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Essays on Policy Evaluation from an Environmental and a Regional Perspective

M. Taha Kasim
Georgia State University

ABSTRACT

ESSAYS ON POLICY EVALUATION FROM AN ENVIRONMENTAL AND A REGIONAL PERSPECTIVE

BY

MOHAMMED TAHA KASIM

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Committee Chair: Dr. H. Spencer Banzhaf

Major Department: Economics

This dissertation consists of three essays, which explore how public policies influence household and firm behavior, and the impact policies could have on environmental outcomes. The essays examine how households respond to price-based policies, the impact information disclosure policies could have on environmental outcomes, and finally the influence of normative appeals and non-pecuniary strategies on behavioral outcomes. Understanding these adjustments in the behavior of the agents is particularly important for policy design and for legislators who intend maximize societal benefit.

The first essay, titled *Matchmaking Between Vehicle Miles Traveled and Fuel Economy: the Role of Gasoline Prices*, studies a potential effect of gasoline prices that has been overlooked in the literature. Due to heterogeneity in demand for vehicle miles traveled (VMT), when gasoline prices increase, the increased cost of operating an inefficient vehicle are greater for households that drive more. Thus, in equilibrium, after an increase in the gasoline prices there should be a stronger matching from households, based on their VMT, to the fuel economy of the cars they own. Potentially, this matching effect could save 15% of US gasoline consumption, even with no effect on individual VMT and no effect on the vehicle fleet. Using confidential data from the National Highway Transportation Survey, the effect of higher gasoline prices on such assortative matching is estimated using a variety of econometric

models. For all the different model specifications, the matching effect is significant and quite robust. This is the first study to analyze this re-allocation or matching effect.

The second essay, titled *Evaluating the Effectiveness of an Environmental Disclosure Policy: an Application to New South Wales*, examines the impact of an environmental information disclosure policy on environmental outcomes. The main purpose of introducing an environmental information disclosure strategy is to reduce informational asymmetries and put pressure on firms to reduce emissions. This paper studies the impact of such a policy on air quality in New South Wales, Australia. A regression discontinuity design is employed and the results show that the pollutant concentration levels were not significantly affected after the implementation of the policy. Empirically, the estimates of the effects under the discontinuity-based Ordinary Lease Squares (OLS) model have the opposite sign for some of the pollutants relative to the estimates from the basic OLS model. Therefore, basing conclusions on the OLS results will engender incorrect inference. Discontinuity-based results are robust to different model specifications.

The third essay, titled *What Determines Citizen Trust: Evaluating the Impact of Campaigns Highlighting Government Reforms in Pakistan* explores how normative appeals and awareness campaigns could influence societal and political trust. This project is in collaboration with Musharraf Cyan and Michael K. Price. The purpose of this study is two-fold. Firstly, the impacts of exposure to violence and conflict on general levels of trust, measures of life-satisfaction, and attitudes towards formal and informal institutions are examined in the province of Khyber Pakhtunkhwa (KPK), Pakistan. Secondly, the impacts of targeted messages, which were designed to inform the citizens regarding new government reforms (aimed at increasing transparency, protecting and strengthening private property rights, and improving service delivery), on general levels of trust and attitudes towards institutions are studied. For the analysis an in-person survey was designed, which was conducted in randomly selected villages throughout KPK. Empirical results show that exposure to violence has a negative impact on trust and measures of life-satisfaction and has positive effects on

formal institutions. The results also suggest that the awareness campaigns affected trust levels and perceptions about the quality of public services positively. Moreover when the effects are allowed to differ based on exposure to conflict, important heterogeneity is identified. The results are robust to different model specifications.

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

Dissertation chair: H. Spencer Banzhaf

Committee: Shanjun Li
Kyle Mangum
Michael K. Price

Electronic Version Approved:

Mary Beth Walker, Dean
Andrew Young School of Policy Studies
Georgia State University
August, 2016

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For self-improvement and personal development we need role models and my adviser, H. Spencer Banzhaf, is one of those people that have inspired me. Without Spencer's guidance, mentor-ship and supervision, I would not be where I am today. He has molded me as an individual and as a professional through his admirable character and exceptional intellect, and indeed this dissertation would not be possible without him. Because of his personality, he is idolized and respected by many students and peers. Every day, I attempt to emulate his kind and humble nature; and his creative and ingenious approach to understanding the world around us.

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My wife repeatedly says that within a household, obtaining a PhD degree is a family affair. I thank my wife for her unconditional love, for being my pillar of strength and for being an exemplary mother to Aadam. This journey without her would have been colorless. I should also acknowledge my brothers, Hamza and Huzaifa, and their families for never being afar.

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I. Introduction

In 2011, private passenger vehicles accounted for 70% of petroleum consumed in the US and 12% of the total US greenhouse gas (GIG) emissions.[1] Besides CO_2, combustion of gasoline also produces other pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x) and volatile organic compounds. Possible health effects of these pollutants include headaches, stress, respiratory issues, heart diseases and death, particularly among children. Studies have shown that *in-uteri* and childhood exposure to these gasses have the potential to affect various health outcomes in the short- and the long-run.[2]

Policies to address such pollution generally fall into two categories: performance-based policies and price-based policies. In the US, the most prominent performance standard is the Corporate Average Fuel Economy (CAFE) standards, first introduced in 1975 with the purpose of improving fuel economy of vehicles. The program requires automobile manufacturers to meet fuel economy standards for passenger cars and light trucks. The current industry-wide combined standard under the program is 29 miles per gallon (MPG), which will eventually increase to 35.5 MPG by 2016.[3] Other performance-based policies are tax credits to households purchasing fuel efficient automobiles, provision of subsidies to households who retire their "gas guzzlers" and giving perks to owners of hybrid vehicles.[4] Taxing

[1]The first statistic was calculated from *US Energy Information Administration (EIA)'s Monthly Energy Review (April 2013)*. The second statistic comes from *Inventory of US Greenhouse Gas Emissions and Sinks 1990-2011* published by the US Environmental Protection Agency (EPA) in 2012. The US EPA prepares this document annually as per the conditions set by the United Nations Framework Convention on Climate Change (UNFCCC).

[2]For a review of these studies *see* Currie et al. (2014) and Zivin and Neidell (2013).

[3]This was announced by President Obama, as part of the National Policy of Fuel Efficiency, on May 19, 2009. These expected US fuel economy standards are not as stringent as those employed in other countries. For example, the European Union and Japan plan on increasing the standards to 60.6 MPG and 55.1 MPG by 2020, respectively. This is highlighted in *Comparison of Actual and Projected Fuel Economy Standards* developed by the International Council for Clean Transportation.

[4]For example, a number of states (Arizona, California, Colorado, Florida, Georgia, New Jersey, New York, Tennessee, Utah and Virginia) have initiated the Clean Air Stickers Program under which "stickered" hybrids are allowed to use the HOV lanes. Bento et al. (2012) studied such a policy for California and found

gasoline is the obvious price-based policy. The US has the lowest gasoline taxes among the developed countries (US Department of Energy). As of 2015, the average gasoline tax in the US was $0.46 per gallon (federal *plus* state) while in Germany and the UK it was $4.10 per gallon and $3.95 per gallon (including VAT), respectively.

One drawback of performance standards like the CAFE is that a decline in emissions through the utilization channel is not optimally exploited. That is, performance standards do not provide incentives for reduction in vehicle miles traveled (VMT) and may even do the opposite.[5] Two effects of changes in gasoline taxes on VMT have been noted. Firstly, gasoline taxes increase gasoline prices and change gasoline consumption through the utilization effect. Secondly, an increase in gasoline prices results in the evolution of the fleet towards more fuel efficient vehicles. This is the "compositional effect" and its magnitude will depend on the elasticity of fleet fuel economy to gas prices.

Bento et al. (2009) is one of the few papers that studies both the utilization and the compositional effects. They use a multi-market simulation model to evaluate the efficiency and the distributional implications of changes in gasoline taxes. They find that most of the reduction in gasoline use is through reduction in VMT and that improvements in fleet-wide fuel economy are small, particularly in the short-run. Over the long-run, the average fuel economy is influenced by changes in fleet composition due to increases in fuel efficient new vehicle sales and price-induced increases in fuel-economy of given models, but still fuel economy accounts for a small share of the decline in aggregate gasoline consumption.

Li et al. (2014) address the question of how people respond to gasoline tax changes. Effects of changes in prices depends on the expectations of future fuel costs. Since automobiles are a durable good, consumers may respond differently to changes in gasoline prices due to taxes (permanent changes) from what they believe to be less permanent shocks (short

that it resulted in a transfer from car-poolers to hybrid owners *plus* net social benefits were negative. Since an average hybrid owner earns more than an average car-pooler, such a policy is probably very regressive (at least in California).

[5]For an overview of literature that studies how CAFE standards affect the new vehicle market, *see* Klier and Linn (2010).

run supply interruptions or changes in the price of crude oil). If consumers believe that oil price shocks are less likely to persist than taxes, consumers might respond relatively more to variation in taxes. The findings of the study suggest that a tax increase shifts demand for fuel efficient cars positively but there is no strong correlation with VMT. Gasoline taxes reduce the sales of low MPG vehicles and increase the sales of high MPG vehicles and these effects are larger than the effects of increases of tax-exclusive prices. The study also finds that gasoline price changes affect the market share of new vehicles more strongly than used cars. The differential impact of taxes and other price shocks on gasoline consumption is driven by the differential impact on the fuel economy of new vehicles.

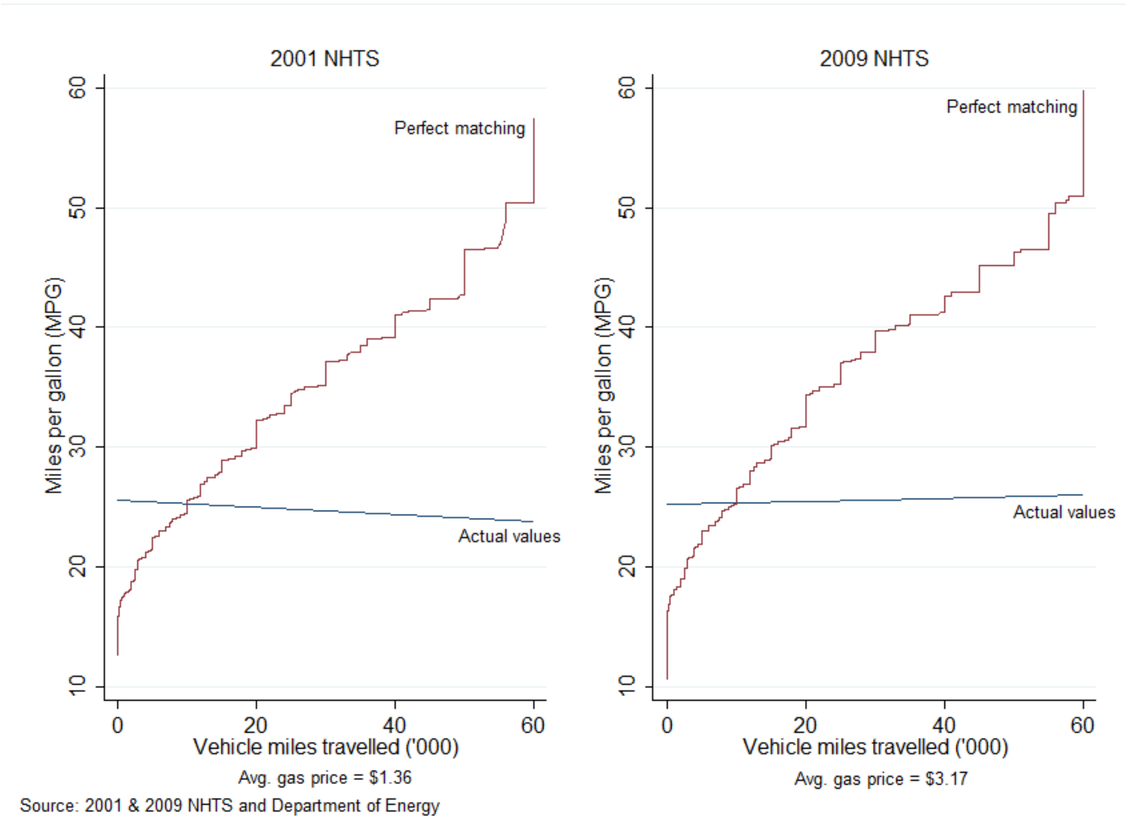
Li et al. (2009) study the compositional effect by explicitly looking at how gasoline prices affect the fleet fuel economy. They find that an increase in gasoline prices shifts the demand modestly for new cars towards more fuel efficient vehicles and lowers the sales of less fuel efficient cars. They also find that fuel efficient used vehicles stay in the market longer in response to a gasoline price increase. Busse et al. (2013) analyze the role of gasoline prices in influencing individual's purchasing decisions and the prices that they pay in the used and the new car markets. Different equilibrium outcomes are expected in the two markets because of differences in the market structures and the supply of new and used cars. The results show that the demand for inefficient cars shifts left relative to efficient cars when gasoline prices increase. In the new car markets this has a price and a quantity effect, whereas in the used car markets it only has a price effect.

The results of Li et al. (2009) and Busse et al. (2013) suggest a potential third effect that has been overlooked in the literature. Increases in gasoline taxes decrease the demand for fuel inefficient cars through the price effect. But there is heterogeneity among agents in the demand for VMT. When gasoline prices rise, the cost of operating an inefficient vehicle increases relative to an efficient car. However, the cost differences are greater for the household that drives more relative to others. Thus, it is probable that the variability in the demand shock results in an increase in the market share of larger, fuel inefficient automobiles for low-VMT types relative to the market share of inefficient vehicles for high-VMT types. As a result, there will be a shift in the matching of cars to households: households who drive more will be even more likely than other households to switch to a more fuel efficient car. Thus, in equilibrium, after an increase in gasoline prices there should be a stronger matching from households, based on the amount of driving they are likely to do, to the fuel economy of the cars they own. This is the first study that analyzes this re-allocation or matching effect.

In Figure 1, miles per gallon (MPG) is plotted against VMT for the years 2001 and 2009. Two things are of interest in Figure 1. The first is the variation in actual values over time. Between 2001 and 2009, as gasoline prices increased, the relationship between these two variables went from slightly decreasing to slightly increasing. The second thing of interest in Figure 1 is the comparison between the actual values and the hypothetical values under "perfect matching". Under “perfect matching”, the highest-VMT households would be driving the most efficient cars and the lowest-VMT households would be driving the least efficient cars. Notice that in this hypothetical scenario, I did not change the amount of miles households are driving (utilization effect) nor did I change the composition of the fleet (compositional effect). A comparison of the two pairs of lines across the years shows that in 2009 when gasoline prices were higher, the matching effect was much stronger. This leads to substantial savings in fuel consumption. To gauge the potential importance of the matching effect, if household demand for VMT and vehicle fuel efficiency were perfectly matched in 2009, gasoline consumption would have been 15% less than actual gasoline consumption, even with no change in the composition of the fleet and no change in individual VMT.[6] The ability to work through this matching channel is another advantage of price-based policies over performance-based policies, one that has been overlooked in the literature.

[6] National Household Travel Survey (NHTS) data was used to make this calculation. In the NHTS survey, counter-factual gasoline consumption for a particular vehicle is being compared to actual gasoline consumption.

Figure 1: Is there a matching effect?



Notes: These graphs were constructed using reported annual miles from the NHTS 2001 and the 2009 confidential survey files and the vehicle fuel economy data from the Department of Energy. Actual values in both the graphs represent a linear regression of fuel economy on vehicle miles traveled (VMT). For perfect matching, vehicles were assigned to households based on their respective VMT.

Econometrically, a basic check for the matching effect would be executing a Difference-in-Difference-in-Differences (DDD) model. This particular model compares the change in fuel economy of high-VMT households to low-VMT households between periods with comparatively high and low gasoline prices. However, an issue with this simple approach is that VMT is endogenous to fuel economy. High-VMT households are more likely to adopt a fuel efficient vehicle. But households with more fuel efficient vehicles might also drive more. To overcome the simultaneity issue, I use an instrumental variables strategy where the interactions of household characteristics with gasoline prices are used as instruments. The purpose of this study is to describe the correlation between the heterogeneous effects of a change in gasoline prices on the type of vehicles different people drive and how those effects are correlated with VMT-propensity. However, due to these instrumental variables, I cannot control for important heterogeneous treatment effects of higher gasoline prices in the second stage. To overcome this problem one could predict the effect of gasoline prices on fuel economy for different households and then regress these predicted effects on predicted VMT to estimate the correlation between the predicted VMT and the treatment effects of higher gasoline prices on MPG. Alternatively, I create instruments for VMT using Bento et al.'s (2009) structural model. VMT in the latter strategy is a non-linear function of demographics. Following this method I could include heterogeneous household effects in the second stage and also obtain a causal matching effect.

For all these different methodologies, the matching effect is significant and quite robust. The matching effect ranges from 0.02 to 0.13. These results indicate that when the gasoline price increases by \$1, a vehicle that is driven 1000 more annual miles, on average gives 0.02 to 0.13 more miles per gallon. The higher coefficients come from the model that uses a non-linear function of VMT as an instrumental variable.

The rest of the chapter is structured as follows: Section II explains the matching effect using a theoretical model, Section III details the different econometric methodologies used to analyze the matching effect, Section IV describes the data, Section V presents and interprets the results and Section VI concludes.

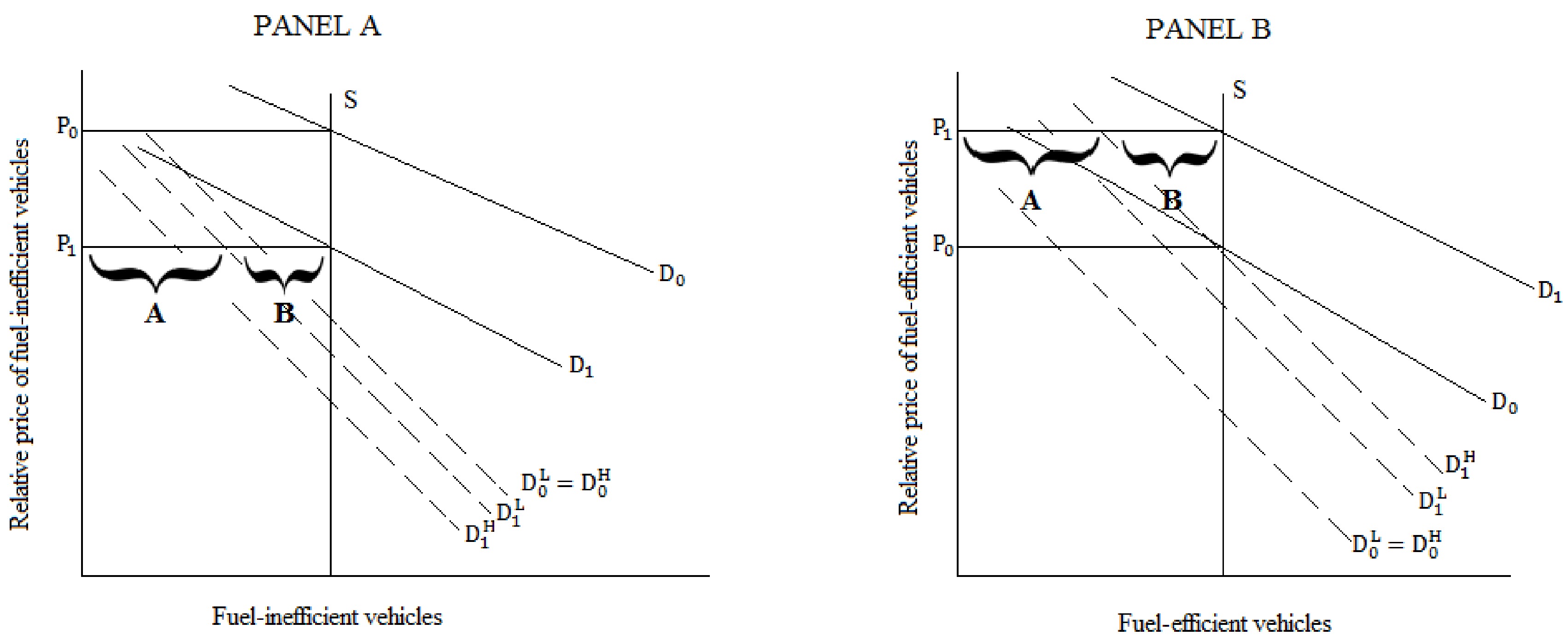
II. Theoretical framework

A partial equilibrium model is sufficient to explain the mechanism of the matching effect. Let there be two types of households that differ only in terms of exogenous demand for VMT: high-VMT households (H) and low-VMT households (L). Let there be two car types: fuel-inefficient (I) and fuel-efficient (E). In Figure 2 Panel A, heterogeneity in demand among agents for VMT is reflected by D^H and D^L, which indicate the relative willingness to pay (WTP) of each respective household-type for inefficient cars relative to efficient cars. This WTP could be positive or negative. I take no stand on whether the high-VMT types or the low-VMT types have a higher WTP. Figure 2 shows an example of a baseline reference scenario where $D_0^H = D_0^L$. The market demand is D_0 for a relative price P_0.

In Figure 2 Panel A when gasoline prices increase, the relative WTP for inefficient vehicles falls. The new market demand is D_1 and the price falls to P_1 in the vehicle market. This is consistent with Busse et al. (2013) and Li et al. (2014). My conjecture is that the relative WTP for an inefficient automobile will particularly decrease for the high-VMT types, as higher gasoline prices translate into greater costs for them. This is shown in this figure where D_1^H is now lower than D_1^L. As a consequence, in equilibrium, the low-VMT types now have a greater share of the inefficient vehicles than before ($\frac{A}{A+B}$ versus $\frac{1}{2}$). By the same logic, as shown in Panel B, the high-VMT types now have a greater proportion of efficient vehicles relative to the baseline case.

The above model can also be represented mathematically. Again consider two types of households $i \in \{H, L\}$ that differ solely on VMT: high-VMT households (H) and low-VMT households (L). I consider a continuum of automobiles that differ only in terms of gallons per mile (GPM) where $\text{GPM} = \frac{1}{\text{MPG}}$. The WTP function for household i is given as follows:

Figure 2: The matching effect explained



Notes: In these diagrams partial-equilibrium models are used to explain the mechanisms of the matching effect. There are two types of households: high-VMT and low-VMT households designated by H and L. There are two types of vehicles: fuel inefficient and fuel efficient. The demand curves D^H and D^L show the relative willingness to pay (WTP) of the two household types for different fuel economies. In both the panels above, the baseline case is given by the scenario where $D_0^H = D_0^L$ and the baseline market demand curve is given by D_0 for a relative price P_0. After an increase in gasoline prices, the relative WTP for inefficient vehicles decreases and the relative WTP for efficient vehicles increases. These new market demand curves are shown by D_1 for a relative price P_1. However, due to the heterogeneity in demand among agents for VMT, the decrease (increase) in the relative WTP for the high-VMT types for inefficient (efficient) vehicles is greater than for the low-VMT types. These situations are shown in the diagrams above when $D_1^H < D_1^L$ in Panel A and $D_1^H > D_1^L$ in Panel B. If it is the case that $\frac{A}{A+B} > \frac{1}{2}$, the low-VMT types will have a greater share of inefficient vehicles and the high-VMT types will have a greater proportion of efficient vehicles when compared with the baseline case.

$$WTP^i(GPM) = f^i(GPM) - VMT^i(P^g) \times GPM \times P^g \tag{1}$$

where $f^i(GPM)$ represents preferences for a particular vehicle type and P^g is the price of gasoline. The WTP of household i for a small change in GPM is given as follows.

$$\frac{\partial WTP^i}{\partial GPM} = \frac{\partial f^i(GPM)}{\partial GPM} - VMT^i(P^g) \times P^g \tag{2}$$

The WTP is a function of marginal preferences, VMT demand and gasoline prices. When gasoline prices increase, the WTP will decrease but ∂WTP^i will differ due to the cost differences between the households based on the amount of driving they do. Consider an increase in gasoline prices by dP^g. Differentiating equation (2) with respect to P^g gives the change in relative WTP for GPM when the gasoline price increases. This is given below:

$$\frac{\partial^2 WTP^i}{\partial GPM \cdot \partial P^g} = \underbrace{-\frac{\partial VMT^i(P^g)}{\partial P^g} \times P^g}_{\substack{elasticity\, of\ VMT^i \\ w.r.t\, P^g \,\times\, VMT}} - \underbrace{VMT^i(P^g)}_{\text{household } i'\text{s } VMT} \tag{3}$$

where the first term is the elasticity of VMT with respect to P^g and the second term represents the respective VMT^i demands. We already know that $VMT^H > VMT^L$. My hypothesis is that when the gasoline price increases, the relative WTP for an inefficient vehicle will decrease much more for a high-VMT household compared to the decrease in relative WTP for an inefficient vehicle for a low-VMT household. That is, $\frac{\partial^2 WTP^H}{\partial GPM \cdot \partial P^g} < \frac{\partial^2 WTP^L}{\partial GPM \cdot \partial P^g}$. Using equation (3) this implies,

$$-\left(\frac{\partial VMT^H(P^g)}{\partial P^g} \times P^g\right) - VMT^H(P^g) < -\left(\frac{\partial VMT^L(P^g)}{\partial P^g} \times P^g\right) - VMT^L(P^g)$$

$$-\epsilon^H VMT^H - VMT^H < -\epsilon^L VMT^L - VMT^L$$

$$VMT^H(\epsilon^H + 1) > VMT^L(\epsilon^L + 1)$$

$$\frac{VMT^H}{VMT^L} > \frac{\epsilon^L + 1}{\epsilon^H + 1} \tag{4}$$

where ϵ^i are VMT^i- gasoline price elasticities for household i. Since $VMT^H > VMT^L$, the LHS in the inequality above is greater than one. The RHS is dependent on relative VMT elasticities with respect to gasoline prices. In the previous literature, average VMT short-run elasticities with respect to gasoline prices are in the range of $[-0.3, -0.1]$ (*see* Bento et al. (2009), Graham and Glaister (2002), Gillingham (2014), Hughes, Knittel, and Sperling (2007), and Small and van Dender (2007)).

Thus, the only threat to the inequality given by (4) is when $|\epsilon^L| < |\epsilon^H|$ and the difference between elasticities is large.[7] However, it is expected that $|\epsilon^H| < |\epsilon^L|$. That is, the high-VMT households are less willing to reduce VMT when gasoline prices increase (they are high-VMT types for a reason after all!). Rather than compromising on VMT by a large margin, it is expected that these households adopt a more fuel efficient vehicle. Hence, it is expected that the inequality given by (4) will most likely hold.[8] This implies that when faced with higher gasoline prices, the high-VMT households are likely to adopt a more fuel efficient vehicle relative to the low-VMT households. Hence, in equilibrium an increase in the gasoline price will result in agglomeration of fuel inefficiency among the low-VMT types and concentration of fuel efficiency among the high-VMT types: the matching effect.

[7]Given that absolute VMT elasticities with respect to gasoline prices have been found to be less than one in the previous literature, I do not consider the cases where absolute elasticities are greater than one.

[8]Given the previous estimates of elasticities, as a worst case scenario consider the low-VMT and the high-VMT households to be on the extremes of this range, i.e. $\epsilon^L \approx -0.1$ and $\epsilon^H \approx -0.3$. The inequality given by (4) then would imply $\frac{0.9}{0.7} \approx 1.29$. As long as the high-VMT households drive 29% more than the low-VMT households, the inequality will hold. In the 2001 and the 2009 NHTS data-sets the average VMT of the 75^{th} percentile is ten times larger than the average VMT of the 25^{th} percentile. Using the NHTS data-sets and the ACCRA gasoline prices, VMT-gasoline price elasticity for the lowest and the highest quartiles are -0.18 and -0.11, respectively. The differences in elasticities between the lowest and the highest quartiles are small *plus* the low-VMT types are relatively more sensitive to price changes. This is also consistent with the Cournot aggregation condition.

III. Econometric methodology

This section details the econometric methods used to estimate the matching effect. The question of interest is determining how the fuel economy of vehicles driven by households that drive more relative to others is affected when gasoline prices increase. A basic check for this would be to run the following Difference-in-Difference-in-Differences (DDD) regression. The DDD model compares the change in fuel economy of high-VMT households to low-VMT households between periods with comparatively high and low gasoline prices.

$$
\begin{aligned}
MPG_{ijct} = \alpha + \beta Price^{gas}_{ct} + \gamma VMT_{ijct} + \theta\left[Price^{gas}_{ct} \times VMT_{ijct}\right] \\
+ \mathbf{X}_{\text{ict}}\boldsymbol{\delta} + [Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}]\boldsymbol{\varphi} + \eta_c + \lambda_t + \varepsilon_{ijct} \quad (5)
\end{aligned}
$$

where, MPG_{ijct} is miles per gallon of vehicle j owned by household i in city c in year t, $Price^{gas}_{ct}$ is the per gallon price of gasoline in city c in year t, VMT_{ijct} is VMT of vehicle j owned by household i in city c in year t, $\mathbf{X}_{\text{ict}}$ are demographic variables of household i, η_c are city fixed effects, λ_t are year fixed effects and ε_{ijct} is the idiosyncratic error term. The matching effect of higher gasoline prices is represented by θ and if the matching effect exists, $\theta > 0$. In equation (5), λ_t is included to control for time-varying unobservables and η_c is included to control for time-invariant city-specific unobservables. The interactions of the household characteristics with gasoline prices are included to control for heterogeneous effects of gasoline prices.

A potential issue with this simple approach, however, is that VMT is endogenous to the fuel efficiency of the car. It is expected that VMT will affect the MPG of the chosen car (VMT $\rightarrow$ MPG). But there is also a greater likelihood that households with more fuel efficient vehicles drive more (MPG $\rightarrow$ VMT). The latter is known as the rebound effect. Due to a more fuel efficient vehicle, cost per mile decreases so households drive more. Therefore, VMT and the interaction term in the above equation are not exogenous. Recent evidence has suggested that this effect is fairly small (Gillingham et al. (2013), and Small and van Dender

(2007)). If so, this endogeneity problem might be small enough to ignore. Accordingly, I first use DDD-OLS to estimate (5).

Nevertheless, the possibility of simultaneity cannot be ignored entirely. Accordingly, I use a Two-Stages Least Squares (2SLS) strategy. One strategy is to use the interactions of household characteristics with gasoline prices as instruments for VMT, while still allowing the household characteristics to enter the MPG equation linearly (just not interacted with gasoline prices). Using this strategy, I estimate the following model:

$$VMT_{ijct} = a + \mathbf{X}_{\text{ict}}\mathbf{b} + cPrice^{gas}_{ct} + [Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}]\boldsymbol{d} + \eta_c + \lambda_t + \mu_{ijct} \tag{6}$$

$$MPG_{ijct} = \alpha + \beta Price^{gas}_{ct} + \gamma \widehat{VMT_{ijct}} + \theta[Price^{gas}_{ct} \times \widehat{VMT_{ijct}}] + \mathbf{X}_{\text{ict}}\boldsymbol{\delta} + \eta_c + \lambda_t + \varepsilon_{ijct} \tag{7}$$

where, $\mathbf{X}_{\text{ict}}$ includes household characteristics and the interactions of these with gasoline prices serve as instruments. These characteristics are the same as those used as controls in the DDD-OLS model. In this particular strategy VMT_{ijct} is first estimated as a linear function of demographics, per gallon price of gasoline in the city and the interactions of these demographics with the gasoline price (equation (6)). In the second-stage (equation (7)), instead of actual VMT, predicted VMT ($\widehat{VMT_{ijct}}$) enters the MPG equation.[9] The matching effect is again represented by θ. An issue with the approach above is that one cannot separately identify $Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}$ in the second stage structural equation given by (7). In other words this model only has a causal interpretation if $\mathbf{X}$ has no effect on the elasticity of MPG with respect to gasoline prices conditioning on VMT. Heterogeneity in the effect of gasoline prices on MPG by VMT cannot be separately identified from heterogeneity in $\mathbf{X}$.

If this restriction is unsatisfactory, two additional approaches can be considered. The first is to give up on a causal interpretation and simply ask how the heterogeneous effects on MPG

[9]Note that there are two endogenous variables in the model given by (5). Since, VMT enters the interaction term that represents the matching effect, $\text{VMT}\times\text{Price}^{\text{gas}}$ is also endogenous. Hence, there are two first stage regressions in the 2SLS strategy.

due to changes in gasoline prices ($\partial MPG/\partial Price^{gas}$) are correlated with predicted VMT ($\widehat{VMT}$). One could predict the effect of gasoline price on fuel economy for different households and then regress these predicted effects on predicted VMT. Consider the following two equations:

$$MPG_{ijct} = \alpha + \mathbf{X}_{\text{ict}}\boldsymbol{\beta} + \delta Price^{gas}_{ct} + [Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}]\boldsymbol{\theta} + \eta_c + \lambda_t + \varepsilon_{ijct} \tag{8}$$

$$VMT_{ijct} = a + \mathbf{X}_{\text{ict}}\boldsymbol{b} + cPrice^{gas}_{ct} + [Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}]\boldsymbol{d} + \eta_c + \lambda_t + \mu_{ijct} \tag{9}$$

where VMT and MPG are simultaneously determined and thus $E[\varepsilon\mu] \neq 0$. Given that $E[\mathbf{X}\varepsilon] = E[Price^{gas}\varepsilon] = E[\mathbf{X}\mu] = E[Price^{gas}\mu] = 0$, (8) and (9) can be estimated with the Ordinary Least Squares (OLS) approach. To accomplish this one could follow the algorithm given below:

1. Estimate equation (8) by OLS and let $\widehat{T} = \widehat{\partial MPG}/\partial Price^{gas} = \widehat{\delta} + \mathbf{X}_{\text{ict}}\widehat{\boldsymbol{\theta}}$ be the treatment effect of a change in gasoline prices on MPG for a household with characteristics $\mathbf{X}$.

2. Estimate equation (9) by OLS and let $\widehat{VMT} = \widehat{a} + \mathbf{X}_{\text{ict}}\widehat{\boldsymbol{b}} + \widehat{c}\overline{Price^{gas}} + \left[\overline{Price^{gas}} \times \mathbf{X}_{\text{ict}}\right]\widehat{\boldsymbol{d}}$ where $\overline{Price^{gas}}$ is the average gasoline price. These are predicted household VMT at the average gasoline price. VMT is predicted at average gasoline prices to overcome the issue of correlation between MPG and VMT.

3. To estimate the correlation between $\widehat{\partial MPG}/\partial Price^{gas}$ and $\widehat{VMT}$, run the following regression.

$$\widehat{T} = \pi_0 + \pi_1\widehat{VMT} + \varphi \tag{10}$$

where the coefficient of interest is π_1.

However, this whole process is equivalent to estimating the following model.

$$MPG_{ijct} = \alpha + \beta Price^{gas}_{ct} + \mathbf{X}_{\text{ict}}\boldsymbol{\gamma} + \theta\left[\widehat{VMT}_{ijct} \times Price^{gas}_{ct}\right] + \eta_c + \lambda_t + \xi_{ijct} \tag{11}$$

where $\widehat{VMT}$ is the predicted VMT at average gasoline prices. The proof in Appendix A shows that estimating equation (11) is equivalent to the procedure laid down by the algorithm. The matching effect in equation (11) is given by the coefficient θ. However, this strategy merely provides a correlation between the predicted VMT and the treatment effect of $dPrice^{gas}$.

An alternative strategy is to use a structural model which identifies both effects through non-linearities. However, to get a causal impact one could re-visit the strategy given by equations (6) and (7) . If VMT is a non-linear function of household characteristics in (6), I could include $Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}$ in (7) and get a causal impact of the matching effect on MPG. One strategy to accomplish this could be creating instruments using Bento et al.'s (2009) structural model. In the latter strategy, VMT will be a non-linear function of demographics and vehicle characteristics. Bento et al. (2009) use the following indirect utility function in their model:

$$V'_{ij} = -\frac{1}{\lambda_i} \exp\left(-\lambda_i \left(\frac{{}^{Y_i}\!/_{T_i} - r_{ij}}{p^x_i}\right)\right) - \frac{1}{\beta_{ij}} \exp\left(\alpha_{ij} + \beta_{ij} \frac{p^M_{ij}}{p^x_i}\right) + \tau_{ij} \tag{12}$$

where, $\alpha_{ij} = \tilde{\alpha}^T_i z^\alpha_{ij}$; $\beta_{ij} = -\exp\left(\tilde{\beta}^T_i z^\beta_{ij}\right)$; $\lambda_i = \exp\left(\tilde{\lambda}^T_i z^\lambda_i\right)$; $\tau_{ij} = \tilde{\tau}^T_i z^\tau_{ij}$; r_{ij} is vehicle rental price; p^M_{ij} is vehicle utilization price; and p^x_i is the Hicksian composite commodity price and Y_i is the household income. T_i is a fixed number of choice occasions and they are set equal to the number of adults in the household plus one.[10] z^α_{ij}, z^β_{ij}, z^τ_{ij} are alternative automobile characteristics (age, make, class dummies) interacted with household demographics and z^λ_i are household characteristics. Using Roy's identity, VMT for household i using car j can be written as:

$$VMT_{ij} = \exp\left(\alpha_{ij} + \beta_{ij} \frac{p^M_{ij}}{p^x_i} + \lambda_i \left(\frac{{}^{Y_i}\!/_{T_i} - r_{ij}}{p^x_i}\right)\right) \tag{13}$$

[10] If the number of adults is less than the number of household vehicles, T_i equals the number of household vehicles.

One can predict $\widehat{VMT}_{ij(i)}$ by using the above model, but $\widehat{VMT}_{ij(i)}$ still would be endogenous to MPG through the vehicle characteristics z, which are simultaneously chosen. However, I can predict VMT of household i at a fixed set of characteristics. In particular, I use the median car attributes in the sample.[11] Using $\widehat{VMT}_{i\bar{j}}$ as an instrument, I then estimate the following model:

$$VMT_{ijct} = a + b\widehat{VMT}_{i\bar{j}ct} + cPrice^{gas}_{ct} + d[\widehat{VMT}_{i\bar{j}ct} \times Price^{gas}_{ct}] + \eta_c + \lambda_t + \mu_{ijct} \qquad (14)$$

$$MPG_{ijct} = \alpha + \beta Price^{gas}_{ct} + \mathbf{X}_{\text{ict}}\boldsymbol{\delta} + [Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}]\boldsymbol{\rho} + \pi\,\widehat{VMT}_{ijct} + \theta\left[Price^{gas}_{ct} \times \widehat{VMT}_{ijct}\right] + \eta_c + \lambda_t + \varepsilon_{ijct} \qquad (15)$$

In the first-stage, VMT is a function of gasoline prices and $\widehat{VMT}_{i\bar{j}ct}$. The matching effect is again given by θ: the coefficient associated with the interaction term between gasoline prices and $\widehat{VMT}_{i\bar{j}ct}$. The model given by equations (14) and (15) overcomes the issues associated with the previous models. An advantage of this particular model over the model given by equations (6) and (7) is that now I can include $Price^{gas}_{ct} \times \mathbf{X}_{\text{ict}}$ in the second-stage. These will capture heterogeneous effects of a change in gasoline prices on MPG. An advantage this particular model has over the model given by equation (11) is that this model gives a causal interpretation to the coefficient of interest. The next section describes the data-set used for the analysis.

IV. Data construction

The data-set being used for the analysis could be divided into three major sections: (i) a random sample of US households illustrating their driving patterns and modal choice from the 2001 and the 2009 *National Household Travel Survey* (NHTS), (ii) quarterly gasoline

[11] Bento et al. (2009) categorized households into twelve different strata based on employment status, average household age and the number and age distribution of children in the household. Vehicles are categorized by vehicle class. For more *see* Bento et al. (2009).

prices data obtained from the American Chamber of Commerce's ACCRA Cost of Living Index (COLI) database and (iii) the fuel economy data from the Department of Energy. These data-sets were merged to produce a distinct data-set which provides information on driving habits, household characteristics, average gasoline prices paid and the fuel economy of vehicles owned by these households.

The 2001 NHTS sample consists of 69,815 households and the 2009 NHTS consists of 150,147 households for both urban and rural areas in the US.[12] The 2001 NHTS was conducted from March 2001 through June 2002 and the 2009 NHTS was conducted between March 2008 and May 2009. Both these data-sets contain information on household driving patterns: vehicle miles traveled and the type of car/s owned by the household (make, model, vintage). Furthermore, the data-sets also provide household (income, number of household members, age distribution, race, work status) and neighborhood characteristics (population density, housing structure, presence of public transport) data and fuel economy data for household vehicles.[13] For the main analysis confidential NHTS data for both years was used. The confidential data details geographic location of each household (state, Metropolitan Statistical Area (MSA), and zip code).[14] After cleaning the data, we are left with 23,739 households in the 2001 sample and 137,610 households in the 2009 sample.[15]

[12] The 2001 NHTS was released in three different versions. Versions 1 and 2, released in 2003 contains data for 26,038 households and Version 3, released in 2004, supplemented earlier versions with data from more than 40,000 add-on interviews.

[13] NHTS collected VMT data through (i) direct questioning; (ii) estimations based on odometer ratings (only for 2001 NHTS); and (iii) estimations based on travel diaries. NHTS data reports two different measures of VMT. (1) Reported VMT which was based on (i) and (2) "bestmiles" based on regression techniques combining information from all three reporting techniques. Since, "bestmiles" requires more information, this variables had more missing values compared to VMT. In the main analysis (1) was used as a measure of VMT and (2) was used wherever (1) is missing. Household with both measures missing were dropped. Both measures ranged from 0 to 200,000 miles. However, mileage below 100 and above 60,000 were considered to be inconceivable and were therefore dropped. This resulted in 25,396 (17%) and 47,247 (14%) observations to be deleted from the 2001 and 2009 NHTS data, respectively. Bento et al. (2009) follow the same strategy. VMT was divided by 1000 for ease of interpretation of the coefficient estimates. The results with these assumptions relaxed are similar to the main results and are available upon request.

[14] I would like to thank the staff at the Department of Transportation (DOT) for assistance in getting access to the confidential NHTS data files.

[15] The data was restricted to vehicles that were driven at least 100 miles and at most 60,000 miles annually. The values not in this range are considered unrealistic and therefore were dropped from the data. Furthermore, vehicles that were more than 24 years old in the samples were dropped. Vehicles older than 24

The question of interest is how these households respond to changes in gasoline prices. Previous studies have suggested that gasoline prices take a random walk and only current prices affect consumer decisions. Berry et al. (1995), Goldberg (1995) and Bento et al. (2009) assume that gasoline prices take a random walk and only current prices matter. However if prices are mean reverting, then historical prices will also affect consumer decisions today. If this is true then studies with the random walk assumption underestimate the long-run effects of a permanent tax increase. David and Hamilton (2004) and Geman (2007) have shown that gasoline prices do actually follow a random walk. Li et al. (2009) also find the lagged gasoline prices have little impact on purchasing decisions. Finally, Anderson et al. (2013) and Anderson et al. (2011) provide empirical evidence, which suggests that on average expected real gasoline prices are equal to current prices. Since only current gasoline prices matter, quarterly gasoline prices for the years 2001, 2002, 2008 and 2009 were purchased from the American Chamber of Commerce's ACCRA Cost of Living Index (COLI) database. ACCRA provides data for more than 300 MSAs. Given the geographical indicators of the NHTS data, these prices were matched with each household in the NHTS data-sets.[16] The US Department of Housing and Urban Development (HUD) USPS ZIP Code Crosswalk Files were used to merge the ACCRA data with the confidential NHTS data-sets. Finally, the fuel economy data was obtained from the Department of Energy's website www.fueleconomy.gov.[17] This website provides the fuel economy data by vehicle

years are not identified in the 2009 NHTS sample. Thus, removal of older vehicles is done to keep the 2001 and the 2009 NHTS data consistent. Finally, only those vehicles were analyzed that use gasoline.

[16]Assignments of gasoline prices were based on the variable "Travel Day" in the NHTS data-sets. During the administration of the household recruitment interview, the Computer-Assisted Telephone Interviewing (CATI) program randomly assigned a travel date to each household. The interviewer revealed the travel date to the household respondent during the interview. Household travel days were assigned for all seven days of the week, including all holidays. All household members who completed a household recruitment interview were sent travel diaries for their travel day. NHTS also reports gasoline prices. These prices were assigned based on the Petroleum Administration for Defense Districts (PADD) designation for a given NHTS household. These districts are similar to Census regions in that each state is assigned to a given region, but the regions are drawn up in such a way as to maximize gasoline distribution. ACCRA and NHTS gasoline prices are highly correlated. I regressed ACCRA gasoline prices on NHTS gasoline prices and used predicted gasoline prices for those NHTS MSAs, which could not be matched with ACCRA data.

[17]The US Department of Energy and Environmental Protection Agency (EPA) sponsor the website www.fueleconomy.org, which contains files for city, highway and combined MPG by vehicles make, model and year for automobiles sold in the US between 1985 - 2014.

make, model and year and these variables were used to match the vehicle fuel economy with the NHTS data.

Table 1 provides demographic statistics of household responses in the NHTS. The first column reports the descriptive statistics for the entire sample. This is broken down by NHTS survey years in columns 2 and 3, respectively. Column 4 compares columns 2 and 3 and reports the differences and standard errors in parentheses. The null hypothesis that is being tested in column 4 is that the variables do not differ between 2001 and 2009. Between 2000 and 2009, average gasoline prices increased, average VMT declined and there was a slight but significant increase in average MPG.[18] Figure 3 plots the distribution of annual VMT and MPG for both surveys. The distributions of both these variables are quite similar for the two surveys.

The average gasoline price in 2001 NHTS was $1.35 and the average gasoline price in 2009 was $3.17 in the sample. The standard deviations of gasoline prices in the data for 2001 and 2009 are 0.18 and 0.69, respectively. This reflects how variation in gasoline prices has changed over the years. A prime reason for this is major fluctuations in gasoline prices during the period 2008-2009. Gasoline prices continued to increase during the first two quarters of 2008 reaching a peak of $4.60 and then started to decline before escalating again in the beginning of 2009.[19] Panel A in Figure 4 shows the kernel densities of gasoline prices for the two survey years. As highlighted earlier, there is more variation in gasoline prices in the 2008 - 2009 time frame relative to variation in gasoline prices in 2001-2002 period. Panel B of Figure 4 plots average MSA gasoline prices in 2009 against average MSA gasoline prices in 2001. The broken line splits the MSAs based on increases in gasoline prices between the two years. For MSAs above the broken line, gasoline prices increased by more than a factor

[18]Combined unadjusted MPG is a weighted average based on the assumption that the automobile was operated 55% under city driving conditions and 45% under highway conditions)

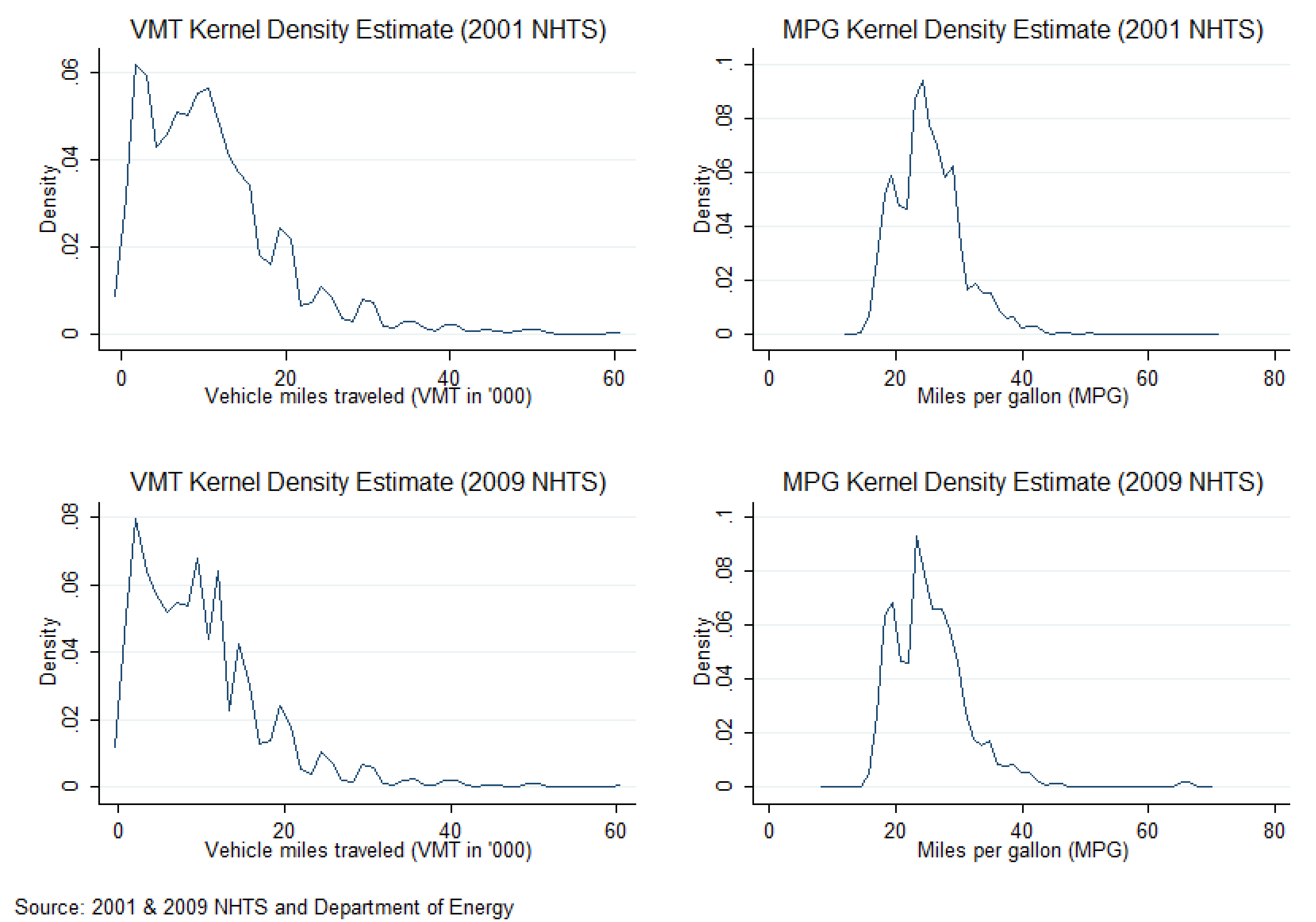
[19]This could also be due to differences in gasoline taxes between states. Some states have been reluctant in changing gasoline taxes between 2001 and 2009, whereas others have been more frequent (Li et al. (2014)).

Table 1: Demographic Statistics: 2001 & 2009 National Household Travel Survey

Panel A	Full sample	2001 NHTS	2009 NHTS	Difference
Variable	(1)	(2)	(3)	(4)
Vehicle miles traveled	10.160	11.244	9.974	-1.271***
(VMT) in '000	(8.259)	(8.881)	(8.132)	(0.045)
Combined unadjusted	25.545	25.224	25.600	0.377***
fuel economy (MPG)	(6.193)	(5.296)	(6.333)	(0.028)
Gasoline price	2.902	1.350	3.168	1.818***
	(0.906)	(0.180)	(0.687)	(0.002)
Household size	2.648	2.847	2.614	-0.233***
	(1.280)	(1.370)	(1.260)	(0.007)
Number of workers in	1.218	1.579	1.156	-0.424***
household	(0.970)	(1.011)	(0.949)	(0.005)
Number of adults	2.090	2.112	2.087	-0.026***
	(0.713)	(0.743)	(0.708)	(0.004)
Fraction of children	0.133	0.175	0.126	-0.049***
	(0.212)	(0.231)	(0.208)	(0.001)
Fraction of women	0.520	0.510	0.522	0.013***
	(0.229)	(0.233)	(0.228)	(0.001)
Panel B				
Distribution of household characteristics		Percentage		
Household income <$25,000	13.64	16.16	13.20	
Household income <$50,000 and ≥$25,000	26.20	32.35	25.14	
Household income <$75,000 and ≥$50,000	19.96	21.66	19.67	
Household income ≥ $75,000	40.20	29.84	41.99	
White, only	87.93	84.90	88.45	
African-American, only	4.92	5.02	4.90	
Asian, only	2.02	1.86	2.04	
Number of households	161,349	23,739	137,610	

Notes: The main entries in columns 1, 2 and 3 report the mean level of the variables with standard deviations in parentheses. Panel A, column 1 reports the means and standard deviations for the whole sample. Columns 2 and 3 of Panel A show the means and standard deviations for the two survey years. In column 4, the null hypothesis that is being tested is that the values in columns 2 and 3 are not different from zero. Differences with standard errors in parentheses are reported in column 4. In Panel B, column 1 distribution of certain household characteristics are displayed for the whole sample. Panel B, columns 2 and 3 report these household characteristics by survey year. ***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 3: Kernel densities of VMT and MPG



Notes: These graphs show the kernel densities of reported vehicle miles traveled (VMT) in thousands and miles per gallon (MPG) per vehicle for the 2001 and the 2009 *National Household Travel Survey* (NHTS). The data was restricted to vehicles that were driven at least 100 miles and at most 60,000 miles annually. Furthermore, vehicles that were more than 24 years old in the samples were dropped. Finally, only those vehicles were analyzed that use gasoline.

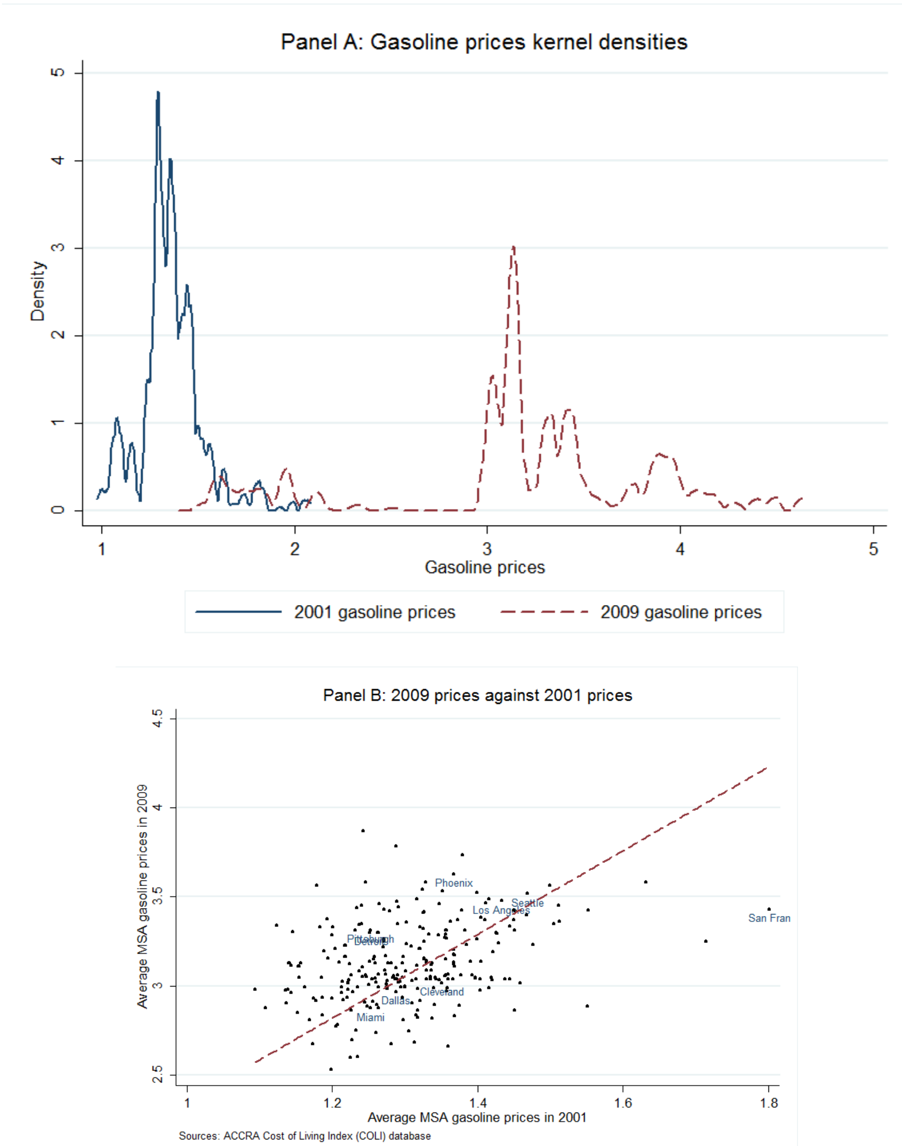
of two; and vice versa for MSAs below the broken line. The results of all the models shown in Section III will now be discussed.

V. How big is the matching effect?

Main results

This section examines the results of the models discussed in Section III. A basic check for the matching effect is running a Difference-in-Difference-in-Differences Ordinary Least Squares (DDD-OLS) approach given by equation (5). Table 2 shows the results of this model under different specifications. In the first column of Table 2, only the main effects of VMT and gasoline prices are included as well as their interaction. The interaction between VMT and gasoline prices represents the matching effect. Time dummies are included in the second column. These time dummies control for time varying unobservables between the survey years. These could include technological changes, changes in lifestyle and preferences or residential dispersions. MSA fixed effects are added in the third column. These fixed effects control for time invariant city specific unobservables. MPG of a vehicle is also dependent on certain household and geographical characteristics. These household characteristics are included in the fourth specification. These controls include number of household members, number of adults in the households, number of workers in the household, the fraction of children (age <18) and women in the household, and household income quartiles. Finally, the last column adds interactions between these demographics and gasoline price to the previous specification. Robust standard errors are reported in parentheses. For all these regressions, the matching effect is positive and statistically significant. This implies that as gasoline prices increase, households that drive more are driving a more fuel efficient vehicle relative to households that drive less. The results of Table 2 indicate that for a $1 increase in gasoline prices, when VMT increases by 1000 annual miles, MPG increases on average by 0.02.

Figure 4: MSA 2009 gasoline prices v. 2001 gasoline prices



Notes: The graph in Panel A shows the kernel densities of gasoline prices for the 2001 and the 2009 ACCRA gasoline prices. The 2001 price distribution is shown by the solid line and the 2009 price distribution is shown by the broken line. Panel B plots 2009 average MSA gasoline prices against 2001 average MSA gasoline prices. For MSAs above the broken line, gasoline prices increased by more than a factor of two. For those below the broken line, gasoline prices increased by less than a factor of two.

Table 2: Difference-in-Difference-in-Differences Ordinary Least Squares (DDD - OLS) results

	(1)	(2)	(3)	(4)	(5)
$\text{Price}^{\text{gas}}$	0.027	0.251***	-0.091***	-0.100***	-0.128*
	(0.019)	(0.028)	(0.033)	(0.035)	(0.078)
VMT	-0.035***	-0.035***	-0.033***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
Matching effect	**0.019*** **	**0.019*** **	**0.018*** **	**0.019*** **	**0.019*** **
	(0.001)	**(0.001)**	**(0.002)**	**(0.003)**	**(0.002)**
Year FE		X	X	X	X
MSA FE			X	X	X
Demographic controls				X	X
$\text{Price}^{\text{gas}} \times$Demographic controls					X
N =	307,977	307,977	304,903	284,605	284,605
R^2	0.002	0.003	0.002	0.016	0.016

Notes: The estimates reported in columns 1-5 are associated with the coefficients estimates from the DDD-OLS model represented by equation (6). The first column shows the results of the basic DDD-OLS model. Year dummies are added in column 2, MSA fixed effects are included in column 3, demographic controls are added in column 4 and the interactions of these demographics with gasoline prices are added in column 5. Demographic controls are number of household members, number of adults in the households, number of workers in the household, the fraction of children (age $<$18) and women in the household and household income quartile. Robust standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

A potential issue with the simple DDD-OLS model is that VMT is endogenous to MPG. It is expected that VMT affects the MPG of the chosen car but there is also a greater likelihood that households with more fuel efficient vehicles drive more. Increase in fuel efficiency decreases the cost of driving and hence households could drive more. Therefore, VMT and the interaction term in the above equation are not exogenous. To overcome this simultaneity problem, I use an instrumental variables strategy. One strategy is to use the interactions of demographics with gasoline prices as instruments for VMT. This is represented by the model shown by equations (6) and (7). The interaction of household income quartile, number of household members, number of adults, number of workers, and fraction of children and women in the household with gasoline prices serve as instruments for VMT and [VMT$\times$Price^{gas}]. These variables were selected based on the household determinants of VMT established by the previous literature (Bento et al. (2009), Small and van Dender (2007), Li et al. (2012)).

Table 3 shows the results with robust standard errors of the second stage of Difference-in-Difference-in-Differences Two-Stages Least Squares (DDD-2SLS) model. In this model the interactions of household characteristics with gasoline prices enter linearly as instruments in the first stage. The second-stage of this model is represented by equation (7). Besides the predicted interaction term, the only controls in the first column of Table 3 are gasoline prices, predicted VMT and demographics. These predictions were made using the results of the first stage. Time dummies and MSA fixed effects are added successively to the columns 2 and 3. Under all specifications the matching effect is positive and statistically significant. The matching effect coefficient decreases in the first column indicating the potential endogeneity embedded in the simple DDD-OLS estimates. This also implies that households drive more particularly, if they reside in low gasoline price regimes.[20] The effect in Table 3 ranges from 0.012 to 0.022. For a $1 increase in gasoline prices, when a vehicle is driven 1000 additional

[20]Also note that the VMT coefficients have become more negative compared to the DDD-OLS results. This also suggests that the DDD-OLS results probably suffer from VMT being endogenous to MPG.

Table 3: Difference-in-Difference-in-Differences w/ linear instruments (DDD - 2SLS) — 2^{nd} stage results

	(1)	(2)	(3)
$\text{Price}^{\text{gas}}$	0.053	0.296***	-0.152**
	(0.069)	(0.078)	(0.074)
VMT	-0.182**	-0.358***	-0.410***
	(0.018)	(0.095)	(0.086)
Matching effect	**0.012****	**0.016*****	**0.022*****
	(0.006)	**(0.007)**	**(0.007)**
Year FE		X	X
MSA FE			X
Demographic controls	X	X	X
$\text{Price}^{\text{gas}}\times$Other controls	Instr.	Instr.	Instr.
N =	287,463	287,463	287,463
F-statistics of excluded instruments			
VMT	10.90	9.54	9.60
$\text{VMT}\times\text{Price}^{\text{gas}}$	315.22	314.94	315.02

Notes: The estimates reported in columns 1-3 are associated with the coefficients estimates from the second stage of the model represented by equation (7). Household characteristics and the interactions between these characteristics and gasoline prices serve as instruments. These household characteristics include the number of household members, number of adults in the households, number of workers in the household, the fraction of children (age <18) and women in the household and household income quartile. The first column shows the results without any additional controls. Year dummies are added in column 2 and MSA fixed effects are included in column 3. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. Robust standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4: Summary statistics for $\widehat{\text{VMT}}$

	Mean	Standard deviation	Correlation w/ reported VMT
Reported VMT	10.160	8.239	1.000
VMT = $f(\overline{\text{Price}^{\text{gas}}}$, year dummies)	10.165	0.377	0.055
VMT = $f(\overline{\text{Price}^{\text{gas}}}$, year dummies, $\mathbf{X}$)	10.258	2.076	0.251
VMT e = $f(\overline{\text{Price}^{\text{gas}}}$, year dummies, $\mathbf{X}$, MSA dummies)	10.252	2.132	0.253

Notes: The correlation between the reported VMT and the predicted VMT are reported here. Predicted VMT is obtained by first running the OLS regression on equation (6) and then using the respective coefficients, predict VMT at average gasoline prices and the interaction of these average prices with number of household members, number of adults in the households, number of workers in the household, fraction of children (age $<$18) and women in the household and household income quartile. The matrix $\mathbf{X}$ contains the demographic variables that determine predicted VMT: number of household members, number of adults in the households, number of workers in the household, fraction of children (age $<$18) and women in the household and household income quartile and the interactions of these variables with average gasoline prices.

annual miles relative to others, this particular vehicle provides on average 0.02 more MPG. Compared to the DDD-OLS model, the matching coefficient estimates of Table 3 are similar in magnitude.

However, an issue with this approach is that the interactions of household characteristics with gasoline prices do not enter the second stage. This is because these interactions serve as instruments and inclusion of these variables will make the DDD-2SLS model unidentified. Inclusion of these instruments will cause the number of instruments to be less than the number of endogenous components. Inability to include these variables and their interactions will result in inability to capture certain household heterogeneous effects on MPG. To overcome this problem, I predict the effect of gasoline prices on MPG for different households and then regress these predicted effects on predicted VMT. To execute this I follow a two-step procedure. In the first step, estimate equation (6) by OLS and predict VMT at average gasoline prices. Note, gasoline prices enter equation (6) as a main effect and are also interacted with households characteristics.[21] The third column of Table 4 shows the correlations between the reported VMT and the predicted VMT. Considering VMT to be a function of average gasoline prices, household characteristics and the interaction of these characteristics with average gasoline prices, year dummies and MSA dummies, the correlation coefficient between actual and predicted values is 0.25. In the second step, estimate equation (11) by OLS and correct the standard errors.

The results of equation (11) with corrected standard errors are shown in Table 5.[22] The first column shows the results of a regression of MPG on gasoline prices and the interaction of gasoline prices with predicted VMT. Time dummies and MSA fixed effects are added in the second and the third column, respectively. Other demographics are inserted for the estimation of equation (11) given by specification of column four. In all these regressions the matching effect is significant. Inclusion of additional controls makes the matching effect positive. The magnitude of the effect is closer to the DDD-OLS results. These results lend support to the fact that controlling for heterogeneous household effects is essential to grasp the true matching effect. In the last three columns predicted VMT is included in the regressions instead of the household characteristics. These particular regressions, due to the inclusion of predicted VMT, are a functional form constraints of the DDD-OLS model. Again after the inclusion of $\widehat{\text{VMT}}$ instead of reported VMT, the magnitude of the matching effect is centered around the basic DDD-OLS results. According to these results when gasoline prices increase by \$1 and household driving increases by 1000 annual miles, these households on average adopt a vehicle that accords 0.015 - 0.021 more MPG.

This particular method gives the correlation between the treatment effect of $dPrice^{gas}$ and predicted VMT propensity. To get a causal matching effect and be able to control for heterogeneous household effects on MPG, I create instruments using Bento et al. (2009)

[21] These household characteristics are the same as those that were used as instruments in the DID-IV given by equations (6) and (7). These are number of household members, number of workers in the households, income quartiles, number of adults in the household, and fraction of women and children in the house.

[22] Since predicted VMT enters equation (11), standard errors have to be corrected.

Table 5: Non-causal estimation of the matching effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Price}^{\text{gas}}$	0.465***	0.704***	0.503***	-0.079	0.021	0.223***	-0.069
	(0.021)	(0.031)	(0.032)	(0.083)	(0.061)	(0.064)	(0.085)
Matching effect	**-0.026*****	**-0.026*****	**-0.041*****	**0.016****	**0.015*****	**0.021*****	**0.015*****
	(0.002)	**(0.002)**	**(0.004)**	**(0.008)**	**(0.006)**	**(0.006)**	**(0.006)**
$\widehat{\text{VMT}}$					-0.130***	-0.150***	-0.179***
					(0.017)	(0.017)	(0.022)
Year FE		X	X	X		X	X
MSA FE			X	X			X
Demographic controls				X			
N =	293,496	293,496	290,601	290,601	293,496	293,496	290,601
R^2	0.002	0.002	0.002	0.014	0.002	0.002	0.002

Notes: The estimates reported in columns 1-7 are associated with coefficients estimates of the model represented by equation (11). The first column shows the results of the regression on gasoline prices and the interaction between gasoline prices and predicted VMT from equation (10). Predicted VMT is a function of average gasoline prices, number of household members, number of adults in the households, number of workers in the household, fraction of children (age $<$18) and women in the household and household income quartile, interactions between these characteristics and average gasoline prices, year dummies and MSA fixed effects. Year dummies are added in the second column and MSA fixed effects are added in the third column. Household income quartile, number of household members and number of adults in the households (**X**) are added in column 4. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age $<$18) and women in the household and household income quartile. In columns 5 - 7, instead of demographic controls, predicted VMT is included. Corrected standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

structural model. The details of this methodology are given by equations (14) and (15). This particular instrument is a function of number of household members, household income quartile, number of children and women in the household, household age distribution, number of adults in the households, and vehicle class, vehicle age and driving cost per mile of the average vehicle. The first stage results for VMT are displayed in Table 6.[23] In the first column of Table 6 only gasoline prices and the instrument were included. Time dummies and MSA fixed effects are included in the second and third columns. Finally, other demographic controls and the interactions of these controls with gasoline prices are added in the last two columns. These demographic controls include all the demographic controls of the DDD-OLS model. Robust standard errors are reported in parentheses. In all these models, the coefficient associated with gasoline prices is negative and statistically significant (except for column three, where it is insignificant). This implies that as gasoline prices increase households drive less and hence satisfying the law of demand. The F-statistic of the excluded instruments is significant in all these first-stage specifications. The values of the first stage F-statistics indicate that the instruments are not weak based on the critical values suggested by Stock and Yogo (2005).

Table 7 shows the results with robust standard errors of the second stage of the DDD-2SLS model given by equation (15). The difference between this model and the model given by (7) is that here VMT is a non-linear function of household characteristics derived from a structural model. An advantage of this method is that the interactions of the household characteristics with gasoline prices can be included in the second stage. The only controls in the first column of Table 7 are gasoline prices and the predicted VMT besides the predicted interaction term. These predictions were made using the results of the first stage. Time dummies, MSA fixed effects, demographic controls and the interaction of these demographics with gasoline prices are added successively to the later columns. The demographic

[23]There are two endogenous variables. VMT and since VMT is also interacted with gasoline prices, VMT $\times$ Price^{gas} is also endogenous. The first stage results of VMT $\times$Price^{gas} not shown here but can be provided upon request.

Table 6: Difference-in-Difference-in-Differences w/ non-linear instruments (DDD - 2SLS) — 1^{st} stage for VMT results

	(1)	(2)	(3)	(4)	(5)
$\text{Price}^{\text{gas}}$	-0.330***	-0.158***	-0.021	-0.053	-0.393***
	(0.023)	(0.037)	(0.039)	(0.038)	(0.0894)
$\widehat{VMT}_{i\bar{j}}$	0.252***	0.256***	0.247***	0.078***	0.100***
	(0.027)	(0.026)	(0.023)	(0.022)	(0.025)
$\widehat{VMT}_{i\bar{j}} \times \text{Price}^{\text{gas}}$	0.069***	0.068***	0.070***	0.008	-0.000
	(0.010)	(0.009)	(0.008)	(0.008)	(0.009)
YEAR FE		X	X	X	X
MSA FE			X	X	X
Demographic controls				X	X
$\text{Price}^{\text{gas}} \times$Demographic controls					X
F-statistic of excluded instruments	1075.46	1096.83	1546.69	67.52	67.98
N =	247,850	247,850	247,850	247,850	247,850

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the first stage of the model represented by equation (15). $\widehat{VMT}_{i\bar{j}}$ serves as the instrument for VMT. $\widehat{VMT}_{i\bar{j}}$ is estimated using Bento et al. (2009) structural model. The instrument is a function of household income, number of household members, number of children and women in the household, household age distribution, number of adults in the households, and vehicle class, vehicle age and driving cost per mile of the average vehicle in the sample. The first column shows the results of the basic DID-IV model. Year dummies are added in column 2, MSA fixed effects are included in column 3, demographic controls are added in column 4 and interactions of these demographics with gasoline prices are added in column 5. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. Robust standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

controls now include all the demographic controls of the baseline DDD-OLS model. Under all specifications the matching effect is positive and statistically significant (except for specification given by columns 1 and 2, where the matching effect is insignificant). Again the matching coefficient is smaller in magnitude in the first column relative to the DDD-OLS results. Hence, compared to the DDD-OLS model and the 2SLS results, it could be claimed that due to the endogeneity of VMT to MPG, the matching effect results given by the DDD-OLS model are probably biased upwards.The effect ranges from 0.04 to 0.13. For a $1 increase in gasoline prices, a household that drives 1000 more annual miles per vehicle relative to others is driving a vehicle that provides on average 0.04 - 0.13 more MPG.

Other results

Thus far, I have estimated the matching effect for all vehicles in the household. To study the robustness of the results the data is restricted to the "top-n" household vehicles. "Top" orders household automobiles by VMT. In Table 8, n $\leq$ number of adults in the household. In Table 9 this restriction is made more stringent and n = 1, that is, the most utilized household vehicle is retained in the data. These tables show the results of the restricted data for all the models. The 1st column shows the DDD-OLS results controlling for the demographic covariates, interactions of these variables with gasoline prices, year dummies and MSA fixed effects. These results are comparable with Table 2, Column 5. The matching coefficient estimate is slightly smaller than the previous DDD-OLS result but is still significant. Columns 2 in these tables use the interactions of demographics with gasoline prices as instruments. These results could be compared with Table 3, Column 3. Again the results are consistent with the main results. Columns 3 and 4 show the results of the non-causal estimation procedure given by equation (11) for the "top-n" automobiles in the households. This particular regression estimates how the the heterogeneous effects on MPG, due to changes in gasoline prices are correlated with predicted VMT. In column 3, covariates include household demographics and year dummies. In column 4 predicted VMT is

Table 7: Difference-in-Difference-in-Differences w/ non-linear instruments (DDD - 2SLS) — 2nd stage results

	(1)	(2)	(3)	(4)	(5)
Price^{gas}	0.021	0.264*	-0.316**	-0.364**	-0.914*
	(0.158)	(0.153)	(0.161)	(0.170)	(0.507)
$\widehat{VMT}_{i\bar{j}}$	-0.108***	-0.115***	-0.250***	-0.212***	-0.006
	(0.043)	(0.043)	(0.046)	(0.081)	(0.185)
Matching effect	**0.014**	**0.016**	**0.038*** **	**0.045*** **	**0.127** **
	(0.014)	**(0.014)**	**(0.015)**	**(0.016)**	**(0.066)**
Year FE		X	X	X	X
MSA FE			X	X	X
Demographic controls				X	X
$\text{Price}^{gas}\times$Demographic controls					X
N =	247,850	247,850	247,850	247,850	247,850
F-statistics of excluded instruments					
VMT	1075.46	1096.83	1546.69	67.52	67.98
$\text{VMT}\times\text{Price}^{gas}$	1044.10	1058.39	1568.65	188.89	58.05

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the second stage of the model represented by equation (16). $\widehat{VMT}_{i\bar{j}ct}$ serves as the instrument for VMT. $\widehat{VMT}_{i\bar{j}ct}$ is estimated using Bento et al. (2009) structural model. The instrument is a function of household income, number of household members, number of children and women in the household, household age distribution, number of adults in the households, and vehicle class, vehicle age and driving cost per mile of the average vehicle in the sample. The first column shows the results without any additional controls. Year dummies are added in column 2, MSA fixed effects are included in column 3, demographic controls are added in column 4 and interactions of these demographics with gasoline prices are added in column 5. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. Robust standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

included in the model. These results are similar to those displayed in Table 5. Finally, the last two columns of Table 8 and Table 9 show the results when $\widehat{VMT_{i\bar{j}}}$ and $\widehat{VMT_{i\bar{j}}} \times \text{Price}^{\text{gas}}$ are used as instruments for reported VMT and the matching effect. $\widehat{VMT_{i\bar{j}}}$ is a non-linear function of VMT and is calculated using Bento et al.'s (2009) structural model. Household demographics are controlled for in column 5 and the interactions of these demographics with gasoline prices are added to the model in column 6. The matching effect is significant in column 5 whereas it is insignificant in column 6. The insignificance in the last column is driven mainly by the interaction between gasoline prices and income quartiles. Moreover, the F-statistics of the excluded instruments are quite close to the critical values suggested by Stock and Yogo (2005). The magnitudes of the results, however, are similar to the results reported in Table 7.

Table 10 replicates the main results with gallons per mile as the dependent variable. The coefficient estimates indicate the change in gasoline consumption (in gallons) when there is a small change in the explanatory variables. The matching effect is negative for all the models implying that when gasoline prices increase by \$1, a household that drives 1000 more annual miles is driving a vehicle that consumes less gasoline. Except for the non-causal models, the coefficient of interest is significant.

The unit of observations for all the results is vehicle. Therefore, the results exploit between as well as within household variation in MPG. However, this strategy also implicitly assumes that household i's vehicle j's MPG is independent of household i's vehicle k's MPG.[24] To estimate the matching effect between households, I regress weighted-MPG on $\frac{\sum_j VMT_{ij}}{\#\, of\, adults}$. Weighted-MPG is equal to $\sum w_{ij} MPG_j$ where w_{ij} are weights and $w_{ij} = \frac{VMT_{ij}}{\sum_j VMT_{ij}}$ for each household. Table 11 shows the results of this strategy for all the econometric

[24] In estimation of the rebound effect Linn (2013) is one of the few studies that does not make the assumption that VMT for vehicle j is independent of vehicle k. To overcome this he controls for fuel economy of the other vehicles in the household in their econometric models.

Table 8: The matching effect for the "top-n" household vehicles: all models

	(1)	(2)	(3)	(4)	(5)	(6)
	DDD-OLS	DDD-2SLS	Non-causal	Non-causal	DDD-2SLS	DDD-2SLS
$\text{Price}^{\text{gas}}$	-0.121	-0.1874***	-0.137*	-0.149*	-0.311*	-1.189
	(0.084)	(0.069)	(0.080)	(0.082)	(0.186)	(1.082)
VMT	-0.032***	-0.381***			0.367**	0.076
	(0.005)	(0.086)			(0.150)	(0.331)
Matching effect	**0.016***	**0.022**	**0.020***	**0.021***	**0.040***	**0.155**
	(0.002)	**(0.006)**	**(0.008)**	**(0.008)**	**(0.017)**	**(0.126)**
$\widehat{\text{VMT}}$ at avg. gasoline prices				-0.180***		
				(0.019)		
Year FE	X	X	X	X	X	X
MSA FE	X	X	X	X	X	X
Demographic controls	X	X	X		X	X
$\text{Price}^{\text{gas}}\times$Demographic controls	X					X
N =	253,348	255,890	256,948	256,948	223,023	223,023
Instruments:		$\text{Price}^{\text{gas}}\times$Demographic controls			$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$	$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$
Compare with:	Table 2, Col. 5	Table 3,Col. 3	Table 5,Col. 4	Table 5,Col. 7	Table 7, Col. 4	Table 7,Col. 5

Notes: The estimates reported in columns 1-6 are associated with the coefficients estimates of the models described in the Econometrics Methodology Section. The "top-n" vehicles were retained in the data-set where "top" sorts VMT within the household in descending order and n≤# of adults. All these regressions control for year dummies, MSA fixed effects, demographic controls and the interactions of these demographics with gasoline prices, unless otherwise stated. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. The interactions between demographic controls and gasoline prices serve as instruments for VMT in the second column. $\widehat{VMT}_{i\bar{j}ct}$ serves as the instrument for VMT in the last two column. $\widehat{VMT}_{i\bar{j}ct}$ is estimated using Bento et al. (2009) structural model. Robust standard errors are reported in parentheses. The unit of observation is vehicle.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 9: The matching effect for the most utilized household vehicle: all models

	(1)	(2)	(3)	(4)	(5)	(6)
	DDD-OLS	DDD-2SLS	Non-causal	Non-causal	DDD-2SLS	DDD-2SLS
$Price^{gas}$	-0.147**	-0.291***	-0.208***	-0.169***	-0.414*	-1.496
	(0.072)	(0.076)	(0.060)	(0.062)	(0.244)	(1.650)
VMT	-0.029***	-0.445***			-0.544*	0.076
	(0.006)	(0.104)			(0.285)	(0.613)
Matching effect	**0.010*** **	**0.022*** **	**0.019*** **	**0.016*** **	**0.041** **	**0.246**
	(0.002)	**(0.005)**	**(0.005)**	**(0.005)**	**(0.019)**	**(0.266)**
$\widehat{\text{VMT}}$ at avg. gasoline prices				-0.161***		
				(0.012)		
Year FE	X	X	X	X	X	X
MSA FE	X	X	X	X	X	X
Demographic controls	X	X	X		X	X
$Price^{gas}$×Demographic controls	X					X
N =	147,858	149,375	148,742	148,742	130,696	130,696
Instruments		$Price^{gas}$×Demographic controls			$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times Price^{gas}$	$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times Price^{gas}$
Compare with:	Table 2, Col. 5	Table 3,Col. 3	Table 5,Col. 4	Table 5,Col. 7	Table 7, Col. 4	Table 7,Col. 5

Notes: The estimates reported in columns 1-6 are associated with coefficients estimates of the models described in the Econometrics Methodology Section. The household vehicle that was driven the most was retained in the data-set. All these regressions control for year dummies, MSA fixed effects, demographic controls and the interactions of these demographics with gasoline prices, unless otherwise stated. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. The interactions between demographic controls and gasoline prices serve as instruments for VMT in the second column. $\widehat{VMT}_{i\bar{j}ct}$ serves as the instrument for VMT in the last two column. $\widehat{VMT}_{i\bar{j}ct}$ is estimated using Bento et al. (2009) structural model. Robust standard errors are reported in parentheses. The unit of observation is vehicle.

***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 10: The matching effect with gallons per mile as the dependent variable: all models

	(1)	(2)	(3)	(4)	(5)	(6)
	DDD-OLS	DDD-2SLS	Non-causal	Non-causal	DDD-2SLS	DDD-2SLS
$\text{Price}^{\text{gas}}$	0.067	0.084	-0.012	-0.028	0.490**	1.353*
	(0.109)	(0.105)	(0.113)	(0.117)	(0.238)	(0.712)
VMT	0.036***	0.576***			-0.315***	0.049
	(0.007)	(0.139)			(0.114)	(0.259)
Matching effect	**-0.024*** **	**-0.020** **	**-0.013**	**-0.012**	**-0.065*** **	**-0.200** **
	(0.003)	**(0.010)**	**(0.011)**	**(0.011)**	**(0.023)**	**(0.093)**
$\widehat{\text{VMT}}$ at avg. gasoline prices				0.323***		
				(0.031)		
Year FE	X	X	X	X	X	X
MSA FE	X	X	X	X	X	X
Demographic controls	X	X	X		X	X
$\text{Price}^{\text{gas}}\times$Demographic controls	X					X
N =	284,605	287,463	290,601	290,601	247,850	247,850
Instruments		$\text{Price}^{\text{gas}}\times$Demographic controls			$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$	$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$

Notes: The estimates reported in columns 1-6 are associated with coefficients estimates of the models described in the Econometrics Methodology Section. The dependent variable in these regressions is 1000×GPM. All these regressions control for year dummies, MSA fixed effects, demographic controls and interactions of these demographics with gasoline prices, unless otherwise stated. Demographic controls are number of household members, number of adults in the households, number of workers in the household, fraction of children (age $<$18) and women in the household and household income quartile. The interactions between the demographic controls and gasoline prices serve as instruments for VMT in the second column. $\widehat{VMT}_{i\bar{j}ct}$ serves as the instrument for VMT in the last two columns. $\widehat{VMT}_{i\bar{j}ct}$ is estimated using Bento et al. (2009) structural model. Robust standard errors are reported in parentheses. The unit of observation is vehicle.

***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 11: The matching effect between households: all models

	(1)	(2)	(3)	(4)	(5)	(6)
	DDD-OLS	DDD-2SLS	Non-causal	Non-causal	DDD-2SLS	DDD-2SLS
$\text{Price}^{\text{gas}}$	-0.109	-0.115**	-0.143***	-0.153***	-0.145*	-0.358
	(0.074)	(0.056)	(0.056)	(0.058)	(0.089)	(0.230)
VMT per adult	-0.035***	-0.249***			-0.026	-0.037
	(0.005)	(0.064)			(0.021)	(0.064)
Matching effect	**0.006*** **	**0.016*** **	**0.020*** **	**0.021*** **	**0.022*** **	**0.026**
	(0.002)	**(0.005)**	**(0.006)**	**(0.006)**	**(0.008)**	**(0.027)**
$\widehat{\text{VMT}}$/adult at avg. gasoline prices				-0.170***		
				(0.013)		
Year FE	X	X	X	X	X	X
MSA FE	X	X	X	X	X	X
Demographic controls	X	X	X		X	X
$\text{Price}^{\text{gas}}\times$Demographic controls	X					X
N =	147,860	149,377	147,858	147,858	137,334	137,334
Instruments:		$\text{Price}^{\text{gas}}\times$Demographic controls			$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$	$\widehat{VMT}_{i\bar{j}}$; $\widehat{VMT}_{i\bar{j}}\times\text{Price}^{\text{gas}}$

Notes: The estimates reported in columns 1-6 are associated with coefficients estimates of the models described in the Econometrics Methodology Section. VMT per vehicle is aggregated for each household. The dependent variable is a weighted average of household vehicle MPGs, where weights are determined by VMT per vehicle. All these regressions control for year dummies, MSA fixed effects, demographic controls and interactions of these demographics with gasoline prices, unless otherwise stated. Demographic controls are number of household members, number of workers in the household, fraction of children (age <18) and women in the household and household income quartile. The interactions between the demographic controls and gasoline prices serve as instruments for VMT in the second column. $\sum_j \widehat{VMT}_{i\bar{j}ct}$ serves as the instrument for aggregated VMT in the last two columns. $\widehat{VMT}_{i\bar{j}ct}$ is estimated using Bento et al. (2009) structural model. Robust standard errors are reported in parentheses. The unit of observation is household.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

methods.[25] The results are robust and significant for most of the models. The magnitude of the matching effect increases when the endogeneity issue is taken care of in columns 2 to 6. The insignificance in the last column is driven mainly by the interaction between gasoline prices and the income quartiles.

Implications

Given the econometric models, the change in household fuel economy due to a small change in gasoline prices is given by $\partial MPG_j / \partial P^{gas} = \beta + \theta VMT_j$. β represents the change in fuel economy from the compositional effect and θ measures the change in household's vehicle choice given household's VMT demand. Both these effects result in gasoline savings. The proportion of the change in gasoline consumption through the matching channel can be measured by equation (16).

$$\begin{array}{c}\triangle \text{ in gasoline consumption} \\ \text{due to the matching effect}\end{array} = 1 - \left(\frac{\sum_j \frac{VMT_j}{MPG_j + \widehat{\beta} + \widehat{\theta} \cdot \overline{VMT}} - \frac{VMT_j}{MPG_j}}{\sum_j \frac{VMT_j}{MPG_j + \widehat{\beta} + \widehat{\theta} \cdot VMT_j} - \frac{VMT_j}{MPG_j}} \right) \tag{16}$$

where $\widehat{\beta}$ and $\widehat{\theta}$ are the parameters estimated by the methods explained in Section III, $\frac{VMT_j}{MPG_j}$ measures the gasoline consumption of vehicle j and $\overline{VMT}$ is the average VMT.

In equation (16), $\widehat{\beta} + \widehat{\theta} \cdot \overline{VMT}$ predicts the average change in MPG due to an increase in gasoline prices. The numerator captures the change in gasoline consumption if each household's fuel economy is increased by this average change and thus measures the change in gasoline consumption via the compositional effect. On the other hand, $\widehat{\beta} + \widehat{\theta} \cdot VMT_j$ predicts the change in fuel economy for each vehicle when gasoline prices increase and thus, the denominator estimates the change in gasoline consumption through both the matching and the compositional effects (total effect). Hence, the proportion of gasoline savings explained by the matching effect is given by (16). Given the econometric model choice, the matching

[25] These results are not comparable with the previous results as these only exploit variation in weighted-MPG between households.

Table 12: Gasoline savings in 2009 due to the matching and the compositional effects

	+\$0.25	+\$0.55	+\$1.00	+\$4.00
DDD-OLS				
Savings via $\triangle$ in composition + matching	5.3%	5.5%	5.8%	7.7%
Savings via $\triangle$ in matching	3.6%	3.7%	3.9%	5.1%
DDD-2SLS (linear IVs)				
Savings via $\triangle$ in composition + matching	1.2%	1.5%	1.9%	4.6%
Savings via $\triangle$ in matching	0.8%	1.0%	1.3%	3.1%
Non-causal estimation				
Savings via $\triangle$ in composition + matching	4.5%	4.8%	5.1%	7.1%
Savings via $\triangle$ in matching	2.4%	2.6%	2.7%	3.8%
DDD-2SLS (non-linear IVs)				
Savings via $\triangle$ in composition + matching	9.1%	10.4%	12.1%	21.1%
Savings via $\triangle$ in matching	6.0%	6.9%	8.0%	13.9%

Notes: This table shows the percentage reduction in gasoline consumption via the ${}^{\partial MPG_j}/{}_{\partial P^{gas}}$ channel when gasoline prices increase. Four different scenarios are considered: +\$0.25, +\$0.55, +\$1.00 and +\$4.00. The reduction in savings depends on the econometric model choice and the estimates of the coefficients under these models. The matching effect is responsible for 54% to 67% of these savings.

effect explains $\frac{1}{2}$ to $\frac{2}{3}$ of the change in gasoline consumption when compared to the total effect.

Table 12 compares gasoline savings via ${\partial MPG_j}/{\partial P^{gas}}$ channels for different hypothetical gasoline tax regimes in 2009. These are increase in gasoline prices of \$0.25 (small increase in prices), \$0.55 which is the increase needed to attain the welfare maximizing level (*see* Parry and Small (2005), \$1 and \$4. The last two are larger increases that will put the US in conjunction with the gasoline taxes enforced in Europe.[26] For example, if gasoline prices in 2009 were \$1 higher, gasoline consumption would have been 2% to 12% lower.[27] Depending on the econometric model choice and the respective coefficient estimates, assortative matching decreases gasoline consumption by 1.3% to 8.1%. If in 2009, the gasoline tax in the US was on par with the European counterparts, gasoline consumption would have been 5% to 21% lower and 54% to 67% of these reductions in consumption could be attributed to the matching effect while the remainder would be due to the compositional effect. Figure 5 plots MPG against VMT for these hypothetical 2009 tax regimes. More matching is observed as gasoline prices increase. Given that annual gasoline consumption for light-duty vehicles in the US in 2009 was 138 billion gallons, if average gasoline tax in the US was at the welfare maximizing level (an increase in gasoline prices by \$0.55 as suggested by Parry and Small (2005)), gasoline consumption would have been 2.1 to 14.3 billion gallons less.[28] Each gallon of gasoline produces 20 pounds of CO_2 when burned, and hence from an environmental perspective these savings imply a reduction in GHG emissions by 14 to 97 million tons via the matching channel.[29]

[26]As of 2015, gasoline taxes in Germany and the UK are \$4.10 and \$3.95 per gallon, respectively.

[27]Note, in making these calculations, I keep the household VMT demand constant when gasoline prices change. The utilization effect will accrue even further gasoline savings.

[28]Annual gasoline consumption data can be found at the US department of Energy, Earth Policy Institute website.

[29]A gallon of gasoline weighs about 6.3 pounds, of which 87% is carbon and 13% is hydrogen and therefore carbon in a gallon of gasoline weighs 5.5 pounds. But most of the weight of CO_2 is produced by oxygen in the air. When gasoline is burned, hydrogen and carbon are separated and carbon interacts with oxygen to produce CO_2. A carbon atom has an atomic weight of 12 and an oxygen atom has an atomic weight of 16; thus each molecule of CO_2 has an atomic weight of 44. Therefore, the amount of CO_2 produced by a gallon of gasoline is ${44}/{12} \times 5.5 = 20$ pounds of CO_2.

Figure 5: MPG - VMT relationship for different tax regimes (Year = 2009)

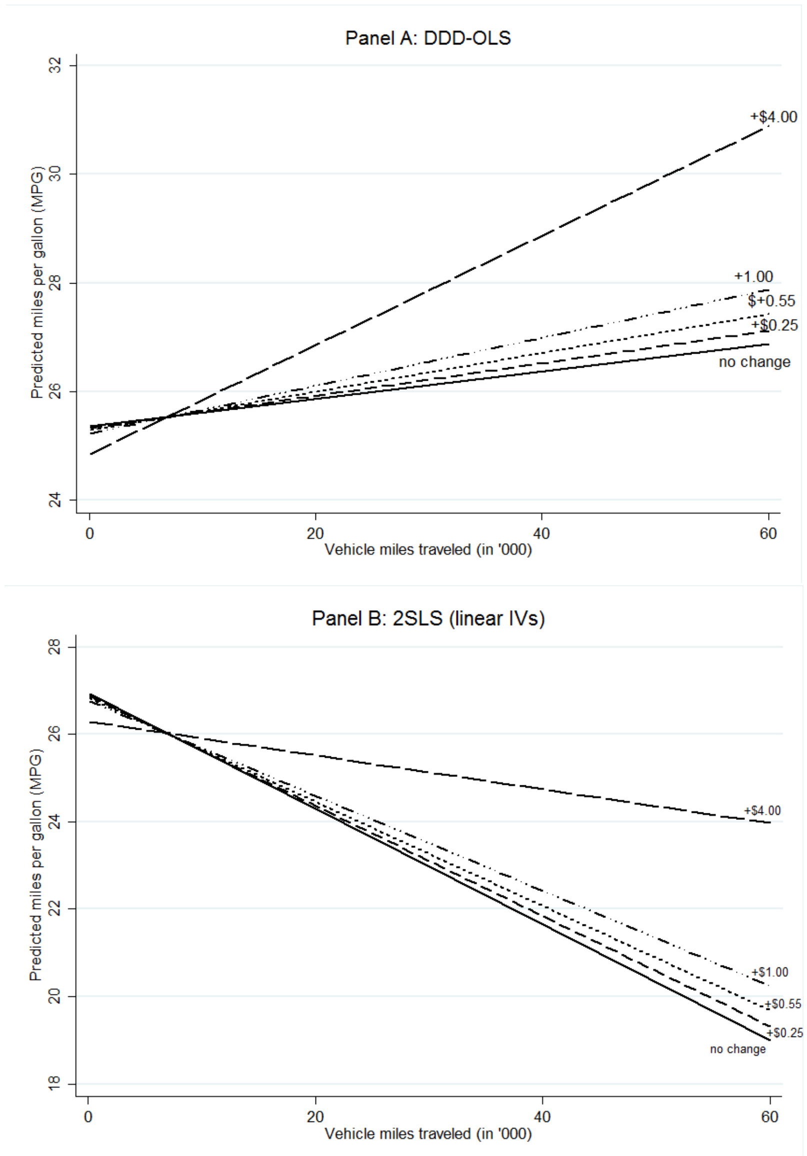
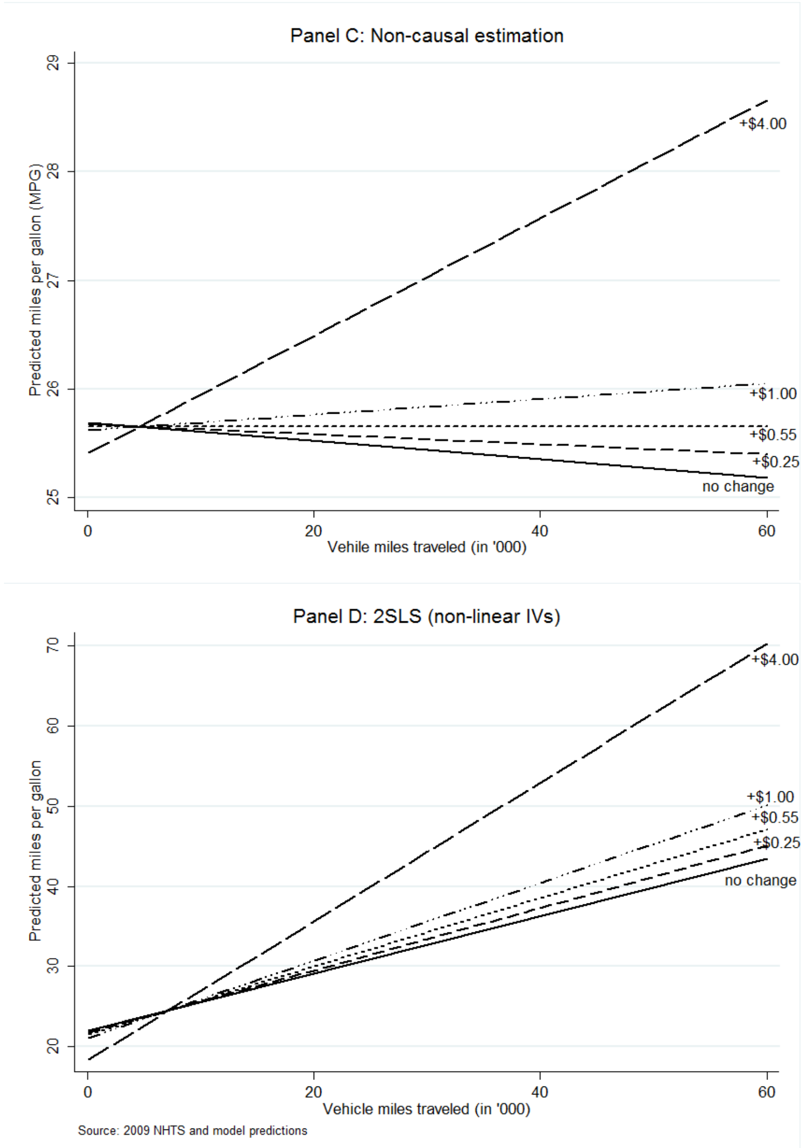


Figure 5 (continued): MPG - VMT relationship for different tax regimes (Year = 2009)



Notes: In the graphs above predicted fuel economies under different tax regimes are plotted against reported annual miles from the NHTS 2009 confidential survey files. Four different tax regimes are considered: +\$0.25, +\$0.55, +\$1.00 and +\$4.00 and these are compared with the case where gasoline prices are unaltered.

VI. Conclusion

Combustion of gasoline has detrimental environmental and health impacts. To reduce these externalities, policies are introduced to influence gasoline prices. Two effects of gasoline prices have been identified in the literature: (i) the utilization effect and (ii) the compositional effect. The former implies that an increase in gasoline prices results in a decrease in the demand for VMT through the direct effect of reduction in gasoline consumption. The latter suggests that due to higher gasoline prices, there is an evolution of fleet towards fuel efficiency. There is a potential third effect of gasoline prices that has been overlooked in the previous studies. Due to heterogeneity in demand for VMT, increase in gasoline prices should particularly affect vehicle choices of households that drive more. In the presence of higher gasoline prices, the costs borne by high-VMT households is greater and hence they are more likely to adopt a fuel efficient vehicle. In equilibrium, there will be matching of fuel efficiency among high-VMT households and fuel inefficiency among low-VMT households. This is the first study that analyzes such assortative behavior.

To embrace the importance of the matching effect, if fuel economy was assigned perfectly to households based on their VMT demand, this particular effect could have saved 15% of US gasoline consumption. The study exploits variation in gasoline prices in the last decade and based on household VMT demand scrutinizes how these prices affect vehicle choice. For this, I use the confidential 2001 and the 2009 NHTS data, the American Chamber of Commerce ACCRA Cost of Living Index (COLI) database and the fuel economy data from the Department of Energy to produce a unique data-set. A variety of econometric methods are employed to estimate the matching effect. The results suggest that when the gasoline price increases by \$1, a vehicle that is driven 1000 more annual miles per vehicle, on average gives 0.02 to 0.13 more miles per gallon. These results are robust to different model specifications.

Given the coefficient estimates, if gasoline prices in 2009 were \$1 higher, gasoline consumption would have been 1% to 8% lower due to the matching effect. These additional benefits of higher prices further favor price-based policies. The obvious strategy is increasing federal and state gasoline taxes. Given the societal costs of gasoline consumption, gasoline taxes in the US are well below the welfare maximizing level. Supply side policies such as restrictions on local oil production, more stringent renewable fuel standards and other environmental regulations (for example Tier 3 regulations) or abatement of crude oil imports through quotas or tariffs would also affect prices positively.[30]

[30]Currently, the Congress has imposed a ban on oil exploration and extraction along the eastern Gulf of Mexico and the Atlantic and Pacific coastlines. The Renewable Fuel Standards (RFS) program created in 2005, requires refineries to blend ethanol into gasoline. According to the Congressional Budget Office 2014 report, such standards could increase gasoline prices by 4% to 9% (13¢ to 26¢). The EPA has approved Tier 3 gasoline regulations, which aim at reducing sulfur concentration in gasoline. Due to additional manufacturing and compliance costs of these regulations, gasoline prices are expected to increase.

Chapter 2: Evaluating the effectiveness of an environmental disclosure policy: an application to New South Wales

I. Introduction

Policy-makers have introduced a variety of instruments (environmental standards, emissions taxes, emissions permits markets) to curb industrial air emissions.[31] One such policy is the disclosure of environmental information. The main purpose of introducing environmental information disclosure policies is to reduce informational asymmetries and put, if necessary, pressure on firms to reduce emissions. Perhaps the most well-known example of such a strategy is the Toxic Release Inventory (TRI), first employed in the US in 1985 and later incorporated into the Pollution Prevention Act of 1990.[32] Other countries and regions have followed the US in this regard and have made disclosure of environmental information part of their laws. It became part of the European Union Constitution in 2002 when the Aarhus Convention was ratified in Denmark to incorporate the new strategy.[33] The British Companies Act of 2006 requires companies listed on the London Stock Exchange to report in their annual Business Review the impact they have on the environment. In 2008, Buenos Aires City Council passed Law # 2598 requiring all firms that employ more than three-hundred workers to create annual sustainability reports that should be available to the public.[34] Several stock exchange markets (Johannesburg Stock Exchange (JSE), Bursa Malaysia, Bovespa

[31] For more on these and others *see* Sterner (2002), Goulder and Parry (2008), and Banzhaf (2012).

[32] TRI was introduced after considering the negative impacts of the toxic releases in the 1984 Bhopal disaster. Under the TRI, 18,500 companies reported 10.4 billion pounds of toxic chemicals released in 1987. In 2005, 23,461 companies reported 4.34 billion pounds of chemicals released in the air; a decline of 54%. However, the rate of reduction in emissions has declined relative to the initial years when the program started. Between 1988 and 1993 there was a reduction in toxic releases by 37%, whereas toxic releases declined by only 10% between 1993 and 1998. Studies evaluating effectiveness of TRI as a policy tool have produced mixed results (*see* Bui and Mayer (2003) and Oberholzer-Gee and Mitsunari (2006)).

[33] Under the Article 2(2)d of the Aarhus Convention, the public (individuals and associations) has the right to environmental information. Public authorities are obliged to provide environmental information that is in their possession. Access to environmental information follows from the first EU Directive on the Freedom of Access to Information on the Environment, the ECE Guidelines on Access to Environmental Information and the Public Participation in Environmental Decision Making of 1995 and the Rio Declaration of 1992.

[34] Firms in Buenos Aires have to comply with the Ethos Principle at the minimum but are encouraged to use Global Reporting Initiative's G3 guidelines when making their reports. For more on this see *The International Corporate Sustainability Reporting Site*.

and the Tel Aviv Stock Exchange) have also introduced measures to enhance environmental information disclosure.[35] These measures have been implanted to increase corporate social responsibilities, with respect to the environment in particular. This paper studies the impact on air pollution of an environmental disclosure policy that was recently implemented in New South Wales (NSW), Australia. Starting from July 1st, 2012 all firms holding an Environmental Protection License (EPL) in NSW are required to provide public access to emissions monitoring data. This is part of NSW's Protection of the Environment Legislation Amendment Act of 2011. To analyze the influence of this new policy, this paper focuses on the two largest cities in NSW: Sydney and Newcastle.

Previous studies have shown the effects of environmental information disclosure policies on various outcomes that are indirectly related to environmental quality (financial performance, environmental injustice, investor behavior, political activism, distribution of housing prices, etc).[36] Perlin et al. (1995) study how effective TRI has been in reducing environmental injustice. Their results show that TRI has *not* been influential in terms of affecting the distribution of environmental justice in the US. In 1990, besides Native Americans, minority groups continued to inhabit more polluted regions relative to whites. Bui and Mayer (2003) find that TRI has no impact on political activism or the distribution of housing prices and advocates for the traditional command-and-control policies. Bui (2005) report that the effects of TRI in reducing emissions are overstated, and it could be that the policy has merely led to substitution to other chemicals that are not necessarily less toxic. Foulon et al. (2001) examines the impacts of traditional policies (fines and penalties) and information disclosure strategies on firm behavior. They studied fifteen plants in the pulp and paper industry between 1987 and 1996 in British Columbia, Canada. They find that information disclosure

[35] Since 2005, Bovespa has been creating a Corporate Sustainability Index in which company stocks are ranked according to sustainability and social responsibility. Similarly in 2004, JSE started producing socially responsible investment (SRI) indices. In the US, Securities and Exchange Commission sometimes requires disclosure of hazardous waste materials. For more on these *see* Lydenberg and Grace (2008).

[36] Hamilton (1995) shows that TRI does affect the behavior of investors and third parties (journalists in their study). Firms that reported higher pollutant emissions, land releases, underground injections, and waste shipped off-site or chemical submissions were more likely to be covered by journalists. Companies that reported information prior to the introduction of TRI were least likely to receive coverage from journalists.

provided additional and stronger incentives for firms to reduce pollution. However, very little work has been done with regards to the effects of such policies on environmental quality.

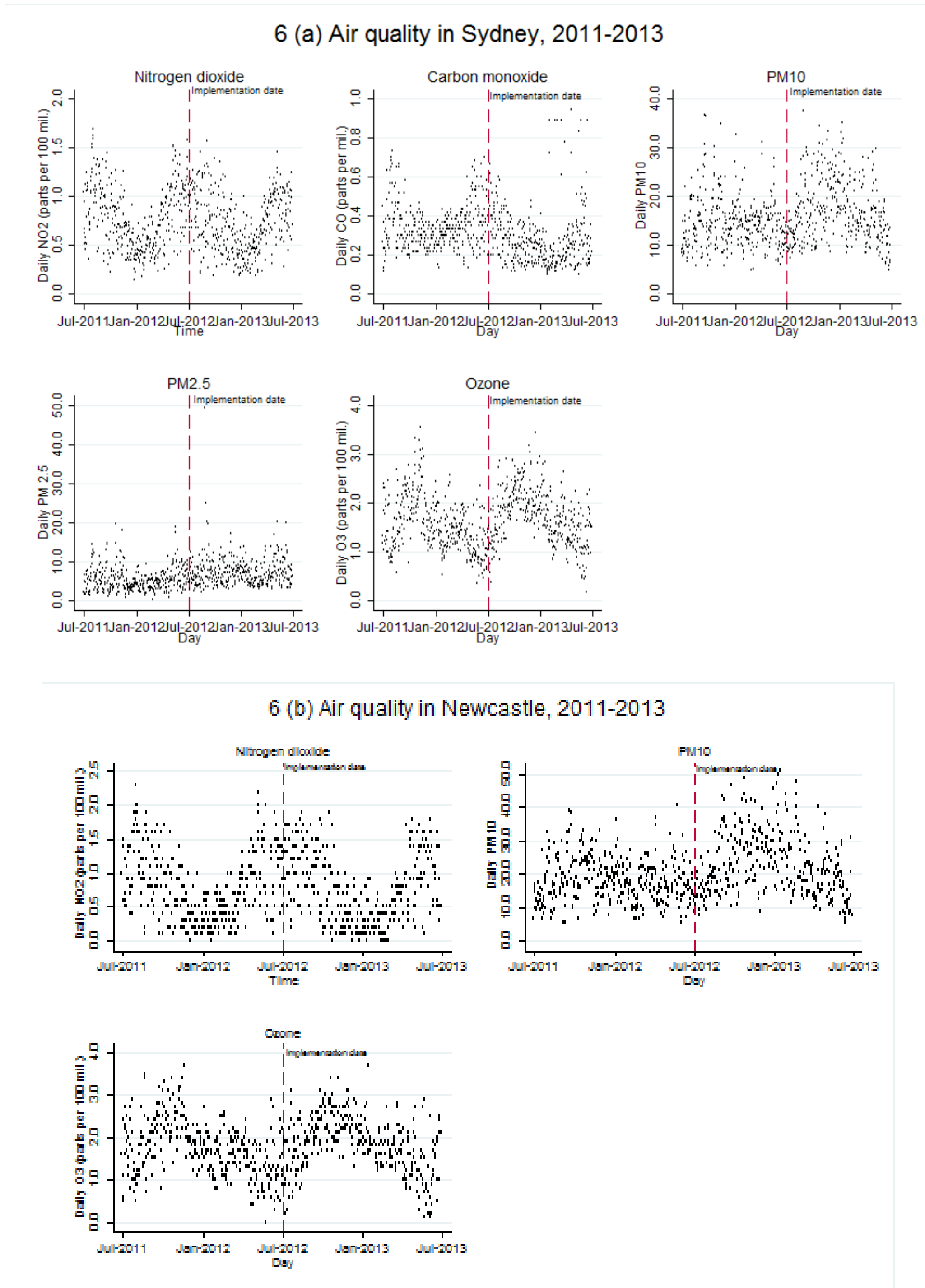
The main purpose of this paper is estimate the impact of an environmental disclosure policy on air pollution. The identification assumption of the study is that there should be a discontinuity in the pollution measure on the date the environmental information disclosure policy is enforced. This assumption implies that in the absence of the policy, air pollution would have changed continuously on July 1st, 2012. To exploit the exogenous shock produced by the policy, a regression discontinuity design is employed. The benefit of such an approach is that the coefficients can be interpreted causally. A requirement for such a methodology, however, is availability of high-frequency data. Fortunately, such data is reported before and after the policy implementation date for NSW.

Air pollution created by industrial activities could be in the form of gases (nitrogen oxides (NO_x), sulfur oxides (SO_x), carbon monoxide (CO)) or solid particles (particulate matter (PM_{10} and $PM_{2.5}$)). Interactions of these pollutants could create additional pollutants. For instance, ground level ozone (O_3) is produced when NO_x, CO and volatile organic compounds (VOCs) react in the presence of sunlight and heat. Air pollution is a major concern today, particularly in urban centers. Inhaling unclean air mainly affects the body's respiratory and the cardiovascular systems and these effects are more prominent among children. Effects of air quality on health and productivity have been documented in numerous studies (Chay and Greenstone (2003) and Currie et al. (2014)).[37] Furthermore, air pollution also damages ecological resources (water and soil quality, plants and animals). The total social costs of air pollution are possibly quite large when one also accounts for household behavioral adjustments to minimize exposure to pollution.[38]

[37]Chay and Greenstone (2003) exploit variation produced by the 1982-84 recession to show a positive causal relationship between exposure to particulate matter and infant mortality. Currie et al. (2014) summarize literature on how exposure to pollution during childhood affects adult outcomes.

[38]Mu and Zhang (2014) report increases in investments in face-masks as air pollution intensifies in China. Defensive investments could also include sorting into neighborhoods with cleaner air (Banzhaf and Walsh, 2008) or expenditures on medicines (Deschenes et al. 2012)).

Figure 6: Air quality in New South Wales (2011-2013)



Notes: These charts display the pollutant concentration levels in Sydney (a) and Newcastle (b) for the years 2011 - 2013. The pollutants displayed are NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3. The broken red line represents the date when the information disclosure policy went into effect.

Figures 6a and 6b plot the average daily pollutant levels for Sydney and Newcastle respectively, for the years 2011-2013. Pollutants shown in Figure 6 are: NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3. The broken line indicates the date (July 1st, 2012), when the policy went into effect. No distinguishable pattern can be ascertained by looking at the distribution of these pollutants. Moreover, using ocular methods a break in air pollutant levels on July 1st, 2012 is hard to detect. Similarly, the discontinuity based results indicate that the information disclosure policy had negligible effects on the pollutant concentration levels in these two cities. These results are robust to different model specifications. There could be a number of reasons for these insignificant results. Air pollution levels in Australian cities is quite low when compared to other developed cities. This could be due to stringent environmental policies already enforced before the realization of this particular policy. It could also be that environmental information might not be asymmetrical between firms and households in NSW before the policy went into effect. These probably did not necessitate any action from the public to curb emissions.

The rest of the paper is structured as follows: Section II provides a brief description of the new policy in NSW, Section III describes the data and the econometric methodologies, Section IV provides the results and Section V concludes.

II. Information disclosure policy in New South Wales

As part of the New South Wales (NSW) government's commitment to revitalize and strengthen the Environmental Protection Agency, the province has developed a new strategy. Starting from 1st of July, 2012 all holders of Environmental Protection Licenses (EPLs) in NSW are required to provide public access to monitoring data recorded under each EPL that they hold. In NSW, there are two types of firms: industrial (EPA Licensed) and commercial (non-EPA Licensed) firms. NSW EPA issues EPLs to proprietors of different industrial establishments under the 1997 POEA Act. Conditions to obtaining a license include monitoring and prevention of pollution and employing environment-friendly production methods. In addition to these, license holders have to prepare pollution incident response management plans and starting from 1st of July, 2012 they have to make monitoring data publicly available. The requirements for complying with the new strategy have been put down in the *Environmental Guidelines: Requirement for Publishing Pollution Monitoring Data*. The main focus of the policy is to provide data to the general public in a meaningful way, so that it is easy for them to understand.

NSW's Protection of the Environment Legislation Amendment Act of 2011 made several changes to the Protection of the Environment Operations Act of 1997 (POEO Act). One of these changes was that EPLs have to make their emissions data public by either publishing the monitoring data on the licensee's website, or if the licensee does not have a website, they have to provide pollution data free of charge to any person requesting it. There are penalties for not complying with the guidelines or for misreporting.[39] The data published must report the summary of the monitoring data at least on a monthly basis. Moreover, EPLs also have to inform the public whether the pollutant discharges met or did not meet the standards set by the NSW EPA.[40] Figure 7 shows examples of how NSW EPA expects EPLs to report data summaries. The POEO Act requires that the monitoring data should be published within fourteen days of the licensee procuring the data. This gives firms enough time to create meaningful summaries for publication on their websites or in print. Currently, there are 4,026 companies in NSW who have an EPL. These establishments include chemical manufacturing, logging-based companies, metal processing, mining, paper and pulp manufacturing, sewage

[39] The penalty for reporting bogus or misleading information regarding asbestos waste or hazardous waste can go up to A$1,500 for an individual and A$5,000 for a corporation. For other types of waste the penalty is A$750 for individuals and A$1,500 for firms.

[40] In addition to these, the EPL number, licensee's name and address also have to be submitted with the pollution data. A complete list of the additional information that should be provided is given in the EPA guidelines.

treatment and transportation companies. Of these EPL holders, 1,183 are located in or near Sydney and 320 in Newcastle.[41]

Emissions from the commercial businesses in NSW are meager when compared to the industrial emissions. EPA-Licensed firms are one of the major sources of air pollutants in the Greater Metropolitan Region (GMR) where 75% of the population resides.[42] Figure 8 displays charts that detail the contributions to the pollutant levels by different sectors in the GMR. EPA-licensed firms are the greatest contributor of CO (69%), PM_{10} (42%) and SO_2 (77%), and the second largest contributor of NO_x (19%; after road and non-road activities) and $PM_{2.5}$ (28%; after household activities) in the region. Figure 9 compares the emissions of these pollutants from EPA-licensed industries and motor vehicles. Besides NO_x, the major producers of pollutants, relative to automobiles, are EPA-licensed firms. Hence, the ambient air pollution is largely determined by the activities of the firms that are affected by the policy. According to the EPA Acting Chief Environmental Regulator Mark Gifford, the new policy will make industries more transparent and accountable for the impact they have on the environment and the community.

III. Econometric framework

Econometric models

This sub-section introduces the empirical approaches employed in the study. First, Ordinary Least Squares (OLS) model is used to estimate the conditional correlation between the introduction of the new policy and air quality in NSW over time. However, the OLS estimates have the potential to suffer from bias due to the correlation between the unobservables and the policy over time. The purpose of using the OLS method is to establish a baseline for

[41] A 25 miles (40 kilometers (km)) radius was drawn around Sydney and a 10 miles (16 km) radius was drawn around Newcastle to calculate the number of EPL holders near these cities. A larger radius was picked for Sydney because the data-set contains many suburbs of Sydney (Randwick, Rozelle, Lindfield, Chullora, Earlwood, Richmond, St. Mary's Vineyard, Prospect, Bargo, Liverpool, Camden and Cambelltown).

[42] GMR is made up of the three largest cities in NSW: Sydney, Newcastle and Wollongong.

Figure 7: New South Wales EPA summaries requirements

Obtained data by sample date – monthly monitoring

Sampled: 28 February 2013

Sampled: 30 January 2013

Sampled: 31 December 2012
Obtained: 31 December 2012 **Licensee: XXX P/L**
Published: 5 January 2013 **EPL No. 5555**

Sampling point	Monitoring frequency required by licence	Pollutant	Measurement	Limit	Unit
1	Monthly	Turbidity	0.06	1.0	NTU
		Salinity	3.6	4	dS/m
		pH	6.9	6.2–7.8	–
2	Monthly	Turbidity	0.09	1.0	NTU
		Salinity	4.0	4	dS/m
		pH	6.7	6.2–7.8	–
3	Monthly	Turbidity	0.8	1.0	NTU
		Salinity	3.9	4	dS/m
		pH	6.7	6.2–7.8	–

Obtained data by sample point – monthly monitoring

Sampling point: 3 **EPL No. 5555** **Licensee: XXX P/L**

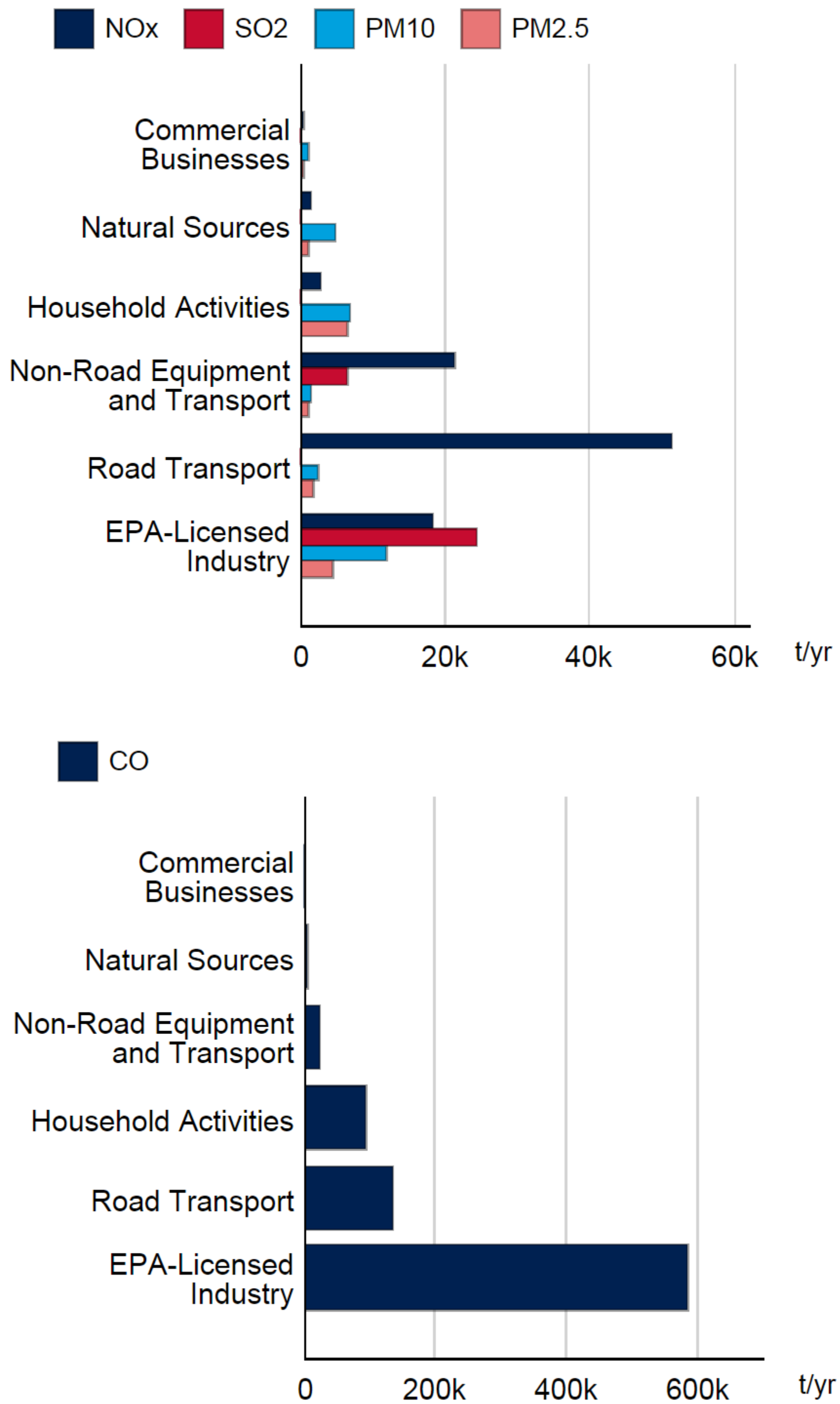
Sampling point: 2 **EPL No. 5555** **Licensee: XXX P/L**

Sampling point: 1 **EPL No. 5555** **Licensee: XXX P/L**

		Pollutant	Measurement	Limit	Units
Sampled	6/6/12	Pollutant X	1.8	2	mg/kL
Obtained	10/6/12				
Published	12/6/12				
Monitoring frequency required by licence	Monthly				
Sampled	6/6/12	Pollutant Y	0.5	2	mg/kL
Obtained	10/6/12				
Published	12/6/12				
Monitoring frequency required by licence	Monthly				

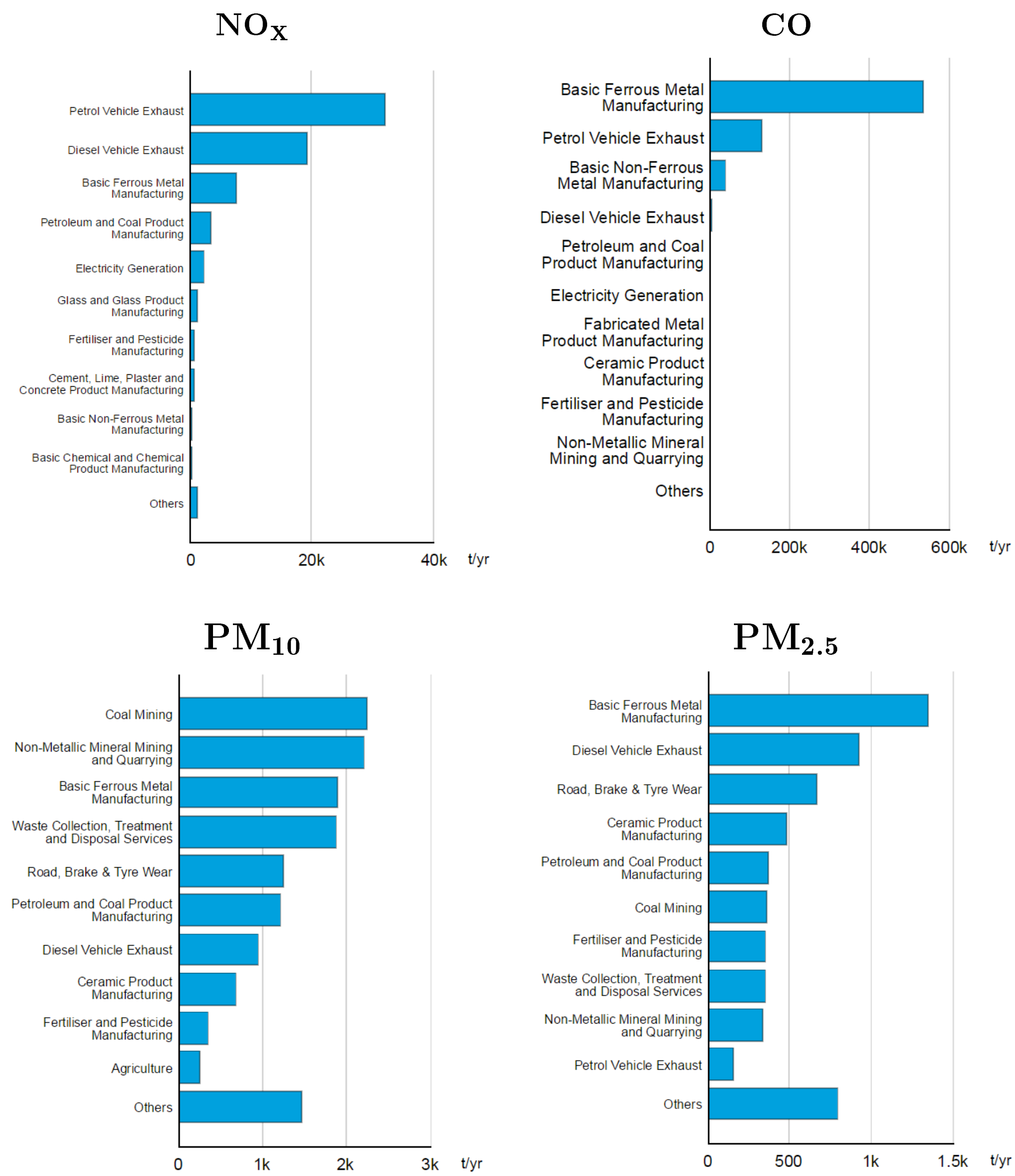
Courtesy: Environmental Guidelines: Requirement for Publishing Pollution Monitoring Data (2012)

Figure 8: Emissions by sector in the Greater Metropolitan Region of New South Wales



Courtesy: NSW Environment Protection Authority (EPA)

Figure 9: Emission activities in the Greater Metropolitan Region of New South Wales



Courtesy: NSW Environment Protection Authority (EPA) the primary estimation strategy. The second approach employed is a Discontinuity Based Ordinary Least Squares (DB-OLS) model. If the unobservables evolve continuously and smoothly around the cutoff on either side of the discontinuity, this approach will solve the issues most likely present in the simple OLS model.

Ordinary Least Squares - The basic OLS model is given below by equation (17). It simply estimates the time series model using OLS.

$$\log(\mathrm{Pollutant_t}) = \delta_0 + \delta_1 \left[1(\tau \geq Policy)\right] + \mathbf{X}_t\delta_2 + \varepsilon_t \tag{17}$$

where $[1(\tau \geq Policy)]$ is an indicator variable that takes a value of 1 when the policy went into effect (July 1$^{\mathrm{st}}$, 2012) and 0 otherwise.[43] $\mathbf{X}_t$ includes quartics in average daily measures of weather variables (temperature, humidity and wind speed), day of the week and month dummy variables; ε_t is the error term. The coefficient of interest in (17) is δ_1, which represents the effect of the policy on air quality. δ_1 is expected to be negative: after the new policy was put in place, air quality is expected to improve (pollutant concentration levels decrease). The new policy might put pressure on firms to reduce emissions and this would affect the environmental quality positively. However, this simple approach has the potential to produce biased estimates of δ_1. A time series regression for NSW that attempts to develop a relationship between air quality and the new information strategy is unlikely to provide an estimate of δ_1 that can be interpreted causally because any other time-varying factors that affect pollution might well be correlated with the policy indicator. This is particularly true for NSW where besides the new strategy, several other environmental instruments (Greenhouse Gas Reduction Scheme (GGAS) (enforced in 2003), Clean Cars Action Plan (enforced in 2010), vapor recovery reporting at petrol station (enforced in 2010)) have been recently

[43] Log-linear models were preferred over linear models as these are relatively more robust.

adopted to improve the environmental quality.[44] These other measures are also likely to decrease pollutant concentration levels indicating an improvement in air quality. Assigning all the credit of these improvements to δ_1 would be inaccurate. Similarly, during the post- (pre-) intervention period, pollutant levels could also increase (decrease) due to a variety of other reasons (changes in economic activity, changes in government policy), which would under- (over-) state the effect of the disclosure policy.[45] Therefore, the coefficient of interest is likely to be biased in this model.

Discontinuity-Based Ordinary Least Squares - To overcome the problem of correlation between the policy indicator and the unobservable determinants of air quality, Discontinuity Based Ordinary Least Squares (DB-OLS) model is estimated. This empirical strategy will exploit the sharp discontinuity presented by the introduction of the new information disclosure policy. The advantage of this approach is the identification of exogenous sources of variation in expected air quality.[46] The DB-OLS model is given below:

$$\log(\mathrm{Pollutant_t}) = \delta_0 + \delta_1 \left[1(\tau \geq Policy)\right] + \mathbf{X}_t\delta_2 + \delta_3\psi(\mathbf{t}) + \mu_t \tag{18}$$

In the model above the coefficient of interest is δ_1, which exhibits the effect of the policy on air pollution. $[1(\tau \geq Policy)]$ is, as before, equal to 1 starting from July 1st, 2012 and equal to 0 before the implementation of the policy. $\mathbf{X}_t$ includes quartics in average weather

[44]The NSW Greenhouse Gas Reduction Scheme (GGAS) was incorporated on 1st January 2003. It is a mandatory greenhouse gas emissions trading scheme. Clean Cars Action Plan came into place after the implementation of Protection of the Environment Operations (Clear Air) Regulation 2010. Vapor recovery reporting at petrol station is also part of this regulation. For more on these *see* http://www.environment.nsw.gov.au/air. Additionally in 2012, electricity prices in NSW were increased by 16%. An increase in electricity prices would decrease its demand. This would reduce mining and combustion of coal used in electricity production, and hence decrease pollutants such as PM_{10}, $PM_{2.5}$, and NO_2.

[45]In 2013 alone, there was at least a 50% increase in air pollution breaches in Newcastle relative to previous years. This was mostly due to increase in mining for coal for electricity production.

[46]Alternatively, one could also employ a difference-in-differences (DID) strategy to analyze the effect of the policy. For DID in addition to NSW pollution data, the researcher would also need pollution data for cities outside the province to form counterfactuals. DID analysis are presented as a robustness check and DB-OLS method is used as the main empirical strategy. The results of both approaches are similar.

covariates (temperature, wind speed and humidity) and day of the week and month dummies to control for seasonality. The vector $\psi(\mathbf{t})$ is a polynomial time-trend that will control for time series variation in pollution that would have occurred in the absence of the new policy in NSW. It is these controls that take account of the changes in economic activity for the time frame being studied. They also account for the changes in air pollution as a result of other polices adopted by NSW that could affect air pollution over time. μ_t is the noise term and it is assumed that $E(\mu_t \mid 1(\tau \geq Policy),\, \mathbf{X}_t,\, \psi(\mathbf{t})) = 0$.

The empirical strategy rests upon the assumption that the only factor that affects air pollution discontinuously on 1st July, 2012 is the implementation of the new information disclosure strategy. By controlling for the non-linear variation in air pollution from other determinants using a polynomial time-trend, the coefficient of interest can be interpreted causally as changes in air quality are attributed solely to the new policy. Any differences in other factors that change continuously around the date the policy was enforced will be captured by the polynomial. Porter (2003) suggests that odd order polynomials should be preferred as they have better econometric properties. Accordingly, I use a third-order polynomial in my base model. However, validity and robustness of these estimates will be tested by considering different specifications. In particular, different polynomial orders will be considered to examine the robustness of the estimates. The DB-OLS approach overcomes the bias associated with the simple OLS time series method as it is not endangered by the other unobservable factors that could affect air quality in the time frame of interest. This approach is similar to the one employed by Davis (2008) and Chen and Whalley (2011).

The coefficient of interest, δ_1, could be negative: the implementation of the new policy improves air quality. However, this effect depends on the behavior of firms in response to the new strategy and how citizens and other third parties react to the new information that becomes available to them. If the combination of pressures of the policy and those concerned about the pollution levels is effective and firms do reduce emissions, $\delta_1 < 0$.[47] On the other hand $\delta_1 \approx 0$, if these pressures are not significant or instrumental in affecting firm behavior. As the precise magnitude of the effect of the new instrument is not clear, estimating the magnitude of δ_1 is considered to be an empirical question. Finally as mentioned above, δ_1 can be given a causal interpretation in model (18) as many sources of spurious correlations are taken care of by the DB-OLS approach.[48]

Data

The empirical analysis requires high-frequency data for air pollution. Fortunately, high quality data for pollutants is available for New South Wales. The data source used for the study is the NSW EPA air quality monitoring network. Currently, NSW EPA monitors air quality at twenty-four different stations. Sydney's air has been monitored since the 1960s, but gradually other cities and towns were included in the network. In June 1998, two major changes were implemented in relation to how air quality was reported in Australia: (i) national standards for measuring air quality were placed and (ii) national reporting was introduced. The five pollutants measured under the 1998 standards are carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), particulate matter (PM_{10} and $PM_{2.5}$) and sulfur dioxide (SO_2). Due to limited data for SO_2, these readings were not collected. The level of CO, NO_2, PM_{10} and $PM_{2.5}$ emissions are reported in the EPA-Licensed firms reports. O_3 is produced when NO_x, CO and volatile organic compounds (VOCs) react in the presence of sunlight and heat and hence is correlated with the reported pollutants. NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3 levels

[47]If $\delta_1 < 0$, there could be significant savings in health costs. For example, a publication by the Department of Environment and Conservation, NSW in 2005 titled *Air Pollution Economics* reported that a contraction of PM_{10} by 10 $\mu g/m^3$ on average has a long-term exposure-response of reducing mortality by 2.6% - 6.1%, respiratory hospital admissions by 0.5% - 1.1% and cardiovascular hospital admissions by 0.6% - 1.3%.

[48]Since this is time-series data, successive observations are likely to be correlated. Both models are estimated using multiple lags and model choice was based on Akaike Information Criterion (AIC) statistic. 5-weeks lagged values serve as an upper bound under the above criterion for all pollutants. The magnitude and significance of the auto-correlation coefficients decrease after lags of 5-weeks. Hence to account for auto-correlation, variance-covariance matrices are constructed such that they allow for correlation within 5-weeks clusters. Chen and Whalley (2001) and Davis (2008) also cluster the standard errors at the 5-weeks level.

Figure 10: Monitoring Sites in New South Wales

Courtesy: NSW Environment Protection Authority (EPA)

for the two largest cities in NSW, Sydney and Newcastle were compiled and are treated as measures of air quality.[49] Figure 10 shows the the locations of the monitoring sites for each city. Daily weather variables (temperature, wind speed and humidity) were collected from Australian Bureau of Meteorology. For the main analysis, averages across monitoring stations in a city were taken to analyze daily time-series of air quality.

The sample period chosen for the empirical analysis includes all observations within a two-year period (2011-2013): twelve months before and twelve months after the introduction

[49]Sydney is the largest city in Australia with a population of 4.75 million and population density equal to 380/km^2 (980/sq. mi). Newcastle is the second largest city in NSW with a population of 308,000 and population density of 1,103 /km^2 (2,860/sq. mi). Geographically, Newcastle is 162 km (101 mi) from Sydney.

of the policy. Since, the main empirical strategy involves usage of a discontinuity based ordinary least squares, expanding the data set beyond June 2013 will not add precision to our estimates. As a matter of fact, conceptually discontinuity based estimates produce local average treatment effects and using data points close to the discontinuity are preferred. On the other hand, precision of the estimates is affected as the sample size decreases. Air quality data is continuous and using observations further from the window would improve the precision of the parameters. Moreover as pointed out by Davis (2008), to control for seasonal variation in air pollution one should at least use data that spans over two-years. Following Davis (2008) and Chen and Whalley (2012) atmospheric conditions are controlled for in the econometric models as they can significantly affect pollution levels.

Table 13 provides the summary statistics for air quality measures and weather variables for both cities. The first column reports the descriptive statistics for the entire sample. This is broken down into pre- and post- policy periods in columns 2 and 3, respectively. Column 4 compares these two columns and reports the differences and standard errors in parentheses. The null hypothesis that is being tested in column 4 is that the variables do not differ between the pre- and the post-policy periods.

Columns 1-3 of Table 13 show the means and variations in the variables across both cities. Glancing across Table 13, one could observe that on average Newcastle had higher levels of NO_2, PM_{10} and O_3.[50] Comparing pollutant concentrations in Sydney and Newcastle to other developed cities of similar sizes lends support to the fact that Australia has some of the best air quality in the world. Average changes in pollutant concentration are mixed in pre- and post-policy scenarios. For instance, on average NO_2 and CO levels declined in Sydney in the post-intervention period. However, PM_{10} , $PM_{2.5}$ and O_3 levels increased. In Newcastle, PM_{10} levels intensified whereas changes to NO_2 and O_3 were not statistically significant. These differences in pre- and post- policy pollutant levels might not only be because of the new information disclosure strategy. There could be other factors, such as

[50] $PM_{2.5}$ is not reported by the monitoring stations in Newcastle. CO readings for Newcastle were dropped due to a large number of missing values.

Table 13: Descriptive statistics: pollutant levels and weather covariates in New South Wales

	Full sample	Pre-policy	Post-policy	Difference	Full sample	Pre-policy	Post-policy	Difference
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Sydney				**Newcastle**			
NO_2(pphm)	0.743	0.765	0.722	-0.044**	0.767	0.780	0.755	-0.025
	(0.309)	(0.321)	(0.297)	(0.023)	(0.504)	(0.506)	(0.502)	(0.037)
PM_{10}(μg/m^3)	15.742	14.645	16.841	2.196***	20.355	18.324	22.379	4.055***
	(5.898)	(5.273)	(6.282)	(0.429)	(8.366)	(6.794)	(9.258)	(0.604)
$PM_{2.5}$(μg/m^3)	6.367	5.396	7.340	1.943***				
	(3.678)	(3.121)	(3.933)	(0.263)				
CO (ppm)	0.316	0.348	0.284	-0.064***				
	(0.139)	(0.116)	(0.151)	(0.010)				
O_3(pphm)	1.633	1.549	1.716	0.167***	1.782	1.744	1.821	0.077
	(0.557)	(0.554)	(0.547)	(0.041)	(0.661)	(0.667)	(0.654)	(0.049)
Temperature (°C)	16.993	16.783	17.204	0.422	17.001	16.666	17.337	0.671*
	(4.441)	(4.236)	(4.635)	(0.328)	(4.435)	(4.197)	(4.642)	(0.327)
Wind speed (m/s)	1.738	1.682	1.793	0.111***	2.259	2.205	2.314	0.109
	(0.570)	(0.559)	(0.577)	(0.042)	(0.840)	(0.845)	(0.831)	(0.062)
Humidity (fraction)	0.731	0.753	0.709	0.043***	0.753	0.778	0.727	0.051***
	(0.126)	(0.121)	(0.128)	(0.009)	(0.127)	(0.006)	(0.007)	(0.009)

Notes: The unit of observation is "day" for all variables across all regions. The main entries in columns 1, 2 and 3 report the mean level of the variables with standard deviations in parentheses. In column 4, the null hypothesis that is being tested is that the values in columns 2 and 3 are not different from zero. Differences with standard errors in parentheses are reported in column 4.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

variations in weather patterns that could explain these changes. Descriptive statistics for the variables associated with weather are also shown in Table 13.

An issue of concern from Table 13 is that there are significant pre- and post- differences in certain weather variables: wind speed for Sydney and humidity for both cities. This could violate the assumption that in the absence of the policy, pollutant concentration level would have changed continuously on the policy implementation date. However, note that these differences are very small. Hence following Davis (2008), a model with a two-year window that controls for these weather measures is estimated. Controlling for atmospheric conditions will only increase the precision of the estimates. Another concern could be that the main results might be driven by these unconventional changes in weather conditions. However to ensure the validity of the estimation method, a model without weather covariates is also estimated.

IV. Results

OLS results

Table 14 reports the coefficient estimates from the simple OLS model (equation (17)). In all the regressions reported, quartics in weather covariates and day of the week and month dummies are included in $\mathbf{X}_t$. Due to auto-correlation, standard errors are clustered at the 5-weeks level. Table 14 produces mixed and at times counter-intuitive results. According to Sydney's OLS results, NO_2 and CO concentration levels declined by 5 percent and 24 percent, respectively. On the other hand, PM_{10}, $PM_{2.5}$ and O_3 levels increased by 10 percent, 34 percent and 5 percent, respectively. The results for Newcastle indicate that NO_2 levels declined by 14 percent and PM_{10} levels increased by 13 percent.

However, as mentioned before these estimates have the potential to suffer from bias associated with unobservables. Other economic behavior or activity not controlled for in equation

Table 14: The effect of the policy on air quality in New South Wales: basic OLS results

Dependent variable:	$Log(NO_2)$	Log(CO)	$Log(PM_{10})$	$Log(PM_{2.5})$	$Log(O_3)$
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
Post-intervention	-0.047*	-0.237***	0.096***	0.341***	0.052**
	(0.024)	(0.038)	(0.024)	(0.033)	(0.023)
# of obs.	9,462	3,196	9,645	2,775	9,634
Panel B: Newcastle					
Post-intervention	-0.143***		0.143***		0.018
	(0.033)		(0.041)		(0.038)
# of obs.	699		723		716

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from basic the OLS model represented by equation (17). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week fixed effects and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

(17) might be driving these results. Discontinuity based OLS results, which overcome these biases are discussed below.

DB-OLS results

The main findings of the study are reported in Table 15, which shows the results for the model represented by equation (18). For each regression, in addition to quartics in weather covariates and day of the week and month fixed effects, a 3^{rd} order polynomial time-trend is included in $\mathbf{X}_t$. The purpose of including these covariates is to control for observed time series variation in factors affecting pollution that would have occurred in the absence of the treatment. The reason for including the polynomial time-trend is to control for time varying unobservables that could potentially influence the coefficient estimates and engender incorrect inference.

According to the results produced in Table 15, the implementation of the disclosure policy had no significant effect on pollutant concentration levels.[51] The results are also quite distinct from Table 14, as the coefficients are larger in magnitude and at times have the opposite sign. These results further increase skepticism of the basic OLS results.[52] These effects are also demonstrated graphically by Figures 11 and 12. In these figures, pollutant time-trends before and after the policy are plotted. A third-order polynomial trend line and the date when the policy was introduced (shown by the broken line) are also incorporated. Breaks in pollutant levels can be observed at the point of discontinuity but these breaks are

[51] If the reason for the null effect is the noise in the data, then one has to be careful with the interpretation. However, I also make use of a Difference-in-Differences (DID) method, which has a different data generating process. The DID strategy produces results that are similar to the DB-OLS strategy. Furthermore, I also re-run the DB-OLS with smaller windows (3 months, 6 months, etc.) and the results do not change. Given the DID results and variations of the actual model, it could be ascertained that δ_1 is most likely capturing the true effect of the disclosure policy.

[52] Estimates of DB-OLS and OLS are not directly comparable. Generally, the average treatment effects with DB-OLS model are estimated at the margin of receiving the treatment. An additional implicit assumption that is being made is that there were no other treatments at the cut-off data (July 1, 2012) that would affect air quality. If this assumption is violated, then these estimates are not totally attributable to the new policy. Moreover, the estimates will be biased if the functional form between the treatment and the outcome is not correctly specified.

Table 15: The effect of the policy on air quality in New South Wales: DB-OLS results

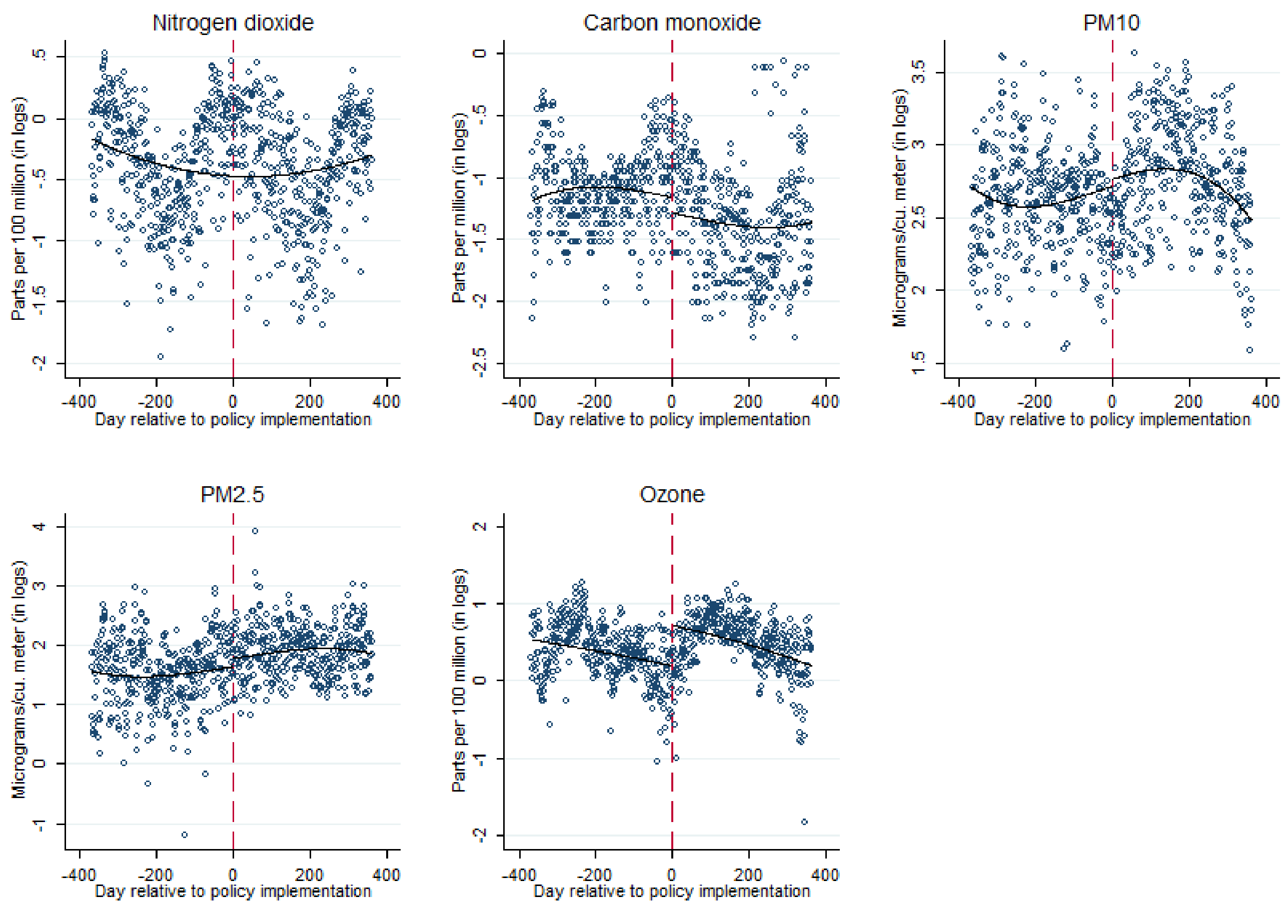
Dependent variable:	$Log(NO_2)$	Log(CO)	$Log(PM_{10})$	$Log(PM_{2.5})$	$Log(O_3)$
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
Post-intervention	0.540	0.293	-0.395	-0.446	0.449
	(0.814)	(0.956)	(0.462)	(0.804)	(0.613)
# of obs.	9,462	3,196	9,645	2,775	9,634
Panel B: Newcastle					
Post-intervention	0.751		-0.361		-0.126
	(1.238)		(0.726)		(1.021)
# of obs.	699		723		716

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

not prominent. The pollutants are approximately moving continuously around the policy date. These graphs provide further support to the identification assumptions. The purpose of showing these graphs is to demonstrate the inconsequential discontinuity that emerges because of the implementation of the policy that is not apparent in the raw data. As demonstrated earlier in Figure 6, detection of a discontinuity without the time-trend could be challenging because of the variations in air pollution.

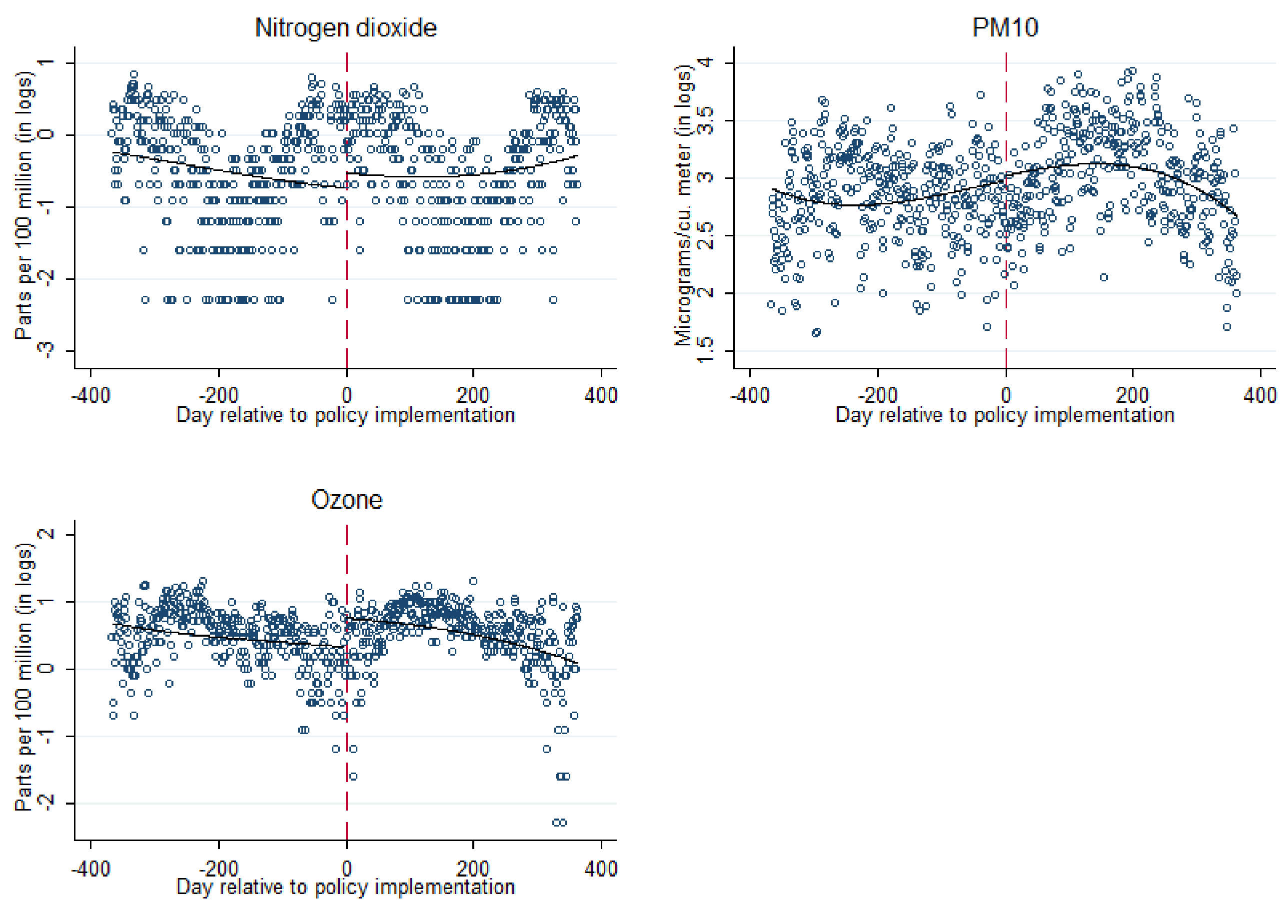
There could be numerous factors that could explain these insignificant responses of pollutant concentration levels. Information disclosure is expected to influence household behavior, particularly if actual emissions are above household's prior beliefs about these emissions. Governments, instead of regulating emissions, make it possible for residents to be made aware of the level of emissions. There are two central players in this game: the polluters and the citizens affected by the pollution. The affected parties can use tools developed by the government (lawsuits or public policy), interest groups (media exposure) or the market (consumer boycotts) to negotiate change. Hence, the government acts as a facilitator rather than a forcing body in the society. If the new information does not conflict with the household's prior beliefs then the behavior of the citizens is unaffected and they do not put any pressure on firms to reduce emissions. In other words, environmental information between the households and the firms in NSW might not be asymmetrical and hence, households did not consider any further action. It could also be that the firms might have predicted that the households are not concerned with the current pollution levels and did not take any necessary avoidance measures. Another potential reason for small effects of the policy could be that the performance of Australian cities is quite superior to that of other developed cities when it comes to air pollution. Industrial emissions were controlled extensively even before the policy went into effect which might have not necessitated any action from the public. Since, continuous management of environmental resources in NSW is surpassing other regions, households do not want to reduce the level of emissions any further by substituting other goods. Lastly, it is also possible that households were unaware of the new policy or

Figure 11: Air quality in Sydney with time-trend



Notes: These graphs display the pollutant concentration levels in Sydney for the years 2011 - 2013. The pollutants displayed are NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3. The broken red line represents the date when the information disclosure policy went into effect. A third-order polynominal trend line (black) is also inserted in these graphs

Figure 12: Air quality in Newcastle with time-trend



Notes: These graphs display the pollutant concentration levels in Newcastle for the years 2011 - 2013. The pollutants displayed are NO_2, PM_{10} and O_3. The broken red line represents the date when the information disclosure policy went into effect. A third-order polynominal trend line (black) is also inserted in these graphs are unconcerned about the environmental issues. However, the media attention that was given to the policy and the environmental performance in NSW historically, this last point probably does not hold.

One criticism that could be raised against the results is that they emerge this way because of the time-trend specification that is used rather than because of the information disclosure strategy. To test for this, polynomials of different orders are tested. Secondly, some of the weather covariates do not move continuously around the implementation date. This could violate the assumption that in the absence of the policy, pollutant concentration level would have changed continuously when the treatment went into effect. Smoothness of these weather covariates is also scrutinized. Finally, if the policy implementation is truly random, it should have no effect on air quality in some other city outside the province of NSW. The next section deals with these and other robustness checks.

Robustness checks

In this sub-section (i) the validity of the identification assumption and (ii) the robustness of the main results are examined. A major criticism regarding the empirical strategy that could be raised is that the firms could have anticipated the policy and acted prior to the policy. Conversely, it could also be true that the firms acted on the policy not on the implementation date but perhaps at a later date. To overcome this, I also evaluate the policy using a Difference-in-Differences (DID) strategy. DID is less sensitive to the exact timing of the effect relative to the DB-OLS method. The DID is identifying off the averages across all the post-treatment months, not just at the discontinuity. This model compares the changes in pollution levels before and after the policy date between Sydney (where the policy was introduced) and Perth (the counter-factual city). Perth, the provincial capital of Western Australia (WA), is the fourth largest city in Australia (after Sydney, Brisbane and Melbourne) and the largest city on the western front. Geographically it is 4,000 km (2,486 mi) from Sydney and due to substantial distance it is highly improbable that air quality in

NSW could affect air quality in WA, or vice versa.[53] The DID model estimated is given by equation (3).

$$\log(\text{Pollutant}_\text{t}) = \beta_0 + \beta_1\left[1(\tau \geq Policy)\right] + \beta_2 Sydney + \beta_3\left[1(\tau \geq Policy) \times Sydney\right] + \mathbf{X}_t\beta_4 + \xi_t \tag{19}$$

In the above model the coefficient of interest is β_3, which captures these differences. Again, $[1(\tau \geq Policy)]$ is an indicator variable that takes a value of 1 when the policy went into effect (July 1$^{\text{st}}$, 2012) and a value of 0 otherwise. *Sydney* is a dummy variable that takes a value of 1 for all monitoring stations in Sydney and a value of 0 for all stations in Perth. $\mathbf{X}_t$ includes quartics in average weather covariates (temperature, wind speed and humidity), a 3$^{\text{rd}}$- order time-trend, and day of the week and month dummies. Table 16 shows the results of the DID model with and without the covariates. The results are similar to the results reported in Table 15. DID results show that the policy mainly had no effect on pollutant concentration levels. The only pollutant that has a negative coefficient is CO indicating that CO levels in Sydney declined in the post-treatment period relative to Perth. On the other hand, $PM_{2.5}$ levels increased in the post-treatment period in Sydney relative to Perth. Secondly, I also do some variants of the DID model, where I drop the first three, six and nine months of the post-treatment period. The results of these specifications, also shown in Table 16, are similar to the general DID results. Given that the trimming of the earliest post-treatment months until the data is only comprised of the last three months of the post-treatment period, does not change the results, one could be confident that the null effects of the policy produced by the DB-OLS results are not due to the timing problem.[54]

[53]Perth has a population of around 2 million and a population density of 310/km^2(800/sq. mi), slightly lower than Sydney's density (*compare* to footnote 21). Main industries in the city are mining, manufacturing and construction. Perth pollutant data for the time time period 2011-2013 was provided by the Department of Environmental Regulation, WA.

[54]Alternatively, I break the data into one month, two months and three months periods and run a dummy regression model to check for discontinuous jumps in the 24-month period. There are significant jumps or underlying time trends in the concentration levels in various months leading up to the policy. These findings

Table 16: The effect of the policy on air quality in New South Wales: DID results

Dependent variable:	Log(NO_2) (1)	Log(CO) (2)	Log(PM_{10}) (3)	Log($PM_{2.5}$) (4)	Log(O_3) (5)
Panel A: No covariates					
Post-intervention × Sydney	-0.070	-0.261**	0.100	0.391***	0.162**
	(0.085)	(0.098)	(0.071)	(0.098)	(0.060)
# of obs.	11,592	4,677	11,096	4,212	11,631
Panel B: Including covariates					
Post-intervention × Sydney	-0.027	-0.204***	0.053	0.382***	0.079
	(0.045)	(0.070)	(0.045)	(0.088)	(0.050)
# of obs.	11,592	4,677	11,096	4,212	11,631
Panel C: Trimming post-intervention					
Post-intervention × Sydney (3 months trimmed)	-0.011	-0.219**	0.078	0.424***	0.095
	(0.044)	(0.081)	(0.047)	(0.092)	(0.058)
Post-intervention × Sydney (6 months trimmed)	-0.047	-0.293***	0.057	0.487***	0.051
	(0.039)	(0.084)	(0.052)	(0.108)	(0.068)
Post-intervention × Sydney (9 months trimmed)	-0.032	-0.243**	0.080	0.674***	-0.032
	(0.052)	(0.093)	(0.074)	(0.126)	(0.063)

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the difference-in-differences model represented by equation (4). In all these regressions quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included unless otherwise stated.. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

Table 17: The effect of the policy on air quality in Perth, Western Australia

Dependent variable:	Log(NO_2)	Log(CO)	Log(PM_{10})	Log($PM_{2.5}$)	Log(O_3)
	(1)	(2)	(3)	(4)	(5)
Fake post-intervention	-1.010	-0.480	0.040	0.112	0.785*
	(0.644)	(0.704)	(0.059)	(0.122)	(0.419)
# of obs.	2,283	1,522	1,522	1,522	1,522

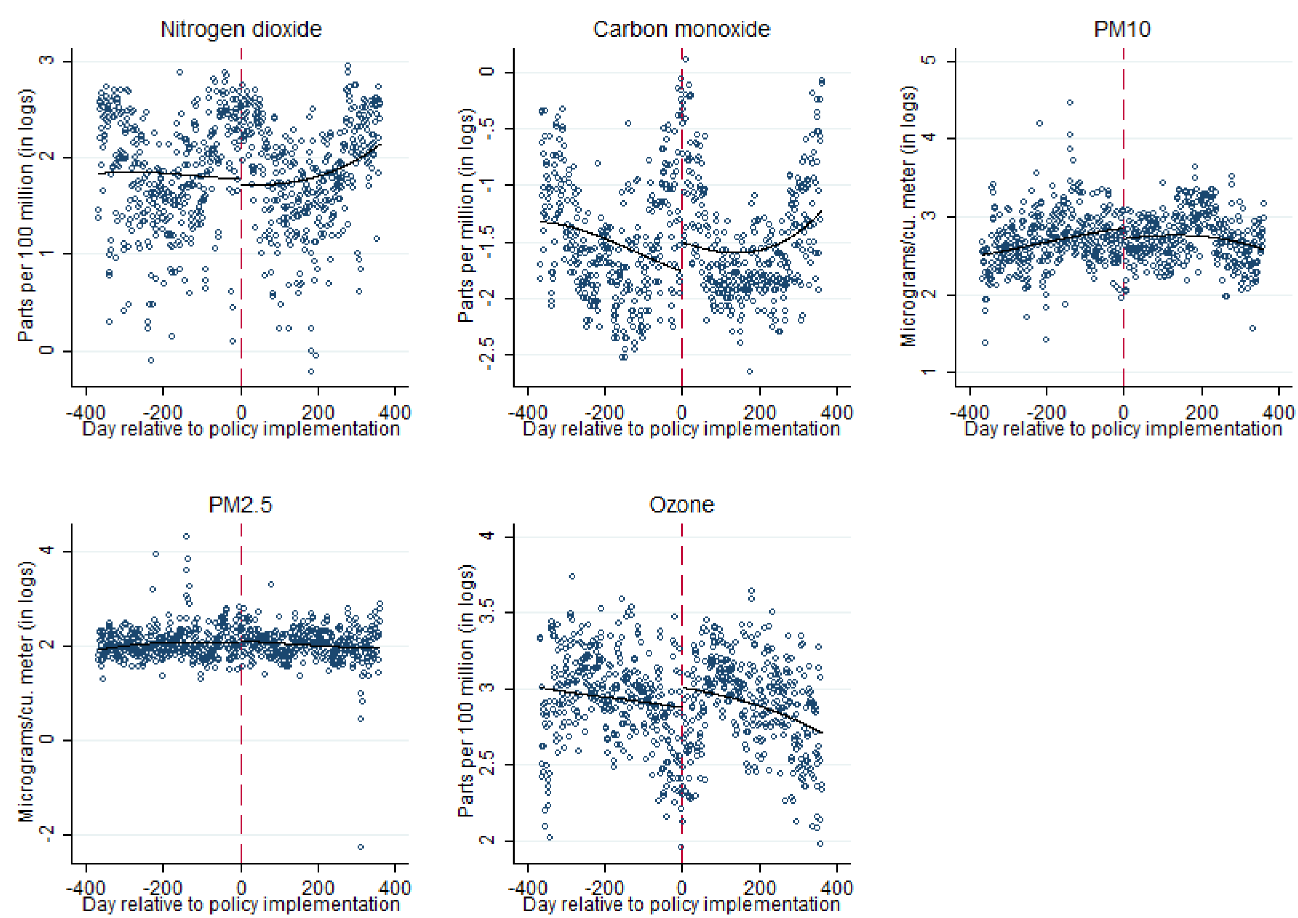
Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

To analyze the randomness of the policy implementation date, one could check for discontinuities where they should not be present. If the authorities could predict industrial emissions on a given date and chose the implementation date based on these predictions then the identification assumption will not hold. If the treatment is truly random then it should not affect the distribution of air pollution in another region of Australia, since it was peculiar to NSW. To examine this, the DB-OLS model is executed for Perth. The results for Perth are shown in Table 17. As expected, the policy had no significant impact on any of the pollutants (besides O_3, coefficient of which is positive) in the counterfactual city. Results of Table 17 are demonstrated graphically in Figure 13. A third-order polynomial time-trend is inserted into this figure. A discontinuity in the distributions of these pollutants in Perth is not apparent on the implementation date.

Another inquiry regarding the randomness of the policy could be observing the effect of a counter-factual policy on the distribution of air pollution. For this, the date of the policy is changed from 1st July, 2012 to 3/6 months prior and 3/6 months post to the actual policy date. These placebo tests are conducted to examine whether a break is observed at the fake-policy dates. Results of the fake-policies are given in Table 18 and Table 19. As shown by

support the assertion made with regards to the OLS methodology: there are presumably some sort of underlying time trends even prior to the policy, and hence the OLS results will be biased.

Figure 13: Air quality in Perth with time-trend



Notes: These graphs display the pollutant concentration levels in Perth for the years 2011 - 2013. The pollutants displayed are NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3. The broken red line represents the date when the information disclosure policy went into effect. A third-order polynominal trend line (black) is also inserted in these graphs

Table 18: The effect of the "fake-prior" policy on air quality in New South Wales: DB-OLS results

Dependent variable:	Log(NO_2) (1)	Log(CO) (2)	Log(PM_{10}) (3)	Log($PM_{2.5}$) (4)	Log(O_3) (5)
Panel A: Sydney					
Intervention 3 months prior to actual date	0.640	0.474	-0.243	-0.332	0.474
	(0.832)	(0.817)	(0.483)	(0.844)	(0.594)
# of obs.	9,551	3,327	9,668	2,805	10,108
Intervention 6 months prior to actual date	0.229	-0.175	-0.261	-0.420	0.117
	(0.864)	(0.583)	(0.435)	(0.767)	(0.854)
# of obs.	9,638	3,411	9,759	2,809	10,032
Panel B: Newcastle					
Intervention 3 months prior to actual date	1.315		0.321		0.184
	(1.268)		(0.777)		(0.964)
# of obs.	715		723		715
Intervention 6 months prior to actual date	1.277		0.073		0.249
	(1.266)		(0.729)		(0.903)
# of obs.	716		725		719

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

the results, the distribution of the pollutants are unaffected in response to the fake-policies. Therefore, it can be stated that a few months prior/post to the the actual-policy, pollutants followed a continuous trend and firms did not act early or late on the policy. These findings further increase the confidence in the main results.

Model (18) assumes that the time-trend before and after the policy implementation is the same. The following model relaxes this assumption by adding interactions between $[1(\tau \geq Policy)]$ and the polynomial time-trend. Adding the interaction term enhances the

Table 19: The effect of the "fake-post" policy on air quality in New South Wales: DB-OLS results

Dependent variable:	Log(NO_2)	Log(CO)	Log(PM_{10})	Log($PM_{2.5}$)	Log(O_3)
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
Intervention 3 months	0.475	0.481	-0.037	0.080	0.476
post to actual date	(0.817)	(0.967)	(0.493)	(0.805)	(0.553)
# of obs.	9,572	3,327	9,768	2,856	10,295
Intervention 6 months	0.500	0.747	-0.346	-0.467	0.274
post to actual date	(0.800)	(0.937)	(0.541)	(0.734)	(0.525)
# of obs.	9,618	3,412	9,878	2,941	10,368
Panel B: Newcastle					
Intervention 3 months	0.509		-0.063		0.113
post to actual date	(1.145)		(0.706)		(0.989)
# of obs.	715		722		717
Intervention 6 months	0.155		-0.240		0.102
post to actual date	(0.942)		(0.695)		(0.985)
# of obs.	714		722		716

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

flexibility of the model as it allows the time-trend to differ after the implementation of the policy.

$$\log(\mathrm{Pollutant_t}) = \delta_0+\delta_1\left[1(\tau \geq Policy)\right]+\mathbf{X}_t\delta_2+\delta_3\psi(\mathbf{t})+\delta_5\left[\psi\left(\mathbf{t}\right)\times 1(\tau \geq Policy)\right]+\lambda_t \quad (20)$$

In the model above the coefficient of interest is δ_1, which represents the effect of the policy on air pollution. $[1(\tau \geq Policy)]$ is as before equal to 1 after the policy and 0 before its implementation. $\mathbf{X}_t$ includes quartics in average weather variables , day of the week and month dummies. The vector $\psi(\mathbf{t})$ is a polynomial time-trend that controls for time series variation in the pollution levels. In addition to the model given by (18), interactions between $[1(\tau \geq Policy)]$ and the polynomial time-trend are added to the DB-OLS regression to differentiate the time-trend in pollution before and after the policy. λ_t is the error term. Table 20 shows the results of the specification shown above. Again the results are consistent with the main results. Even after allowing for differences in time-trend before and after the policy implementation date the effects of the policy were negligible. Furthermore, the coefficient estimates of Table 15 and Table 20 are quite similar. These findings lend support to the claim that for each city, before and after the policy, the time-trend was approximately the same.

One concern from Table 13 were differences in humidity and wind speed in pre- and post- policy periods. This has the potential to violate a crucial assumption of the DB-OLS estimation method. Table 21 examines the smoothness of the weather covariates. Again equation (18) is employed but atmospheric conditions replace the pollutants as the dependent variables and all weather covariates are excluded from $\mathbf{X}_t$. According to Table 21, all weather covariates move smoothly around the policy implementation date for both cities. Furthermore, differences in these variables between the pre- and post- policy periods are not a major concern as the coefficient estimates without the weather covariates (see Table 22,

Table 20: The effect of the policy on air quality in New South Wales: DB-OLS results with the interaction between the treatment and the polynomial time-trend

Dependent variable:	$Log(NO_2)$	Log(CO)	$Log(PM_{10})$	$Log(PM_{2.5})$	$Log(O_3)$
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
Post-intervention	0.566	0.316	-0.395	-0.415	0.503
	(0.634)	(0.884)	(0.462)	(0.696)	(0.557)
# of obs.	9,462	3,196	9,645	2,775	9,634
Panel B: Newcastle					
Post-intervention	0.686		-0.360		-0.069
	(1.038)		(0.651)		(0.875)
# of obs.	699		723		716

Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (20). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

Table 21: Smoothness of the weather covariates

Dependent variable:	Temperature	Wind speed	Humidity
	(1)	(2)	(3)
Panel A: Sydney			
Post-intervention	-10.479	1.173	-0.397
	(7.063)	(0.915)	(0.318)
# of obs.	731	731	731
Panel B: Newcastle			
Post-intervention	-9.408	1.197	-0.222
	(6.531)	(1.428)	(0.291)
# of obs.	731	731	731

Notes: The estimates reported in columns 1-3 are associated with coefficients estimates from discontinuity-based OLS model represented by equation (18). Instead of pollutant levels, weather covariates are used as dependent variables. In all these regressions day of the week and month fixed effects were included. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

row 1 for each Panel) are similar to the main results. Even though without the weather controls one observes small differences in magnitudes of the estimates, conclusions drawn from the main results remain intact and it does not appear to be atmospheric conditions that are driving the results.

In Table 22, alternative polynomial orders are also tested. Equation (18) is executed with 5^{th}- and 7^{th}- order polynomials (rows 3 and 4 for each Panel in Table 22). Porter (2003) recommended that odd-order polynomials have better econometric properties. Higher order polynomials were chosen based on Akaike Information Criterion (AIC) statistics. Again significance of the coefficient estimates are unaffected under higher polynomial orders. Lastly, Table 22 also reports the estimation results with Newey-West standard errors (row 2 for each Panel, Table 22). These standard errors allow for correlation between the observations within a five-weeks lag. The results remain insignificant with Newey-West standard errors. These analyses were also replicated for Wollongong, the third largest city in NSW. The results for Wollongong are similar to the results for Sydney and Newcastle.

Another criticism that could be raised is with regards to the time period used in the main empirical method. In the main results a one-year window before and after the policy is used. Since the main estimation strategy is discontinuity-based, there should be no harm in using a smaller window. I re-run the DB-OLS model shown by equation (18) for a 3-months window without the weather covariates and the time-trend. These results are shown in Table 23. The significance of the coefficient estimates is mainly unaffected. The only coefficient estimates that are significant are those associated with CO and O_3. When a smaller time-frame is considered, CO levels declined and O_3 levels increased after the introduction of the policy.[55] The corresponding graphs of Table 23 are presented in Figures 14 and 15.

V. Conclusion

Information disclosure policies attempt to reduce information asymmetries between firms, citizens and third parties (governments, NGOs, journalists). It is anticipated that such policies should produce reactions from the citizens and other third parties, particularly, when emissions are beyond what was initially expected. These pressures should coerce firms to modify their behavior so that the emissions produced by them are in align with what people believe to be acceptable. If the firms do alter their behavior due to the introduction of the disclosure policy, air quality should improve. This paper studies the impact of such a disclosure policy in NSW, Australia. A regression discontinuity design was employed and the results show that the concentration levels of pollutants were mainly unaffected in NSW. The discontinuity based OLS results are quite robust to different model specifications. Hence,

[55] Even though a positive relationship between O_3 and the policy is counter-intuitive, it is not surprising. O_3 is produced when NO_x, CO and volatile organic compounds (VOCs) react in the presence of sunlight and heat. Its is produced through a non-linear process, which depends on local atmospheric conditions and fluctuates with space and time. This was also noted by Chen and Whalley (2012). Also *see* Seinfeld and Pandis (1998).

Table 22: The effect of the policy on air quality in New South Wales: alternative specifications

Dependent variable:	$\text{Log}(NO_2)$	Log(CO)	$\text{Log}(PM_{10})$	$\text{Log}(PM_{2.5})$	$\text{Log}(O_3)$
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
No weather controls	-0.060	-0.330	-0.625	-1.228	0.344
	(0.772)	(0.777)	(0.577)	(0.759)	(0.621)
Newey-West std. errors	0.540	0.293	-0.395	-0.446	0.449
	(0.791)	(0.924)	(0.572)	(0.908)	(0.585)
5^{th} order polynomial	0.670	0.381	-0.293	-0.263	0.569
	(0.776)	(0.942)	(0.426)	(0.728)	(0.587)
7^{th} order polynomial	0.584	0.304	-0.341	-0.337	0.494
	(0.515)	(0.816)	(0.404)	(0.574)	(0.490)
Panel B: Newcastle					
No weather controls	0.231		-0.777		0.074
	(1.441)		(0.692)		(0.885)
Newey-West std. errors	0.751		-0.361		-0.126
	(1.223)		(0.779)		(0.957)
5^{th} order polynomial	0.634		-0.231		0.064
	(1.222)		(0.681)		(0.875)
7^{th} order polynomial	0.540		-0.353		-0.017
	(0.870)		(0.611)		(0.781)

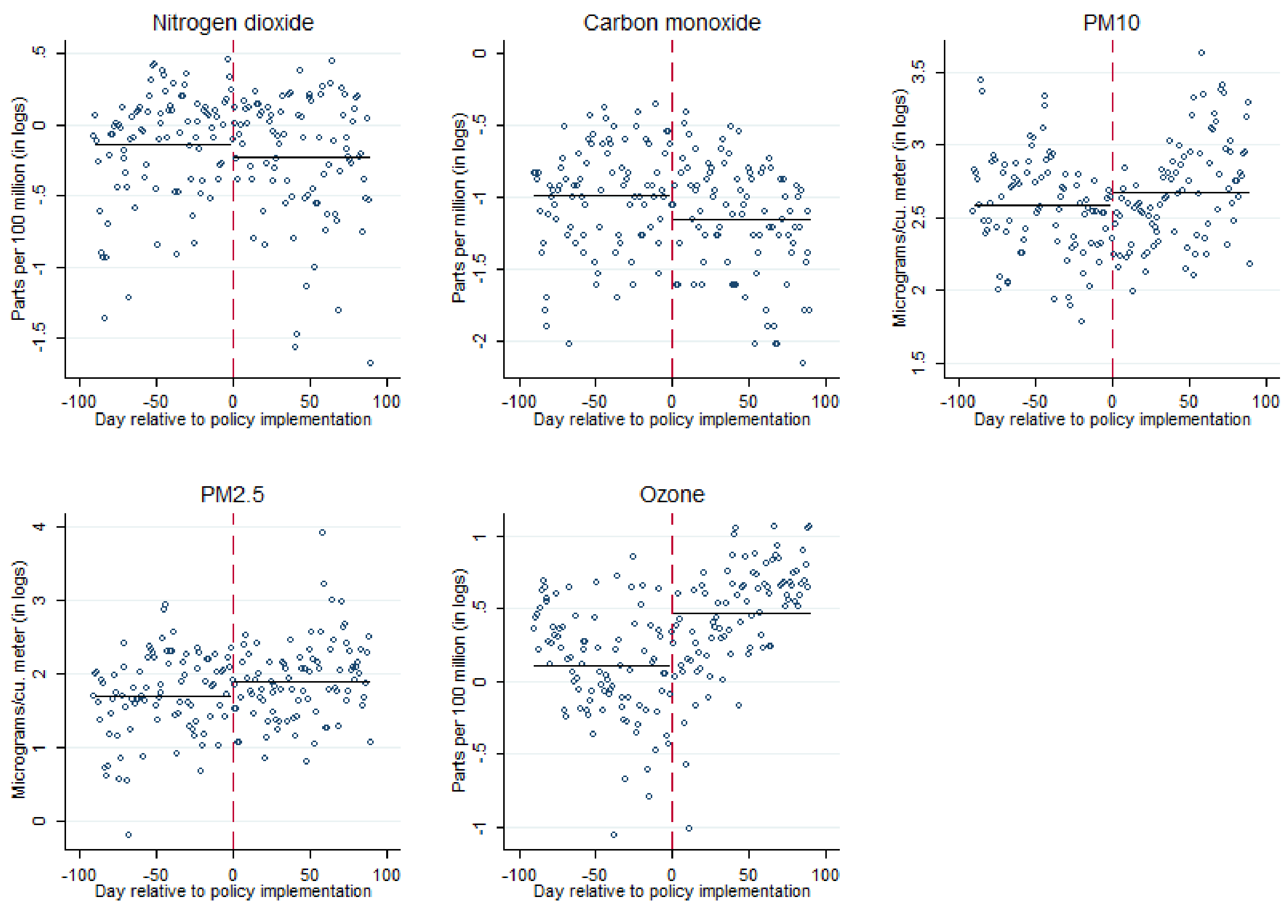
Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included unless otherwise stated. In the first regression, equation (18) is estimated without weather covariates. In the second regression, equation (2) is estimated with Newey-West standard errors. In the third and fourth regressions, a 5^{th} order and a 7^{th} order polynomial replaces the 3^{rd} order polynomial in equation (18), respectively. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

Table 23: The effect of the policy on air quality in New South Wales: DB-OLS results — 3 months window

Dependent variable:	Log(NO_2)	Log(CO)	Log(PM_{10})	Log($PM_{2.5}$)	Log(O_3)
	(1)	(2)	(3)	(4)	(5)
Panel A: Sydney					
Post-intervention	-0.091	-0.168*	0.086	0.191	0.358**
	(0.083)	(0.082)	(0.087)	(0.199)	(0.117)
# of obs.	2,402	835	2,466	690	2,432
Panel B: Newcastle					
Post-intervention	0.064		0.083		0.300*
	(0.063)		(0.108)		(0.128)
# of obs.	171		177		177

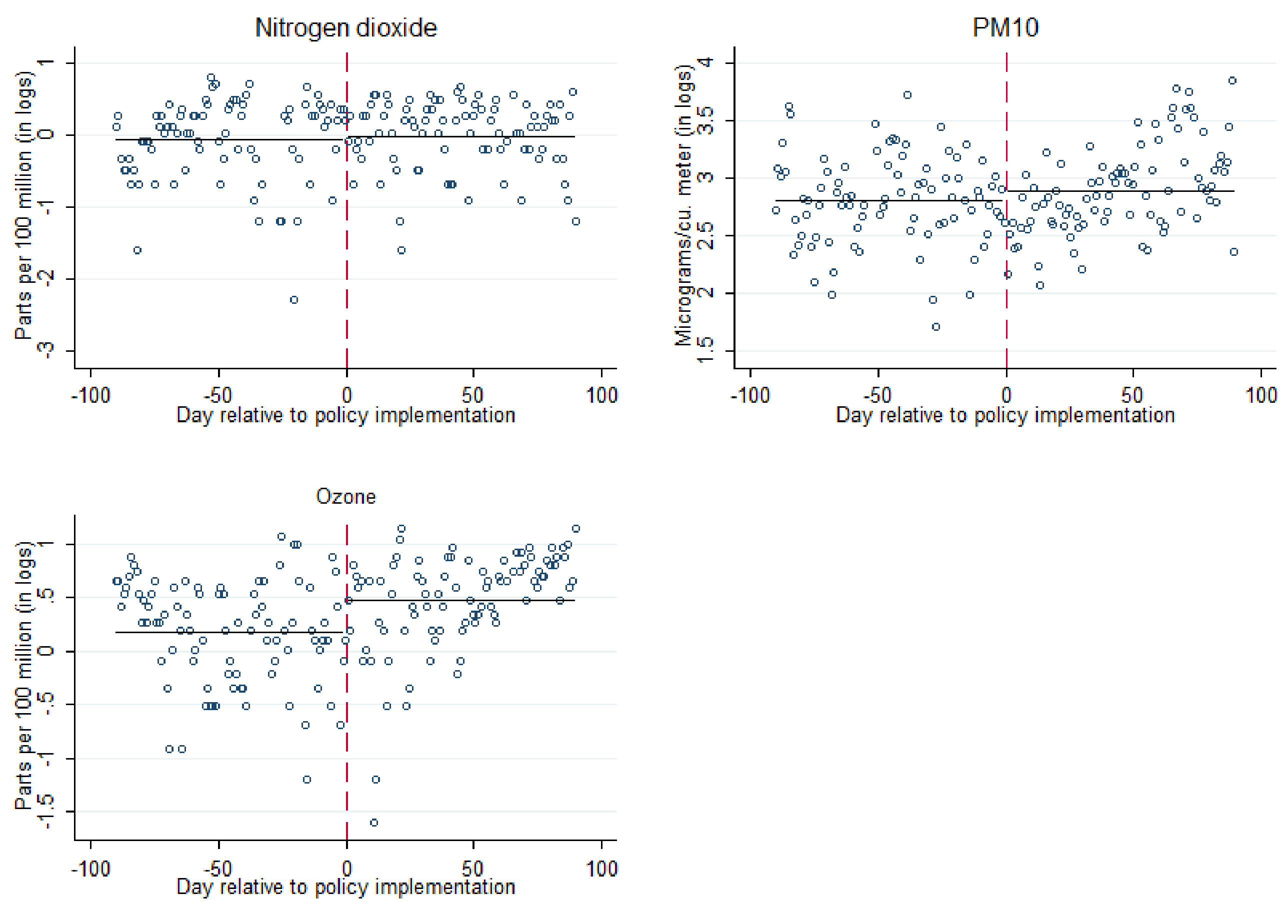
Notes: The estimates reported in columns 1-5 are associated with coefficients estimates from the discontinuity-based OLS model represented by equation (18). In all these regression, quartics in average weather covariates (temperature, wind and humidity), day of the week and month fixed effects were included unless otherwise stated. The unit of observation is day. Standard errors, which were clustered at 5-week level, are reported in parentheses.
***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 1 percent level.

Figure 14: Air quality in Sydney — smaller window



Notes: These graphs display the pollutant concentration levels in Sydney for a three month window. The pollutants displayed are NO_2, CO, PM_{10}, $PM_{2.5}$ and O_3. The broken red line represents the date when the information disclosure policy went into effect. A third-order polynominal trend line (black) is also inserted in these graphs

Figure 15: Air quality in Newcastle — smaller window



Notes: These graphs display the pollutant concentration levels in Newcastle for a three month window. The pollutants displayed are NO_2, $PM_{10}$and O_3. The broken red line represents the date when the information disclosure policy went into effect. A third-order polynominal trend line (black) is also inserted in these graphs the policy was not instrumental in reducing the concentration levels of the contaminants in the air. One potential reason for the negligible effects of the policy could be that pollutant concentration levels in NSW are already too low and an additional instrument will have little or no impact on reducing pollutant intensity. Another reason for the null effects could be that information with regards to emissions between the public and the firms is not asymmetrical and hence did not necessitate any action from the households.

This study focused only on the short-term impacts of the policy; long-term effects are not analyzed. It is probable that the level of current consumption that individuals are willing to give up for an improvement in the environment, might fade off with time. This will decrease pressure exerted on firms and air quality might worsen even in the presence of environmental policies. Furthermore, the effects are expected to vary from region to region and should also depend on socio-economic characteristics. Therefore, it is not clear what would be the relative effectiveness of such a policy in different demographics. Before implementing information-based regulations policy-makers should evaluate the mechanisms and the regions where they are most likely to be effective.

Chapter 3: What determines citizen trust: evaluating the impact of campaigns highlighting government reforms in Pakistan

I. Introduction

Higher levels of trust within a society promote economic activity as trust reduces transaction costs by eliminating the need to undertake costly efforts to learn about the trustworthiness of others. The influence of trust on economic development and societal well-being has been well documented in the previous literature. For example, Knack and Keefer (1997), and LaPorta et al. (1997) provide evidence that shows a linkage between trust and growth and the impact trust has on the effective management of large organizations, respectively. A similar construct used to measure life-satisfaction is that of subjective well-being. Based on the previous literature, subjective well-being is a good measure of overall well-being (Krueger and Schkade (2008)) and is affected by changes in real income and living standards (Sacks et al. (2010)). Subjective well-being also is often used to evaluate the effectiveness of government policies on the target population.[56]

The significance of trust on economic growth and the relationship between subjective well-being and living standards are more meaningful for countries like Pakistan where citizens have been exposed to severe militancy, conflict and violence in recent decades. Exposure to conflict affects both the general levels of trust (Glaeser et al. (2000), Alesina and LaFerrara (2002)) and subjective well-being (Frey et al. (2009), Dolan and Metcalfe (2012)). In this paper, I first evaluate how exposure to violence affects these measures for the citizens in the province of Khyber Pakhtunkhwa (KPK) in Pakistan, which has been affected the most by conflict and radical militancy in the country. Secondly, the effectiveness of certain reforms that were recently introduced in the province are also analyzed. The purpose of these reforms was to strengthen human and property rights, increase local government transparency and improve

[56] For example, Frijters et al. (2004) studied the effects of German re-unification on subjective well-being in East Germany and Gruber and Mullainathan (2005) evaluated the impact of cigarette taxes on subjective well-being of smokers.

service delivery. The motivation for these provincial reforms was to facilitate economic growth and enhance trust in the local government institutions, which has the potential to reduce militancy and radicalism. However given the short time-horizon, these outcomes could not be measured directly. Instead, the focus of the study is on the impact of these reforms on political and societal trust.

For the analysis, survey data was collected from a cross-section of the adult population in KPK. Information was collected using longer in-person questionnaires, which were administered by the University of Peshawar, as well as a shorter set of questions that were administered by a robot caller. The first wave of the data collection was conducted during the fall of 2014 and the second wave was initiated approximately six months later. A targeted messaging campaign that informed the citizens about the new government reforms along with the underlying motivation for these reforms was held in-between the two waves. The policies could not be randomized, however, the awareness with regards to the policies was randomized. Thus, the assumption of this strategy is that by making the government reforms salient through these messages, I was able to (exogenously) shock beliefs about property rights and the transparency of local institutions. The messaging campaign was started in December 2014. Robot-calls were delivered to a subset of all the cellular phone numbers in randomly selected *tehsils* throughout KPK.[57]

The empirical results show that exposure to violence and conflict have a negative and a significant effect on general levels of trust and subjective well-being, whereas violence has a positive effect on civil services and district courts (local formal institutions). Empirical results provide mixed evidence on the efficacy of the messaging campaigns. The messages had a positive impact on the levels of trust, subjective well-being and opinions about the quality of local services. However, the effects are significant only for the general levels of trust and perceptions about the local governance, and insignificant for subjective well-being. However, when the effects are allowed to differ between those who were more exposed to

[57] A *tehsil* is an administrative unit in Pakistan. Usually it consists of a city/town that serves as the administrative center and additional towns and villages. It is similar to a county in the US.

violence relative to others, some of these effects become more definite. The impacts of these awareness campaigns on the satisfaction with the local governmental services and confidence in the justice system provide an important first step in rebuilding and restoring the overall levels of trust in the region.

The rest of the paper is structured as follows: Section II describes the study design and the messaging campaigns, Section III discusses the survey results and determinants of trust and Section IV concludes.

II. Study design and the messaging campaign

The purpose of this study is two-fold. Firstly, I examine how exposure to violence and conflict impacts (i) general levels of trust; (ii) attitudes towards public and religious institutions; and (iii) subjective well-being. A number of studies have established that exposure to conflict impairs general level of trust (*see* Glaeser et al. (2000), Alesina and LaFerrara (2002)) and well-being (*see* Frey et al. (2009), Dolan and Metcalfe (2012)). However, these questions have not been explored in the context of conflict-prone regions like Pakistan, KPK in particular. In KPK households have been exposed to extreme levels of violence, conflict and militancy in the last two decades. Secondly, I analyzed whether targeted messages, which were designed to make salient certain government reforms in the province, affected levels of trust, confidence in institutions, political trust and measures of well-being. The reforms were introduced to increase government transparency, improve service delivery and sustain property and human rights. As noted by the previous literature, the outcomes of interest are important as they are integral for economic development and growth in the region.

For the analysis, an in-person survey was designed that was conducted in randomly selected villages throughout KPK. Appendix B contains a copy of the in-person survey. These surveys were conducted in two waves by the University of Peshawar. The data collection for the first wave was accomplished by October 2014 and the second wave was completed by April 2015. Messaging campaigns were held in-between the two waves. Table 24 lists the villages in KPK where the in-person survey was administered by the number of surveys in each village. The table also indicates whether a village was randomly assigned to receive cellular messages. In total, 3,741 surveys were administered in 34 villages (10 urban and 24 rural) located in 8 *tehsils* in the province. 1,823 of the total surveys were done in the 1st wave and 1,918 surveys were conducted during the 2nd wave.

To expand the scope of the data collection efforts and the analysis, a shorter survey (*see* Appendix C) was organized using robot callers. The phone surveys allowed us to interview citizens that were unreachable for the in-person survey due to the military operations against insurgents in those areas. Table 25 lists the *tehsils* in KPK that received the phone survey. Table 25 also contains an indicator of whether the in-person surveys were conducted in these *tehsils* and whether a particular *tehsil* received the cellular messages or not. The final phone survey sample for KPK includes data from 30,473 individuals drawn from 46 *tehsils*. 15,005 of these phone surveys were done in the 1st wave and 15,468 were conducted during the 2nd wave. Of the 46 *tehsils* included in the phone survey, 8 *tehsils* included villages that were sampled as part of the in-person survey efforts.

Reforms and messages in KPK

The focus of the messaging campaigns in KPK was on three reforms that were recently implemented by the provincial government: (i) the Right to Information (RTI) Act; (ii) the Right to Services (RTS) Act; and (iii) an e-Grievance Redressal System established as part of the Peshawar High Court. The RTI Act was passed by the provincial government in October 2013 and accepted by the governor of KPK in November. The objective of the RTI was to provide access to the citizens to the information in the government departments and therefore increase transparency and accountability of the government. Under the Act, an electronic platform was developed for citizens to submit requests for public information and

Table 24: List of villages with in-person surveys in Khyber Pakhtunkhwa

Tehsil	Message type	Village	Wave 1	Wave 2
Buner	RTI	Agarai	50	49
		Sura	49	48
		Charorai	50	49
		Nagrai	50	48
Battagram	RTI	Ajmera	44	49
Mastuj	RTI, RTS	Charun	53	50
Kohat	RTI, PHC	Urban 5	50	55
		Jerma	50	56
		Billitang	49	55
		Shah Pur	50	55
Balakot	RTI	Balakot	48	62
Mansehra	PHC	Masehra City	67	68
		Dodyal	58	67
		Bufa	60	52
Tangi	—	Dhkakki	51	50
		Tangi Bazar	47	50
		Mandani	49	50
Puran	RTI, RTS, PHC	Puran	51	48
Peshawar	RTI, PHC	Tehkal	61	59
		Gulbahar	60	60
		Gulahan Rehman	60	60
		Faqirabad	60	60
		Gulberg		60
		Dalazaq	60	60
		Afhan Colony	60	60
		Pawakay	61	61
		Qisa Khwani	60	60
		Palosai	61	59
		Bazik Khel	56	59
		Safaid Dary	60	59
		Achini	58	60
		Ashpando	60	60
		Surizai Payan	58	60
		Musa Zai	58	60

Notes: The table shows the list of villages by waves where the in-person surveys were conducted. The first wave was completed in October 2014 and the second wave was completed in April 2015.

Table 25: List of *tehsils* with phone surveys in Khyber Pakhtunkhwa

Tehsil	Message type	Wave 1	Wave 2
Aali	RTI, PHC	74	74
Abbotabad	RTI, RTS, PHC	836	836
Alpuri	RTI	47	47
B. Daud Shah	RTI, RTS, PHC	410	410
Balakot	RTI	35	35
Bannu	RTS, PHC	453	453
Battagram	RTI	38	38
Besham	RTS	52	52
Bunner	RTS	195	195
Chakisar	PHC	35	35
Charsada	PHC	1,067	1,067
Chitral	RTI, RTS, PHC	36	36
D.I. Khan	RTS, PHC	395	395
Dassu	RTI	37	37
Dir	PHC	609	609
F. R. Kaladhaka	RTS	31	31
Ghazi	PHC	8	8
Hangu	RTS	36	36
Haripur	—	698	698
Havalian	RTI, RTS	75	75
Jandool	RTI, RTS, PHC	49	49
Karak	RTI, RTS	208	208
Kohat	RTI, PHC	409	409
Kulachi	RTI, PHC	409	409
Lahore	RTI, RTS	37	37
Lakki	—	257	257
Mansehra	PHC	297	297
Mardan	RTI, RTS, PHC	1,532	1,532
Martoong	—	25	25
Mastuj	RTI, RTS	41	41
Matta	RTI, PHC	31	31
Nowshera	RTS, PHC	816	816
Oghi	—	271	271
Paharpur	RTI	409	409
Palas	RTS	25	25
Pattan	PHC	37	37
Peshawar	RTI, PHC	3,220	3,683
Puran	RTI, RTS, PHC	36	36
Sam Ranizai	RTS, PHC	457	457
Swabi	RTS, PHC	284	284
Swat	RTI	483	483
Takht Bai	RTI, RTS	106	106
Takht-e-Nusrati	RTS, PHC	257	257
Tank	RTS	65	65
Tangi	—	-	-
Temergara	RTI, RTS	52	52
Wari	—	25	25

an independent statutory body was created to oversee these requests and ensure that these requests are processed in a timely manner.[58] The RTS Act was passed by the provincial assembly in January 2014 and approved by the governor in the same month. The goal of the RTS was to improve public service delivery. There are time limits and other requirements under the Act for the delivery of public services. Failure to meet these guidelines and requirements could result in penalties for the civil servants. The RTS Act also contains a grievance feedback mechanism, which allows the citizens to file complaints if they are not satisfied or believe that a public servant failed to meet the guidelines.[59] Finally, the e-Grievance Redressal System was established by the human rights directorate of the Peshawar High Court in affiliation with the World Bank. The purpose of the System is to provide an on-line platform to the citizens to file complaints and grievances regarding violations of basic human and property rights. The System allows the citizens to track the progress of their complaints and receive feedback on the ultimate dispensation.[60]. Hence, all these three reforms intend to strengthen human/property rights and increase transparency in all the governmental sectors.

To inform the population on these reforms, a series of targeted messages were designed in association with the support of the provincial government in KPK. These messages were disseminated via robot-calls to randomly selected cellular phone users in the province. The message on the RTI robot-call, for instance, in part reads as follows:

> ...Khyber Pakhtunkhwa's RTI laws and commission allow you to gather information from any government office in Khyber Pakhtunkhwa. A public commission officer has been appointed in every governmental department who will provide information about the particular department. For more information...go to www.kprti.gov.pk. Thank you...

[58]For more on the RTI Act, *see* http://www.kprti.gov.pk/rti/index.php

[59]On the RTS website it states that a potential outcome of this reform is to establish the "much needed trust between the citizens and the state". For more on the RTS Act, *see* http://www.rts.gkp.pk/rtsweb/

[60]For more on the e-Grievance Redressal System, *see* http://www.hrdphc.com/index.php

The initial robot-call was immediately followed by a Short Message Service (SMS). These messages varied in composition but included language that was centered on three fundamental motifs: (i) the law provides everyone the right to know the management of the governmental system; (ii) the law was designed to enhance government transparency, and (iii) the law ascertains that the government is working for the citizens.

For the RTS messaging, the robot-calls were followed by two subsequent rounds of SMS messages. The RTS message in part reads as follows:

> ...government has passed the Right to Services Act 2014 which now ensures that citizens should get certain services as a right without inconvenience or facing coercion...You can contribute to strengthening this system by answering a few short questions regarding your use of any of these services...

The recipient of the RTS message was also informed about the list of services covered under the Act and was asked to press *1* if they had used any of the listed services in the last three months and whether they would like to give feedback on those services. Those who did press *1* were sent a follow-up text inquiring about the service/s accessed and their experiences.

Finally, the messaging campaign for the e-Grievance System followed a procedure similar to the RTI robot-calls. At the end of the call, the recipient was asked about violation of their rights and interest in using the new service. In particular, the recipient was asked if they believe (i) their rights were violated and they would like to use the new service; (ii) their rights were violated and they would *not* like to use the new service; and (iii) their rights were not violated and hence they do not want to use the new service currently. A random sample of cellular phone users received a robot-call that in part reads as follows:

> ...The High Court has established a system where you can record your grievance if you feel your basic rights have been violated. You can record your grievance by visiting the website....

Why targeted messages?

The goals of these reforms was to increase transparency and efficiency of the local government, strengthen the rights of the individuals, and provide the citizens with a platform to report and track complaints if they believed their rights were being violated. For the analysis, a series of targeted messages that informed the citizens about new provincial government reforms were designed to inform the public about these reforms. These messages were sent out via text messages and/or robot-calls to a random sample of cellular phone users in KPK. The timing of the message delivery was between the 1^{st} and the 2^{nd} waves of the in-person and phone surveys. Given the study design, one can implement a difference-in-differences approach to study the impact of these messages on the levels of trust and attitudes towards institutions. A number of studies in recent years have investigated the effects of targeted messages and normative appeals on various behavioral outcomes. For example, studies have looked at energy and water conservation (Allcott (2011), Ferraro and Price (2013)), charitable contributions (Croson and Shang (2009), DellaVigna et al. (2012)) and tax compliance (Kleven et al. (2011), Hallsworth et al. (2014)). The assumption of this study is that these awareness campaigns exogenously shock beliefs about the strength and reliability of local institutions and individual rights and hence, the study design will allows us to identify the importance of these beliefs on the general levels of political and societal trust.

Experimental design

Before the data collection efforts, the *tehsils* in KPK were randomly assigned either to a control group that received no messages about the reforms or were assigned to one of the seven treatment groups that received the messages about some subset of the reforms. The messaging campaign was started in the 2$^{\text{nd}}$ week of December and continued through the remainder of the month. Table D.1 in the Appendix D lists the *tehsils* that were assigned to these treatment/control groups. The table also provides 2013 *tehsil* population data and the number of individuals that received the messages of a given type. Our partners in the governance support had limited budget for the messaging campaign and this is reflected in the small fraction of residents in any *tehsil* that actually received a message. For example, 1.8 percent of the total population in Swat received the RTI message. In the treatment groups, if the residents were informed about more than one reform, the recipients of any one message represented independent draws from the set of known cellular phone numbers for recipients in the *tehsil*. For example, in Lahore, 1.7 percent of the total population received the RTI information whereas another 1.2 percent were informed about the RTS Act. Hence, there is variation in both the intensity of the treatment within a *tehsil* and the range of reforms that were publicized during the awareness campaigns.

III. Survey results and the determinants of trust

General levels of trust

First, the effects of violence and the impact of awareness campaigns on the overall levels of trust and beliefs about the intentions of others are evaluated. For the attitudinal measures of trust and intentions, the previous literature (Alesina and LaFerrara (2002), Glaeser et al. (2000)) is followed and the focus is on three questions in the in-person survey. General levels of trust are based on responses to the following two questions:

1. Would you say that most people can be trusted or you cannot be too careful when dealing with strangers?

2. Do you agree with this statement: when dealing with strangers, one is better-off using caution before trusting them?

The first question is binary, where "most people can be trusted" takes a values of 1 and "cannot be too careful" takes a value of 0. The second question is on a Likert-scale where "strongly agree" takes a value of 5 and "strongly disagree" takes a values of 1.[61] Beliefs about intentions is based on the following question from the in-person survey, which reads as follows:

3. Would you say that most of the time people are trying to be helpful, or they are mostly looking out for themselves?

The question above is also binary, where "most people are helpful" takes a value of 1 and "are mostly looking out for themselves" takes a value of 0.

To measure exposure to violence, an indicator for violence is developed, which is based on question # 45 in the in-person survey and reads as follows:

How much violence have you or a member of your family witnessed over the past year?

The question above is on a scale of 1 to 10, where "witnessed extreme amount of violence" takes a value of 10 and "have not witnessed any violence" takes a value of 0. These responses were normalized to generate a standardized scale that has a standard normal distribution.

[61]The Likert-scale questions on a scale of 1 to 5 were dichotomized such that responses greater than or equal to 4 were assigned a value of one and responses less than 4 were assigned a value of zero. Variations of such dichotomizations produced similar results.

These responses were converted as $v_i^N = \frac{v_i - \overline{v}}{\sigma_v}$, where v_i is the response to the violence question by individual i, and $\overline{v}$ and σ_v are the mean and standard deviation of the responses, respectively.[62] To study the impact of exposure to violence the focus is on the responses in the first wave and the linear probability models of the following form are estimated:

$$y_i = \alpha + \beta v_i^N + \gamma \mathbf{X_i} + \varepsilon_i \tag{21}$$

where y_i are the i^{th} individual's responses to the trust questions, v_i^N is the normalized measure of violence, $\mathbf{X_i}$ is a vector of household characteristics and ε_i is the idiosyncratic error term.[63]

Table 26 shows the results of model (21) for the trust questions. As the results show, exposure to violence lowers trust. Respondents that were exposed to violence are 6.1 percentage points less likely to report that people can be trusted. This result is consistent with Alesina and LaFerrara (2002) where they showed that exposure to trauma erodes trust. Exposure to violence has a similar impact on the question about intentions of others. Those that were more exposed to violence were 5 percentage points less likely to report that others are helpful. Both these responses are statistically significant at the 1% level using a test of proportions. On the question with regards to usage of caution, the effect of violence is positive, which implies that respondents that were more exposed to violence used greater caution when dealing with strangers. However, the coefficient of interest is insignificant: the differences in responses on the usage of caution with strangers for those who were exposed to violence relative to those who were not, is on average centered around 0.

Having shown than exposure to violence affects general levels of trust and beliefs about intentions negatively, the effects of the experimental interventions on the same outcomes is explored. The repeated nature of the in-person surveys is exploited and the fact that only

[62]Other indicators for exposure to violence were also considered such as (i) responses greater than the mean ($v_i \geq \overline{v}$) and (ii) responses greater than one-standard deviation above the mean ($v_i \geq \overline{v} + \sigma_v$). The results are not affected when these indicators were used to define exposure to violence.

[63]To estimate how exposure to violence affects general levels of trust, (i) probit/order probit models, and (ii) transformations of the Likert-scale questions to a standard normal distribution were also considered. The qualitative nature of the results relative to (21) remain unchanged with these two strategies.

Table 26: The effect of exposure to conflict on trust

	People can be trusted		People are helpful		Be careful w/ strangers	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to violence	-0.061***	-0.060***	-0.050***	-0.048***	0.017	0.012
	(0.023)	(0.023)	(0.018)	(0.015)	(0.024)	(0.022)
Demographics		X		X		X
No. of observations	1765	1646	1740	1624	1771	1652
R^2	0.01	0.04	0.01	0.04	0.01	0.02

Notes: The questions represented by columns 1 - 4 are binary. The question represented by columns 5 - 6 was asked on a scale of 1 - 5 and was dichotomized by setting the values ≥ 4 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

a subset of the villages in the sample received the treatment (messages). A difference-in-differences model is employed that allows us to extract a causal impact of the messaging campaigns and keep all other unobservables, which could influence the outcomes of interest, constant. In particular, a series of linear probability models of the following form are estimated:

$$y_{it} = \alpha + \beta T_i + \delta W_t + \theta \left(T_i \times W_t\right) + \gamma \mathbf{X_{it}} + \xi_{it} \tag{22}$$

where y_i is the response of the individual i in wave t, T_i is an indicator that takes a value of 1 if the respondent resides in a village that received the cellular messages, W_t is a wave dummy, which equal 1 for the post-intervention period, $\mathbf{X_{it}}$ are demographic variables and ξ_i is the idiosyncratic error term.[64] To account for correlation within a village, the standard errors are clustered at the village level. The effect of the treatment on the associated outcome of interest is captured by θ.

Empirical results for trust and beliefs about intentions are contained in Table 27. The results suggest that the messaging campaigns had a positive impact on the levels of trust and beliefs about others. Respondent who resided in treated villages were 31.7 percentage point

[64]These models were also estimated using (i) probit/order probit models, and (ii) transforming the Likert-scale questions to a standard normal. The qualitative nature of the results relative to (22) remain unchanged with these two strategies.

less likely to report that others could be trusted in the first wave of the in-person survey relative to the respondents residing in the control villages. However in the post-intervention period, respondents from the treated villages are 11 percentage points more likely to report that others could be trusted when compared to the control group. Moreover, this difference-in-differences result is significant at the $p < 0.01$ level. Similar results are observed for beliefs about intentions of others. As noted in column 3, respondents from the treated villages were 13.4 percentage points less likely to report that others are helpful in the pre-intervention period, relative to the respondents in the control villages. However, this difference decreases by more than 81 percent in the post-intervention period and this difference is significant at the $p < 0.10$ level. On the use of caution with strangers, the difference-in-differences coefficient in the 5$^{\text{th}}$ column is negative suggesting that in the post-intervention period, respondents believed that it is less important to use caution when dealing with strangers. However, this coefficient is not significant. Collectively, these results suggest that the awareness of these new reforms reduced the impacts of conflict and violence on societal trust.

I also explore whether the effects are more prominent for those who were more exposed to violence relative to others. To estimate this, the model given by (22) is augmented by including an indicator for exposure to violence (v_i^N) and a triple interaction term that equals 1 for a respondent living in the treated village who was exposed to violence and was surveyed in the post-intervention period. In particular, the following regressions are estimated:

$$y_{it} = \alpha + \beta T_i + \delta W_t + \lambda v_i^N + \theta\left(T_i \times W_t\right) + \tau\left(v_i^N \times W_t\right) + \rho\left(v_i^N \times T_i\right) + \phi\left(v_i^N \times T_i \times W_t\right) + \gamma \mathbf{X_{it}} + \mu_{it} \tag{23}$$

Since v_i^N has a standard normal distribution with mean 0, the average treatment effect is given by θ. The results of model (23) are given in columns 2, 4 and 6. The results indicate that the treatment had a smaller effects on the attitudinal measures of trust on those who were more exposed to violence. Respondents who were more exposed to violence, on average were 13 percentage points less likely to report that others could be trusted in the post-intervention period relative to those who were less exposed to violence. Additionally, this

Table 27: The impact of messaging campaigns on general levels of trust

	People can be trusted		People are helpful		Be careful w/ strangers	
	(1)	(2)	(3)	(4)	(5)	(6)
Wave 2	-0.631***	-0.591***	-0.237***	-0.214***	0.374***	0.381***
	(0.065)	(0.091)	(0.056)	(0.055)	(0.104)	(0.084)
Treatment	-0.317***	-0.272***	-0.134**	-0.107*	-0.114	-0.110
	(0.047)	(0.062)	(0.060)	(0.063)	(0.078)	(0.070)
Wave 2 × Treatment	0.427***	0.386***	0.108*	0.081	-0.171	-0.176*
	(0.078)	(0.100)	(0.066)	(0.065)	(0.111)	(0.093)
Exposure to violence		-0.197***		-0.116**		-0.052
		(0.079)		(0.056)		(0.055)
Exposure to violence × Wave 2		0.199***		0.066**		0.001
		(0.063)		(0.031)		(0.028)
Exposure to violence × Treatment		0.154*		0.077		0.072
		(0.082)		(0.058)		(0.058)
Exposure to violence × Wave 2 × Treatment		-0.131*		-0.012		-0.020
		(0.069)		(0.037)		(0.038)
No. of observations	3569	3546	3546	3524	3577	3552
R^2	0.10	0.11	0.05	0.05	0.07	0.08

Notes: The questions represented by columns 1 - 4 are binary. The question represented by columns 5 - 6 was asked on a scale of 1 - 5 and was dichotomized by setting the values ≥ 4 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

difference is significant at the 10% level. From a policy perspective, these heterogeneous effects are notable given the prior literature that has noted that lower levels of trust are associated with higher crime rates (Sampson et al. (1999), Kawachi et al. (1998)).

Satisfaction with the government and trust in institutions

A fundamental motivation underlying these reforms was to enhance political trust and improve service delivery. Next, the above analyses are repeated for the local institutions. In order to estimate the effects of exposure to violence on confidence towards institutions, model (21) is executed for three institutions in particular and these are: (i) the civil services, (ii) the district court, and (iii) the mosque. Respondents were asked on a Likert-scale of 1 to 10 about their attitudes towards these institutions where "very high confidence" takes a value of 10 and "no confidence" takes a value of 0.[65] Exposure to violence is again measured by v_i^N, which is produced by normalizing question # 45. Again only the 1$^{\text{st}}$ wave cross-sectional data is used for model (21) and the results of these regressions are given by Table 28. As the results show, exposure to violence has a positive effect on civil services and district courts (formal local institutions). Confidence towards institutions increased by 1 to 2 percentage points for respondents that were more exposed to violence. However, these coefficients are not statistically significant. On the other hand, confidence towards mosques (informal local institutions) is declining in violence. On average, increase in exposure to violence reduced confidence towards mosque by 5 percentage points. This result is noteworthy, particularly, from a policy perspective. As conflict worsens in a region, trust and confidence in formal institutions increases.

The impact of the messaging schemes on trust in these public and religious institutions is also explored. Using data from both waves of the in-person survey, the responses to the

[65]The Likert-scale questions on a scale of 1 to 10 were dichotomized such that responses greater than or equal to 7 were assigned a value of one and responses less than 7 were assigned a value of zero. Variations of such dichotomizations produced similar results.

Table 28: The effect of exposure to conflict on confidence in local institutions

	Civil services		Mosque		District court	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to	0.015	0.016	-0.042***	-0.043***	0.010	0.007
violence	(0.017)	(0.017)	(0.015)	(0.013)	(0.020)	(0.019)
Demographics		X		X		X
No. of observations	1766	1650	1716	1602	1754	1637
R^2	0.01	0.03	0.01	0.06	0.00	0.03

Notes: The questions represented by columns 1 - 6 were asked on a scale of 1 - 10 and were dichotomized by setting the values ≥ 7 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

confidence questions as the dependent variable are used in the econometric model given by (22). Empirical results of these models are given in Table 29. The results suggest that the messaging campaign increased confidence in local institutions but the result is significant only for district courts. The difference-in-differences coefficient in column 5 implies that there was a 0.83 standard deviation increase in confidence towards district courts after the messaging campaigns. The awareness campaigns also had negligible effects on confidence towards the federal government. The null effects of the campaign towards the mosque and the federal government are not surprising as the reforms were intended for the public offices at the provincial level. Secondly, these results also confirm that the differential effects for the treated villages compared to the control villages in the post-intervention period are being driven by the messaging campaigns and are not due to unobserved shocks at the village level. Lastly, political trust is learned behavior that captures attitudes across wide array of services that are formed over a long time horizon (Ridley (1997), Newton (2007)). Thus, the awareness campaigns did have small effects on political trust and confidence towards local institutions but rebuilding and restoration of such trust requires time.

To examine the effects of the messaging campaign on satisfaction with public institutions and service delivery, the difference-in-differences approach is utilized on the following three questions:

Table 29: The impact of messaging campaigns on trust in institutions

	Civil services		Mosque		District court		Federal government	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wave 2	-0.034	-0.038	-0.073**	-0.072**	-0.257*	-0.259**	-0.052	-0.058
	(0.027)	(0.024)	(0.032)	(0.030)	(0.131)	(0.115)	(0.068)	(0.060)
Treatment	0.171***	0.167***	-0.143***	-0.140***	-0.345***	-0.349***	0.085*	0.076*
	(0.030)	(0.031)	(0.048)	(0.047)	(0.107)	(0.091)	(0.050)	(0.046)
Wave 2 × Treatment	0.068	-0.023	0.097	0.085	0.308**	0.311***	-0.074	-0.061
	(0.182)	(0.051)	(0.062)	(0.062)	(0.133)	(0.118)	(0.074)	(0.067)
Exposure to violence		0.014		-0.018		0.024		0.022*
		(0.009)		(0.018)		(0.104)		(0.013)
Exposure to violence × Wave 2		-0.017		-0.029*		-0.011		-0.045***
		(0.036)		(0.017)		(0.080)		(0.013)
Exposure to violence × Treatment		-0.004		-0.024		-0.010		0.016
		(0.019)		(0.024)		(0.105)		(0.021)
Exposure to violence × Wave 2 × Treatment		0.021		0.012		-0.011		0.028
		(0.045)		(0.032)		(0.083)		(0.025)
No. of observations	3573	3550	3532	3502	3562	3537	3562	3546
R^2	0.02	0.02	0.04	0.05	0.05	0.05	0.05	0.05

Notes: The questions represented by columns 1 - 8 were asked on a scale of 1 - 10 and were dichotomized by setting the values ≥ 7 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

1. I am satisfied with the quality of services provided by the political administration.

2. Over the past year, the provincial government has taken efforts that have improved the system of justice in your district.

3. Over the past year, the government has taken actions to improve the governance system in your region.

On these questions, the respondents were asked to indicate on a scale of 1 to 10, whether they agreed with these statement where "strongly agree" is equivalent to 10 and "strongly disagree" takes a value of 0. Empirical results of these regressions are given by Table 30 and suggest that the messaging campaign had a positive impact on the responses to these questions, particularly regarding perceptions about quality of public services. The difference-in-differences coefficient in column 1 corresponds to 0.86 standard deviation increase in satisfaction towards quality of services provided by the political administration. The difference-in-differences coefficient in columns 3 and 5 are smaller in magnitude and insignificant. The triple interaction coefficients columns 4 and 6 indicate that the effect of the treatment on perceptions about justice and governance diminishes as violence increases. Given the prior literature that has formed an association of political trust with confidence in public institutions and perceptions about quality and performance of these institutions (Hetherington (2005), Newton (2007), Hutchison and Johnson (2011)), the impacts that the messaging campaign had on these perceptions about governance is important from a policy perspective. Such changes represent a necessary first step in reconstructing and restoring trust in the state and local public institutions.

Table 30: The impact of messaging campaigns on satisfaction with governmental services

	Quality of services		Improvement in justice		Improvement in governance	
	(1)	(2)	(3)	(4)	(5)	(6)
Wave 2	-0.303*	-0.308**	-0.201	-0.194	-0.159	-0.154
	(0.157)	(0.141)	(0.203)	(0.201)	(0.200)	(0.197)
Treatment	-0.191	-0.200	-0.181	-0.180	-0.141	-0.141
	(0.144)	(0.133)	(0.164)	(0.158)	(0.171)	(0.170)
Wave 2 × Treatment	0.378**	0.386***	0.223	0.224	0.117	0.120
	(0.167)	(0.152)	(0.206)	(0.204)	(0.205)	(0.202)
Exposure to violence		0.000		-0.044		0.031**
		(0.061)		(0.028)		(0.014)
Exposure to violence × Wave 2		-0.023		0.094***		0.016**
		(0.063)		(0.019)		(0.008)
Exposure to violence × Treatment		0.008		0.083**		0.075***
		(0.065)		(0.036)		(0.024)
Exposure to violence × Wave 2× Treatment		0.002		-0.122***		-0.041*
		(0.071)		(0.030)		(0.023)
No. of observations	3508	3478	3579	3547	3564	3533
R^2	0.04	0.04	0.02	0.02	0.02	0.03

Notes: The questions represented by columns 1 - 6 were asked on a scale of 1 - 10 and were dichotomized by setting the values ≥ 7 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses

*** significant at 1% level; ** significant at 5% level; * significant at 10% level

Next, the impacts of exposure to violence and the messaging campaigns on measures of subjective well-being are explored. Previous literature has established that subjective well-being is a good measure of well-being (Krueger and Schkade (2008)) and has been utilized to estimate policy effectiveness. For example, Frijters et al. (2004) studied the effects of German re-unification on subjective well-being in East Germany and Gruber and Mullainathan (2005) evaluated the impact of cigarette taxes on subjective well-being of smokers. Prior literature has also established that conflict affects subjective well-being negatively (Frey et al. (2009), Dolan and Metcalfe (2012)). I extend on this literature and explore the effects of exposure to violence and the awareness campaigns on measures of subjective well-being in KPK. Exposure to violence is again defined by v_i^N. The focus is on the following two questions from the in-person survey:

1. How satisfied are you with the financial situation of your household?
2. All things considered, how satisfied are you with your life as a whole these days?

On these questions, the respondents were asked to rate on a scale of 1 to 10 their level of satisfaction, where "very satisfied" is equivalent to 10 and "very unsatisfied" takes a value of 0. The responses to these questions are used as the dependent variable in the econometric models.

The results for model (21) with measures of subjective well-being as the dependent variable are given by Table 31. Similar to the findings in the previous literature, exposure to violence and conflict have a negative effect on subjective well-being. The coefficient of interest is negative and significant for both these questions. Those that were more exposed to violence were 8 to 9 percentage points less likely to report that they are satisfied with their life and 7 percentage points less likely to indicate that they are satisfied with their financial

Table 31: The effect of exposure to conflict on subjective well-being

	Satisfaction w/ financial situation		Satisfaction w/ life as a whole	
	(1)	(2)	(3)	(4)
Exposure to violence	-0.079*** (0.031)	-0.075*** (0.027)	-0.090*** (0.030)	-0.082*** (0.029)
Demographics		X		X
No. of observations	1731	1618	1733	1618
R^2	0.02	0.08	0.03	0.08

Notes: The questions represented by columns 1 - 4 were asked on a scale of 1 - 10 and were dichotomized by setting the values ≥ 7 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses.
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

situation. Both these responses are statistically significant at the 1% level using a test of proportions. Empirical results of model (22) with well-being measures as the dependent variables are given by Table 32. The results suggest that the awareness campaigns had a positive but a negligible impact on subjective well-being. The difference-in-differences coefficients in columns 1 and 3 are approximately one-fourth of a standard deviation increase in satisfaction with one's financial situation and satisfaction with life, respectively. However, both these coefficients are insignificant. En masse, these results suggest that the awareness campaigns had a positive and a substantial impact on trust and confidence in local institutions but did not affect life satisfaction significantly.

An important robustness check - phone surveys

For a variety of reasons, the in-person survey results discussed above could be seen with skepticism. Firstly, the surveys were done for a small subset of villages in KPK and include observations from one control *tehsil*. Therefore, the unobserved shocks to the villages within the control *tehsil* from the effect of the awareness campaigns on villages within the treated *tehsils* cannot be completely disentangled. Secondly, given the small sample sizes, there is a possibility that the regression models may be under-powered and thus unable to detect

Table 32: The impact of messaging campaigns on subjective well-being

	Satisfaction w/ financial situation		Satisfaction w/ life as a whole	
	(1)	(2)	(3)	(4)
Wave 2	-0.049	-0.032	-0.049	-0.039
	(0.161)	(0.153)	(0.157)	(0.160)
Treatment	-0.246***	-0.219**	-0.262***	-0.241**
	(0.090)	(0.085)	(0.093)	(0.096)
Wave 2 × Treatment	0.110	0.078	0.097	0.071
	(0.169)	(0.161)	(0.166)	(0.169)
Exposure to violence		-0.094***		-0.054
		(0.023)		(0.054)
Exposure to violence × Wave 2		0.043**		-0.004
		(0.018)		(0.070)
Exposure to violence × Treatment		0.026		-0.025
		(0.037)		(0.063)
Exposure to violence × Wave 2× Treatment		-0.001		0.056
		(0.045)		(0.084)
No. of observations	3541	3518	3541	3518
R^2	0.05	0.06	0.05	0.07

Notes: The questions represented by columns 1 - 4 were asked on a scale of 1 - 10 and were dichotomized by setting the values ≥ 7 to 1. Demographic controls included in the regressions are: age, education, ethnicity, gender, home ownership and marital status. Standard errors clustered at the village level are reported in parentheses.

*** significant at 1% level; ** significant at 5% level; * significant at 10% level

Table 33: Messaging campaigns and the telephone survey responses

	Trusting others	Satisfaction w/ local govt. services	Satisfaction w/ life
	(1)	(2)	(3)
Wave 2	-0.495***	-0.337***	-0.225***
	(0.016)	(0.018)	(0.017)
Treatment	-0.072***	-0.081***	-0.055***
	(0.012)	(0.012)	(0.011)
Wave 2 × Treatment	0.289***	0.232***	-0.016
	(0.017)	(0.018)	(0.018)
No. of observations	29535	29385	29535
R^2	0.15	0.15	0.14

Notes: The questions represented by columns 1 - 3 were asked on a scale of 1 - 5 and were dichotomized by setting the values ≥ 4 to 1. Demographic controls included in the regressions are: age, education, gender, and marital status. Standard errors clustered at the *tehsil* level are reported in parentheses.
*** significant at 1% level; ** significant at 5% level; * significant at 10% level

notable changes. Lastly, the in-person surveys could suffer from subject-to-desirability bias or other effects that could reflect characteristics of the surveyor instead of the respondent.

To address these concerns, a phone survey was also administered that included three questions of interest:

1. Do you trust others?
2. Are you satisfied with the quality of the services provided by the local political administration?
3. How satisfied are you with your life these days?

These questions were asked on a five-point Likert scale. The phone surveys did not include any questions regarding exposure to violence and thus I am restricted to the baseline econometric model given by (22), where the responses to these questions are the dependent variables. Moreover, in the phone surveys the respondents are observed at the *tehsil* level and therefore the standard errors are clustered at the *tehsil* level instead of the village level.

The empirical results with the phone survey data are given in Table 33. The results given by the table are consistent with the earlier in-person survey results. The awareness campaigns had a positive impact on trust and satisfaction with governance. For instance, the messaging campaign caused a three-fifth of a standard deviation increase in trust towards others and a 0.45 of a standard deviation increase in satisfaction with the quality of services of the local government. Both these effects are significant at the $p < 0.01$ level. The effect of the awareness campaign on satisfaction with life and hence well-being was insignificant. The effects with the phone based survey data are qualitatively similar to the effects produced with the in-person survey data and thus the concerns of the in-person survey raised earlier could be ignored. The awareness campaigns had a sizable effect on general levels of trust and quality of the services provided by the government under both, the in-person and the phone surveys and also highlight the advantage of including the phone survey results as an important robustness check.

IV. Conclusion

The purpose of this study is two-fold. Firstly, I explore how exposure to conflict and violence affects general levels of trust, attitudes toward local institutions and subjective well-being. Prior literature has established that conflict has the potential to erode societal and political trust, and hence create frictions in the system, which in turn hamper growth and development. For the analysis, the target population is the province of Khyber Pakhtunkhwa (KPK) in Pakistan, which has experienced severe militancy, conflict and violence in recent years. Erosion of trust is particularly detrimental for countries like Pakistan, since it affects economic development in the region. Secondly, the effects of targeted messages, which inform the citizens of the region regarding new governmental reforms, on societal trust, confidence in institutions and life-satisfaction are also examined. The goals of these reforms was to increase government transparency, improve service delivery and strengthen property rights. The underlying motivation for these provincial reforms was to enhance political trust in the state and improve attitudes in the local government institutions, which have the potential to reduce militancy and radicalism. A series of targeted messages were designed that make salient these government reforms and their underlying motivation. These messages were delivered to randomly selected cellular phone users via text messages and/or robot-calls.

For the analysis, an in-person survey was designed, which were conducted in randomly selected villages before and after the messaging campaigns. The results suggest that exposure to violence and conflict have negative effects on general levels of trust and subjective well-being, which is consistent with findings in the previous literature. Importantly, conflict increases confidence in formal local institutions relative to informal local institutions. Results on the awareness campaigns suggest that the targeted messages did have a positive and a significant impact on societal trust and attitudes towards local institutions. Moreover, the treatment had a larger effect on societal trust among respondents who were relatively more exposed to violence. As a placebo test, the awareness campaigns had no effect on informal institutions (religious institutions) or the federal government, since the reforms and the messages were intended for the local public institutions. Finally, the awareness campaigns had a negligible impact on subjective well-being and life satisfaction. To check the validity of these results, a phone survey was also conducted before and after the awareness campaigns in randomly selected villages. One of the advantage of the phone surveys over the in-person surveys was the sample size *plus* those villages could be reached that were inaccessible for the in-person interviews. Qualitatively, the results of the phone-survey data and the in-person survey data are similar. These results are noteworthy particularly from a policy perspective. The messaging campaigns had a significant effect on the attitudinal measures of trust and perceptions towards governance. Such changes represent a necessary first step in reconstructing and restoring societal and political trust in the state and the local public institutions.

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Appendix A: Proof of the non-causal model in Chapter 1

Consider the following two simultaneous equations:

$$y_1 = \alpha + \beta x_1 + \delta x_2 + \theta\left[x_1 \cdot x_2\right] + \varepsilon \tag{A.1}$$

$$y_2 = a + bx_1 + cx + d\left[x_1 \cdot x_2\right] + \mu \tag{A.2}$$

where $\mathrm{E}(\varepsilon\mu) \neq 0$ and $\mathrm{E}(x_1\varepsilon) = \mathrm{E}(x_2\varepsilon) = \mathrm{E}(x_1\mu) = \mathrm{E}(x_2\mu) = 0$. Let $\mathbf{X_1} = [1 \quad x_1]$, $\mathbf{X_2} = [x_2 \quad x_1 \cdot x_2]$, $\mathbf{X} = [\mathbf{X_1} \quad \mathbf{X_2}]$, $\mathbf{A_1} = [\alpha \quad \beta]'$ and $\mathbf{A_2} = [\delta \quad \theta]'$. Given the orthogonality conditions, (A.1) and (A.2) can be estimated by OLS. By Frisch-Waugh-Lovell (FWL) theorem:

$$\widehat{\mathbf{A_2}} = \left(\mathbf{X_2'M_1X_2}\right)^{-1}\mathbf{X_2'M_1}y_1 \tag{A.3}$$

where $\mathbf{M_i} = \mathbf{I} - \mathbf{P_{X_i}} = \mathbf{I} - \mathbf{X_i}(\mathbf{X_i'X_i})^{-1}\mathbf{X_i'}$, $\mathbf{P_{X_i}}$ is the projection matrix onto the space spanned by the columns of $\mathbf{X_i}$ and $\mathbf{X_i'M_i} = \mathbf{0}$.[66] $\frac{\partial \mathrm{E}(y_1|\mathbf{X})}{\partial x_2} = \widehat{\delta} + \widehat{\theta}x_1 = \mathbf{X_1}\widehat{\mathbf{A_2}}$. Call this $\widehat{T}$; this is the estimated treatment effect of x_2. To estimate how ∂x_2 is correlated with $\widehat{y_2}$, estimate the following regression:

$$\widehat{T} = \pi_0 + \pi_1\widehat{y_2} + \omega \tag{A.4}$$

where $\widehat{y_2} = \widehat{a} + \widehat{b}x_1 + \widehat{c}\,\overline{x_2} + \widehat{d}\left[x_1 \cdot \overline{x_2}\right]$, the structural parameters are estimated by OLS and $\overline{x_2} = \sum_{i=1}^{N}\frac{x_{2_i}}{N}$. Let $\mathbf{X_3} = [1 \quad \widehat{y_2}]$ and $\mathbf{\Pi} = [\pi_0 \quad \pi_1]'$.

$$\widehat{\mathbf{\Pi}} = \left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'}\widehat{T}$$
$$\widehat{\mathbf{\Pi}} = \left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'X_1}\widehat{\mathbf{A_2}}$$
$$\widehat{\mathbf{\Pi}} = \left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'X_1}\left(\mathbf{X_2'M_1X_2}\right)^{\mathbf{-1}}\mathbf{X_2'M_1}y_1 \tag{A.5}$$

Now consider the following model:

$$y_1 = \alpha + \beta x_1 + \pi_0 x_2 + \pi_1\left[\widehat{y_2} \cdot x_2\right] + \xi \tag{A.6}$$

[66] $\mathbf{M_i}$ is sometimes referred to as the residual-maker or the annihilator matrix and it creates residuals out of $\boldsymbol{y}$. $\mathbf{M_i}$ projects onto the orthogonal complement of the column space of $\mathbf{X_i}$. Both $\mathbf{M_i}$ and $\mathbf{P_{X_i}}$ are symmetric and idempotent.

where $\mathbf{X_4} = [x_2 \quad \widehat{y}_2 \cdot x_2]$ and $\mathbf{B} = [\pi_0 \quad \pi_1]'$. By Frisch-Waugh-Lovell (FWL) theorem:

$$\widehat{\mathbf{B}} = \left(\mathbf{X_4'M_1X_4}\right)^{-1}\mathbf{X_4'M_1}y_1 \tag{A.7}$$

Note that the projection of y_1 onto the space defined by $\mathbf{X_1}$ will be the same for (A.1) and (A.6). This implies that $\mathbf{M_2} = \mathbf{M_4}$: the partial effects of $\mathbf{X_1}$ in (A.1) can be obtained when the residuals from a regression of y_1 on $\mathbf{X_2}$ are regressed on the set of residuals obtained when each column of $\mathbf{X_1}$ is regressed on $\mathbf{X_2}$. The partial effects of $\mathbf{X_1}$ in (A.6) can be obtained when the residuals from a regression of y_1 on $\mathbf{X_4}$ are regressed on the set of residuals obtained when each column of $\mathbf{X_1}$ is regressed on $\mathbf{X_4}$. Hence, in both cases the residual-maker is the same and $\mathbf{M_2} = \mathbf{M_4}$. Given this result, the fact that $\mathbf{X_i'M_i} = \mathbf{0}$ and using (A.5) and (A.7) we have,

$$\begin{aligned}
\left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'X_1}\left(\mathbf{X_2'M_1X_2}\right)^{-\mathbf{1}}\mathbf{X_2'M_2M_1}y_1 &= \left(\mathbf{X_4'M_1X_4}\right)^{-1}\mathbf{X_4'M_4M_1}y_1 \\
\left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'X_1}\left(\mathbf{X_2'M_1X_2}\right)^{-\mathbf{1}}\mathbf{X_2'M_2M_1}y_1 &= \left(\mathbf{X_4'M_1X_4}\right)^{-1}\mathbf{X_4'M_2M_1}y_1 \\
\left(\mathbf{X_3'X_3}\right)^{-1}\mathbf{X_3'X_1}\left(\mathbf{X_2'M_1X_2}\right)^{-\mathbf{1}}\mathbf{X_2'M_1}y_1 &= \left(\mathbf{X_4'M_1X_4}\right)^{-1}\mathbf{X_4'M_1}y_1 \\
\widehat{\mathbf{\Pi}} &= \widehat{\mathbf{B}} \quad \blacksquare
\end{aligned} \tag{A.8}$$

Appendix B: Citizen trust survey conducted in Khyber Pakhtunkhwa

Q1. Age (years)
1 = 18 - 25
2 = 26 - 35
3 = 36 - 45
4 = 46 - 55
5 = 56 - 65
6 = 66 - 75
7 = Above 75

Q2. Gender
1 = male
2 = female

Q3. Marital status
1 = single
2 = married
3 = widowed

Q4. Number of children

Q5. Education
1 = none (illiterate)
2 = primary school
3 = middle school
4 = Secondary School Certificate (SSC) (high school)
5 = FA/FSc. (some college)
6 = BA/BSc.
7 = MA or higher
8 = Professional degree (MBBS, etc.)
9 = *Dars-e-Nizami*

Q6. Occupation
1 = private employee
2 = government employee
3 = agriculture
4 = self-employed
5 = housewife
6 = jobless
7 = student

Q7. Ethnicity
1 = Pashtun
2 = Hindko
3 = Chitrali
4 = Gujjar
5 = Hazara
6 = Punjabi
7 = Other

Q8. What type of vehicle do you own?
1 = car
2 = motorcycle
3 = bicycle
4 = other motorized vehicle
5 = do not own a vehicle

Q9. Do you own a home?
1 = yes
2 = no

Q10. How much land do you own? — in Marla

Q11. Five-digit location code

Q12. Many people claim that FATA has a special status due to its tribal traditions; therefore, it should have a special administrative arrangement. In your opinion, which of the following administrative structures should FATA have?
1 = a political agent appointed by the government to maintain law and order and manage development in the area
2 = an elected local government to management agency, town and village level development
3 = a combination of a political agent and an elected local government
4 = don't know
5 = does not apply to me
6 = don't care

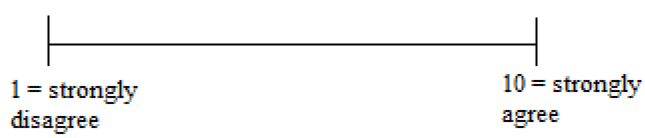
Q13. Many people claim that FATA has a special status due to its tribal traditions; therefore, it should have a special administrative arrangement. In your opinion, which of the following administrative structures should FATA have?

1 = a separate province with all the provincial political and administrative structure
2 = merged into KPK.
3 = remain a federally administered special entity.
4 = don't know
5 = does not apply to me
6 = don't care

Q14. In your opinion, which of the following entities would best improve service delivery in your district or agency?

1 = the government in Islamabad
2 = provincial government officials
3 = district or agency civil servants
4 = community based organization
5 = tribal councils
6 = don't know
7 = does not apply to me
8 = don't care

For Q15 – Q31 use the following grid:



Q15. I am satisfied with the quality of the services provided by the political administration.

Q16. The government is responsible for creating employment opportunities.

Q17. The government does a good job of providing employment opportunities for the people in your village.

Q18. The Office of the Political Agent is essential for development in FATA.

Q19. The Office of the Political Agent is essential for maintaining peace and security.

Q20. The Office of the Political Agent is essential for ensuring that there is a fair and transparent system of justice.

Q21. Over the past year, the Provincial government has made investments that have improved the schools in your district.

Q22. Over the past year, the Provincial government has made investments that have improved healthcare in your district.

Q23. Over the past year, the Provincial government has taken efforts that have improved the system of justice in your district.

Q24. Over the past year, government actions have improved the governance systems (like the right to information) in your region.

Q25. Over the past year, Federal government investments have improved large scale infrastructure – we should give examples here - in your region

Q26. Over the past year, Provincial government investments have improved the local infrastructure in your region.

Q27. Over the past year, the Federal government has taken actions that have aided the rehabilitation of IDPs in your region.

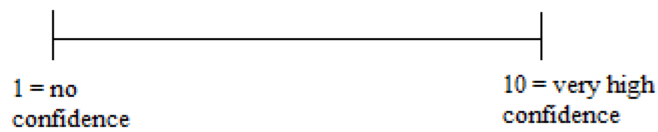
Q28. Over the past year, the Provincial government has taken actions that have aided the rehabilitation of IDPs in your region.

Q29. Over the past year, the Federal government has taken efforts that have helped to control militancy in your region.

Q30. Over the past year, the Provincial government has taken actions that have aided the rehabilitation of IDPs in your region.

Q31. Over the past year, the local government has taken actions that have aided the rehabilitation of IDPs in your region.

Trust in institutions: for Q32 – Q40 use the following grid:



Q32. Mosque (or other religious institution)

Q32b. Jirga

Q33. The municipality

Q34. Police

Q35. District or PA court

Q36. WAPDA

Q37. State media

Q38. Private media

Q39. Government in Islamabad

Q40. Civil services

Q41. How satisfied are you with the financial situation of your household?

1 = dissatisfied

10 = satisfied

Q42. All things considered, how satisfied are you with your life as a whole these days?

1 = dissatisfied

10 = satisfied

Q43. How interested would you say you are in politics?

1 = not interested

10 = very interested

Q44. How proud are you to be a Pakistani?

1 = not at all

10 = very proud

Q45. How much violence have you or a member of your family witnessed over the past year?

1 = Haven't witnessed any violence

10 = Witnessed extreme amount of violence

Q46. How much violence have you or a member of your family witnessed over the past year?

1 = Heard them often — 10 = Never heard them

Q47. Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?

1 = most people can be trusted
2 = can't be too careful

Q48. Do you think most people would try to take advantage of you if they got the chance, or would they try to be fair?

1 = would take advantage of you
2 = would try to be fair

Q49. Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?

1 = try to be helpful
2 = looking out for themselves

Q50. I like to help others.

1 = strongly agree
2 = agree
3 = undecided
4 = disagree
5 = strongly disagree

Q51. I trust others.

1 = strongly agree
2 = agree
3 = undecided
4 = disagree
5 = strongly disagree

Q52. When dealing with strangers, one is better off using caution before trusting them.
1 = strongly agree
2 = agree
3 = undecided
4 = disagree
5 = strongly disagree

Q53. How often have you benefited from the generosity of a person you did not know?
1 = very often
2 = often
3 = sometimes
4 = rarely
5 = never

Q54. How often do you leave your house or car door unlocked?
1 = very often
2 = often
3 = sometimes
4 = rarely
5 = never

Q55. How often do you lend personal possessions other than money to others?
1 = very often
2 = often
3 = sometimes
4 = rarely
5 = never

Q56. Taking all things together, how satisfied are you with your life as a whole these days?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q57. Overall, how satisfied are you with your life at home these days?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q58. Overall, how satisfied are you with your present job these days?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q59. Overall, how satisfied are you with your present health?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q60. Overall, how satisfied are you with the community in which you live these days?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q60b. In the past 3 months, did you or someone in your family go an entire day without eating, for reason other than for religious fasting?
1 = yes
2 = no

Q60c. If "yes" to Q60b., for how many days?

Q60d. In the past 3 months, has there been a time when you or a dependent family member needed health care but could not obtain it because of cost?
1 = yes
2 = no

Q60e. In the past 3 months, has there been a time when you or a dependent family member needed health care but could not obtain it because you were unable to travel?
1 = yes
2 = no

Q60f. If "yes" to Q60d. why you or a dependent family member was unable to travel to obtain health care?
1 = patient too weak
2 = there was no vehicle available
3 = fare was too high
4 = route was problematic
5 = no one to accompany the patient
6 = other

Q60g. You could not access healthcare with which of the following?
1 = doctor
2 = nurse
3 = lady health visitor (LHV)
4 = *Hakeem*
5 = *Dai*
6 = other *desi* health provider
7 = village hospital
8 = district hospital

Q60h. Which of the following doctors have you visited in the past three month?
1 = doctor
2 = nurse
3 = lady health visitor (LHV)
4 = *Hakeem*
5 = *Dai*
6 = other *desi* health provider

Q61. Have you ever used internet or mobile to access any service offered by government?
1 = yes (go to Q63.)
2 = no (go to Q62.)

Q62. Why you have not used these internet or mobile services?
1 = I am illiterate
2 = I am shy/afraid of these services
3 = I don't know about these services
4 = I don't have internet or mobile to use these services
5 = I don't know how to use these services online or on mobile
6 = these services are too complicated
7 = these services are in English, which is difficult
8 = I tried but mobile services/ website had too many problems
9 = these services are ridiculous

Q63. Where did you get to know about the above services?
1 = radio
2 = television
3 = newspaper
4 = government official
5 = non-governmental organization (NGO)
6 = *Hujra*
7 = family or friend
8 = other

Appendix C: Telephone survey conducted in Khyber Pakhtunkhwa

Q1. Taking all things together, how satisfied are you with your life as a whole these days?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q2. Do you trust others?
1 = strongly agree
2 = agree
3 = undecided
4 = disagree
5 = strongly disagree

Q3. Are you satisfied with the quality of the services provided by the local dist or political administration?
1 = very satisfied
2 = satisfied
3 = neutral
4 = unsatisfied
5 = very unsatisfied

Q4. What is your age?
1 = Less than 15
2 = 15 - 18
3 = 19 - 25
4 = 26 - 35
5 = 36 - 45
6 = 46 - 55
7 = 56 - 65
8 = 66 - 75
9 = Above 75

Q5. Gender
1 = male
2 = female

Q6. Marital status
1 = single
2 = married
3 = widowed

Q7. Number of children

Q5. Education
1 = none (illiterate)
2 = primary school
3 = middle school
4 = Secondary School Certificate (SSC) (high school)
5 = FA/FSc. (some college)
6 = BA/BSc.
7 = MA or higher
8 = engineer
9 = doctor
10 = lawyer
11 = chartered accountant
12 = other

Appendix D: Khyber Pakhtunkhwa experimental study design

Table D.1: Experimental design: Khyber Pakhtunkhwa messaging campaign

	Estimated population in 2013	RTI calls made	RTS calls made	PHC calls made
Control group				
Tangi	411,000	0	0	0
Haripur	728,000	0	0	0
Lakki	790,000	0	0	0
Oghi	248,000	0	0	0
Martoong	930,000	0	0	0
Wari S/D	366,000	0	0	0
Treatment 1				
Abbottabad	863,784	14,101	10,343	X
Chitral S/D	270,000	4,487	2,343	X
B. Daud Shah	156,000	3,278	2,210	X
Jandool	317,000	5,456	4,011	X
Mardan	1,661,000	27,297	18,375	X
Puran	130,000	2,324	1,983	X
Treatment 2				
Havelian	297,216	5,003	3,922	0
Mastuj S/D	197,000	3,245	2,591	0
Karak	264,000	4,589	3,491	0
Temergara	885,000	16,331	10,611	0
Takht Bai	639,000	11,360	7,344	0
Lahore	475,000	8,178	5,734	0
Treatment 3				
Bannu	1,033,000	0	11,639	X
D. I. Khan	832,000	0	10,429	X
Takht-e-Nasrati	284,000	0	3,781	X
Sam Ranizai	313,000	0	3,981	X
Nowshera	1,355,000	0	15,699	X
Swabi	1,133,000	0	13,243	X
Treatment 4				
Allai	175,000	3,071	0	X
Kulachi	246,000	4,101	0	X
Kohat	919,000	15,570	0	X
Swat Ranizai	439,000	7,709	0	X
Peshawar	3,452,000	56,785	0	X
Matta	410,000	6,965	0	X
Treatment 5				
Battagram	267,000	4,540	0	0
Paharpur	319,000	5,677	0	0
Dassu S/D	189,000	3,489	0	0
Balakot	293,000	5,421	0	0
Alpuri	277,000	4,501	0	0
Swat	1,680,000	30,844	0	0

Table D.1 (continued): Experimental design: Khyber Pakhtunkhwa messaging campaign

	Estimated population in 2013	RTI calls made	RTS calls made	PHC calls made
Treatment 6				
Tank	382,000	0	4,862	0
Besham	101,000	0	1,582	0
Buner	904,000	0	10,874	0
Hangu	514,000	0	6,102	0
Palas S/D	215,000	0	2,891	0
F. R. Kaladhaka	338,000	0	4,211	0
Treatment 7				
Charsadda	1,171,000	0	0	X
Ghazi	163,000	0	0	X
Pattan S/D	124,000	0	0	X
Mansehra	808,000	0	0	X
Chakisar	111,000	0	0	X
Dir S/D	508,000	0	0	X

VITA

M. Taha Kasim was born on July 12, 1988 in Karachi, Pakistan. He graduated from the University of Minnesota, Duluth (UMD) in 2011 with a Bachelor of Arts degree in Economics and a Bachelor of Science degree in Mathematics. While at UMD, he worked as a research assistant for the Bureau of Business and Economic Research. He enrolled into the Economics PhD program at Georgia State University in 2011.

At Georgia State University, Taha has been awarded the University Fellowship, the Jack Blicksilver Award, the George Malanos Economics Scholarship and the Quantitative Economics Award.

He has worked as a research assistant for Barry T. Hirsch (2011 – 2013) and Kyle Mangum (2013 – 2016) and has taught the principles of macroeconomics (Summer, 2014) and intermediate microeconomics (Spring, 2015) classes at Georgia State University.

Taha has presented his research at various platforms including the Center for Environmental and Resource Economic Policy (CEnREP) Conference and the Southern Economics Association Conference. He has accepted a non-tenure-track faculty position as an Assistant Professor of Economics at Furman University in Greenville, South Carolina. To contact Taha, visit his website at https://sites.google.com/site/tahakasim/.