own interpretation of the parameter obtained from the OLS estimation of (2.6)(in matrix notation):

$$\tilde{\varphi}^{OLS} = (r'_{-1}(I - P_V)r_{-1})^{-1} r'_{-1}(I - P_V)r$$

Replacing r by its components defined in (A.1), we obtain:

$$\tilde{\varphi}^{OLS} = [(r'_{-1}(I - P_V)r_{-1})^{-1}]r'_{-1}(I - P_V)$$
$$[Mr_{-1} + MZ^d\gamma + M\epsilon + (I - M)\,X\beta + (I - M)\,Z\gamma + (I - M)\,e]$$

To gain some intuition, suppose that $r_{-1}$is orthogonal to V, and that M is orthogonal to r_{-1} (or m_i is independent from r_{i-1}). Then, the first term of $\tilde{\varphi}^{OLS}$ will become:

$$\frac{\sum_{i=1}^{N} m_i r_{i-1}^2}{\sum_{i=1}^{N} r_{i-1}^2} \tag{B.1}$$

As is, B.1 can be an estimator for the mean incidence, given that on average the r_{i-1} included and excluded from the denominator have the same magnitude. However, even when $(I - P_v)$ cancels out with X, and Z; and P_v does with e; the remaining terms do not vanish automatically and impose a bias in the mean estimator:

$$E\left[bias\right] = [(r'_{-1}r_{-1})^{-1}]E\left[r'_{-1}[MZ^d\gamma + M\epsilon - MX\beta - MZ\gamma - Me]\right] \tag{B.2}$$

This term is difficult to interpret and to determine the direction of the bias. Moreover, if we lift the assumption of r_{-1}being orthogonal to V, then we need to include the matrix $(I - P_v)$ in the estimation of the numerator and denominator of B.1, which turns more complicated its interpretation. Oliva (2010) followed a different approach to determine if the OLS estimator is biased and also found that the estimator will not be consistent, with a bias of direction difficult to determine.

APPENDIX C

THE ESTIMATOR FOR THE MEAN INCIDENCE OF CLEAN PIPING (λ)

The estimator for the mean incidence of clean piping (λ) can be explicitly obtained from the following FOC .

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \lambda_j} =& \sum_{i=1}^{N_j}\{\frac{\lambda_j}{\sigma_1} exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right) \\ &+\frac{1-\lambda_j}{\sigma_2} exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\}^{-1} \\ &\times\{\frac{1}{\sigma_1} exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right) \\ &-\frac{1}{\sigma_2} exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\} = 0 \end{aligned} \tag{C.1}$$

Multiplying numerator and denominator by $\frac{1}{\sqrt{2\pi}}$ we obtain:

$$\frac{\partial \mathcal{L}}{\partial \lambda_j} = \sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} = 0$$

where μ_i^1 and μ_i^2 are respectively $(\varepsilon_i - e_{i-1})$ and e_i from (2.7).$\phi(.)$ is the normal standard density function. Then, C.1 implies:

$$\sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right)}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} = \sum_{i=1}^{N_j} \frac{\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} \tag{C.2}$$

To gain some intuition, consider the case where for a subset of observations (N_{j1}) the probability of being a clean piping case is positive ($\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) > 0$) and the probability of being an honest case is very small ($\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right) \to 0$). For the other observations (N_{j2}), consider the opposite situation, the probabilities of being clean piping are very remote ($\frac{1}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) \to 0$), and the probabilities of being honest are at least positive ($\frac{1}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right) > 0$). For having this case, we would need that each observation is clearly assigned to only one of the possible cases. We will have then that 2.20 will collapse to:

$$\begin{aligned}
\sum_{i=1;i\in N_{j1}}^{N_j}\frac{1}{\lambda_j} &= \sum_{i=1;i\in N_{j2}}^{N_j}\frac{1}{1-\lambda_j}\\
\frac{N_{j1}}{\lambda_j} &= \frac{N_{j2}}{1-\lambda_j}\\
\lambda_j &= \frac{N_{j1}}{N_{j1}+N_{j2}}
\end{aligned} \tag{C.3}$$

Then, the incidence parameter will represent the share of observations that are clean piping. In case the specifications assign the same probabilities to each observation, then C.2 will collapse to the equality $N_j = N_j$, which implies that any λ will satisfy the FOC, and the parameter will not be identifiable.

To check which other assumptions are necessary to obtain consistent parameters, we list the FOC from the log-likelihood function. These FOC are required as regularity conditions in order to apply the usual properties of MLE estimators, including consistency and asymptotic normality.

The FOC with respect to β is:

$$\begin{aligned}
\frac{\partial\mathcal{L}}{\partial\beta} =& \sum_{i=1}^{N_j}\{\frac{\lambda_j}{\sigma_1}exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right)\\
&+\frac{1-\lambda_j}{\sigma_2}exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\}^{-1}\\
\{\frac{1-\lambda_j}{\sigma_2}&exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\frac{1}{\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)X_i\} = 0
\end{aligned} \tag{C.4}$$

then:

$$\frac{\partial\mathcal{L}}{\partial\beta} = \sum_{i=1}^{N_j}\frac{\frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)\frac{1}{\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)X_i}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)} = 0$$

Considering again the case where we can assign clearly one regime to each observation, the preceding expression collapses to:

$$\frac{\partial\mathcal{L}}{\partial\beta} = \sum_{i=1;i\in N_{j2}}^{N_j} \left(r_i - X_i\beta - Z_i\gamma\right) X_i = 0$$

For this expression to hold we need the error term in the second specification (honest cases) to be orthogonal to the X_i. In case both linear specifications receive the same probability to each observation, the previous condition needs to be true as well, but for all the observations.

The third FOC that have to hold is:

$$\begin{aligned}
\frac{\partial\mathcal{L}}{\partial\gamma} =& \sum_{i=1}^{N_j}[\frac{\lambda_j}{\sigma_1} exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right) \\
&+\frac{1-\lambda_j}{\sigma_2} exp\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)]^{-1} \\
&\times[\frac{\lambda_j}{\sigma_1} exp\left(-\frac{1}{2\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)^2\right) \\
&\times\frac{1}{\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)\left(Z_i - Z_{i-1}\right) \\
+\frac{1-\lambda_j}{\sigma_2} exp&\left(-\frac{1}{2\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right)^2\right)\frac{1}{\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right) Z_i] = 0
\end{aligned} \tag{C.5}$$

then:

$$\begin{aligned}
\frac{\partial\mathcal{L}}{\partial\gamma} =& \sum_{i=1}^{N_j}[\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)]^{-1} \\
\times[\frac{\lambda}{\sigma_1}\phi\left(\frac{\mu_i^1}{\sigma_1}\right)&\left[\frac{1}{\sigma_1^2}\left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)\left(Z_i - Z_{i-1}\right)\right] \\
&+\frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_i^2}{\sigma_2}\right)\left[\frac{1}{\sigma_2^2}\left(r_i - X_i\beta - Z_i\gamma\right) X_i\right]] = 0
\end{aligned}$$

Again, under perfect discrimination, we obtain:

$$\frac{\partial \mathcal{L}}{\partial \gamma} = \frac{1}{\sigma_1^2} \sum_{i=1; i \in N_{j1}}^{N_j} \left(r_i - r_{i-1} - \left(Z_i - Z_{i-1}\right)\gamma\right)\left(Z_i - Z_{i-1}\right) + \frac{1}{\sigma_2^2} \sum_{i=1; i \in N_{j2}}^{N_j} \left(r_i - X_i\beta - Z_i\gamma\right) X_i = 0$$

So, a sufficient condition to satisfy this FOC is that the error terms from each specification have to be orthogonal to the variables $(Z_t - Z_{t-1})$ for the manipulation cases, and to X_i for the honest cases. Here also, if both specifications assign the same probability to each observation, then the previous conditions have to be satisfied for all the observations of the sample.

Finally, the FOC with respect to the variance estimators are:

$$\frac{\partial \mathcal{L}}{\partial \sigma_1^2} = \sum_{i=1; i \in N_{j1}}^{N_j} \frac{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_{it}^1}{\sigma_1}\right)\left[\frac{1}{\sigma_1^2}\left(r_{it} - r_{i-1t-1} - \left(Z_t - Z_{t-1}\right)\gamma\right)^2 - 1\right]}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_{it}^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_{it}^2}{\sigma_2}\right)} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \sigma_2^2} = \sum_{i=1; i \in N_{j2}}^{N_j} \frac{\frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_{it}^2}{\sigma_2}\right)\left[\frac{1}{\sigma_2^2}\left(r_{it} - X_i\beta - Z_t\gamma\right)^2 - 1\right]}{\frac{\lambda_j}{\sigma_1}\phi\left(\frac{\mu_{it}^1}{\sigma_1}\right) - \frac{1-\lambda_j}{\sigma_2}\phi\left(\frac{\mu_{it}^2}{\sigma_2}\right)} = 0$$

Again, in case observations can be perfectly discriminated by the specification, they collapse to:

$$\sigma_1^2 = \frac{1}{N_j} \sum_{i=1; i \in N_{j1}}^{N_j} \left(r_{it} - r_{i-1t-1} - \left(Z_t - Z_{t-1}\right)\gamma\right)^2$$

$$\sigma_2^2 = \frac{1}{N_j} \sum_{i=1; i \in N_{j2}}^{N_j} \left(r_{it} - X_i\beta - Z_t\gamma\right)^2$$

As can be seen, the variance estimators are the average squared error terms.

APPENDIX D

SWITCHING REGRESSION MODEL RESULTS

Table D.1—Switching Regression Model Estimates: Manipulation Equation

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Differences in Weight	-0.068	0.005	-0.002	0.119
Std. Error	0.010	0.009	0.006	0.032
z-stat	-6.692	0.578	-0.365	3.691
Diff. in Weight ˆ 2	0.016	-0.001	-0.044	0.001
	0.005	0.004	0.026	0.030
	3.172	-0.339	-1.706	0.029
Diff. in Weight ˆ 3	-0.004	0.065	0.063	-0.014
	0.002	0.017	0.024	0.013
	-1.778	3.732	2.655	-1.099
Diff. in Displacement	0.086	-0.018	-0.010	-0.043
	0.010	0.016	0.010	0.015
	8.554	-1.134	-0.976	-2.867
Diff. in Displacement ˆ 2	0.012	0.011	0.050	-0.001
	0.009	0.007	0.012	0.002
	1.346	1.628	4.227	-0.715

continued on next page

Table D.1—Continued

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Diff. in Displacement ˆ 3	-0.006	0.054	-0.021	-0.004
	0.004	0.008	0.006	0.001
	-1.393	6.754	-3.206	-5.248
Manual Transmission	0.023	0.003	-0.006	-0.001
	0.005	0.002	0.003	0.000
	4.847	1.943	-2.176	-1.948
Diff. in Temperature	0.013	0.000	0.001	0.000
	0.003	0.001	0.002	0.001
	4.612	0.588	0.905	0.400
Diff. in Temperature ˆ 2	-0.002	0.000	-0.009	-0.001
	0.001	0.000	0.004	0.001
	-1.670	0.526	-2.194	-0.784
Diff. in Temperature ˆ 3	-0.001	-0.007	0.001	0.000
	0.001	0.001	0.003	0.000
	-0.862	-6.731	0.209	0.929
Diff. in Humidity	-0.004	0.000	0.000	-0.961
	0.002	0.001	0.001	0.003
	-2.370	0.358	0.235	-360.629

continued on next page

Table D.1—Continued

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Diff. in Humidity ˆ 2	-0.001	0.000	0.128	0.015
	0.001	0.000	0.007	0.002
	-0.917	-0.348	18.530	8.875
Diff. in Humidity ˆ 3	0.000	-0.008	-0.056	0.005
	0.000	0.001	0.004	0.000
	0.432	-6.658	-15.663	23.898
Diff. in Dilution Factor	0.086	-0.003	0.005	0.007
	0.003	0.000	0.000	0.002
	33.229	n/a	12.423	4.295
Diff. in Dilution Factor ˆ 2	-0.030	0.001	-0.022	0.001
	0.001	0.000	0.005	0.001
	-27.466	n/a	-4.051	1.480
Diff. in Dilution Factor ˆ 3	0.003	0.002	0.035	-0.003
	0.000	0.001	0.003	0.000
	23.071	1.784	13.164	-7.602

Table D.2—Switching Regression Model Estimates: Honest Equation

	Hydro– carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Weight	-0.023	0.005	-0.006	-0.009
Std. Error	0.002	0.001	0.001	0.002
z-stat	-9.685	8.616	-4.923	-5.594
Weight ˆ 2	0.024	-0.001	-0.033	-0.008
	0.001	0.000	0.006	0.001
	21.145	-3.275	-5.743	-6.160
Weight ˆ 3	-0.005	-0.013	0.030	0.004
	0.001	0.001	0.005	0.001
	-8.899	-9.113	6.349	5.781
Displacement	0.015	0.004	-0.001	-0.001
	0.003	0.001	0.002	0.001
	6.097	3.318	-0.604	-1.264
Displacement ˆ 2	-0.003	0.004	0.003	-0.009
	0.002	0.001	0.002	0.001
	-1.402	7.461	1.442	-11.543
Displacement ˆ 3	0.007	0.000	0.081	-0.003
	0.001	0.001	0.003	0.000
	6.800	-0.169	30.043	n/a

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Table D.2—Continued

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Manual Transmission	-0.008	0.018	0.005	0.000
	0.001	0.001	0.002	0.000
	-7.502	27.622	2.820	n/a
Odometer	0.037	0.004	-0.001	-0.016
	0.001	0.000	0.000	0.001
	31.635	36.658	-6.636	-15.447
Odometer ˆ 2	0.000	0.000	0.151	-0.008
	0.001	0.000	0.004	0.001
	0.834	n/a	39.426	-6.414
Odometer ˆ 3	0.000	0.030	-0.047	0.004
	0.000	0.001	0.005	0.000
	-5.471	33.579	-10.095	8.646
Age	0.069	0.014	0.006	0.002
	0.002	0.001	0.002	0.002
	42.205	12.286	3.453	0.994
Age ˆ 2	-0.002	-0.008	0.013	0.002
	0.002	0.000	0.008	0.002
	-0.950	-18.781	1.523	0.977

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Table D.2—Continued

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Age ˆ 3	-0.007	-0.003	-0.015	0.000
	0.001	0.002	0.017	0.000
	-9.253	-1.678	-0.835	n/a
Repairs performed	-0.002	-0.002	-0.002	0.000
	0.003	0.002	0.005	0.000
	-0.628	-0.917	-0.408	n/a
Trial number	-0.009	-0.001	0.000	-0.010
	0.004	0.000	0.000	0.001
	-2.614	n/a	0.770	-10.931
Trial number ˆ 2	0.000	0.000	-0.055	-0.024
	0.000	0.000	0.033	0.001
	n/a	n/a	-1.684	-45.112
Trial number ˆ 3	0.000	-0.026	0.013	-0.018
	0.000	0.026	0.016	0.002
	n/a	-1.002	0.800	-8.253
Constant	-0.075	-0.013	-0.008	-0.011
	0.018	0.013	0.007	0.001
	-4.280	-0.982	-1.156	-17.001

Table D.3—Switching Regression Model Estimates: Error Term Variance-Covariance Matrix

	Hydro–carbons	Carbon Monoxide	Nitric Oxide	Carbon Dioxide
Manipulation Equation Error Term Variance-Covariance Matrix				
Hydrocarbons	0.245	0.237	0.191	-0.028
Carbon Monoxide	0.237	0.763	0.091	-0.373
Nitric Oxide	0.191	0.091	1.612	0.084
Carbon Dioxide	-0.028	-0.373	0.084	2.857
Honest Equation Error Term Variance-Covariance Matrix				
Hydrocarbons	0.052	0.018	0.044	-0.008
Carbon Monoxide	0.018	0.016	0.028	-0.007
Nitric Oxide	0.044	0.028	0.276	-0.012
Carbon Dioxide	-0.008	-0.007	-0.012	0.023

Note: Variances and covariances between predicted error terms are reported.

APPENDIX E

TEXT OF SURVEY TO RETAILERS ASKING FOR IDENTIFICATION OF CUSTOMERS WITH INCENTIVES TO RESPOND TO WHOLESALE SPOT PRICES

ERCOT is attempting to improve its understanding of how electric system demand changes during periods of high market prices. Toward this end, ERCOT requests that each Competitive Retailer (CR) identify its retail customers whose contract includes a financial incentive or requirement to reduce consumption in response to high wholesale spot prices. ERCOT will analyze the behavior of these Loads, using industry-standard load modeling methodologies, to evaluate the amount of load reduction that typically occurs when Balancing Energy market prices are unusually high.

CRs are required to comply with this request by Public Utility Commission of Texas (PUCT) Substantive Rule 25.505(e)(5), which states: (5) Load serving entities (LSEs) shall provide ERCOT with complete information on load response capabilities that are self-arranged or pursuant to bilateral agreements between LSEs and their customers.

Contractual offerings that provide a financial incentive or requirement for a retail customer to reduce consumption in response to high wholesale spot prices may include variations of the following:

- Real-time pricing, in which customers are subject to prices that change every 15 minutes based on the ERCOT Market Clearing Price of Energy (MCPE);
- Critical-peak pricing (CPP), in which customers are encouraged to curtail Load during periods when MCPEs exceed some threshold value;

- Any retail pricing structure (including overall discounting) or incentive clause that provides the retail customer an incentive to reduce load in response to high MCPEs. (Such load reductions may be triggered or instructed by the REP or undertaken unilaterally by the customer.)

Please note the following:

- Identify ESI IDs that may be on "hybrid" versions of such plans; for example, customers that are exposed to market prices only during certain hours, or customers that have only a portion of their overall Load subject to price exposure.

- The study applies only to customers who are metered with Interval Data Recorders (IDRs). There are approximately 11,000 such customers in the competitive choice areas of the ERCOT Region.

- Do not identify ESI IDs for customers subject to Time-of-Use (TOU) pricing (subject during fixed blocks of hours to different prices that are known in advance).

- ERCOT's study is limited to ESI ID numbers. No other customer identification will be used.

ERCOT will treat all CR-specific data as Protected Information pursuant to the ERCOT Protocols, Sec. 1.3.1. Aggregated results may be reported to the PUCT, published by ERCOT, or otherwise released to the public. No results will be released if the identity of a particular Market Participant or customer may be discerned.

Your response to this questionnaire will assist ERCOT in operating the electric grid reliably and efficiently. A better understanding of the amount of price responsive Load in the region will help ERCOT anticipate how the total demand on the electric system is subject to change during periods of high market prices.

Attached is an Excel file that includes the list of IDR-metered ESI IDs specific to your company, as well as an introductory instruction page. Please read the instructions carefully, and modify the ESI ID worksheet according to the instructions and return the completed file to ______@ercot.com by April 1, 2009.

APPENDIX F

DAYS SELECTED FOR ELASTICITY BY SIZE ESTIMATION

The days utilized for the elasticity by size estimation were during the summer of 2008 when the prices were unusually high. The criteria used for defining an unusually high price was 1.5 times the standard deviation above the mean price for the interval and congestion zone. Four congestion zones were considered for the ERCOT region: Houston, North, West, and South. Using this criteria, 50 days between June and August 2008 were selected. The detail of the days selected by congestion zone and interval can be found in tables F.1, F.2, F.3 and F.4. The means and standard deviations correspond to the electricity price between 06/01/2008 and 08/30/2008 and the units are US$ per MWH.

Table F.1—Days Selected by Interval: Houston Congestion Zone

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
1	91	104.9	123.4	3	604.0	526.1
2	91	81.9	20.9	7	124.9	7.5
3	91	74.1	18.8	6	112.1	5.0
4	91	69.2	19.3	5	109.2	2.7
5	91	74.2	22.0	9	118.0	5.9
6	91	70.7	21.1	8	114.2	5.4
7	91	68.2	20.2	8	110.7	7.9
8	91	65.5	19.3	8	105.6	7.3

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Table F.1—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
9	91	64.1	21.0	8	107.2	9.4
10	91	60.8	21.7	8	105.2	10.6
11	91	57.1	21.3	8	99.7	7.5
12	91	54.8	21.0	8	96.0	7.3
13	91	52.6	21.9	7	96.4	7.1
14	91	50.1	21.7	5	95.5	6.5
15	91	49.0	21.3	7	91.6	4.9
16	91	46.6	21.8	7	90.7	4.0
17	91	45.9	21.6	7	92.1	3.8
18	91	45.8	21.4	7	91.6	4.2
19	91	47.4	20.6	8	87.5	7.2
20	91	48.2	20.9	7	88.2	5.4
21	91	46.4	22.6	9	86.5	5.9
22	91	48.7	22.7	7	88.3	4.6
23	91	55.1	23.0	6	95.3	2.5
24	91	50.8	23.0	6	89.3	4.2
25	91	39.1	17.7	6	67.8	1.3
26	91	44.3	17.7	1	70.9	.
27	91	47.8	17.5	1	74.2	.
28	91	48.2	17.5	0	.	
29	91	46.8	18.2	1	76.2	.

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Table F.1—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
30	91	47.7	18.1	2	75.8	.
31	91	51.1	18.3	2	90.1	1.5
32	91	53.5	17.9	2	99.5	13.4
33	91	54.7	17.5	3	92.4	12.2
34	91	60.1	16.2	5	94.9	9.3
35	91	65.6	17.1	6	105.7	10.2
36	91	69.5	21.5	3	139.8	52.4
37	91	69.9	20.5	6	112.2	14.9
38	91	75.3	21.0	5	119.3	16.2
39	91	82.0	27.3	1	250.6	.
40	91	87.4	39.4	1	400.6	.
41	91	82.7	21.9	3	131.1	7.0
42	91	88.9	23.2	4	142.1	19.4
43	91	98.9	39.8	4	248.3	58.6
44	91	100.1	39.3	5	221.6	70.8
45	91	84.7	20.4	4	125.7	7.4
46	91	91.9	21.5	3	143.1	7.6
47	91	97.2	23.2	4	153.5	5.6
48	91	116.8	131.4	1	1322.9	.
49	91	96.6	26.9	2	217.1	50.7
50	91	102.3	30.3	4	201.7	44.1

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Table F.1—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
51	91	110.9	49.5	4	297.3	96.6
52	91	129.1	136.5	1	1344.0	.
53	91	102.7	24.8	3	173.4	25.7
54	91	110.1	32.9	4	220.0	21.6
55	91	147.8	213.7	2	1391.4	859.3
56	91	170.4	280.6	2	1995.5	4.9
57	91	118.4	47.7	4	288.7	90.0
58	91	147.1	203.7	1	1999.0	.
59	91	186.3	306.7	3	1777.9	383.0
60	91	187.9	269.1	3	1551.7	387.4
61	91	168.2	223.3	3	1332.4	21.3
62	91	151.5	141.0	3	723.5	528.6
63	91	177.1	240.2	2	1666.2	470.6
64	91	208.4	327.4	4	1667.9	382.4
65	91	223.4	415.0	4	1975.0	890.8
66	91	197.3	268.0	3	1554.0	385.4
67	91	188.9	268.1	3	1564.9	376.1
68	91	210.0	310.1	5	1436.0	322.7
69	91	174.2	259.7	3	1499.5	440.6
70	91	163.1	238.4	2	1666.2	470.6
71	91	141.9	201.3	1	1999.0	.

continued on next page

Table F.1—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
72	91	120.7	42.9	7	223.0	42.7
73	91	177.5	296.8	3	1712.1	433.0
74	91	116.2	37.5	7	203.8	33.2
75	91	107.5	30.5	6	179.8	19.3
76	91	102.8	27.6	5	170.6	14.0
77	91	118.1	121.3	1	1227.2	.
78	91	99.4	23.4	4	143.8	10.9
79	91	94.8	22.8	4	138.8	13.8
80	91	91.7	21.5	3	132.5	4.9
81	91	107.9	131.4	1	1329.5	.
82	91	92.3	20.3	3	131.5	4.9
83	91	92.5	19.4	3	130.9	7.1
84	91	92.8	18.7	3	125.0	1.6
85	91	96.4	21.1	3	139.6	17.6
86	91	93.1	20.8	3	131.8	4.3
87	91	88.6	20.4	2	123.4	4.9
88	91	82.5	20.4	4	116.3	2.0
89	91	195.0	325.8	3	1842.2	456.8
90	91	98.7	22.9	5	145.3	12.2
91	91	90.3	19.4	2	122.6	3.6
92	91	84.4	17.8	4	112.1	0.6

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Table F.1—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
93	91	97.5	39.5	3	254.0	117.8
94	91	85.2	19.2	7	117.7	3.9
95	91	78.6	18.2	7	109.1	.
96	91	71.7	18.0	7	103.2	2.8

Table F.2—Days Selected by Interval: North Congestion Zone

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
1	91	91.3	38.6	3	252.1	83.4
2	91	80.4	19.8	6	121.1	6.5
3	91	72.3	19.8	5	111.9	5.5
4	91	67.8	20.1	4	108.4	2.1
5	91	71.9	22.4	8	116.9	5.2
6	91	69.4	21.3	7	114.4	5.8
7	91	67.6	19.2	7	108.5	6.5
8	91	65.1	18.8	8	104.1	8.4
9	91	63.8	20.7	8	106.8	9.7
10	91	60.6	21.4	8	104.9	10.9
11	91	56.9	21.1	8	99.4	7.6
12	91	54.5	20.8	8	95.1	8.1

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Table F.2—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
13	91	52.3	21.8	7	95.7	7.9
14	91	49.8	21.6	6	93.3	7.8
15	91	48.7	21.3	7	91.6	4.9
16	91	46.2	21.8	7	90.7	4.0
17	91	45.5	21.7	7	92.1	3.8
18	91	45.7	21.3	7	91.6	4.2
19	91	47.3	20.5	8	87.5	7.2
20	91	48.0	20.8	7	88.2	5.4
21	91	46.2	22.5	9	86.5	5.9
22	91	48.5	22.6	7	88.3	4.6
23	91	55.0	23.0	6	95.3	2.6
24	91	50.8	22.9	6	89.3	4.2
25	91	39.0	17.8	6	67.8	1.3
26	91	44.3	17.7	0	.	.
27	91	47.8	17.5	0	.	.
28	91	48.1	17.7	0	.	.
29	91	46.7	18.4	1	76.0	.
30	91	47.5	18.3	1	76.7	.
31	91	50.8	18.7	2	90.0	1.4
32	91	53.2	18.3	2	99.3	13.2
33	91	54.5	17.8	3	92.3	12.1

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Table F.2—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
34	91	60.1	16.2	5	94.8	9.3
35	91	65.6	17.1	6	105.7	10.2
36	91	69.5	21.5	3	139.8	52.4
37	91	69.9	20.5	6	112.2	14.9
38	91	74.9	20.7	5	119.3	16.2
39	91	81.6	27.2	1	250.6	.
40	91	87.0	39.4	1	400.6	.
41	91	82.6	21.8	3	131.1	7.0
42	91	88.6	23.0	4	142.1	19.4
43	91	98.6	39.7	4	248.3	58.6
44	91	99.8	39.3	5	221.6	70.8
45	91	83.9	20.2	5	122.4	8.8
46	91	90.5	21.5	3	143.1	7.6
47	91	94.8	22.3	4	148.7	13.0
48	91	101.4	30.7	5	195.6	30.1
49	91	94.2	27.2	2	217.1	50.7
50	91	98.8	31.4	4	201.7	44.1
51	91	106.7	49.9	4	297.3	96.6
52	91	111.5	43.7	5	252.1	53.5
53	91	100.0	24.4	4	164.9	27.1
54	91	106.0	29.4	3	209.8	8.6

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Table F.2—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
55	91	137.7	203.1	1	1999.0	.
56	91	167.3	281.0	2	1995.5	4.9
57	91	115.4	47.1	4	288.7	90.0
58	91	143.1	204.0	1	1999.0	.
59	91	168.3	282.0	2	1999.0	0.0
60	91	156.1	207.6	1	1999.0	.
61	91	123.4	55.6	5	314.4	83.6
62	91	129.6	61.0	5	339.3	76.6
63	91	154.5	206.3	1	1999.0	.
64	91	171.2	280.3	2	1999.0	0.0
65	91	154.2	203.1	1	1999.0	.
66	91	158.4	204.4	1	1999.0	.
67	91	153.3	203.7	1	1999.0	.
68	91	152.4	203.8	1	1999.0	.
69	91	141.5	202.7	1	1999.0	.
70	91	142.3	204.0	1	1999.0	.
71	91	134.7	201.4	1	1999.0	.
72	91	111.5	35.3	5	210.7	48.8
73	91	157.0	276.5	2	1961.8	52.6
74	91	109.0	33.4	4	211.9	45.1
75	91	102.0	25.4	3	168.1	37.0

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Table F.2—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
76	91	98.0	22.5	2	152.8	22.4
77	91	101.8	27.5	2	203.9	69.5
78	91	96.0	21.2	3	131.0	4.5
79	91	91.5	20.5	3	126.3	2.3
80	91	88.3	19.9	2	120.6	1.6
81	91	91.5	20.9	2	141.2	11.4
82	91	89.4	18.9	2	127.4	9.4
83	91	89.1	18.0	4	120.5	6.4
84	91	89.8	17.7	4	119.4	2.9
85	91	92.6	20.4	4	135.1	16.8
86	91	89.2	21.0	3	125.5	7.6
87	91	84.8	20.7	2	116.0	0.1
88	91	78.6	20.4	4	111.6	1.9
89	91	177.8	303.5	2	2099.5	142.1
90	91	96.5	23.2	6	143.1	12.1
91	91	88.2	19.6	4	120.2	3.4
92	91	83.2	19.1	2	112.5	0.1
93	91	95.3	40.2	3	254.0	117.8
94	91	82.9	21.3	6	118.3	3.8
95	91	76.1	20.9	6	108.9	1.2
96	91	69.2	20.8	5	104.3	2.2

Table F.3—Days Selected by Interval: South Congestion Zone

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
1	91	114.8	207.6	1	2038.4	.
2	91	82.9	22.6	6	133.8	16.5
3	91	75.3	19.7	7	113.6	6.0
4	91	70.1	20.1	6	109.8	7.6
5	91	75.7	24.2	10	123.2	14.4
6	91	71.5	22.1	10	114.7	6.5
7	91	68.5	21.1	9	113.1	10.9
8	91	65.5	19.7	9	105.8	7.9
9	91	64.1	21.2	9	106.6	9.1
10	91	60.7	21.9	9	104.7	10.1
11	91	56.9	21.5	9	99.6	7.0
12	91	54.8	21.1	9	96.3	6.9
13	91	52.6	21.9	8	96.0	6.8
14	91	50.2	21.8	7	93.1	6.7
15	91	49.0	21.3	8	90.3	5.8
16	91	46.7	21.8	7	90.7	4.0
17	91	46.1	21.7	8	91.4	4.1
18	91	45.8	21.4	8	90.0	5.9
19	91	47.4	20.6	8	87.5	7.2
20	91	48.2	21.0	6	89.6	4.3
21	91	46.3	22.7	9	86.5	5.9

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Table F.3—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
22	91	48.7	22.7	7	88.3	4.6
23	91	54.9	22.9	6	94.7	3.2
24	91	50.7	22.8	5	90.0	4.4
25	91	39.0	17.5	5	67.9	1.5
26	91	44.1	17.6	0	.	.
27	91	47.6	17.5	0	.	.
28	91	48.0	17.4	0	.	.
29	91	46.7	18.1	1	74.0	.
30	91	47.5	17.8	1	74.8	.
31	91	51.1	18.0	2	88.3	0.9
32	91	53.4	17.6	2	97.5	10.6
33	91	54.6	17.3	3	91.4	10.5
34	91	59.9	16.2	5	94.8	9.1
35	91	65.4	17.1	6	105.7	10.2
36	91	69.4	21.5	3	139.8	52.4
37	91	69.8	20.4	7	110.2	14.4
38	91	75.3	21.5	6	121.4	15.3
39	91	82.0	27.6	2	190.5	85.0
40	91	87.3	39.6	1	400.6	.
41	91	82.5	21.7	4	127.1	9.8
42	91	88.7	23.1	5	138.5	18.6

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Table F.3—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
43	91	98.8	39.9	4	248.3	58.6
44	91	100.0	39.4	5	221.6	70.8
45	91	84.9	21.0	5	129.1	6.5
46	91	92.5	22.4	5	139.7	7.2
47	91	98.6	25.4	5	158.8	18.6
48	91	127.8	226.4	1	2243.3	.
49	91	98.0	28.4	4	181.3	50.9
50	91	104.5	33.2	5	206.3	30.2
51	91	113.6	52.2	4	314.2	73.6
52	91	142.0	230.7	1	2263.5	.
53	91	104.6	26.8	5	166.8	20.9
54	91	113.1	42.3	4	254.9	90.4
55	91	155.2	237.7	2	1662.9	475.4
56	91	172.1	280.4	2	1995.5	4.9
57	91	120.2	48.9	4	293.6	83.1
58	91	150.0	204.0	1	1999.0	.
59	91	199.0	356.0	3	2084.5	148.1
60	91	211.6	370.8	3	2167.0	145.6
61	91	201.7	385.9	3	2256.6	21.5
62	91	166.9	233.3	1	2253.6	.
63	91	192.9	302.4	2	2126.3	180.0

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Table F.3—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
64	91	235.4	415.1	4	2129.4	150.6
65	91	252.7	507.7	4	2514.1	692.9
66	91	226.4	373.5	3	2169.3	147.5
67	91	215.5	371.9	3	2180.3	157.8
68	91	253.2	466.2	5	2155.8	143.3
69	91	197.7	355.1	3	2081.7	148.5
70	91	177.5	300.2	2	2126.1	179.8
71	91	146.0	202.1	1	1999.0	.
72	91	125.1	50.4	9	244.2	36.7
73	91	190.3	334.6	3	1962.9	85.1
74	91	120.1	43.2	8	221.4	30.0
75	91	110.2	35.7	6	205.0	23.5
76	91	105.1	32.3	5	189.4	36.4
77	91	130.0	206.8	1	2054.2	.
78	91	101.6	27.0	7	155.8	16.0
79	91	97.0	26.2	5	153.2	22.7
80	91	93.9	24.6	6	142.6	7.7
81	91	119.9	227.1	1	2249.4	.
82	91	94.2	23.0	8	135.7	8.7
83	91	94.7	22.9	6	140.9	15.7
84	91	94.8	21.7	6	137.7	9.2

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Table F.3—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
85	91	98.9	24.8	8	147.0	7.6
86	91	95.8	24.5	7	143.4	7.0
87	91	91.2	23.9	6	138.2	9.8
88	91	85.1	24.3	6	134.8	18.6
89	91	207.8	372.4	3	2148.9	132.0
90	91	100.3	24.2	5	148.7	9.7
91	91	91.8	20.9	2	134.1	12.7
92	91	85.2	18.4	1	121.1	.
93	91	98.9	40.3	4	230.7	106.8
94	91	86.8	20.2	4	122.8	3.6
95	91	80.2	19.0	6	114.0	6.0
96	91	73.4	18.5	6	105.4	3.3

Table F.4—Days Selected by Interval: West Congestion Zone

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
1	91	81.4	52.4	3	266.3	58.8
2	91	71.9	34.6	3	125.7	2.2
3	91	64.5	42.7	1	299.0	.
4	91	61.6	40.6	1	299.0	.

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Table F.4—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
5	91	65.4	32.7	5	119.4	4.7
6	91	62.4	32.5	5	117.2	3.8
7	91	60.1	30.8	4	113.1	4.6
8	91	55.8	33.0	3	113.4	4.0
9	91	54.0	35.2	3	117.7	5.6
10	91	50.2	35.6	4	113.4	8.7
11	91	46.4	34.5	3	108.4	1.8
12	91	43.8	33.2	5	99.9	6.0
13	91	42.5	33.3	5	99.4	5.8
14	91	42.3	31.4	4	97.7	4.8
15	91	41.4	29.9	7	91.6	4.9
16	91	38.8	30.2	7	90.7	4.0
17	91	41.6	42.4	1	326.5	.
18	91	41.7	42.2	1	326.5	.
19	91	43.1	42.2	1	326.5	.
20	91	44.3	41.9	1	326.5	.
21	91	41.3	28.5	5	90.8	4.3
22	91	43.3	28.3	4	91.2	4.0
23	91	47.8	30.9	4	96.2	2.8
24	91	43.9	30.4	2	94.6	1.4
25	91	32.4	25.9	0	.	.

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Table F.4—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
26	91	38.0	26.2	0	.	.
27	91	40.9	27.4	0	.	.
28	91	40.0	28.8	0	.	.
29	91	40.3	28.0	0	.	.
30	91	40.1	28.8	0	.	.
31	91	42.6	29.1	1	89.0	.
32	91	44.3	28.9	1	90.0	.
33	91	48.8	25.3	0		
34	91	54.1	26.5	1	97.1	.
35	91	58.4	29.7	3	112.4	10.7
36	91	63.2	31.1	2	156.6	61.6
37	91	63.8	29.1	2	127.3	20.2
38	91	68.0	30.4	3	126.3	18.4
39	91	73.0	38.7	1	250.6	.
40	91	75.5	51.0	1	400.6	.
41	91	70.8	38.3	2	133.9	7.0
42	91	76.6	40.9	2	156.8	15.8
43	91	85.1	55.1	4	248.3	58.6
44	91	84.6	56.5	3	258.8	69.7
45	91	69.8	40.9	1	133.8	.
46	91	79.0	40.7	2	147.5	0.8

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Table F.4—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
47	91	83.5	41.2	3	154.6	6.3
48	91	91.0	46.2	4	206.4	20.9
49	91	86.9	38.9	2	217.1	50.7
50	91	92.2	41.3	3	218.2	35.8
51	91	102.4	54.2	4	297.3	96.6
52	91	106.6	50.6	5	252.1	53.5
53	91	94.8	34.0	3	173.4	25.7
54	91	100.8	37.1	3	209.8	8.6
55	91	131.3	205.8	1	1999.0	.
56	91	161.4	283.5	2	1995.5	4.9
57	91	110.3	54.1	3	321.2	76.1
58	91	137.3	206.7	1	1999.0	.
59	91	163.5	284.2	2	1999.0	0.0
60	91	151.5	210.4	1	1999.0	.
61	91	119.0	65.0	6	298.4	84.4
62	91	122.8	68.7	5	339.3	76.6
63	91	147.3	209.5	1	1999.0	.
64	91	165.3	283.2	2	1999.0	0.0
65	91	149.7	206.9	1	1999.0	.
66	91	152.2	207.7	1	1999.0	.
67	91	146.9	206.6	1	1999.0	.

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Table F.4—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
68	91	150.4	205.5	1	1999.0	.
69	91	137.5	204.9	1	1999.0	.
70	91	137.0	206.2	1	1999.0	.
71	91	126.6	204.8	1	1999.0	.
72	91	103.2	47.3	4	220.1	50.9
73	91	130.5	206.9	1	1999.0	.
74	91	100.7	45.9	3	228.1	38.4
75	91	92.2	41.4	1	210.5	.
76	91	87.3	40.9	1	168.6	.
77	91	92.0	46.4	2	233.6	27.5
78	91	83.4	41.2	0	.	.
79	91	79.8	39.0	0	.	.
80	91	76.7	38.2	0	.	.
81	91	79.8	40.1	1	149.3	.
82	91	77.9	38.7	0	.	.
83	91	78.7	36.2	0	.	.
84	91	80.1	35.7	0	.	.
85	91	84.0	37.1	1	160.0	.
86	91	80.0	36.4	0	.	.
87	91	73.7	37.4	0	.	.
88	91	67.0	36.9	0	.	.

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Table F.4—Continued

	Whole Sample			Selected Sample		
Interval	Days	Mean	Std. Dev.	Days	Mean	Std. Dev.
89	91	173.3	305.5	2	2099.5	142.1
90	91	92.7	30.4	3	152.6	9.8
91	91	85.3	26.3	1	125.2	.
92	91	77.3	29.5	0	.	.
93	91	87.8	49.4	3	254.0	117.8
94	91	77.2	31.8	1	126.0	.
95	91	69.6	31.9	0	.	.
96	91	62.0	31.6	0	.	.

APPENDIX G

3-DIGIT NAICS DEFINITION

- NAICS 541: Industries in the Professional, Scientific, and Technical Services subsector group establishments engaged in processes where human capital is the major input. These establishments make available the knowledge and skills of their employees, often on an assignment basis, where an individual or team is responsible for the delivery of services to the client. The individual industries of this subsector are defined on the basis of the particular expertise and training of the services provider. The distinguishing feature of the Professional, Scientific, and Technical Services subsector is the fact that most of the industries grouped in it have production processes that are almost wholly dependent on worker skills. In most of these industries, equipment and materials are not of major importance, unlike health care, for example, where high tech machines and materials are important collaborating inputs to labor skills in the production of health care. Thus, the establishments classified in this subsector sell expertise. Much of the expertise requires degrees, though not in every case.

- NAICS 311: Industries in the Food Manufacturing subsector transform livestock and agricultural products into products for intermediate or final consumption. The industry groups are distinguished by the raw materials (generally of animal or vegetable origin) processed into food products. The food products manufactured in these establishments are typically sold to wholesalers or retailers for distribution to consumers, but establishments primarily engaged in retailing bakery and candy products made on the premises not for immediate consumption are included. Establishments primarily engaged in manufacturing beverages are classified in Subsector 312, Beverage and Tobacco Product Manufacturing.

- NAICS 325: The Chemical Manufacturing subsector is based on the transformation of organic and inorganic raw materials by a chemical process and the formulation of products. This subsector distinguishes the production of basic chemicals that comprise the first industry group from the production of intermediate and end products produced by further processing of basic chemicals that make up the remaining industry groups. This subsector does not include all industries transforming raw materials by a chemical process. It is common for some chemical processing to occur during mining operations. These beneficiating operations, such as copper concentrating, are classified in Sector 21, Mining, Quarrying, and Oil and Gas Extraction. Furthermore, the refining of crude petroleum is included in Subsector 324, Petroleum and Coal Products Manufacturing. In addition, the manufacturing of aluminum oxide is included in Subsector 331, Primary Metal Manufacturing; and beverage distilleries are classified in Subsector 312, Beverage and Tobacco Product Manufacturing. As in the case of these two activities, the grouping of industries into subsectors may take into account the association of the activities performed with other activities in the subsector.

- NAICS 621: Industries in the Ambulatory Health Care Services subsector provide health care services directly or indirectly to ambulatory patients and do not usually provide inpatient services. Health practitioners in this subsector provide outpatient services, with the facilities and equipment not usually being the most significant part of the production process.

- NAICS 424: Industries in the Merchant Wholesalers, Nondurable Goods subsector sell nondurable goods to other businesses. Nondurable goods are items generally with a normal life expectancy of less than three years. Nondurable goods merchant wholesale trade establishments are engaged in wholesaling products, such as paper and paper products, chemicals and chemical products, drugs, textiles and textile products, apparel, footwear, groceries, farm products, petroleum and petroleum products, alcoholic beverages, books, magazines, newspapers, flowers and nursery stock, and tobacco products. The detailed industries within the subsector are organized in the classification structure based on the products sold. Business to business electronic markets, agents, and brokers primarily engaged in wholesaling nondurable goods, generally on a commission or fee basis, are classified in Subsector 425, Wholesale Electronic Markets and Agents and Brokers.

- NAICS 522: Industries in the Credit Intermediation and Related Activities subsector group establishments that (1) lend funds raised from depositors; (2) lend funds raised from credit market borrowing; or (3) facilitate the lending of funds or issuance of credit by engaging in such activities as mortgage and loan brokerage, clearinghouse and reserve services, and check cashing services.

- NAICS 423: Industries in the Merchant Wholesalers, Durable Goods subsector sell capital or durable goods to other businesses. Merchant wholesalers generally take title to the goods that they sell; in other words, they buy and sell goods on their own account. Durable goods are new or used items generally with a normal life expectancy of three years or more. Durable goods merchant wholesale trade establishments are engaged in wholesaling products, such as motor vehicles, furniture, construction materials, machinery and equipment (including household-type appliances), metals and minerals (except petroleum), sporting goods, toys and hobby goods, recyclable materials, and parts. Business-to-business electronic markets, agents, and brokers primarily engaged in wholesaling durable goods, generally on a commission or fee basis, are classified in Subsector 425, Wholesale Electronic Markets and Agents and Brokers.

- NAICS 326: Industries in the Plastics and Rubber Products Manufacturing subsector make goods by processing plastics materials and raw rubber. The core technology employed by establishments in this subsector is that of plastics or rubber product production. Plastics and rubber are combined in the same subsector because plastics are increasingly being used as a substitute for rubber; however the subsector is generally restricted to the production of products made of just one material, either solely plastics or rubber. Many manufacturing activities use plastics or rubber, for example the manufacture of footwear, or furniture. Typically, the production process of these products involves more than one material. In these cases, technologies that allow disparate materials to be formed and combined are of central importance in describing the manufacturing activity. In NAICS, such activities (the footwear and furniture manufacturing) are not classified in the Plastics and Rubber Products Manufacturing subsector because the core technologies for these activities are diverse and involve multiple materials. Within the Plastics and Rubber Products Manufacturing subsector, a distinction is made between plastics and rubber products at the industry group level, although it is not a rigid distinction, as can be seen from the definition of Industry 32622, Rubber and Plastics Hoses and Belting Manufacturing. As materials technology progresses, plastics are increasingly being used as a substitute for rubber; and eventually, the distinction may disappear as a basis for establishment classification. In keeping with the core technology focus of plastics, lamination of plastics film to plastics film as well as the production of bags from plastics only is classified in this subsector. Lamination and bag production involving plastics and materials other than plastics are classified in the NAICS Subsector 322, Paper Manufacturing.

- NAICS 812: Industries in the Personal and Laundry Services subsector group establishments that provide personal and laundry services to individuals, households, and businesses. Services performed include: personal care services; death care services; laundry and drycleaning services; and a wide range of other personal services, such as pet care (except veterinary) services, photofinishing services, temporary parking services, and dating services. The Personal and Laundry Services subsector is by no means all-inclusive of the services that could be termed personal services (i.e., those provided to individuals rather than businesses). There are many other subsectors, as well as sectors, that provide services to persons. Establishments providing legal, accounting, tax preparation, architectural, portrait photography, and similar professional services are classified in Sector 54, Professional, Scientific, and Technical Services; those providing job placement, travel arrangement, home security, interior and exterior house cleaning, exterminating, lawn and garden care, and similar support services are classified in Sector 56, Administrative and Support, Waste Management and Remediation Services; those providing health and social services are classified in Sector 62, Health Care and Social Assistance; those providing amusement and recreation services are classified in Sector 71, Arts, Entertainment and Recreation; those providing educational instruction are classified in Sector 61, Educational Services; those providing repair services are classified in Subsector

811, Repair and Maintenance; and those providing spiritual, civic, and advocacy services are classified in Subsector 813, Religious, Grantmaking, Civic, Professional, and Similar Organizations.

- NAICS 722: Industries in the Food Services and Drinking Places subsector prepare meals, snacks, and beverages to customer order for immediate on-premises and off-premises consumption. There is a wide range of establishments in these industries. Some provide food and drink only; while others provide various combinations of seating space, waiter/waitress services and incidental amenities, such as limited entertainment. The industries in the subsector are grouped based on the type and level of services provided. The industry groups are full-service restaurants; limited-service eating places; special food services, such as food service contractors, caterers, and mobile food services; and drinking places. Food and beverage services at hotels and motels; amusement parks, theaters, casinos, country clubs, and similar recreational facilities; and civic and social organizations are included in this subsector only if these services are provided by a separate establishment primarily engaged in providing food and beverage services.

- NAICS 331: Industries in the Primary Metal Manufacturing subsector smelt and/or refine ferrous and nonferrous metals from ore, pig or scrap, using electrometallurgical and other process metallurgical techniques. Establishments in this subsector also manufacture metal alloys and superalloys by introducing other chemical elements to pure metals. The output of smelting and refining, usually in ingot form, is used in rolling, drawing, and extruding operations to make sheet, strip, bar, rod, or wire, and in molten form to make castings and other basic metal products. Primary manufacturing of ferrous and nonferrous metals begins with ore or concentrate as the primary input. Establishments manufacturing primary metals from ore and/or concentrate remain classified in the primary smelting, primary refining, or iron and steel mill industries regardless of the form of their output. Establishments primarily engaged in secondary smelting and/or secondary refining recover ferrous and nonferrous metals from scrap and/or dross. The output of the secondary smelting and/or secondary refining industries is limited to shapes, such as ingot or billet, that will be further processed. Recovery of metals from scrap often occurs in establishments that are primarily engaged in activities, such as rolling, drawing, extruding, or similar processes. Excluded from the Primary Metal Manufacturing subsector are establishments primarily engaged in manufacturing ferrous and nonferrous forgings (except ferrous forgings made in steel mills) and stampings. Although forging, stamping, and casting are all methods used to make metal shapes, forging and stamping do not use molten metals and are included in Subsector 332, Fabricated Metal Product Manufacturing. Establishments primarily engaged in operating coke ovens are classified in Industry 32419, Other Petroleum and Coal Products Manufacturing.

VITA

Cesar Alfredo Theodoro Cancho Diez was born in Lima, Peru, in 1978. He received his Bachelor's degree in Social Sciences with mention in Economics from the Pontificia Universidad Catolica del Peru in 2003. He was awarded the Fulbright Scholarship for doctoral studies in 2005, and entered the graduate program in Economics at Texas A&M University in August 2006. He received his Doctor of Philosophy degree in August 2012. Under the supervision of Dr. Steven L. Puller, his research interests include empirical industrial organization, applied microeconometrics, and labor economics.

Dr. Cancho may be reached at The World Bank, 1818 H Street NW, MSN MC7-703, Washington, DC, 20433, USA. His email address is ccancho@worldbank.org.