Price Stabilization Policy, Gasoline Consumption, and Health Externality: Evidence from Brazil*

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Abstract: Petroleum product price controls are often justified as a means to curb inflation and/or help the poor cope with the adverse effects of higher oil prices. Notwithstanding, a price ceiling for petroleum products may lead to negative health externalities. In this study, we examine the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and infant health across municipalities in Brazil over the period 2005-2016. To estimate the causal effects of interest, we leverage comprehensive data and an instrumental variables approach based on refinery oil prices and sugarcane quality. We have three main findings. First, gasoline consumption has become more responsive to prices over time, likely due to the diffusion of flexible-fuel vehicles. Second, gasoline consumption generates sizable negative externalities in terms of both higher local air pollution and higher pediatric hospitalization for respiratory conditions. Third, back-of-the-envelope calculations indicate that such externalities reinforce the public sector deficit generated by gasoline price stabilization policies. On the one hand, direct price control at the federally-owned oil company reduces federal corporate revenue, and fuel tax reduction lowers federal tax revenue. On the other hand, the additional pollution-driven hospitalizations are mostly paid for by the federal government through the publicly-funded universal health care system. Thus, not only federal revenue decreases, but also federal spending increases.

JEL Codes: H23, H51, I18, Q53, Q56
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1 Introduction

Petroleum product price controls are prevalent around the world. They are often justified as a means to curb inflation and/or help the poor cope with the adverse effects of higher oil prices (Kojima, 2013). Like any other price control policies – e.g., minimum wage, rent control, and agricultural price floors – a price ceiling for petroleum products may lead to reallocation, misallocation, and externalities.[1] Its effects can be even more consequential in the presence of a well-developed market for biofuels, which are less polluting substitutes.

In this study, we examine the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and infant health across municipalities in Brazil over the period 2005-2016. The Brazilian federal government has pursued gasoline price stabilization via direct price controls and federal fuel taxes. Brazil has a state-owned oil company – Petrobras – which has the monopoly on the production and imports of petroleum products. In addition, Brazil has a mature market for the biofuel ethanol, which has been developed since the 1980s, and for flexible-fuel vehicles, which were introduced in 2003 and run smoothly on gasoline and/or ethanol. Hence, there is ample opportunity for fuel substitution.

We leverage comprehensive data to obtain instrumental variable estimates of the causal effects of interest. Our data for fuel prices and fuel consumption come from a representative survey of gas stations across the nation, our pollution data come from satellite-derived particle pollution, and our health utilization data come from administrative records of the Brazilian Ministry of Health. Our instrumental variable approach builds on Levin, Lewis and Wolak (2017) and rests mostly on supply (cost)

[1] Minimum wage has been shown to lead to reallocation of workers to high-paying firms (Dustmann et al., 2022), rent control to misallocation of housing units (Glaeser and Luttmer, 2003) and externalities to neighboring units (Autor, Palmer and Pathak, 2014), and agricultural price floors to distortion of farmer behavior (Annan and Schlenker, 2015).

shifters for retail gasoline price. In fact, the main instruments are refinery (production) oil prices plus federal fuel taxes.

Our identifying assumption is that conditional on municipality, month-of-year, and state-by-year fixed effects, and additional climatic and economic control variables, our instrument only affects gasoline demand via gasoline prices, and only affects air pollution and pediatric hospitalization for respiratory illnesses via gasoline consumption. This assumption appears to be supported by auxiliary analysis showing that our instruments have relatively low predictive power for changes in municipal population, GDP, and hospital beds – which would reflect local economic conditions and amenities – conditional on our fixed effects and other covariates.

We highlight three main findings. First, gasoline consumption seems to become more responsive to prices with the diffusion of flexible-fuel vehicles. The overall price elasticity of demand for gasoline during our sample period 2005-2016 is estimated to be -1.46, but jumps from -0.90 in 2005-2009 to -2.56 in 2010-2016, when the majority of the Brazilian automobile fleet turns flex-fuel. These estimates suggest that price stabilization policies may have become more effective in altering consumer behavior more recently.

Second, gasoline consumption generates sizable negative externalities. Increases in gasoline consumption lead to both higher air pollution and higher pediatric hospitalization. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to a 0.22% increase in satellite-derived PM2.5 concentration.[2] Similarly, a 1% increase in monthly gasoline sales leads to a 1.46% increase in hospitalization rates for respiratory conditions for children aged 0 to 5 years. This translates into over 67,000 additional pediatric hospitalizations annually.

Third, the negative health externalities of gasoline consumption may reinforce the

[2] Particulate matter 2.5 (PM2.5) refers to fine particles or droplets in the air that are two and a half microns or less in width.

fiscal effects of gasoline price stabilization policies in Brazil. On the one hand, direct price control at the federally-owned oil company – Petrobras – reduces federal corporate revenue, and fuel tax reduction reduces federal tax revenue. On the other hand, about half of the additional pollution-driven hospitalizations are paid for by the federal government because of the publicly-funded universal health care system (Ministério da Saúde, 2006). Thus, not only federal revenue decreases, but federal spending also increases. It is important to point out that the hospitalization increases are smaller in poorer municipalities, as measured by an indicator for below the national median of municipal GDP. Therefore, despite generating federal deficit, price stabilization policies might lead to more equitable health outcomes.

Our study makes three main contributions to the literature. First, it contributes to the literature on the consequences of price stabilization policies – e.g., minimum wage (Cengiz et al., 2019; Dustmann et al., 2022), rent control (Autor, Palmer and Pathak, 2014; Diamond, McQuade and Qian, 2019), and agricultural price floors (Annan and Schlenker, 2015). These papers have shown evidence of the following responses: misallocation, reallocation, and spillovers. To the best of our knowledge, we provide the first analysis of vehicle fuel price stabilization policies, which are ubiquitous around the world. We show that governments may not only lose revenue because of gasoline tax reduction or direct price control, as in Brazil, but may also increase spending in publicly-funded healthcare because of potential pollution impacts on public health.

Second, our study contributes to the literature estimating the paramount price elasticity of demand for gasoline (Hughes, Knittel and Sperling, 2008; Alves and Bueno, 2013; Levin, Lewis and Wolak, 2017) and investigating vehicle fuel choices among consumers (Salvo and Huse, 2011, 2013; Salvo, 2018). The more recent literature has highlighted aggregation bias in previous work leading to the underestimation of elasticities, and the role of new technologies in making consumer responses more elastic.

We provide evidence indicating that the estimation with more granular data and the diffusion of flexible-fuel vehicles are indeed associated with larger price elasticities of demand for gasoline.

Third, our study contributes to the literature examining the impacts of transportation emissions on air pollution and health (Currie and Walker, 2011; Schlenker and Walker, 2016; Marcus, 2017; Salvo and Wang, 2017; He, Gouveia and Salvo, 2018; Alexander and Schwandt, 2022; Hansen-Lewis and Marcus, 2022). This literature has demonstrated the deleterious effects of transportation emissions, mostly in developed countries or in large cities in the developing world. We provide the first nationwide estimates of the effects of vehicle emissions on air pollution and infant health in a large developing country, where environmental quality is relatively poor and the willingness to pay for environmental improvements is relatively lower (Greenstone and Jack, 2015).

The paper proceeds as follows. Section 2 provides background information on price stabilization policies in Brazil. Section 3 introduces a conceptual framework to understand the effects of price control and taxes on the adoption of clean(er) driving and health outcomes. This framework generates negative selection in the adoption of gasoline with respect to hospitalization. Section 4 describes the comprehensive data used in the analysis, and discusses some descriptive statistics. Section 5 presents the empirical strategy based on instrumental variables. Section 6 reports and discusses the results, including robustness checks and heterogeneity analysis. Lastly, Section 7 provides some concluding remarks.

2 Background

The period 2000-2016 was eventful for fuel markets in Brazil. It witnessed the end of the legal monopoly held by Petrobras – the Brazilian state-owned refinery,[3] the introduction of a new flexible-fuel vehicle technology allowing for easy substitution between gasoline and ethanol at the pump, changes in wholesaler competition, and a series of price controls exerted by the federal government.

The end of the legal monopoly did not translate into the end of Petrobras' leadership. Instead, it motivated a series of research and development projects that led to the discovery of new oil fields, expanding Petrobras' relevance and making Brazil self-sufficient in oil production by 2005. Because of its state-owned status, Petrobras has not been free from political influences. In fact, because most of the gasoline and other fossil fuels consumed in Brazil come from Petrobras, price control has been an instrument that the federal government has used to minimize oscillations of international oil prices and keep inflation under control.

Figure 1 displays nominal prices for domestic gasoline and Brent crude oil, and how Petrobras prices remained virtually constant for long periods of time. Inflation reached 12.53% in 2002 and 9.3% in 2003, during the presidential transition from a more centrist party to the leftist Labor Party. Keeping inflation under control and close to the target imposed by the Brazilian Central Bank was crucial for the success of the new government. Thus, controlling fuel prices became a tool to isolate Brazil from external oil price oscillations.

Another source of price control is tax reduction. Figure 2 shows how federal taxes have been used to control gasoline prices. The Brazilian tax system is highly complex and some taxes generate a cascading effect. On gasoline, for instance, we have

[3] Up to 1997, Petrobras held monopoly over research, extraction, production, and refinery of petroleum in Brazil. As of 2022, Petrobras is still the major producer and refiner, responsible for around 94% of all the petroleum produced.

PIS/COFINS and CIDE (federal taxes)[4] and ICMS (state taxes).[5] While PIS/Cofins and CIDE are paid by the refinery, ICMS is applied over the final consumer prices and generates a cascade effect.[6]

It is important to point out that the federal government exerted at least two different types of price control during the period of our analysis. From 2003 to 2010, there was an indirect price policy, where the main mechanism was adjustments in federal taxes. From 2011 to 2014, the government used a more direct action by imposing a price ceiling and also an indirect control by changing federal taxes.

Figure 3 illustrates the influence of Petrobras production price and federal fuel taxes on retail gasoline price. The decomposition in the figure is for December 2012. At that time, Petrobras price represented almost 48% of the gasoline retail price, and federal fuel taxes almost 10%. Notice that anhydrous ethanol also helps determine gasoline retail price. Since the 1970s the Brazilian government has made it mandatory to blend anhydrous ethanol with gasoline.[7] In the past two decades, the blend has been kept around 25%.

On top of the direct and indirect fuel price controls, there was a key technological change in the automobile market. Figures 4 and 5 show the evolution of the Brazilian

[4]PIS (Program of Social Integration) and COFINS (Contribution for the Financing of Social Security) are federal taxes based on monthly billings of companies, defined as the turnover of sales of goods and services. PIS is intended to finance the unemployment insurance system, and COFINS to fund Social Security. CIDE (Contribution for Intervention in the Economic Domain) is an instrument of economic policy to deal with situations that may require government intervention in the economy. It can be levied in many sectors of the economy. The CIDE-fuels targets importation and commercialization of oil, natural gas, and others fuels in the internal market. It aims at financing environmental projects and transportation infrastructure, but also at providing subsidies for fuel prices and transportation.

[5]ICMS (Tax on the Circulation of Goods and Services) is a state-level value added tax applied to the commerce of any goods or services. To minimize tax evasion, the refinery is the statutory payer of the ICMS due to its goods and services and the ICMS for all other players in the chain (called ICMS-ST, for distributors and retailers in the case of gasoline).

[6]Total ICMS = Petrobras' ICMS + ICMS-ST.

[7]Ethanol raises the octane rating of unleaded gasoline, so it boosts the performance of the engine. Also, because of its high oxygen content, ethanol burns more completely than ordinary unleaded gasoline and reduces harmful tailpipe emissions.

car fleet. In 2003, the first flex-fuel vehicle (FFV) was introduced in Brazil, allowing for easy substitution between gasoline and ethanol. The main contribution of this new engine was to allow for the decision on which fuel to use to be made at the pump, instead of forcing consumers to decide it only when purchasing a new vehicle. Flex-fuel cars were being developed simultaneously by many manufacturers, which resulted in a relatively fast adoption. According to the Brazilian Association of Automotive Vehicle Manufacturers (ANFAVEA), by 2010 above 95% of the new cars produced and sold were FFV. By 2011, the FFV fleet was already larger than the gasoline-only fleet.

Regarding market structure, as a result of the Petroleum Law of 1997, in the early 2000s the Brazilian fuel market experienced a period of increasing competition in the distribution and retailer segments. This was followed by an intense concentration process by the end of the decade. There were changes in competition in both segments. In addition, up to 2019 Petrobras was the owner of the leading distributor and retailer brand called BR Distribuidora.[8] The relevance of Petrobras in all segments of the Brazilian fuel market reinforces any price policy enforced by the refinery.

Finally, there is the International Price Parity (PPI) policy enacted in 2015, at the end of the period of our analysis. This policy mandated that Petrobras would follow international oil prices to adjust domestic fuel prices. It was approved after the end of the Labor Party government to minimize political influence over Petrobras. Since the first effects of this law were felt only by the end of 2016 and beginning of 2017, we do not investigate further into this policy. But it provides context on the political pressures related to fuel markets in Brazil.[9]

[8]Petrobras owned BR Distributor until 2021, but started the process of selling its stocks in 2019.

[9]The PPI policy was abolished by the current Lula administration on May 16, 2023.

3 Conceptual Framework: Health Investment and the Adoption of Gasoline vs. Ethanol for Driving

To fix ideas and set the stage for the empirical analysis, we develop a simple model that generates selective adoption of gasoline vs. ethanol for driving. Gasoline is considered a relatively dirtier and less sustainable vehicle fuel than ethanol, both in terms of local pollution and greenhouse gas emissions (Coelho et al., 2006; Goldemberg, 2007; Goldemberg, Coelho and Guardabassi, 2008).

Suppose that health capital is a function $f(\alpha, A)$ of latent health at birth, α, and defensive investments, A, chosen by a representative individual (or by their parents). Defensive investments refer to various actions individuals can take to protect themselves from the negative effects of pollution. These investments can include avoiding outdoor activities altogether, consuming medication to attenuate the consequences of pollution exposure, or adopting practices aimed at reducing emissions during highly polluted days such as carpooling or working from home. Suppose further that $f(\alpha, A)$ is a strictly concave function with $f_\alpha(\alpha, A) > 0$, $f_A(\alpha, A) > 0$, and $f_{A\alpha}(\alpha, A) > 0$ (so the marginal value of defensive investments is higher for high latent health endowment individuals).[10] Then if w is the market return to health capital and s is the per unit cost of defensive investment, individuals maximize lifetime utility, given by

$$U(A) = wf(\alpha, A) - sA. \tag{1}$$

[10]Relatedly, Pope et al. (2015) have pointed out that although there is strong evidence that fine particulate matter (PM2.5) air pollution contributes to increased risk of disease and death, recent evidence suggests that the concentration–response function between PM2.5 and mortality risk may be *concave* across wide ranges of exposure. In their words, "[s]uch results imply that incremental pollution abatement efforts may yield greater benefits in relatively clean areas than in highly polluted areas" (p.516). Similarly, Miller, Molitor and Zou (2021) provide the first causal estimates of the concentration-response function of PM2.5 exposure, leveraging wildfire smoke that produces ground-level air quality shocks of widely varying intensity. They find that small air pollution shocks have disproportionately larger mortality effects than large air pollution shocks. Again, "[t]his *concave* concentration-response relationship points to large benefits of additional air quality improvements in the U.S. despite pollution levels being already low" (our emphasis).

Individuals choose the level of defenses that solves $wf_A(\alpha, A^*) = s$. Standard arguments lead to sensible comparative statics: $\frac{\partial A^*}{\partial w} > 0$, $\frac{\partial A^*}{\partial s} < 0$, and $\frac{\partial A^*}{\partial \alpha} > 0$.

With this basic model of health capital accumulation in mind, consider a decision of driving with gasoline vs. ethanol. Like other defenses, driving with ethanol would constitute a form of investment. In particular, consider a representative individual of a city experiencing a dirty environment (e.g., bad air quality), who needs a higher return on health capital to compensate for the environmental disamenity: $w_D > w_C$. If individuals incur the cost r of adopting cleaner driving via ethanol consumption, they would enjoy a cleaner environment (e.g., better air quality). Thus, individuals compare utility in a dirty versus a cleaner environment, i.e.,

$$U_D^* = w_D f(\alpha, A_D^*) - sA_D^*, \quad \text{and} \tag{2}$$

$$U_C^* = w_C f(\alpha, A_C^*) - sA_C^* - r, \tag{3}$$

where defensive investment is chosen optimally in each case, which for any α gives $A_D^* > A_C^*$.

This model predicts "selective adoption of gasoline vs. ethanol for driving." Let $\hat{\alpha}$ be the level of latent health endowment such that a representative individual is indifferent between adopting gasoline and ethanol, i.e., the value of α for which (2) and (3) are equal. Then individuals with latent health endowment lower than $\hat{\alpha}$ will drive with ethanol, while those with higher health endowment will drive with gasoline. This selection complicates attempts to empirically evaluate the effect of gasoline-driven pollution on individual health outcomes. Observed differences in characteristics between individuals using gasoline vs. ethanol – in terms of income, health, etc. – could be the consequence of city residents' vehicle fuel choices, but could also be due to unobserved differences in traits of adopters and non-adopters of gasoline. Within this framework, we are interested in estimating an effect that might reasonably be thought of as "the causal impact of gasoline-driven air pollution on hospitalization." In so doing, we want to allow for the possibility that hospitalization, y, is negatively related to latent health endowment or health capital more generally, both of which are unobservable.

The key to identifying causal effects of pollution is to exploit variation in fuel prices. This is a consequence from the following comparative static,

$$\frac{\partial \hat{\alpha}}{\partial r} = \frac{1}{w_C f_\alpha(\hat{\alpha}, A_C^*) - w_D f_\alpha(\hat{\alpha}, A_D^*)} < 0; \tag{4}$$

an increase in the cost of adopting cleaner driving r – say an increase in the relative price of ethanol – shifts downward the cleaner driving threshold.

To see how variation in fuel prices helps with identification, suppose that there are only two relative prices for ethanol: low and high. Let α_0 be the health endowment threshold for cleaner driving for individuals facing low relative price of ethanol and let $\alpha_1 < \alpha_0$ be the corresponding threshold for those facing high relative price. We can divide individuals into three groups. First, those whose latent health endowment level is above α_0 are "never adopters" of ethanol, who do not use ethanol even when its relative price is low. Conversely, this could be seen as the group of "always adopters" of gasoline, set A. Second, those whose latent health endowment is below α_1 are "always adopters" of ethanol, who would use ethanol regardless of high relative prices. Similarly, this could been seen as the group of "never adopters" of gasoline, set N. Finally, individuals for whom $\alpha_1 < \alpha < \alpha_0$ are "compliers," set C. This group is so named because conceptually they are people who "comply" with the proposed instrument – adopt gasoline if its relative price is low, but adopt ethanol if the relative price of gasoline is high.

Now let $D = 1$ designate a representative individual's decision to adopt gasoline for driving and $D = 0$ the decision to adopt ethanol. Let $y_{D=1}$ be the hospitalization status for an individual if she uses gasoline, while $y_{D=0}$ is the hospitalization status if she uses ethanol – noting that one of these is observed, while the other is an unknown counterfactual. Notice that we are considering the behavior of a representative individual; hence, the choice reflects adoption of gasoline vs. ethanol at a city level. We can estimate $E(y_{D=1}|A)$ and $E(y_{D=0}|N)$, respectively, by means $\bar{y}_{D=1,Z=0}$ and $\bar{y}_{D=0,Z=1}$, where $Z = 1$ indicates low relative price of gasoline and $Z = 0$ high price. Remarkably, simple algebra shows that we can recover both $E(y_{D=1}|C)$ and $E(y_{D=0}|C)$, under the following assumptions: the relative price of gasoline, $Z \in \{0, 1\}$, induces some individuals to adopt gasoline for driving who otherwise would have not adopted (as predicted by our model), and it is statistically independent of $(y_{D=1}, y_{D=0})$.

The Wald estimator $\frac{\bar{y}_{Z=1}-\bar{y}_{Z=0}}{\bar{D}_{Z=1}-\bar{D}_{Z=0}}$ for $E(y_{D=1} - y_{D=0}|C)$ recovers an estimate of the "local average treatment effect (LATE)" (Imbens and Angrist, 1994; Angrist, Imbens and Rubin, 1996). The term "local" emphasizes the fact that the estimate pertains to a particular subset of the population, and the term "treatment effect" refers to the impact of gasoline-driven air pollution. Indeed, as clarified by our theoretical setup, our estimate applies to the middle-health endowment group only; impacts might differ for higher- and lower-endowment individuals. Furthermore, the estimated effect includes the impact of behavioral responses made in anticipation of adoption of gasoline for driving (e.g., increased defensive investments in some margins). Lastly, if adopters are negatively selected into gasoline consumption, the LATE estimate will be *larger* than the corresponding OLS coefficient of the regression of hospitalization on gasoline sales.

Because we will be using a continuous instrument, the probability of adopting gasoline for driving $p(z) = E[D|Z = z]$ is also a continuous function of z. In this case, we use infinitesimal changes in the adoption probability to uncover LATE. Heckman (1990), Heckman and Vytlacil (1999, 2001), and Carneiro, Heckman and Vytlacil (2003) use a selection model to interpret such a marginal effect. In this case, adoption of gasoline for driving is a function of Z and unobservable component λ. That is, $D = 1$

if $g(z) - \lambda \geq 0$, and $D = 0$ otherwise.

Under the usual instrumental variable assumptions, the latent model implies that we can rank individuals according to the unobservable component. If such component for individual i is smaller than for individual j (i.e., $\lambda_i < \lambda_j$), then $D_i(z) \geq D_j(z)$ for all z. Given this ranking, we can define the marginal treatment effect (MTE) conditional on λ as $\beta(\lambda) = E[y_{i,D=1} - y_{i,D=0}|\lambda_i = \lambda]$. This effect relates directly to the limit of the LATE defined for values of λ such that there exists a value z that satisfies $g(z) = \lambda$. That is, $\beta(\lambda) = \beta(z)$ for $g(z) = \lambda$.

To understand this parameter as LATE, let's consider the simpler case where $g(Z)$ is a linear function of Z. In this case, the LATE estimator for two points in the distribution of z can be expressed as

$$\beta^{LATE}(z, z^*) = \frac{E[y|Z = z] - E[y|Z = z^*]}{E[D|Z = z] - E[D|Z = z^*]}, \tag{5}$$

and we can think of the MTE as the LATE estimator when z gets arbitrarily close to z^*. That is,

$$\beta^{MTE}(z) = \frac{\partial E[y|Z = z]}{\partial E[D|Z = z]}. \tag{6}$$

4 Data

We use three main sources of data to estimate the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and infant health across municipalities in Brazil from 2005-2016.

Fuel market data are provided by the National Petroleum Agency (ANP). Price data are collected weekly through surveys of a rotating sample of gas stations in representative cities across Brazil. The survey covers a total of 555 cities, including state capitals and the Federal District, and represents approximately 70% of Brazil's annual gasoline consumption. The data obtained includes retail prices, wholesale distribution prices, and Petrobras refinery prices categorized by state.[11] All data have been deflated. Additionally, the survey captures information such as the date of the survey and the brand of the gas station. Volume data are sourced from self-reported sales by wholesale distributors, allowing for identification at the city and month level. To visualize the sample, Figure 6 illustrates the geographical distribution of all 555 municipalities included in our study, along with the respective annual gasoline volumes for 2015.

Health data come from the SUS Department of Informatics (DATASUS), the Ministry of Health's agency responsible for gathering information from all publicly-funded healthcare providers. There is universal health coverage in Brazil. We obtained detailed data on hospitalizations of children aged 0 to 5 years, with any respiratory illnesses.[12] We also obtained patient demographics – age, gender, city of residence, etc. – and the costs associated with hospitalizations and other treatments.

Air pollution and climatic data come primarily from the Global Modeling and Assimilation Office (GMAO) and Goddard Earth Sciences Data and Information Services Center (GES DISC). They provide particulate matter (PM 2.5) data and other atmospheric information (temperature, precipitation) using satellite data (MERRA-2).

Regarding control variables, GDP and population come from the Brazilian Institute of Geography and Statistics (IBGE). Research centers such as UNICA/CEPEA/ESALQ have provided information on ethanol and sugar prices. We have also obtained commodity prices from the International Monetary Fund (IMF), and U.S. gasoline prices from the U.S. Energy Information Administration (EIA).

[11] Petrobras is the major producer of gasoline in Brazil, refining around 98% of all gasoline consumed. Its price policy is set according to the state of the distributor and type of transportation.

[12] The list of respiratory illnesses includes asthma, bronchitis, pneumonia, rhinitis, sinusitis, tuberculosis, influenza, among others. Many respiratory illnesses can be treated without the need for hospitalization. Thus, our estimates should be seen as a lower bound for the true impact of PM 2.5 on infant health, because we are only considering the cases when hospitalization was necessary.

For the instruments used in the analysis, we gathered Petrobras producer prices, federal fuel taxes, and a measure of sugarcane quality. Producer price has wholesaler-level variability, comprising a total of 18 states and 38 wholesaler centers. We used average price by state, averaging from neighboring states when a specific state does not receive fuel directly from Petrobras. Sugarcane quality is a measure of sugarcane crop potential. To assess the quality of the sugarcane production, we used a measure of the total recoverable sugar (ATR, in Portuguese) that evaluates the monetary potential of each crop production according to the quality of their energy content. It represents the total value of sugar production – sucrose, glucose, and fructose – that can be transformed either into sugar or ethanol. Sugarcane production data come from the National Supply Company (CONAB), a public company under the Brazilian Ministry of Agriculture. The ATR information comes from the National Association of Bioenergy (UDOP). To create the measure of sugarcane quality, we obtained total crop by state, adjusting by each region seasonality, and three distinct sugarcane quality prices: from Northern Brazil (Alagoas), Center (São Paulo), and Southern Brazil (Paraná).

Regarding summary statistics, the bottom of Table 1, Panel A, shows that the average monthly gasoline and ethanol sales for the 555 municipalities in our sample are 3.74 and 1.44 million liters, respectively. The share of gasoline sales increased slightly from 2005-2009 to 2010-2016, but remained around 70%. The average monthly pediatric hospitalization rate per million population is 215.32. Hospitalization rate is measured as the number of hospital admissions for respiratory illnesses for children aged 0 to 5 years per million population. The average monthly PM2.5 from the satellite-derived data is $8.6\mu g/m^3$, ranging from 2.4 to 240.5 $\mu g/m^3$. For comparison, the average satellite-derived PM2.5 concentration in China over the period 1990-2019 was about $25\mu g/m^3$, peaking at $28.9\mu g/m^3$ in 2010 (Yin, 2021). For India, the decadal satellite-derived PM2.5 concentration was $23.51\mu g/m^3$ in 1990, $34.38\mu g/m^3$ in 2000,

$37.76\mu g/m^3$ in 2010, and $44.91\mu g/m^3$ in 2021 (Kumar et al., 2023). For the United States, the satellite-derived PM2.5 concentration dropped from $9.2\mu g/m^3$ in 2003 to $7.5\mu g/m^3$ 2012 (Di et al., 2016).[13]

5 Empirical Strategy

In order to quantify the extent to which gasoline price control may worsen the negative externalities of pollution and the fiscal standing of the federal government, we proceed in three steps. First, we estimate the price elasticity of demand for gasoline to assess the responsiveness of consumers to gasoline prices. Second, we estimate the effect of gasoline consumption on air pollution, as measured by satellite-derived particulate matter. Third, we estimate the impact of gasoline consumption on pediatric hospitalizations due to respiratory illnesses.

Our ultimate goal is to quantify the fiscal effects of the price control policy. The federal government is a majority shareholder of Petrobras – the petroleum monopolist in Brazil – and funds the Sistema Único de Saúde (SUS) – Brazil's national health system that reaches universal health coverage. Armed with the price elasticity of demand, we can assess how much the gasoline price control affects gasoline consumption. Then, we can plug the estimated change in gasoline consumption in the other estimated equations, and measure the effects on air pollution and pediatric hospitalization. We are then able to quantify the loss of revenue from the price control policy, plus the increased health expenditures due to higher pollution.

[13] van Donkelaar et al. (2016) compares the satellite-derived PM2.5 concentrations across the globe in 2010. They report, for example, $59.8\mu g/m^3$ in East Asia, $58.3\mu g/m^3$ in South Asia, $15.1\mu g/m^3$ in Western Europe, $8.5\mu g/m^3$ in Latin America, and $7.9\mu g/m^3$ in the United States and Canada.

5.1 Estimating the price elasticity of demand for gasoline

We use an instrumental variables approach to estimate the price elasticity of demand for gasoline. The estimating equation is

$$ln(Q_{it}^{G}) = \alpha + \eta_{G} ln(P_{it}^{G}) + \eta_{E} ln(P_{it}^{E}) + X_{it}\gamma + \theta_{i} + \delta_{t} + \phi_{sy} + \epsilon_{it}, \quad (7)$$

where Q_{it}^{G} denotes gasoline consumption for municipality i in month-of-sample t, P^{G} the price of gasoline, and P^{E} the price of ethanol. Ethanol is a close substitute to gasoline in Brazil, especially after the introduction of flex-fuel vehicles (FFV), which has given drivers the option to choose the fuel at the pump. X represents the following control variables: ln(GDP), ln(population), and climatic variables (minimum and maximum temperatures, and precipitation). θ_{i} represents a set of municipality fixed effects, δ_{t} month-of-sample fixed effects, ϕ_{sy} state-by-year fixed effects, and ϵ_{it} the error term.

The main parameter of interest is η_{G}, the price elasticity of demand for gasoline, which is expected to be negative. The cross-price elasticity regarding ethanol, η_{E}, will be positive if gasoline and ethanol are substitutes, as expected, or negative if they are complements.

We instrument the price of gasoline with the Petrobras production price plus federal fuel taxes. Petrobras delivers gasoline at different prices for the 27 Brazilian states, primarily due to transportation costs, so gasoline price varies by state s and month-of-sample t. We use Petrobras refinery prices because of the political control that the Brazilian federal government has over their pricing policy. Also, there is considerable variation in federal fuel taxes over time, as displayed in Figure 2. Under the assumption that the state variation in Petrobras prices plus federal taxes is relatively unaffected by temporary city-specific demand fluctuations, using this IV approach helps eliminate any remaining endogeneity generated by the correlation between city-level prices and local demand shocks. This identification strategy builds on Levin, Lewis and Wolak (2017), who use spot market (wholesale) gasoline prices from three large regional refining centers (New York Harbor, the Gulf Coast, or Los Angeles) as instruments for local retail prices.[14]

Notice that we do not model the change in technology induced by the introduction of FFV, but instead focus on the change of elasticities along that transition. Having been introduced in 2003, many car manufacturers rapidly switched production to FFV, partially motivated by tax incentives and subsidies to diffuse the new technology. Consumer adoption happened organically, buying FFV when they were on the market for new cars. The Brazilian fleet was over 50% FFV already in 2010, as shown in Figure 5. Based on this, we will explore the heterogeneity of our results regarding two periods – 2005-2009 and 2010-2015 – to understand how elasticities evolved as FFV became the majority of the fleet.

The flex-fuel engine changed consumers' decision making process by allowing the choice of fuel to happen at the pump rather than when they purchase a new car. This change has implications for fuel substitutability. Consumers do not need to lock-in to a durable and expensive asset to reap the savings of the best cost-benefit fuel.

Yet, the efficiency of gasoline and ethanol is not the same. Ethanol contains about one-third less energy than gasoline. Ethanol prices must be equal or lower than 70% the gasoline prices for consumers to benefit from its use. More recent engines and changes in the composition of gasoline have raised that threshold to roughly 75%. Under this scenario, we expect a considerable increase in the price elasticities of demand due to the increase in fuel substitutability.[15]

[14] Other previous work has used as instruments wholesale prices (Cuiabano, 2018; Anderson, 2012), diesel, kerosene, and oil prices (Dahl, 1979; Ramsey, Rasche and Allen, 2011), disruptions in supply (Coyle, DeBacker and Prisinzano, 2012), and changes in gasoline tax (Davis and Kilian, 2011).

[15] Previous studies have estimated price elasticities for the demand of gasoline in Brazil to range from approximately -0.6 to -0.4. Cuiabano (2018) examined a collusion among retailers in the southern cities of Londrina and Cambé using monthly data from 2007 to 2009, and found a price elasticity of

For the price of ethanol, we use as instrument the regional value of the total recoverable sugar (ATR, in Portuguese) – sucrose, glucose, and fructose – from the sugar cane production. ATR is a measure of sugarcane quality, which depends on weather, soil quality, fertilizers, and other production inputs. In Brazil, ethanol is made out of sugar cane, so its distillation competes directly with sugar production. Like in Levin, Lewis and Wolak (2017), we have monthly variation in ATR value from three regions: Northern Brazil (Alagoas), Center Brazil (São Paulo), and Southern Brazil (Paraná).

5.2 Estimating the impacts of gasoline consumption on air pollution and pediatric hospitalization

We use a similar instrumental variables approach to estimating the extent of the negative externalities of gasoline consumption. For the impacts on air pollution and pediatric hospitalization, this is the estimating equation:

$$ln(Y_{it}) = \alpha + \beta ln(Q_{it}^G) + X_{it}\gamma + \theta_i + \delta_t + \phi_{sy} + \epsilon_{it}, \tag{8}$$

where Y_{it} represents satellite-derived PM2.5 or pediatric hospitalization in municipality i in month-of-sample t. Q^G denotes gasoline consumption, and X represents ln(GDP), ln(population), hospital beds per 1 million population, and climatic variables (minimum and maximum temperatures, and precipitation).[16] θ_i represents a set of municipality fixed effects, δ_t month-of-sample fixed effects, ϕ_{sy} state-by-year fixed effects, and

-0.57. Her sample is small, and may not be representative for all cities in Brazil. Alves and Bueno (2013) estimated an elasticity of -0.46 using co-integration and error-correcting models and annual aggregated data from 1984 to 1999. Although more comprehensive, their study does not account for the introduction of FFV in 2003, and uses aggregated data, which has been shown to make elasticities more inelastic (Levin, Lewis and Wolak, 2017).

[16] In robustness checks, we also control for ethanol consumption and the results are relatively similar. We do not add ethanol to our main specification because it does not seem to affect air pollution levels (PM2.5 and ground-level ozone) when both gasoline and ethanol are included in the same equation, as reported in Appendix Table B.1. Furthermore, gasoline and ethanol consumption have a high positive correlation (0.815), which could generate multicollinearity issues.

ϵ_{it} the error term.

Following the same strategy from the estimation of price elasticity of demand for gasoline, we instrument gasoline consumption by the state-level Petrobras gasoline price plus federal fuel taxes. Our identification assumption is that the instrument would affect PM2.5 or pediatric hospitalization only through gasoline consumption.[17] Because gasoline prices could affect local economic activity more broadly, we control for municipal GDP and population, as mentioned above. These variables should capture several dimensions of local economic shocks.

It is important to recognize the challenge of identifying the impact of gasoline consumption on pediatric hospitalization only through its effect on fine particle pollution. The concentration of one air pollutant is usually highly correlated to the concentration of a number of other pollutants. The use of fine particle pollution (PM2.5) as our main pollution variable, however, should address some of those issues because it represents a variety of pollutants. As explained by EPA, particulate matter is a mixture of solid particles and liquid droplets found in the air. These particles come in many sizes and shapes and can be made up of hundreds of different chemicals. Some are emitted directly from a source, such as construction sites, unpaved roads, fields, smokestacks, or fires. Most particles, however, form in the atmosphere as a result of complex reactions of other chemicals such as sulfur dioxide (SO2) and nitrogen oxides (NOx), which are pollutants emitted from power plants, industries, and automobiles. Notwithstanding, we provide evidence that gasoline consumption may affect ground-level ozone as well, but decreasing rather than increasing its concentration.[18]

[17]This assumption seems backed by additional analysis, presented in Appendix Table B.2, indicating that our instruments exhibit relatively limited predictive capability concerning shifts in municipal population, GDP, and hospital bed counts. The first stage F-statistics are just a fraction of the F-statistic from our main analysis, which is reported in the first column. These factors typically mirror local economic circumstances and amenities, conditional on the fixed effects and other variables.

[18]This evidence is consistent with Salvo and Geiger (2014), who show that ground-level ozone concentrations fell by about 20% as the share of flex-fuel vehicles burning gasoline rather than ethanol rose from 14 to 76%. A similar pattern is found in Salvo and Wang (2017): increased ethanol use in

6 Results

We present the results in four parts. First, we report the estimates of the price elasticity of demand for gasoline. Second, we present the estimated impacts of gasoline consumption on air pollution and pediatric hospitalization. Third, we discuss the fiscal implications of gasoline price stabilization policies. Lastly, we discuss some distributional impacts of price controls.

6.1 Price elasticity of demand for gasoline

Table 1, Panel A, column 2, reports the IV estimated price elasticity of demand for gasoline of approximately -1.46.[19] In column 1, the OLS estimate is slightly smaller (-1.19), but we cannot rule out it is identical to the IV estimate. Prior studies have focused on different locations and time periods, have used different methodologies, and have reported estimates ranging from about -0.5 (Alves and Bueno, 2013, time series analysis for Brazil over the period 1974-1999) to about -3.0 (Salvo, 2018, price field experiment in Sao Paulo from May 2011 to March 2012).

The price elasticity of gasoline seems to have increased over our sample period 2005-2016. In column 3, the estimate for the earlier period 2005-2009 drops by about 40%. In column 4, the estimate for the later period 2010-2016 is closer the largest elasticity reported in the literature. Recall that about half of car fleet in Brazil was FFV in 2010. Having the option to choose the fuel at the pump appears to have increased consumer sensitivity to gasoline prices.

The cross-price elasticity of demand regarding ethanol is estimated to be relatively

the gasoline-ethanol vehicle fleet leads to higher ozone concentrations in urban Sao Paulo's ambient air. Interestingly, however, they find no significant relationship between ethanol versus gasoline use and PM2.5 levels.

[19] Our main analysis uses an unbalanced panel of municipalities, but results are similar if we restrict our sample to a balanced panel (about 30% of our main sample), as reported in Appendix Table A.1.

low. Focusing on the estimate in Panel A, column 2, a 1% increase in ethanol prices increases demand for gasoline by 0.44%. Once more, we cannot rule out that the OLS estimate is identical to the IV estimate. Since ethanol and gasoline are primarily substitutes, a positive sign for the cross elasticity is expected. Although its value is slightly lower than the estimate of 0.48 reported by Alves and Bueno (2013), it seems to have increased over time as well.

The instruments generate relatively strong first stages for gasoline and ethanol prices in the main model, as reported in Panels B and C, respectively. The first stage F-statistic is close to 18 for the whole sample period, but falls below 10 for the subperiods 2005-2009 and 2010-2016. In Appendix Table A.2 we report estimates using alternative instruments such as Petrobras prices aggregated by region and sugar export prices. All price elasticities remain numerically similar and statistically the identical. Our choice for the preferred instruments was due to greater data variability across the country.

The first column in Table 1, Panel B, shows that the Petrobras gasoline price – which is a state-level price that includes production costs, federal fuel taxes, and transportation costs – affects retail gasoline price positively. A 1% increase in Petrobras price increases the retail price by 0.44%. Likewise, in the first column of Panel C, sugarcane quality – which depends on weather, soil quality, fertilizers, and other production inputs – affects gasoline retail price positively as well. This is not surprising because, as shown in Figure 3, ethanol is added to gasoline for the retail market. A 1% in sugarcane quality increases gasoline retail price by approximately 0.02%.

Appendix Tables A.3 and A.4 reveal a similar pattern for the price elasticity of demand for ethanol. The estimate for the whole period of analysis is -1.95, but increases from -1.58 in 2005-2009 to -3.50 in 2010-2016. For comparison, Salvo (2018) reports estimates of up to -4.1 for his field experiment across four large cities in Brazil over the period May 2011 to March 2012. In contrast, the cross-price elasticity regarding gasoline is much larger, but still increases over time.[20]

Appendix Table A.6 shows that only a small portion of the more elastic demand for gasoline could be attributable to aggregation bias (Levin, Lewis and Wolak, 2017). The estimate of the price elasticity of demand for gasoline drops from -1.46 to -1.21 in Panel A, when we switch from analysis at the city-by-month to state-by-month level. We cannot rule out that they are statistically the same. This finding reinforces the prominence of FFV as a technological innovation that fostered fuel substitutibility and, consequently, more sensitive responses by consumers. Notice, however, that there does not seem to be aggregation bias for the cross-price elasticity regarding ethanol.

Gasoline and ethanol are not one-to-one substitutes because they differ in energy efficiency. When the price of ethanol is approximately 70% of the price of gasoline, the price of both fuels for a unit of energy are equivalent. Below this cutoff, ethanol has a better benefit-cost ratio. To test for consumer sensitivity to different prices, we perfomed additional tests.

Table 2, columns 2 and 3, show that consumers in poorer municipalities in Brazil – those below the national GDP median – are more sensitive to gasoline and ethanol prices. The interaction effects reinforce the absolute value of our main estimates for the price elasticity of demand for gasoline and the cross-price elasticity regarding ethanol, reproduced in column 1 for comparison.

Column 4 reports how the price elasticity varies if the price ratio of ethanol and gasoline falls into different quartiles of the distribution of relative prices. We observe a strong impact (-2.35) when ethanol has a better benefit-cost ratio (first quartile), a slightly inelastic impact when both are approximately equivalent (-0.95 between

[20]Both gasoline and ethanol price elasticities of demand are estimated to be similar if we consider simultaneous estimation using a seemingly unrelated regression (SUR) approach, as reported in Appendix Table A.5.

quartiles 1 and 4), and somewhat inelastic, though not statistically significant, when gasoline has a better benefit-cost ratio (-0.21, fourth quartile).

Results presented in column 5 follow a similar pattern. That column reports estimates regarding the gap between gasoline and ethanol prices instead of the quartiles of the relative price distribution. When the difference between gasoline and ethanol prices is large, the gasoline price elasticity is relatively elastic (-1.89). When that difference decreases, the elasticity drops to -0.83, becoming relatively inelastic.

6.2 Impacts of gasoline consumption on air pollution and pediatric hospitalization

Table 3 highlights the links between gasoline consumption, pollution concentration, and pediatric hospitalization.[21] Panel A reports a sizable response of pediatric hospitalization for respiratory illnesses to gasoline consumption. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to roughly a 1.46% increase in hospitalization rates for respiratory conditions for children aged 0 to 5 years.[22] The average monthly gasoline sales in a typical municipality is about 9.4 million liters, so a 1% change means about 94,000 liters (or 25,000 gallons). The first stage is strong, with an F-statistic of the gasoline instrument of about 416. The OLS estimate is considerably smaller, consistent with the negative selection in the adoption of gasoline vs. ethanol for driving. Recall that our simple model predicted that gasoline adopters would be negatively selected into gasoline consumption, and the LATE estimate would

[21]This table presents results arising from our preferred specification without including ethanol consumption in the right-hand side. Again, this choice was guided by evidence pointing to gasoline consumption as the main driver of local pollution in a horse race with ethanol consumption, as shown in Appendix Table B.1. Nevertheless, the results are remarkably similar if we control for ethanol in our main specification, as reported in Appendix Table B.3.

[22]This estimate is remarkably stable as we include control variables one by one, as reported in Appendix Table B.4. Also, in Appendix Table B.5, we present separate estimates for children under 1 and children 1 to 5 years old. The main results for hospitalization and gasoline are somewhat similar, but the results for hospitalization and pollution seem to be driven by children aged 1 to 5 years.

be larger than the OLS estimate.

Panel B of the same table reports considerable impacts of gasoline consumption on air pollution. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to a 0.22% increase in satellite-derived PM2.5 concentration. The first stage is also relatively strong, with an F-statistic of the gasoline instrument of about 69. The OLS estimate is also smaller than the IV estimate. This pattern is not surprising. Recall that our simple model predicted higher defensive investments (e.g., carpooling) when the air quality is bad. That generates a negative omitted variable bias. Table 4 reveals that most of the impacts on pediatric hospitalization are driven by asthma, bronchitis and pneumonia. Acute exacerbation of these illnesses have been linked to exposure to air pollution.

If a change in PM2.5 concentration is the only channel through which gasoline consumption affects hospital admissions for respiratory conditions, Panel C of Table 3 shows that a 1% increase in PM2.5 concentration increases pediatric hospitalization by about 0.28%.[23] This is a nontrivial effect. It is comparable to the magnitude of elasticity of infant mortality to total suspended particulates (TSP) estimated by Chay and Greenstone (2003) for the United States over the period 1980-1982. These authors find that a 1% reduction in TSP results in a 0.35% decline in the infant mortality rate at the county level.

6.3 Fiscal impacts of gasoline price stabilization policies

When the federal government uses gasoline price stabilization policies, there are sizable revenue losses. Notwithstanding, they have been used prominently in Brazil in

[23] Appendix Table B.1 provides evidence that there may be a trade-off between PM2.5 and ambient ozone as a consequence of gasoline use. These estimates are consistent with results from Salvo and Geiger (2014) and Salvo and Wang (2017), which show a reduction in ozone concentrations in the metropolitan area of Sao Paulo due to a shift from ethanol to gasoline use. On the other hand, Salvo and Wang (2017) find no significant relationship between ethanol versus gasoline use and PM2.5 levels.

the past two decades. Prices at the refinery have been controlled, and federal taxes have been lowered to keep prices stable.

Based on our estimated price elasticity of demand for gasoline, a 10% price reduction implies a 3.5 billion (2020 Reais) loss of federal revenue per year.[24] This loss is equivalent to about 20% of the budget allocated to the Brazilian Ministry of Transportation.[25] To make it easier to understand, a 10% of gasoline price implies an increase in gasoline consumption of about 9.3 liters (2.5 gallons) per family per month.[26]

Federal gasoline price stabilization policies also reduce state tax revenue. The ICMS (Tax on the Circulation of Goods and Services) is a state-level sales tax imposed on the commerce of goods and services. For gasoline, its calculation is based on the average retail price, surveyed biweekly by ANP, the Brazilian National Agency of Petroleum, Natural Gas, and Biofuels. Thus, the ICMS calculation includes the price at the refinery and the federal taxes. Any price reduction implemented at the federal level will have implications for state tax revenue.

The federal government does not only lose Petrobras corporate revenue and tax revenue, but also increases spending due to the negative health externalities of pollution. There is a publicly-funded healthcare system in Brazil, which covers all treatments, including surgeries and medications. For children aged 0 to 5 years – a subgroup of the population that is disproportionately sensitive to pollution and the focus of our analysis – hospitalizations rates for respiratory illnesses increase. Indeed, we have shown that higher gasoline consumption because of the price stabilization policies leads to increases in PM2.5 concentration.

[24]This calculation uses 2015 prices as the baseline prices, and considers $0.26 reais per liter for PIS/COFINS and $0.54 reais per liter for CIDE.

[25]See budget for 2012-2022 at https://www.gov.br/transportes/pt-br/assuntos/dados-de-transportes/bit/bit-publicacoes.

[26]A 10% reduction in the price of gasoline is not unreasonable. Comparing the price in December 2022 to December 2021, for example, there was a reduction of federal fuel taxes of $0.69 reais per liter, which corresponds to a reduction of 10.2% in the price per liter.

Based on our estimated hospitalization impacts, a 10% increase in monthly gasoline consumption in a typical Brazilian municipality leads to 67,350 additional pediatric hospitalizations for respiratory illnesses per year. This corresponds to a 26% increase in annual pediatric hospitalizations for respiratory conditions. At the average cost of hospitalization for those conditions, the additional expenditure is roughly 66.35 million (2020 Reais), representing approximately 6% of the budget allocated to the Brazilian Ministry of the Environment.[27]

6.4 Distributional impacts of gasoline price stabilization policies

Price control policies are often justified as a means to help the poor balancing their budget because of higher gasoline prices. But those policies may backfire, and disproportionately harm the poor. The car fleet might be older and more polluting among the poor. Thus, the additional gasoline consumption resulting from price controls might disproportionately increase pollution in poorer municipalities. As a consequence, hospitalization rates might be higher in those locations as well. Because of these trade-offs, this is an empirical question.

Table 5 reveals that pediatric hospitalization rates for respiratory illnesses are lower in poorer municipalities. The coefficient of the interaction between gasoline consumption and the indicator for municipal per capita GDP below the median is negative and statistically significant.[28]

One potential explanation for this pattern is the relatively lower level of gasoline consumption overall and per capita in poorer municipalities. As Panels B and C report, the average overall gasoline consumption in municipalities with per capita GDP

[27] See budget for 2010-2017 at https://antigo.mma.gov.br/mma-em-numeros/orçamento.html.

[28] As reported in Appendix Table B.6, the pattern of results is similar when we break down the analysis for children under 1 and children 1 to 5 years old.

below the median is less than a fourth of the municipalities above the median. In per capita terms, gasoline consumption is about half in poorer relative to richer municipalities. This pattern appears to spill over exposure to air pollution. Average PM2.5 concentration is about a fourth in poorer relative to richer municipalities.

7 Concluding Remarks

This study has examined the impact or gasoline price stabilization policies on fuel consumption, local air pollution, and pediatric hospitalization for respiratory conditions. We have estimated a rather elastic consumer response to gasoline prices – particularly in more recent years – which makes price control and tax reduction quite effective in altering fuel consumption patterns in Brazil. These policies can meaningfully shift consumption away from ethanol, the biofuel that competes closely with gasoline due to the widespread adoption of flexible-fuel vehicles.

We have also found that higher gasoline consumption leads to both higher fine particle pollution and higher pediatric hospitalization rates for respiratory conditions. These results suggest that fuel price stabilization policies generate nontrivial negative externalities from the transportation sector.

Taken these findings together, public sector deficits are likely to emerge from fuel price stabilization policies. Price control and tax reduction should decrease federal revenue from gasoline sales. Additional pollution-driven hospitalizations should increase federal spending, because they are covered by a publicly-funded universal health care system in Brazil. Therefore, the fiscal standing of the federal government should deteriorate with the implementation of those policies.

Two lessons could be drawn from the impacts of the Brazilian fuel price stabilization policies. First, fuel tax reduction to ease inflationary pressures on the poor may backfire. In the United States, for example, research has shown that transportation emissions can deteriorate public health (Currie and Walker, 2011; Knittel, Miller and Sanders, 2016; Schlenker and Walker, 2016; Marcus, 2017; Alexander and Schwandt, 2022; Hansen-Lewis and Marcus, 2022). Because individuals may take defensive actions to either avoid or remediate the consequences of exposure to pollution, their household finances may be affected. Moreover, to the extent that the the poor and the elderly are covered by Medicaid or Medicare, respectively, the additional spending by the federal and state governments may deteriorate their fiscal standing.

Second, fuel price stabilization policies may favor petroleum over alternative sources of energy in transportation. In Brazil, where most cars can run on gasoline and ethanol, those policies may induce substitution away from the most important biofuel in the country. In other settings, the alternative may be electricity or natural gas, for example. If society wants to transition to cleaner energy sources as fast as possible, such trade-offs should be considered in the policy debate.

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Figures and Tables

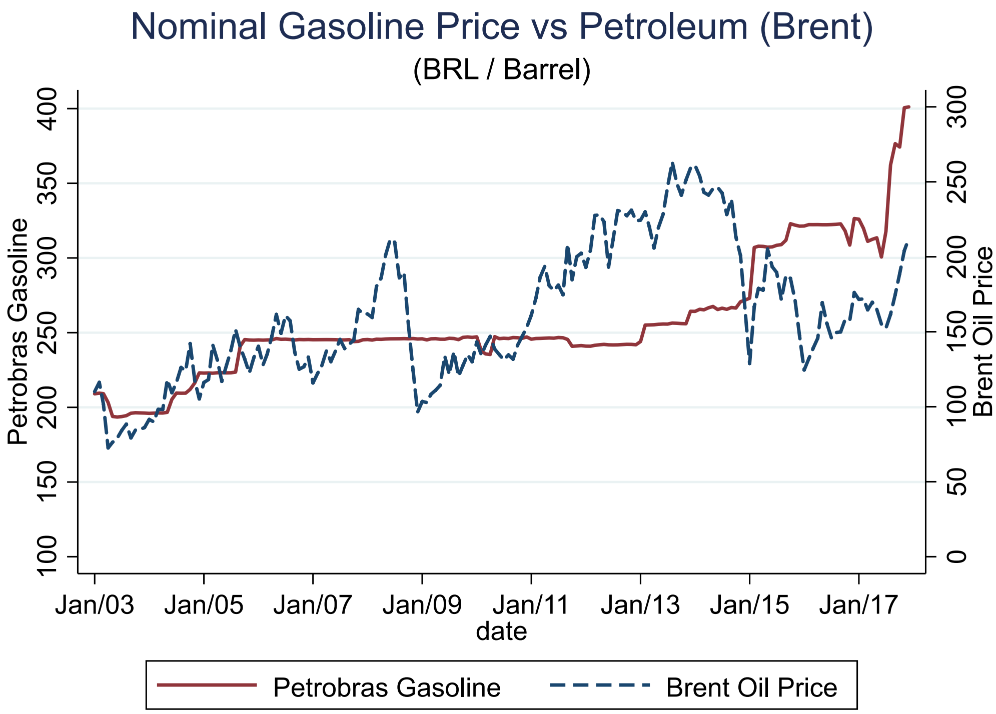

Figure 1: Nominal Gasoline Price and Brent Oil Prices (BRL / Barrel)

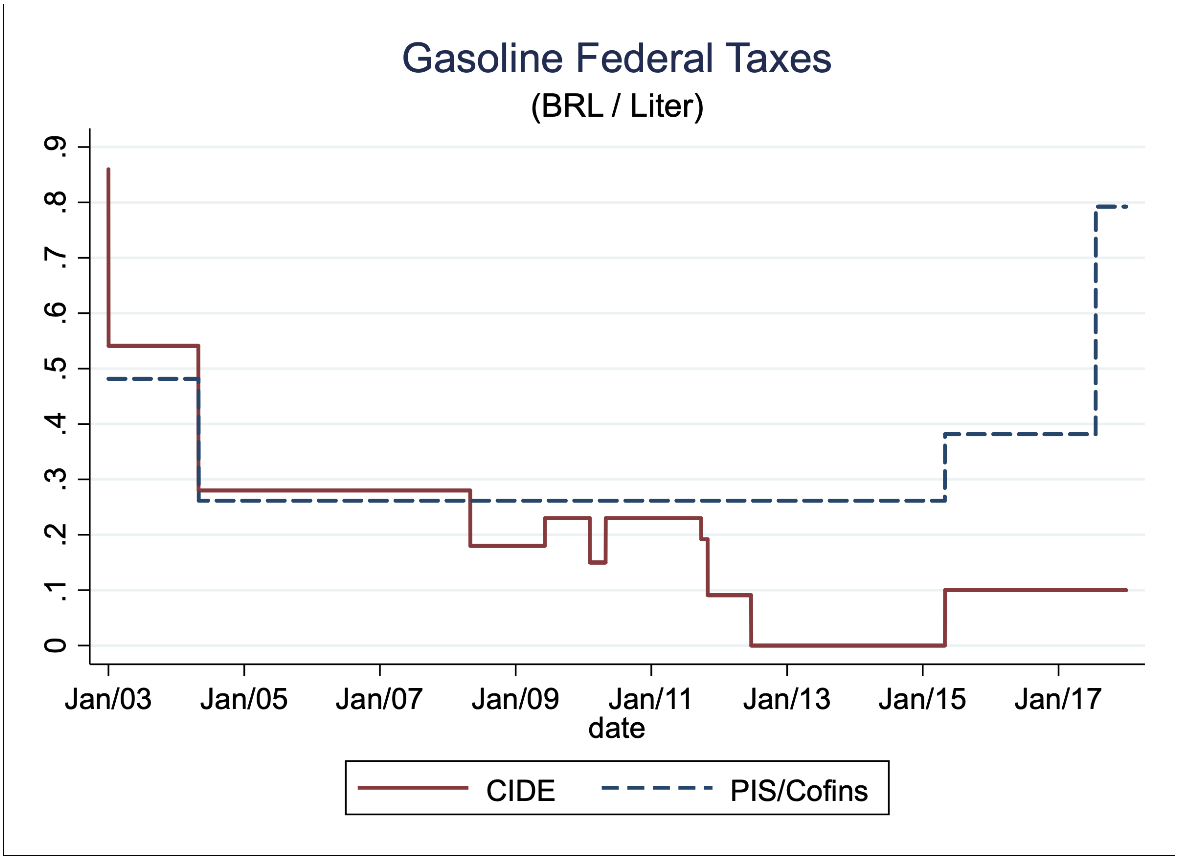

Figure 2: Federal Taxes Affecting Gasoline Prices

Notes: This figure displays the evolution of the two federal taxes that can influence the retail price of gasoline: CIDE and PIS/COFINS. CIDE (Contribution for Intervention in the Economic Domain) is an instrument of economic policy to deal with situations that may require government intervention in the economy. It can be levied in many sectors of the economy. The CIDE-fuels targets importation and commercialization of oil, natural gas and others fuels in the internal market. It aims at financing environmental projects and transportation infrastructure, but also at providing subsidies for fuel prices and transportation. PIS (Program of Social Integration) and COFINS (Contribution for the Financing of Social Security) are federal taxes based on monthly billings of companies, defined as the turnover of sales of goods and services. PIS is intended to finance the unemployment insurance system, and COFINS to fund Social Security.

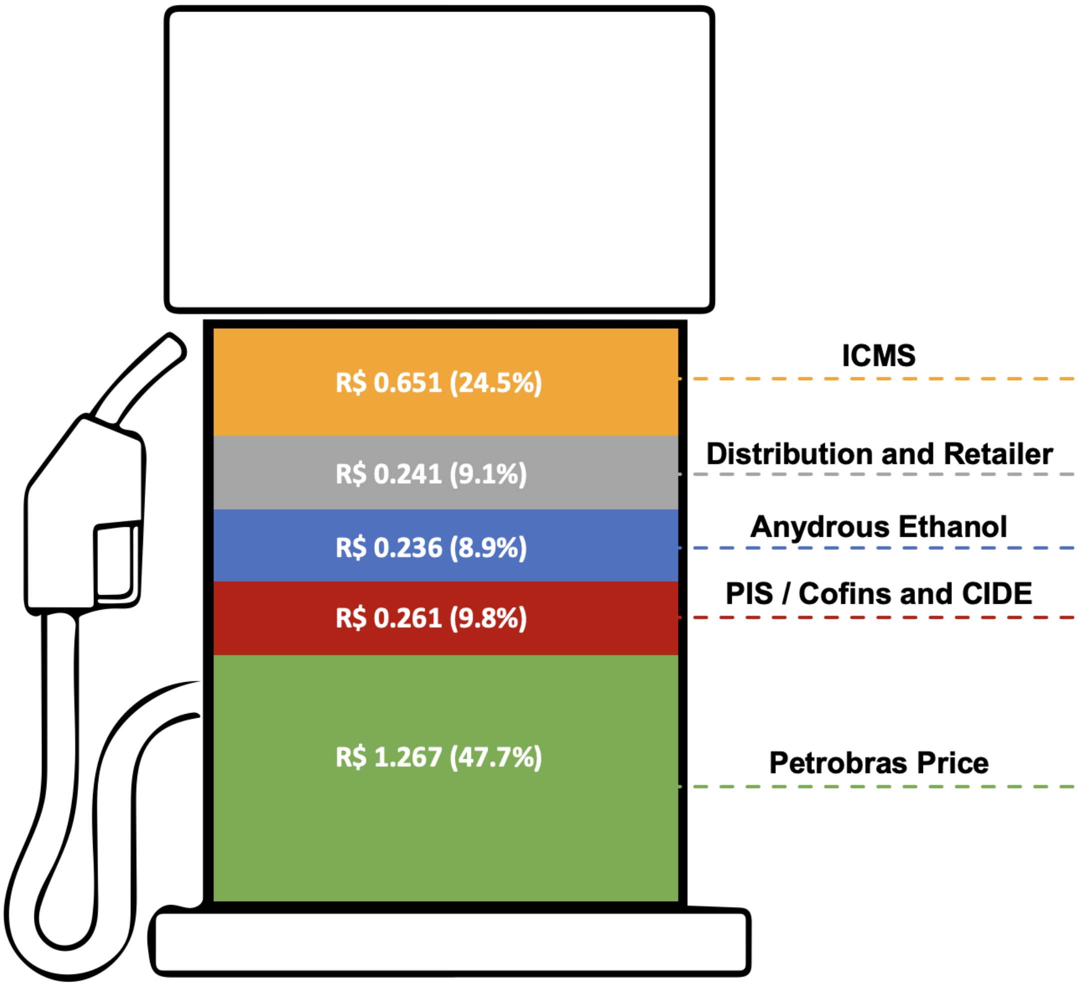

Figure 3: Gasoline Price Decomposition – December 2012 Example

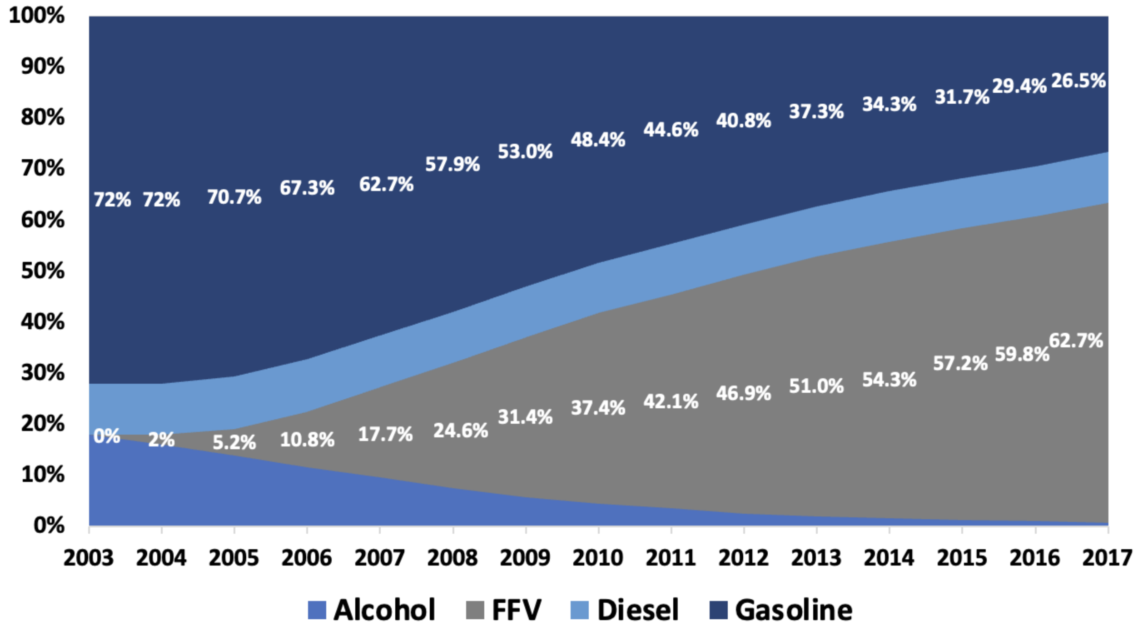

Figure 4: Share of Fleet by Fuel Type

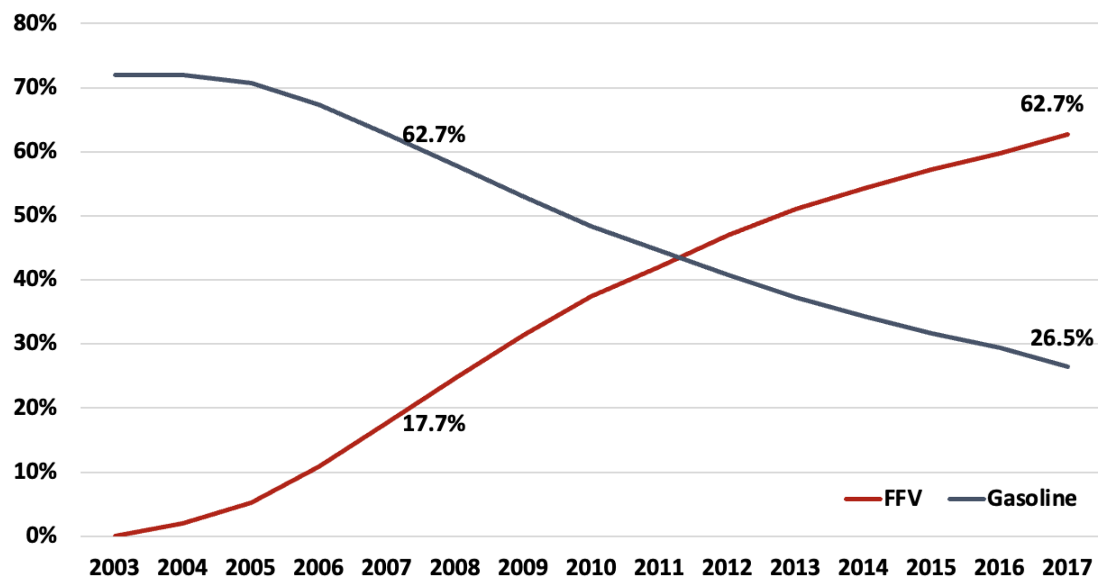

Figure 5: Adoption of Flex Fuel Vehicles

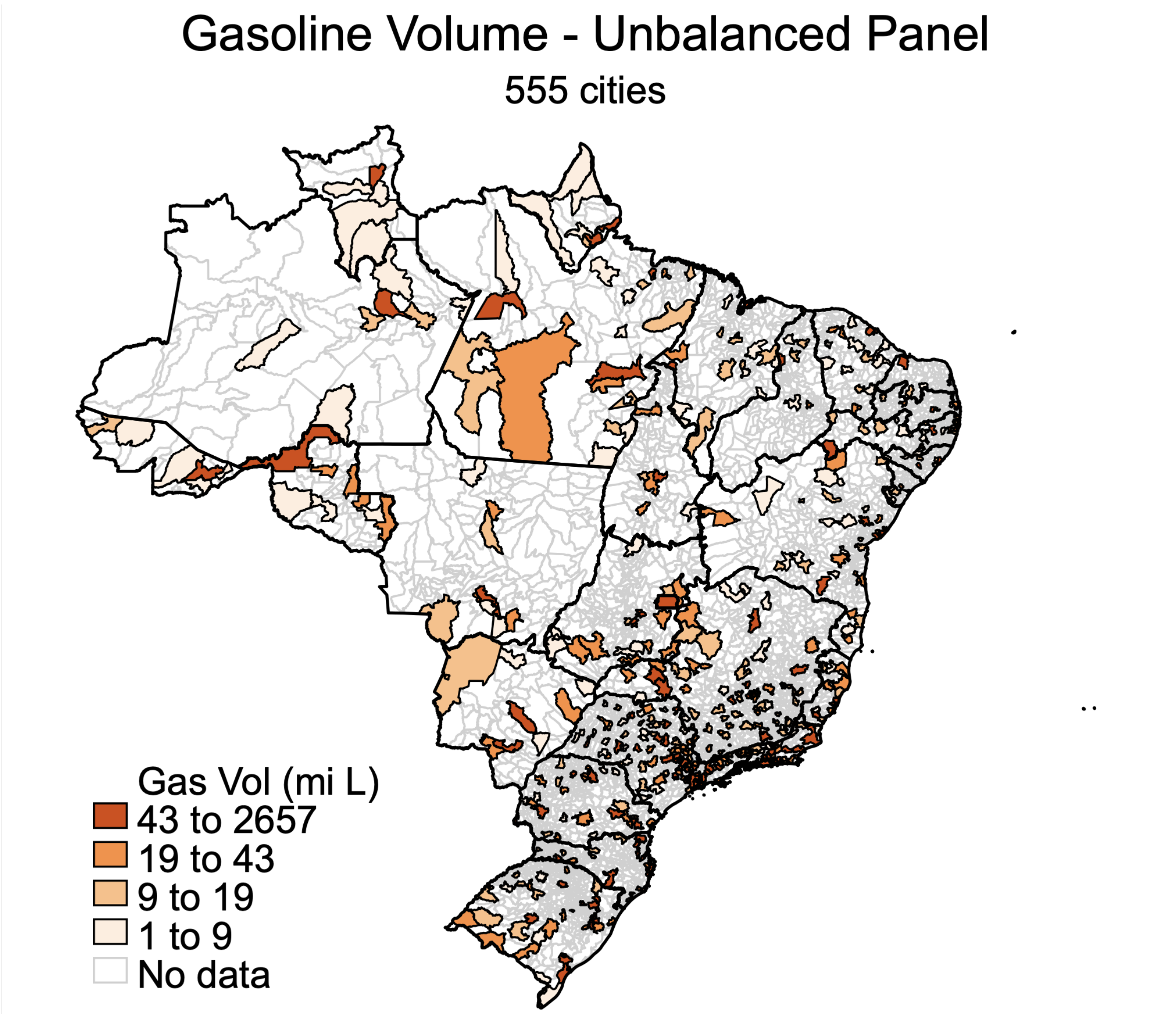

Figure 6: Annual Gasoline Sales – (Unbalanced) Sample of 555 Cities in 2015

Table 1: Gasoline Demand Model

Panel A: Gasoline Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	-1.1944***	-1.4559***	-0.8950***	-2.5586***
	(0.1292)	(0.3052)	(0.3334)	(0.5673)
	[-1.4476,-0.9412]	[-2.0541,-0.8577]	[-1.5484,-0.2415]	[-3.6705,-1.4467]
Ethanol Price	0.1228*	0.4402***	0.2208**	1.0062***
	(0.0654)	(0.1026)	(0.1007)	(0.1572)
	[-0.0054,0.2510]	[0.2392,0.6413]	[0.0233,0.4183]	[0.6980,1.3143]
N	73,353	73,353	30,019	43,334
F-Stat		18.03	7.65	4.10
Gas Vol (Mean & SD)	3.74 (11.59)	3.74 (11.59)	2.82 (9.59)	4.40 (12.81)
Etl Vol (Mean & SD)	1.44 (6.55)	1.44 (6.55)	1.23 (5.85)	1.59 (7.02)
Gas Price (Mean & SD)	4.07 (0.46)	4.07 (0.46)	4.47 (0.38)	3.78 (0.25)
Etl Price (Mean & SD)	2.83 (0.64)	2.83 (0.64)	2.88 (0.74)	2.79 (0.56)
Panel B: First Stage for Gasoline Price				
		GAS:05-16	GAS:05-09	GAS:10-16
Petrobras Gasoline Price		0.4402***	0.7076***	0.2531**
		(0.0734)	(0.0296)	(0.0973)
Sugarcane Quality		0.0199**	0.0230***	0.0338**
		(0.0086)	(0.0082)	(0.0132)
N		73,353	30,019	43,334
Panel C: First Stage for Ethanol Price				
		ETL:05-16	ETL:05-09	ETL:10-16
Petrobras Gasoline Price		0.1455	0.4356***	0.0426
		(0.1244)	(0.1626)	(0.1861)
Sugarcane Quality		0.2191***	0.2435***	0.2227***
		(0.0406)	(0.0625)	(0.0406)
N		73,353	30,019	43,334

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

4. 95% Confidence intervals in brackets.

Table 2: Gasoline Model – Interactions and Price Ratio tests

Dependent Variable: Gasoline Demand	Main Model	+ GDP	+ Population	+ Price Ratio	+ Price Levels
Gasoline Price	-1.4559***	-1.1514***	-1.1687***		
	(0.3052)	(0.3132)	(0.3141)		
Ethanol Price	0.4402***	0.0561	0.0833		
	(0.1026)	(0.1347)	(0.1334)		
Gas Price x 1(City GDP $\leq$ Median Brazil GDP)		-0.6022***	-0.7587***		
		(0.1428)	(0.2212)		
Etl Price x 1(City GDP $\leq$ Median Brazil GDP)		0.7904***	0.9964***		
		(0.1868)	(0.2902)		
Gas Price x 1(City Pop $\leq$ Median Brazil Pop)			0.1958		
			(0.1850)		
Etl Price x 1(City Pop $\leq$ Median Brazil Pop)			-0.2591		
			(0.2375)		
Gas Price x 1(Pr Etl / Pr Gas $\leq$ Q1 (0.640))				-2.3474***	
				(0.4515)	
Gas Price x 1(Q1 (0.640) $\leq$ Pr Etl / Pr Gas $\leq$ Q3 (0.775))				-0.9530**	
				(0.3646)	
Gas Price x 1(Pr Etl / Pr Gas $\geq$ Q3 (0.775))				-0.2084	
				(0.5467)	
Etl Price x 1(Pr Etl / Pr Gas $\leq$ Q1 (0.640))				1.5270***	
				(0.3115)	
Etl Price x 1(Q1 (0.640) $\leq$ Pr Etl / Pr Gas $\leq$ Q3 (0.775))				-0.5060*	
				(0.2602)	
Etl Price x 1(Pr Etl / Pr Gas $\geq$ Q3 (0.775))				-1.3170***	
				(0.4764)	
Gas Price x 1(Pr Gas - Pr Etl $\geq$ R$1.50)					-1.8874***
					(0.4226)
Gas Price x 1(R$1.00 $\leq$ Pr Gas - Pr Etl $\leq$ R$1.50)					-1.5190***
					(0.4096)
Gas Price x 1(Pr Gas - Pr Etl $\leq$ R$1.00)					-0.8313**
					(0.4047)
Etl Price x 1(Pr Gas - Pr Etl $\geq$ R$1.50)					0.7728***
					(0.1892)
Etl Price x 1(R$1.00 $\leq$ Pr Gas - Pr Etl $\leq$ R$1.50)					0.2296
					(0.2460)
Etl Price x 1(Pr Gas - Pr Etl $\leq$ R$1.00)					-0.5691*
					(0.2895)
N	73,353	73,353	73,353	73,353	73,353

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 3: Hospitalization Models – Children from 0 to 5 years old

Panel A: Hospitalization and Gasoline		
	OLS	IV
	Log(Hosp Rate)	Log(Hosp Rate)
Log(Gas vol)	0.0515**	1.4550***
	(0.0251)	(0.1914)
N	67,554	67,554
F-Stat		416.26
Panel B: Pollution and Gasoline		
	OLS	IV
	Log(PM 2.5)	Log(PM 2.5)
Log(Gas vol)	0.0288***	0.2153***
	(0.0093)	(0.0273)
N	63,499	63,499
F-Stat		68.61
Panel C: Hospitalization and Pollution		
	OLS	IV
	Log(Hosp Rate)	Log(Hosp Rate)
Log(PM 2.5)	-0.0025	0.2800**
	(0.0147)	(0.1111)
N	57,226	57,226
F-Stat		159.72

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Hospitalization rate measured as the number of respiratory diseases in children between 0 and 5 years old per 1 mi population. Average number of hospitalizations per 1 mi population: 215.32.

2. Average PM2.5 from satellite data: $8.6 \mu g/m^3$. Range: [2.41,240.53]. Dataset includes 555 cities spread across 27 states.

3. Controls included: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population.

4. Fixed effects by panel: city (all), year (A and B), month-of-year (A), month-of-sample (C), and year-by-state (A and B).

5. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

6. Standard errors in parentheses clustered by city.

Table 4: Hospitalization Model by Categories of Illnesses

	Asthma	Bronchitis	Pneumonia	Others
Log(Gas vol)	1.5912***	1.6442***	1.4727***	0.6499**
	(0.2944)	(0.2941)	(0.2194)	(0.2608)
N	43,433	41,925	65,314	50,782
F-Stat	216.79	169.72	371.00	223.60
Gas Vol (Mean)	3.74	3.74	3.74	3.74
Gas Vol (SD)	11.59	11.59	11.59	11.59
Hospitalization (Mean)	31.08	20.54	129.48	34.67
Hospitalization (SD)	59.28	35.55	147.42	66.53

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Dependent variable: log of hospitalization rate of each respiratory illness in children between 0 and 5 years old per 1 mi population.
2. Controls included: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.
3. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.
4. Standard errors in parentheses clustered by city.

Table 5: Hospitalization Model – Interactions – Children from 0 to 5 years old

Panel A: Hospitalization Rates					
	Main Model	+ Population	+ GDP	+ Hosp Beds	+ Inf. Mortality
Log(Gas vol)	1.4356***	1.4805***	0.8844***	0.6287*	0.6479*
	(0.1892)	(0.2213)	(0.3101)	(0.3496)	(0.3557)
Log(Gas vol) x Population		-0.1076	0.0483	0.0407	0.0401
		(0.0670)	(0.0729)	(0.0709)	(0.0707)
Log(Gas vol) x GDP			-0.1830**	-0.1535**	-0.1532**
			(0.0692)	(0.0697)	(0.0693)
Log(Gas vol) x H. Beds				-0.1064**	-0.1071**
				(0.0502)	(0.0501)
Log(Gas vol) x Infant Mortality					-0.0080
					(0.0684)
N	67,554	67,554	67,554	67,554	67,554
Kleibergen-Paap F-Stat by First Stage Regression					
Gasoline Volume	422.00	208.87	140.71	104.14	83.85
Population Interaction		392.99	266.10	225.24	184.05
GDP Interaction			251.43	209.47	170.48
Hospital Beds Interaction				110.26	87.91
Log(Gas vol) x Infant Mortality					270.60

Summary Statistics

Panel B: observations below the median of GDP					
	Gasoline Consumption (1 MM Liters)	Gasoline Consumption (Liters / person)	Hospitalizations per 1 mi pop.	Pollution (PM 2.5) ($\mu g/m^3$)	Infant Mortality
Mean	1.96	10.88	237.44	8.71	31
SD	6.25	4.75	219.24	4.35	15
Q1	0.51	7.29	93.41	6.09	21
Q2	0.97	10.87	173.52	7.87	26
Q3	1.77	14.11	309.24	10.43	40
Panel C: observations above the median of GDP					
	Gasoline Consumption (1 MM Liters)	Gasoline Consumption (Liters / person)	Hospitalizations per 1 mi pop.	Pollution (PM 2.5) ($\mu g/m^3$)	Infant Mortality
Mean	5.69	20.69	174.37	8.55	29
SD	15.14	8.83	170.35	3.71	13
Q1	1.25	16.00	66.58	6.10	20
Q2	2.25	19.48	125.49	7.69	24
Q3	4.99	23.94	221.78	10.28	36

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Panel A: Second Stage models. First column represents original second stage. Other columns include interactions as additional controls. Standard errors in parentheses clustered by city and month-of-year.
2. Panel B: summary statistics for the subset of observations below the respective state median GDP values.
3. Panel C: summary statistics for the subset of observations above the respective state median GDP values.

A Appendix: Fuel Markets

Table A.1: Gasoline Demand Model – Balanced Panel

Panel A: Gasoline Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	-1.0296***	-1.4140***	-0.8075**	-2.6075***
	(0.1663)	(0.3046)	(0.3335)	(0.5124)
	[-1.3556,-0.7037]	[-2.0111,-0.8169]	[-1.4613,-0.1538]	[-3.6119,-1.6032]
Ethanol Price	0.2271***	0.4255***	0.2195**	1.0047***
	(0.0711)	(0.0962)	(0.1029)	(0.1462)
	[0.0878,0.3665]	[0.2370,0.6141]	[0.0179,0.4211]	[0.7182,1.2913]
N	21,906	21,906	8,970	12,936
F-Stat	.	22.42	7.55	5.20
Gas Vol (Mean & SD)	9.51 (20.50)	9.51 (20.50)	7.42 (17.18)	11.00 (22.46)
Etl Vol (Mean & SD)	3.64 (11.77)	3.64 (11.77)	3.17 (10.60)	3.97 (12.52)
Gas Price (Mean & SD)	4.00 (0.44)	4.00 (0.44)	4.39 (0.35)	3.72 (0.23)
Etl Price (Mean & SD)	2.82 (0.44)	2.82 (0.44)	2.85 (0.53)	2.79 (0.35)
Panel B: First Stage for Gasoline Price				
		GAS:05-16	GAS:05-09	GAS:10-16
Petrobras Gasoline Price		0.4499***	0.6972***	0.2938***
		(0.0738)	(0.0329)	(0.0975)
Sugarcane Quality		0.0264***	0.0284***	0.0410***
		(0.0093)	(0.0092)	(0.0132)
N		21,906	8,970	12,936
Panel C: First Stage for Ethanol Price				
		ETL:05-16	ETL:05-09	ETL:10-16
Petrobras Gasoline Price		0.1903	0.4078**	0.1454
		(0.1151)	(0.1645)	(0.1661)
Sugarcane Quality		0.2437***	0.2638***	0.2504***
		(0.0453)	(0.0679)	(0.0418)
N		21,906	8,970	12,936

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

4. 95% Confidence intervals in brackets.

Table A.2: Gasoline Demand Model - Instrument Robustness Check

	Main Model	Model 2	Model 3	Model 4
Panel A: Gasoline Demand				
	Main Model	Model 2	Model 3	Model 4
Gasoline Price	-1.4559***	-1.3863***	-1.5116***	-1.4511***
	(0.3052)	(0.3205)	(0.3368)	(0.3428)
Ethanol Price	0.4402***	0.2769**	0.4464***	0.2878**
	(0.1026)	(0.1177)	(0.1050)	(0.1169)
N	73,353	73,353	73,353	73,353
F-Stat	18.03	24.44	15.75	29.03
Panel B: First Stage for Gasoline Price				
	Main Model	Model 2	Model 3	Model 4
Petrobras Price (27 states)	0.4402***	0.4275***		
	(0.0734)	(0.0705)		
Petrobras Price (5 regions)			0.6084***	0.5926***
			(0.0605)	(0.0584)
ATR Value	0.0199**		0.0224***	
	(0.0086)		(0.0081)	
Sugar Export Price		0.0265***		0.0246**
		(0.0092)		(0.0094)
N	73,353	73,353	73,353	73,353
Panel C: First Stage for Ethanol Price				
	Main Model	Model 2	Model 3	Model 4
Petrobras Price (27 states)	0.1455	0.0437		
	(0.1244)	(0.1154)		
Petrobras Price (5 regions)			0.2153	0.0689
			(0.1392)	(0.1418)
Sugarcane Quality	0.2191***		0.2199***	
	(0.0406)		(0.0404)	
Sugar Export Price		0.2299***		0.2295***
		(0.0303)		(0.0303)
N	73,353	73,353	73,353	73,353

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

4. 95% Confidence intervals in brackets.

Table A.3: Ethanol Demand Model – Unbalanced Panel

Panel A: Ethanol Demand				
	OLS: 2005-15	IV: 2005-15	IV: 2005-09	IV: 2010-15
Gasoline Price	2.3074***	4.5915***	1.5070**	9.8780***
	(0.3486)	(0.9429)	(0.6590)	(2.2997)
	[1.6241,2.9907]	[2.7434,6.4396]	[0.2154,2.7985]	[5.3707,14.3852]
Ethanol Price	-2.0887***	-1.9459***	-1.5823***	-3.5057***
	(0.1627)	(0.3601)	(0.3279)	(0.5841)
	[-2.4077,-1.7698]	[-2.6518,-1.2401]	[-2.2249,-0.9397]	[-4.6505,-2.3608]
N	72,904	72,904	29,878	43,026
F-Stat		18.40	7.80	4.09
Gas Vol (Mean & SD)	3.74 (11.59)	3.74 (11.59)	2.82 (9.59)	4.40 (12.81)
Etl Vol (Mean & SD)	1.44 (6.55)	1.44 (6.55)	1.23 (5.85)	1.59 (7.02)
Gas Price (Mean & SD)	4.07 (0.46)	4.07 (0.46)	4.47 (0.38)	3.78 (0.25)
Etl Price (Mean & SD)	2.83 (0.64)	2.83 (0.64)	2.88 (0.74)	2.79 (0.56)
Panel B: First Stage for Gasoline Price				
		GAS:05-15	GAS:05-09	GAS:10-15
Petrobras Gasoline Price		0.4404***	0.7073***	0.2535**
		(0.0734)	(0.0297)	(0.0975)
Sugarcane Quality		0.0200**	0.0232***	0.0338**
		(0.0086)	(0.0082)	(0.0132)
N		72,904	29,878	43,026
Panel C: First Stage for Ethanol Price				
		ETL:05-15	ETL:05-09	ETL:10-15
Petrobras Gasoline Price		0.1456	0.4363***	0.0424
		(0.1247)	(0.1627)	(0.1865)
Sugarcane Quality		0.2206***	0.2452***	0.2239***
		(0.0406)	(0.0623)	(0.0409)
N		72,904	29,878	43,026

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

4. 95% Confidence intervals in brackets.

Table A.4: Ethanol Demand Model – Balanced Panel

Panel A: Ethanol Demand				
	OLS: 2005-15	IV: 2005-15	IV: 2005-09	IV: 2010-15
Gasoline Price	3.2542***	4.8573***	1.7743***	9.3311***
	(0.5073)	(0.9407)	(0.5302)	(1.9761)
	[2.2600,4.2483]	[3.0135,6.7011]	[0.7351,2.8135]	[5.4579,13.2042]
Ethanol Price	-2.2239***	-1.9818***	-1.5070***	-3.5579***
	(0.2159)	(0.3296)	(0.2660)	(0.5778)
	[-2.6470,-1.8007]	[-2.6277,-1.3358]	[-2.0283,-0.9856]	[-4.6904,-2.4254]
N	21,879	21,879	8,944	12,935
F-Stat		22.20	7.52	5.20
Gas Vol (Mean, SD)	9.51 (20.50)	9.51 (20.50)	7.42 (17.18)	11.00 (22.46)
Etl Vol (Mean, SD)	3.64 (11.77)	3.64 (11.77)	3.17 (10.60)	3.97 (12.52)
Gas Price (Mean, SD)	4.00 (0.44)	4.00 (0.44)	4.39 (0.35)	3.72 (0.23)
Etl Price (Mean, SD)	2.82 (0.44)	2.82 (0.44)	2.85 (0.53)	2.79 (0.35)
Panel B: First Stage for Gasoline Price				
		GAS:05-15	GAS:05-09	GAS:10-15
Petrobras Gasoline Price		0.4491***	0.6965***	0.2938***
		(0.0739)	(0.0331)	(0.0975)
Sugarcane Quality		0.0264***	0.0284***	0.0410***
		(0.0093)	(0.0092)	(0.0132)
N		21,879	8,944	12,935
Panel C: First Stage for Ethanol Price				
		ETL:05-15	ETL:05-09	ETL:10-15
Petrobras Gasoline Price		0.1896	0.4052**	0.1455
		(0.1154)	(0.1652)	(0.1661)
Sugarcane Quality		0.2437***	0.2638***	0.2504***
		(0.0454)	(0.0680)	(0.0418)
N		21,879	8,944	12,935

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

4. 95% Confidence intervals in brackets.

Table A.5: Simultaneous Demand Models – Balanced Panel

Panel A: Cross-Elasticity Restrictions				
Gasoline Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	-1.3310***	-1.7085***	-0.9390***	-3.5801***
	(0.0220)	(0.0592)	(0.0615)	(0.1088)
Ethanol Price	0.4386***	0.5331***	0.2501***	1.3070***
	(0.0095)	(0.0267)	(0.0310)	(0.0392)
N	72,904	72,904	29,878	43,026
Ethanol Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	0.4386***	0.5331***	0.2501***	1.3070***
	(0.0095)	(0.0267)	(0.0310)	(0.0392)
Ethanol Price	-1.6106***	-1.2219***	-1.2904***	-1.7580***
	(0.0295)	(0.0871)	(0.1282)	(0.0879)
N	72,904	72,904	29,878	43,026
Panel B: No Cross-Elasticity Restrictions				
Gasoline Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	-1.2489***	-1.4443***	-0.8857***	-2.5411***
	(0.0226)	(0.0606)	(0.0627)	(0.1092)
Ethanol Price	0.4076***	0.4317***	0.2261***	0.9980***
	(0.0097)	(0.0271)	(0.0315)	(0.0387)
N	72,904	72,904	29,878	43,026
Ethanol Demand				
	OLS: 2005-16	IV: 2005-16	IV: 2005-09	IV: 2010-16
Gasoline Price	1.6654***	4.5915***	1.5070***	9.8780***
	(0.0788)	(0.2139)	(0.2879)	(0.3319)
Ethanol Price	-1.8719***	-1.9459***	-1.5823***	-3.5057***
	(0.0339)	(0.0956)	(0.1446)	(0.1176)
N	72,904	72,904	29,878	43,026

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.6: Gasoline Demand With Aggregated Data

Panel A: Unbalanced Panel				
	City-Month OLS	City-Month IV	State-Month OLS	State-Month IV
Gasoline Price	-1.2654***	-1.4559***	-0.7876***	-1.2125***
	(0.1184)	(0.3052)	(0.1488)	(0.2753)
Ethanol Price	0.4099***	0.4402***	0.3998***	0.4219***
	(0.0448)	(0.1026)	(0.0641)	(0.1283)
N	73,353	73,353	3,840	3,840
F-Stat		18.03		8.72
Panel B: Balanced Panel				
	City-Month OLS	City-Month IV	State-Month OLS	State-Month IV
Gasoline Price	-1.2583***	-1.4140***	-0.9272***	-1.2114***
	(0.1257)	(0.3046)	(0.1281)	(0.2811)
Ethanol Price	0.4863***	0.4255***	0.4685***	0.4584***
	(0.0523)	(0.0962)	(0.0575)	(0.1195)
N	22,176	21,906	3,744	3,699
F-Stat		22.42		9.71

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.

2. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

3. Standard errors in parentheses clustered by city and month-of-year.

B Appendix: Hospitalization and Pollution Models

Table B.1: Pollution Models

Panel A: Pollution and Fuels: PM 2.5 Models			
	IV 01	IV 02	
Log(Gas vol)	0.2628***		0.2745***
	(0.0304)		(0.0350)
Log(Etl vol)		-0.0444**	0.0261
		(0.0178)	(0.0221)
N	57,652	57,652	57,652
F-Stat	87.76	7.47	7.43

Panel B: Pollution and Fuels: Ozone Models			
	IV 01	IV 02	
Log(Gas vol)	-0.0729***		-0.0771***
	(0.0062)		(0.0076)
Log(Etl vol)		0.0353***	-0.0074
		(0.0120)	(0.0056)
N	68,470	68,470	68,470
F-Stat	134.10	7.00	5.34

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects,year fixed effects and year-by-state fixed effects.

2. Average PM2.5: 8.68 $\mu g/m^3$.

3. Average Ozone: 41.79 $\mu g/m^3$.

4. Clustered by city.

Table B.2: Instrument Robustness Models - Children from 0 to 5 years-old

Dep. Variable:	Gasoline Volume	GDP	Hospital Beds	Population
Petrobras Gasoline Price	-0.6170***	-0.0525**	0.0607	-0.0041
	(0.0256)	(0.0208)	(0.0398)	(0.0037)
Sugarcane Quality	0.0794***	-0.0159***	0.0024	0.0037***
	(0.0061)	(0.0030)	(0.0072)	(0.0009)
N	67,554	67,554	67,554	67,554
F-Stat	131.71	8.06	1.92	7.65

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. First Stage model table. First column represents original first stage. Other columns replace the dependent variable (Gasoline Volume) by either GDP, Hospital Beds or Population.
2. Controls included in column 2: GDP, hospital beds, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects.
3. Additional control: gasoline volume is replaced by each non-environmental control in columns 3 to 5 and used as control variable in those regressions.
4. Clustered by city.

Table B.3: Hospitalization Models – Ethanol as Control

Panel A: Hospitalization and Gasoline		
	OLS	IV
	Log(Hosp Rate)	Log(Hosp Rate)
Log(Gas vol)	0.0054	1.2248***
	(0.0374)	(0.1597)
N	66,067	66,067
F-Stat		387.29
Panel B: Pollution and Gasoline		
	OLS	IV
	Log(PM 2.5)	Log(PM 2.5)
Log(Gas vol)	0.0445***	0.2363***
	(0.0101)	(0.0283)
N	61,676	61,676
F-Stat		104.44
Panel C: Hospitalization and Pollution		
	OLS	IV
	Log(Hosp Rate)	Log(Hosp Rate)
Log(PM 2.5)	-0.0005	0.2903**
	(0.0149)	(0.1137)
N	55,712	55,712
F-Stat		156.97

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Hospitalization rate measured as the number of respiratory diseases in children between 0 and 5 years old per 1 mi population. Average number of hospitalizations per 1 mi population: 215.32.

2. Average PM2.5 from satellite data: $8.6\mu g/m^3$ microgram per cubic meter. Range: [2.41,240.53]. Dataset includes 555 cities spread across 27 states.

3. Controls included: Ethanol volume, GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population.

4. Fixed effects by panel: city (all), year (A and B), month-of-year (A), month-of-sample (C), and year-by-state (A and B).

5. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.

6. Standard errors in parentheses clustered by city.

Table B.4: Hospitalization Model – Specification Checks

	IV1	IV2	IV3	IV4
Log(Gas vol)	1.4415***	1.4428***	1.4478***	1.4550***
	(0.1911)	(0.1907)	(0.1909)	(0.1914)
Log(GDP)		-0.2520***	-0.2582***	-0.2443***
		(0.0744)	(0.0740)	(0.0733)
# Beds / 1 mi pop			0.0001***	0.0000***
			(0.0000)	(0.0000)
Log(Population)				-0.3130
				(0.3050)
City FE	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y
State-by-Year FE	Y	Y	Y	Y
Climate Variables	Y	Y	Y	Y
N	67,554	67,554	67,554	67,554
F-Stat	421.18	416.98	416.01	416.26

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Dependent variable: hospitalization rate of respiratory illnesses in children between 0 and 5 years old per 1 mi population. Average number of hospitalizations per 1 mi population: 137.60.
2. Other controls included: city fixed effects, month-of-year fixed effects and year-by-state fixed effects.
3. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.
4. Standard errors in parentheses clustered by city.

Table B.5: Hospitalization Models by Age Groups

Panel A: Hospitalization and Gasoline				
	OLS: 0 to 1	IV: 0 to 1	OLS: 1 to 5	IV: 1 to 5
	Log(Hosp Rate)	Log(Hosp Rate)	Log(Hosp Rate)	Log(Hosp Rate)
Log(Gas vol)	0.0823***	1.2651***	0.0451*	1.6722***
	(0.0254)	(0.2174)	(0.0260)	(0.2053)
N	64,068	64,068	66,008	66,008
F-Stat		402.67		369.83
Panel B: Pollution and Gasoline				
	OLS: 0 to 1	IV: 0 to 1	OLS: 1 to 5	IV: 1 to 5
	Log(PM 2.5)	Log(PM 2.5)	Log(PM 2.5)	Log(PM 2.5)
Log(Gas vol)	0.0288***	0.2153***	0.0288***	0.2153***
	(0.0093)	(0.0273)	(0.0093)	(0.0273)
N	63,499	63,499	63,499	63,499
F-Stat		68.61		68.61
Panel C: Hospitalization and Pollution				
	OLS: 0 to 1	IV: 0 to 1	OLS: 1 to 5	IV: 1 to 5
	Log(Hosp Rate)	Log(Hosp Rate)	Log(Hosp Rate)	Log(Hosp Rate)
Log(PM 2.5)	-0.0186	-0.0635	-0.0006	0.4852***
	(0.0163)	(0.1232)	(0.0146)	(0.1205)
N	54,415	54,415	55,899	55,899
F-Stat		153.43		160.76

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Hospitalization rate measured as the number of respiratory diseases in children between 0 and 5 years old per 1 mi population. Average number of hospitalizations per 1 mi population: 215.32.
2. Controls included: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population.
3. Fixed effects by panel: city (all), year (A and B), month-of-year (A), month-of-sample (C), and year-by-state (A and B).
4. The first-stage F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage.
5. Standard errors in parentheses clustered by city.

Table B.6: Hospitalization Model – Interactions by Age Group

Panel A: Log(Hospitalization Rate) – Children from 0 to 1 year old				
	Main Model	+ GDP	+ Hosp Beds	+ Population
Log(Gas vol)	1.2651***	1.0631***	0.8533**	0.6893**
	(0.2174)	(0.3085)	(0.3312)	(0.3180)
Log(Gas vol) x GDP		-0.0894*	-0.0711	-0.1105*
		(0.0528)	(0.0544)	(0.0624)
Log(Gas vol) x H. Beds			-0.1168**	-0.0996**
			(0.0461)	(0.0446)
Log(Gas vol) x Population				0.0959
				(0.0618)
N	64,068	64,068	64,068	64,068
Kleibergen-Paap F-Stat by First Stage Regression				
Gasoline Volume	402.67	193.69	125.09	94.57
GDP Interaction		338.14	266.46	212.22
Hospital Beds Interaction			138.54	109.64
Population Interaction				230.32
Panel B: Log(Hospitalization Rate) – Children from 1 to 5 years old				
	Main Model	+ GDP	+ Hosp Beds	+ Population
Log(Gas vol)	1.6722***	1.2192***	0.7095**	0.5616
	(0.2053)	(0.3268)	(0.3576)	(0.3475)
Log(Gas vol) x pcGDP		-0.1467**	-0.0981	-0.1267*
		(0.0606)	(0.0601)	(0.0694)
Log(Gas vol) x H. Beds			-0.1308**	-0.1157**
			(0.0508)	(0.0493)
Log(Gas vol) x Population				0.0728
				(0.0697)
N	66,008	66,008	66,008	66,008
Kleibergen-Paap F-Stat by First Stage Regression				
Gasoline Volume	369.83	179.13	111.87	84.80
GDP Interaction		337.92	259.87	205.63
Hospital Beds Interaction			136.93	108.03
Population Interaction				224.38

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

1. Second Stage models. First column represents original IV model. Other columns include interactions of gasoline consumption with other variables.

2.Standard errors in parentheses clustered by city and month-of-year.