Regional Science and Urban Economics xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regec

Identifying the elasticity of driving: Evidence from a gasoline price shock in California

Kenneth Gillingham

Yale University, 195 Prospect Street, New Haven, CT 06511, United States

ARTICLE INFO

Article history:
Received 23 February 2013
Received in revised form 27 May 2013
Accepted 8 August 2013
Available online xxxx

JEL classification:
R2
R4
Q4
Q5

Keywords:
Urban transportation
Heterogeneity
Vehicles
Gasoline taxes

ABSTRACT

There have been dramatic swings in retail gasoline prices over the past decade, along with reports in the media of consumers changing their driving habits — providing a unique opportunity to examine how consumers respond to changes in gasoline prices. This paper exploits a unique and extremely rich vehicle-level dataset of all new vehicles registered in California in 2001–2003 and then subsequently given a smog check in 2005–2009, a period of steady economic growth but rapidly increasing gasoline prices after 2005. The primary empirical result is a medium-run estimate of the elasticity of vehicle-miles-traveled with respect to gasoline price for new vehicles of −0.22. There is evidence of considerable heterogeneity in this elasticity across buyer types, demographics, and geography. Surprisingly, the vehicle-level responsiveness is increasing with income, perhaps due to within-household switching of vehicles. The estimated elasticity has important implications for the effectiveness of price policies, such as increased gasoline taxes or a carbon policy, in reducing greenhouse gases. The heterogeneity in the elasticity underscores differing distributional and local air pollution benefits of policies that increase the price of gasoline.

1. Introduction

Starting in 2004 and early 2005, retail gasoline prices in the United States began creeping upwards, culminating in an increase of over 100% by 2008, the largest since the Mideast oil supply interruptions in the 1970s. Consumers can respond to gasoline price shocks on both intensive and extensive margins by changing driving behavior, purchasing a more fuel-efficient vehicle or scrapping an old gas guzzler. Quantifying exactly how consumers respond has been a research topic of great interest to economists for decades, yet it remains just a relevant as ever for policy analysis of price policies to reduce greenhouse gas emissions from the vehicle fleet.

This paper focuses on the intensive margin of consumer response to the recent gasoline price shock by providing new evidence on the utilization elasticity for vehicles, i.e., the elasticity of vehicle-miles-traveled (VMT) with respect to the cost of driving. This study estimates the response in driving to changes in gasoline price by bringing together a novel vehicle-level dataset in which vehicle characteristics, vehicle purchaser characteristics, the odometer reading several years later, the location at both registration and at time of the odometer reading, and the relevant gasoline prices over the time period are all observed. This rich dataset, along with a careful research design, helps to overcome key identification challenges, while at the same time allowing for a closer look into the heterogeneity in consumer response at the demographic and geographic levels.

The empirical literature on the responsiveness of consumers to changes in gasoline prices has a long history going back to studies of traffic counts, a few empirical studies estimating a utilization elasticity, and an extensive literature estimating the price elasticity of gasoline demand. Austin (2008) reviews the older literature and finds that the utilization elasticity has been estimated to range from −0.10 to −0.16 in the short run and −0.26 to −0.31 in the long run.[1] Several of these empirical studies, such as Goldberg (1998) and West (2004), use cross-sectional survey data for VMT and estimate a utilization elasticity along with vehicle choice using the framework developed in Dubin and McFadden (1984).

More recent evidence suggests that the utilization elasticity is becoming more inelastic over time. One of the more notable studies in this literature is Small and Van Dender (2007), who simultaneously estimate a system of equations capturing the choice of aggregate VMT per capita, the size of the vehicle stock, and the fuel efficiency of the fleet. Small and Van Dender estimate this system on panel data of US states over the period 1966–2001 and find that at the sample averages of the variables the preferred short-run and long-run utilization elasticities are −0.045 and −0.222 respectively. They find less responsiveness in the period 1997–2001, a result they attribute to the growth of income

[1] The National Academies of Sciences' report on CAFE standards had a similar range (National Research Council, 2002).

E-mail address: kenneth.gillingham@yale.edu.

0166-0462/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.regsciurbeco.2013.08.004

and lower fuel prices over the time frame of their study. Hymel et al. (2010) use the same methodology with more recent data to reach similar conclusions. These results indicating a declining utilization elasticity (in absolute value) are then interpreted as evidence of a declining "rebound effect," which can most intuitively be thought of as the elasticity of driving with respect to fuel economy improvements.[2] The idea behind this interpretation is that the cost per mile of driving would change with both a change in gasoline prices and a change in fuel economy, so a rational consumer would treat both the same.

Recent evidence on the gasoline price elasticity of demand also indicates that the responsiveness may be declining over time. Specifically, Hughes et al. (2008) find that the short-run gasoline price elasticity is in the range of −0.21 to −0.34 for 1975–1980, but by 2001–2006 consumers are significantly less responsive, with an elasticity in the range of −0.03 and −0.08. Small and Van Dender (2007) also calculate a gasoline price elasticity and find evidence that it too is becoming closer to zero over time, with a preferred short-run estimate of −0.087 over 1966–2001 and −0.066 over 1997–2001. Older estimates of the gasoline price elasticity from the 1970s and 1980s often indicate much greater price responsiveness (e.g., see the survey by Graham and Glaister (2002)).

There is surprisingly limited empirical evidence quantifying the heterogeneity in consumer responsiveness across any dimension for either the gasoline price or utilization elasticity. West (2004) uses the 1997 Consumer Expenditure Survey to find that the lowest income decile has over a 50% greater responsiveness to gasoline price than the highest income decile, along with a U-shaped pattern of responsiveness. West and Williams (2004) also find that the lowest expenditure quintile (elasticity of −0.7) has over three times the responsiveness of the highest expenditure quintile (elasticity of −0.2), but with no U-shaped pattern. Bento et al. (2009) find that families with children and owners of trucks and sport utility vehicles are more responsive to changes in gasoline prices, but the differences are relatively minor. Wadud et al. (2009) use Consumer Expenditure Survey data to find a U-shaped pattern of price elasticities of gasoline demand across income quintiles, while Wadud et al. (2010) use a different empirical strategy to find that the responsiveness to gasoline prices declines with income.

This paper uses observed VMT to provide new evidence on the gasoline price elasticity of driving and explore the heterogeneity in this elasticity. A primary result is an estimate of the medium run elasticity of VMT with respect to the price of gasoline for vehicles in their first several years of use in the range of −0.22. This result suggests that consumer responsiveness to the gasoline price shock of recent years was not inconsequential. Moreover, the results point to important heterogeneity by income group and geography, and some degree of heterogeneity by buyer type and demographics.

The paper is organized as follows. Section 2 describes the unique dataset assembled for this study. Section 3 discusses the estimation strategy and the basis for identification. Section 4 presents the empirical results, and Section 5 concludes.

2. Data

2.1. Data sources

The dataset used in this study was assembled from several sources. I begin with data from R.L. Polk's National Vehicle Population Profile on all new vehicle registrations in California from 2001 to 2003. An observation in this dataset is a vehicle, identified by the 17 digit vehicle identification number (VIN). There are roughly two million vehicles registered in each of these years, and the date of registration is observed. The dataset includes a variety of characteristics of the vehicle such as make, model, model year, trim, transmission type, fuel, doors, body type, engine size (liters), engine cylinders, and the presence of a turbo- or super-charger. The dataset also includes some details about the purchaser of the vehicle, such as the zip code in which the vehicle is registered, the transaction type (personal, firm, rental or government), and whether the vehicle was leased. The income of the purchaser is observed on a subsample of the dataset, primarily based on forms filled out at the dealership relating to a financing agreement and supplemented by R.L. Polk with data from marketing companies. I match this dataset with vehicle safety ratings from the National Highway Transportation Safety Administration (NHTSA) Safercar.gov website. The Safercar.gov safety ratings are based on a 5 star rating scheme, and can be considered comparable to the ratings from the Insurance Institute for Highway Safety and Consumer Reports.

Since 1984, every vehicle in most counties in California is required to get a smog check to ensure the effectiveness of the vehicle emissions control system. The smog check program has been subsequently updated several times, and currently requires vehicles to get a smog check within six years of the initial registration of the vehicle.[3] If the ownership of a vehicle is transferred, any vehicle more than four years old is required to have a smog check unless the transfer is between a family member or a smog check has already been submitted within 90 days of the transfer date. Thus, some smog checks are observed as early as four years after the initial registration, and as late as seven years or more years if the owner is violating the law.

The California smog check program currently covers 40 of the 58 counties in California and all but a few percent of the population (see Appendix A for a list of counties covered by the program). At the time of the smog check, the VIN, characteristics of the vehicle (e.g., make, model, model year, transmission type), odometer reading, pollutant readings, and test outcome (pass or fail) are all sent to the California Bureau of Automotive Repair (BAR) and Department of Motor Vehicles to ensure compliance. I observe the smog check results for all vehicles in 2005 to 2009, and match these by VIN to the vehicle registrations in the R.L. Polk dataset. There are some VIN miscodings, so to ensure a perfect match, I only retain tests for VIN matches where the make and model also match. Approximately 0.1 million tests each year are not included due to miscoding, exemption from the smog check, scrapping, violating the law, or being in a location that does not require a smog check at the time of the smog check. Furthermore, I am interested in only those vehicles for which I can match a gasoline price that the consumers observe over the entire period for which the odometer reading is taken. Thus, I only retain VIN matches where the county in which the vehicle was registered when it was new matches either the county of registration at the time of the smog test or the county of the smog test station (if the registration county is unavailable). An additional 0.1 to 0.2 million vehicles are dropped from each year for this reason. This leaves me with a dataset with the first smog test matched by VIN for over 85% of the new registrations each year.

The primary question of this study is how consumers respond to changing gasoline prices, so the gasoline price data is of great importance. The Oil Price Information Service (OPIS) has retail gasoline prices throughout the United States based on credit card transactions at gas stations. For this analysis, I acquire county-level, monthly average retail gasoline prices in California for 2000 to 2010.[4] All counties except Alpine County are fully represented in the data. Fig. 1 shows how retail gasoline prices (in real terms) in California were relatively flat until around 2005,

[2] It is called a "rebound effect" due to the idea that people driving more is a "rebound" that reduces the benefits of fuel economy improvements.

[3] Exempted vehicles are: hybrids, electric vehicles, motorcycles, trailers, gasoline powered vehicles 1975 or older, diesel vehicles 1998 or older or greater than 14,000 lbs, or natural gas vehicles greater than 14,000 lbs. Interestingly, many of these vehicles, particularly hybrids, show up in my dataset anyway, perhaps because the vehicles had ownership transferred to a dealer who performed the smog check, or because the owners were not aware of the exception.

[4] I also use Cushing, OK (WTI) oil prices from the Energy Information Administration for a robustness check. Given the extremely high correlation between oil prices at different locations during this time period, WTI prices can be taken as a good measure of the global oil price.

Please cite this article as: Gillingham, K., Identifying the elasticity of driving: Evidence from a gasoline price shock in California, Regional Science and Urban Economics (2013), http://dx.doi.org/10.1016/j.regsciurbeco.2013.08.004