ABSTRACT

Title of dissertation: ESSAYS IN PERSONAL TRANSPORTATION DEMAND AND CONSUMER FINANCE

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This dissertation is composed of three essays covering two areas of interest. The first topic is personal transportation demand with a focus on price and fuel efficiency elasticities of mileage demand, challenging assumptions common in the rebound effect literature. The second topic is consumer finance with a focus on small loans.

The first chapter creates separate variables for fuel prices during periods of increasing and decreasing prices as well as an observed fuel economy measure to empirically test the equivalence of these elasticities. Using a panel from Germany from 1997 to 2009 I find a fuel economy elasticity of mileage of 53.3%, which is significantly different from the gas price elasticity of mileage during periods of decreasing gas prices, 4.8%. I reject the null hypothesis or price symmetry, with the elasticity of mileage during period of increasing gas prices ranging from 26.2% and 28.9%.

The second chapter explores the potential for the rebound effect to vary with

income. Panel data from U.S. households from 1997 to 2003 is used to estimate the rebound effect in a median regression. The estimated rebound effect independent of income ranges from 17.8% to 23.6%. An interaction of income and fuel economy is negative and significant, indicating that the rebound effect may be much higher for low income individuals and decreases with income; the rebound effect for low income households ranged from 80.3% to 105.0%, indicating that such households may increase gasoline consumption given an improvement in fuel economy.

The final chapter documents the costs of credit instruments found in major mail order catalogs throughout the 20th century. This study constructs a new dataset and finds that the cost of credit increased and became stickier as mail order retailers switched from an installment-style closed-end loan to a revolving-style credit card. This study argues that revolving credit's ability to decrease salience of credit costs in the price of goods is the best explanation for rate stickiness in the mail order industry as well as for the preference of revolving credit among retailers.

ESSAYS IN PERSONAL TRANSPORTATION DEMAND AND CONSUMER FINANCE

by

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It is impossible to remember all, and I apologize to those I've inadvertently left out.

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List of Abbreviations

APR	Annual Percentage Rate
ARRA	American Recovery and Reinvestment Act
CAFE	Corporate Average Fuel Economy
CARD	Credit Card Accountability Responsibility and Disclosure Act
CEX	Consumer Expenditure Survey
EPA	Environmental Protection Agency
EVs	Electric Vehicles
IRR	Internal Rate of Return
NHTSA	National Highway Traffic Safety Administration
PHEVs	Plug-in Hybrid Electric Vehicles
TILA	Truth in Lending Act

Chapter 1: Introduction

Government policies often have unintended consequences, both positive and negative. The Corporate Average Fuel Economy (CAFE) standards, for example, aim to reduce fuel consumption by increasing fuel economy, but the reduced cost to drive may cause some drivers to increase their miles driven following an improvement in efficiency, a phenomenon known as the rebound effect. As another example, the Truth in Lending Act (TILA) of 1968 was intended to protect consumers by allowing for easier comparison of credit instruments through the use of one common interest rate, the annual percentage rate (APR). This regulation may have influenced interest rates themselves, or if it constrained competition between lenders through the cost of credit, may have induced changes in product prices. This work provides insight into the effects of these policies.

This proposal is composed of three essays covering two areas of interest. The first topic is personal transportation demand with a focus on price and fuel efficiency elasticities of mileage demand. The second topic is consumer finance with a focus on small dollar loans for nondurable goods.

Mileage elasticities have received much interest in the economic literature, especially since the Arab Oil Embargo in the 1970s. In this expansive literature authors make a variety of assumptions regarding consumer responses to changes in important policies such as gasoline taxes and the CAFE standards which regulate fuel economy. I am particularly interested in assumptions commonly made in the literature on the "rebound effect", specifically i) that consumers respond equally to increasing and decreasing oil prices, ii) that households respond in the same way to changes in fuel economy as to changes in fuel prices, and iii) that households of different income levels respond equally to changes in fuel economy. This research strives to test these assumptions empirically. In my first essay, I allow for an asymmetric household response to fuel prices by decomposing fuel price into a decreasing price variable, historical price maximum, and price increase below the historical maximum. I then compare these elasticities to an elasticity of mileage with respect to fuel economy. In my second essay, through the inclusion of an interaction term, I allow for households of varying income levels to react differently to fuel economy improvements.

Although many studies examine loans for large durable items such as automobiles and mortgages, smaller installment loans receive little attention. Quantitative investigation of small dollar loans is almost nonexistent. In my final essay, my coauthor, Dr. Mary Zaki, and I explore the effects of providing the APR on the cost of credit to consumers and argue that disclosure of the APR did not increase public understanding of the cost of credit.

In the first essay, "The Household Response to Increasing Fuel Prices, Decreasing Fuel Prices, and Fuel Economy," I develop an empirical framework in which to compare fuel economy standards to fuel taxes, as well as the potential for these policies to induce an increase in miles driven. I examine the equivalence of the response to fuel economy and fuel prices and test for an asymmetric response to prices. A panel dataset from Germany from 1997 to 2009 provides me with a unique opportunity to estimate household-level mileage elasticity outside of the U.S. I use observed fuel economy (rather than manufacturer specs), and create separate variables for fuel prices during periods of increasing and decreasing prices to empirically test these assumptions. I find an overall fuel economy elasticity of mileage of which is significantly different than the gas price elasticity of mileage during periods of decreasing gas prices. I could also reject the null hypothesis of price symmetry.

My second essay, "Does the Rebound Effect Vary With Income? A Microdata Study," deals more explicitly with the rebound effect, the magnitude of the increase in miles driven following an improvement in fuel efficiency. This study explores the potential for the rebound effect to vary with income. Panel data from U.S. households from 1997 to 2003 is used to estimate the rebound effect in a median regression. The estimated rebound effect independent of income ranges from 17.8% to 23.6% in the median regressions. An interaction of income and fuel economy is negative and significant, indicating that the rebound effect may be much higher for low income individuals and decreases with income. In the baseline median regressions, the rebound effect for low income households was large enough to indicate that such households may increase gasoline consumption given an improvement in fuel economy.

The final essay, "Historical Cost of Consumer Credit, Interest Rate Stickiness and Salience: Evidence from Mail Order Catalogs" documents the costs of credit instruments found in major mail order catalogs from the 1920s through the 1990s. We construct a new dataset and find that the cost of credit generally increased and became stickier as mail order retailers switched from an installment-style plan (closed-end loan) to a revolving-style plan (credit card). Subsequently, interest rates on major sources of revolving credit remained sticky in the market for the next 30 years. Previous works have attributed credit card interest rate stickiness, which became evident in the 1980s, to search costs, switching costs and adverse selection. Some of these explanations are more applicable to the mail order catalog setting than others. This study adds revolving credit's ability to decrease salience of credit costs in the price of goods as another explanation for rate stickiness as well as for the preference of this form of credit over closed-end credit among retailers.

Section 2 presents the first essay regarding an asymmetric response to prices and the equivalence of the fuel economy elasticity of mileage and the fuel price elasticity of mileage. Section 3, contains the second essay, which examines whether consumers of different income levels respond differently to changes in fuel economy. Finally, Section 4 includes the final essay regarding the cost of credit for small dollar installment loans.

Chapter 2: The Household Response to Increasing Fuel Prices, Decreasing Fuel Prices, and Fuel Economy

2.1 Introduction

Many governments are using vehicle regulations in an effort to reduce the greenhouse gas emissions that contribute to climate change. In the US the CAFE standards are used to reduce fuel consumption by increasing fuel economy. Specifically, each auto manufacturer must meet a certain production-weighted harmonic mean fuel economy across their current model year fleet. This regulation was first introduced in 1975 in response to the Arab Oil Embargo and quickly led to myriad studies on the effect of the standards on fuel consumption and miles driven. [1] Of course, many other aspects of the CAFE standards have also been studied such as the effect on auto manufacturers,[2] the cost of the standards passed on to consumers,[3] the impact of tightening the standards,[4] and the effect of CAFE on vehicle safety.[5]

[1]Mayo and Mathis (1988); Greene (1992); Yee (1991); Goldberg (1998); Greene et al. (1999); West (2004); Small and Van Dender (2007); Frondel et al. (2008); Greene (2012); Goulder et al. (2012); Jacobsen (2013a) to name a few.

[2]Goldberg (1998); Austin and Dinan (2005); Anderson and Sallee (2011); Jacobsen (2013a)

[3]Goldberg (1998); Austin and Dinan (2005)

[4]Goldberg (1998); Kleit (2004); Fischer et al. (2007)

[5]Jacobsen (2011, 2013b)

Several studies also look at how the CAFE standards impact other similar policies[6] and directly compare the impact of these standards to gasoline taxes.[7]

In the EU, emissions pollutants are regulated instead of fuel economy. As in the U.S. these regulations were first put into law in the 1970s, though they were changed more often than the CAFE standards, most notably with changes in 1992-93, 1996, 2000, 2009, 2011, and 2014. More recent regulation in both Europe and the U.S. that restricts the emission of carbon dioxide is synonymous with fuel economy regulation, due to an inverse relationship between fuel economy and carbon dioxide.

This paper examines the household travel demand response to changes in fuel prices and fuel economy. Following Frondel and Vance (2013), this study uses household-level travel diary data from the German Mobility Panel to answer two key and related research questions. First, I test for an asymmetric response to prices. Then, I explicitly test the equivalence of mileage elasticities with respect to fuel economy and gas prices. If these elasticities differ, it is important to include both fuel economy and fuel prices in the mileage equation to avoid biasing the estimate through imposing coefficients of equal size, as well as to be able to report accurately on the more effective environmental policy. If the coefficients are not equal and opposite, then fuel economy policy and gas taxes will yield different results.

Both fuel economy (MPG) and the price of fuel (P_F) affect the cost per mile (P_M), given as $P_M = \frac{P_F}{MPG}$. If fuel economy improves, it becomes cheaper to drive.

[6] Bento et al. (2009); Goulder et al. (2012)

[7] Goldberg (1998); Austin and Dinan (2005); Anderson et al. (2011); Jacobsen (2013a)

Therefore, if mileage is highly elastic with respect to fuel economy, then an improvement in fuel economy will cause an increase in miles driven, a phenomenon known as the rebound effect. While this change can increase the welfare of the individual driver, the increase in mileage may mitigate much, or possibly all,[8] of the reduction in emissions and oil consumption induced by the technological improvement. Note also that these are not the only externalities associated with mileage; a high elasticity would also mean increases in congestion and accidents.

Similarly, if the gas price elasticity of mileage is sufficiently low, then regulations hoping to influence mileage through the price of gas, such as gasoline taxes, may fail to reduce oil consumption or to help avert climate change. Drivers may have inelastic demand for miles with respect to gas prices, especially in the US where public transit options are slim and long distances must often be driven as part of a daily commute to work.

Due to their relationship regarding the fuel cost per mile, the fuel economy elasticity of mileage and the fuel price elasticity of mileage are assumed to be of equal magnitude and opposite sign. Thus a study may use the response to gas prices to say something about fuel economy regulation such as the CAFE standards, or combine the two variables in a cost per mile to make use of the higher variation in gas prices as compared to fuel economy; [9] however, this assumption is rarely tested, and in cases when it is, it is often rejected.[10]

[8] Brookes (1990); Khazzoom (1980)

[9] Greene (1992); Jones (1993); Goldberg (1998); Small and Van Dender (2007); Frondel et al. (2008); Barla et al. (2009); Gillingham (2014); Gillingham et al. (2015)

[10] Wheaton (1982); Small and Van Dender (2007); Linn (2013)

The assumption is even less likely to hold when you consider that consumers may respond differently to increasing prices than to decreasing prices. Although there is some evidence of this asymmetric response to prices in a transportation context, [11] little has been done to quantify and test the differences in elasticity.

Most studies use data from the US. These elasticities may be higher in European countries due to the higher quality of public transit and higher fuel prices. If fuel prices rise, drivers may substitute miles driven for traveling by public transit which has stickier prices. The high fuel prices mean that fuel costs are a larger portion of overall travel costs, increasing the elasticity of mileage demand. Studies which do use European data often find larger elasticities, especially in the mileage elasticity with respect to fuel price;[12] for example, Wheaton (1982) finds a fuel economy elasticity of 0.06 and a fuel price elasticity of -0.50.

This paper extends the work of Frondel and Vance by making use of within-year variation in the data to gain additional observations per household per year. This allows me to quantify the consumer responses to gasoline prices and fuel economy with more longitudinal data than Frondel and Vance (2013) as well as to test for asymmetric short term responses to price decreases, maximums, and recoveries. [13]

By using each trip to the gas station as an observation, the number of observations available increases from 1100 to 12,180. With as many as 25 observations per

[11] Dargay (1992); Gately (1992); Dargay and Gately (1995, 1997); Gately and Huntington (2002); Griffin and Schulman (2005)

[12] Wheaton (1982); Johansson and Schipper (1997); Frondel et al. (2008)

[13] Traill et al. (1978); Dargay (1992); Gately (1992); Dargay and Gately (1994, 1997); Gately and Huntington (2002); Griffin and Schulman (2005)

household per year, the effect of these price maxima can be estimated more precisely than ever before. This is also the first paper to use the dummy variable method first proposed by Tweeten and Quance (1969) to decompose prices into maxima, recoveries, and decreases.

The estimated fuel economy elasticity of mileage is 0.533. This elasticity is significantly different from the gas price elasticity of mileage during periods of decreasing gas prices, which is -0.048 in my preferred specification. Though there was no evidence that consumers distinguished between historical maxima and other price increases, there was a significant difference between the elasticity of gas prices during periods of increasing prices, ranging from -0.262 to -0.289, and the elasticity of gas prices during periods of decreasing prices. This indicates that an improvement in fuel economy will increase miles driven by a large amount, while an increase in the fuel tax will cause a decrease in mileage.

2.2 Background and Policy Context

The CAFE standards were first introduced in 1975 in response to the Arab Oil Embargo, but after an initial increase in fuel economy, they remained unchanged at 27.5 mpg for 20 years, from 1990 to 2010.[14] Beginning in model year 2011, the standards began to rise again. Recently, the lead agency, the National Highway Traffic Safety Administration (NHTSA) has published estimated CAFE levels for passenger cars that increase approximately 1.5 miles per gallon (mpg) each year

[14] National Highway Traffic Safety Administration (2011)

over the next 3 years, then increase by even larger margins, up to 2.4 mpg, for 2017 to 2025.[15] This is the most rapid increase in stringency in the history of the CAFE standards. The U.S. Environmental Protection Agency (EPA) projects that this will cut 6 billion metric tons of greenhouse gases over the lifetimes of the vehicles sold in model years 2012-2025, save families more than $1.7 trillion in fuel costs, and reduce America's dependence on oil by more than 2 million barrels per day in 2025.[16]

Although the CAFE standards remained unchanged from 1990 to 2010, the U.S. did establish vehicle emissions standards in 1991 which were phased in from 2000 to 2004. These vehicle emissions standards were tightened with regulation passed in 1999, effective 2004, in response to an average increase in miles driven of 3% per year from 1970 to 1997 and a growth in the sale of SUVs.[17] In addition to reducing the allowed grams of nitrous oxide per mile to 0.07, this was also the first time that light-duty trucks, including SUVs, were held to the same standards as passenger cars.

The EPA has also decreased the amount of sulfur allowed in gasoline, capping total production as well as corporate average sulfur levels since 2004.[18] Carbon dioxide was not regulated until 2010 and those regulations are only just now going into effect with model year 2016. Other emissions levels and sulfur levels in gasoline are also facing tighter restrictions in model years 2017 to 2025 as of new regulations

[15] National Highway Traffic Safety Administration (2012)

[16] U.S. Environmental Protection Agency (2015c)

[17] U.S. Environmental Protection Agency (1999)

[18] U.S. Environmental Protection Agency (1999)

passed in March 2014.

In the EU, emissions pollutants are regulated instead of fuel economy, with different standards set for diesel engines versus gasoline engines. The regulation covers nitrous oxide, hydrocarbons, carbon monoxide, and particulate matter. As in the U.S. these regulations were first put into law in the 1970s, though they were changed more often than the CAFE standards, most notably with changes in 1992-93, 1996, 2000, 2009, 2011, and 2014. The levels of carbon monoxide, hydrocarbons, and nitrous oxide allowed in 1992 were the same for both diesel and gasoline engines, but after that a pattern emerged in which diesel engines were allowed higher levels of nitrous oxide, but lower levels of carbon monoxide. Gasoline engines did not face particulate matter restrictions until 2009.

The EU also introduced stricter sulfur regulation for fuel starting in 2000; the maximum level decreased from 350 ppm in diesel engines and 150 ppm in gasoline engines to 50 ppm in both in 2005. Sulfur-free (< 10 ppm) fuels became mandatory in 2009.[19] Carbon dioxide was addressed through voluntary agreements in 1998, and initially there were large reductions in this pollutant, but when emissions reductions stagnated in 2004, a mandatory program was created. Regulation adopted in 2009 set a goal of 130 g/km to be reached by 2015, while regulation passed in 2014 set a target of 95 g/km to be reached by 2021.[20]

There is an extensive literature estimating mileage elasticities with respect to fuel price and fuel economy, though the variety of data types, model structure, and

[19] European Commission (2001)

[20] Mock (2014)

estimation technique have led to a wide range of estimates; a few examples may be seen in Table 2.1 . These estimates range from -0.045 to -0.69, though there is some consensus just above -0.20.

Table 2.1: Mileage Elasticity Literature

Study	*Type of elasticity*	*Estimated Value*
Gately (1990)	U.S. fuel cost per mile elasticity 1966-1988	-0.07 to -0.09
Greene (1992)	U.S. fuel cost per mile elasticity 1966-1989	-0.05 to -0.15
Schimek (1996)	U.S. fuel economy elasticity and fuel price elasticity	Short-run: -0.05 to -0.07; Long-run: -0.21 to -0.29
Greene et al. (1999)	U.S. fuel cost per mile elasticity 1979-1994	-0.23
Puller and Greening (1999)	U.S. fuel price elasticity 1980-1990	-0.69
Small and van Dender (2007)	U.S. fuel cost per mile elasticity 1966-2001	Short-run: -0.045; Long-run: -0.222
Barla et al. (2009)	Canada fuel cost per mile elasticity 1990-2004	Short-run: -0.08; Long-run: -0.16 to -0.18
Gillingham (2014)	California fuel price elasticity	-0.22
Gillingham et al. (2015)	Pennsylvania fuel price elasticity 2000-2010	-0.10

Note: This is only a small sample of such mileage elasticity estimates

In its purest form, the rebound effect is the elasticity of fuel demand with respect to fuel economy. By making several assumptions, a variety of other definitions are often used instead, including the own price elasticity of fuel demand, the own price elasticity of mileage demand, the elasticity of mileage demand with respect to fuel economy, and the fuel price elasticity of mileage demand.

These elasticities have importance beyond their potential equivalence to the rebound effect. For example, the fuel price elasticity of mileage gives insight into the effect that a gas tax increase has on miles driven, which in turn provides insight into the effect that such a policy would have on other externalities such as congestion and accidents. Similarly, the elasticity of mileage demand with respect to fuel economy can reveal how fuel efficiency regulation such as the CAFE standards impact these same externalities, without compromising the insight into fuel demand.

Because of the relationship between miles driven, fuel efficiency, and fuel consumption, $Miles = fuel\ efficiency \times liters\ of\ fuel$, the elasticity of fuel demand with respect to fuel economy is equal to the elasticity of mileage demand with respect to fuel economy minus one. As a result, the rebound effect literature includes many of the same elasticities that this study explores here, but this work provides insight into several economic policies and issues, with the rebound effect as only a small part of this.

2.3 Methodology

Regulation such as the CAFE standards, which are designed to improve the fuel economy of new vehicles available for sale, is put in place to reduce greenhouse gas emissions and to reduce the consumption of gasoline; however, if the reduction in cost per mile induces an increase in miles driven, then these types of regulation may not create the desired decrease in pollution. This requires an estimation of Equation 2.1, based on a double log demand function for miles as a function of price per mile.

$$ln(Miles_{it}) = \alpha + \alpha_{P_F} ln(p_{it}) + \alpha_{MPG} ln(MPG_{it}) + \alpha_x x_{it} + \xi_i + \nu_{it} \tag{2.1}$$

Many datasets do not contain fuel economy data, and when they do there is often measurement error or limited variation in the efficiency variable, making it unsuitable for use in empirical work. The measurement error often results from obtaining fuel economy based on the make, model, and model year of the vehicle when more specific trim level information is unavailable, though it can also be a result of inaccurate self-reporting by drivers. If efficiency data is unavailable or likely measured in error, then energy prices may be used instead. Because of the relationship between fuel economy (MPG) and fuel prices (P_F) in the calculation of fuel cost per mile (P_M), $P_M = \frac{P_F}{MPG}$, these variables are expected to have an equal and opposite effect on mileage.

Because fuel economy and emission regulations are concerned with *improvements* in fuel economy, the appropriate counterpart of an improvement in fuel economy would be a decrease in gas prices, since a decrease in fuel prices has an equivalent effect on cost per mile as an improvement in fuel economy. If the consumer response to an increase in gas prices is equal and opposite to a decrease in gas prices, price data may be included in a symmetric model like that found in Equation 2.1. As discussed above, however, households may not respond symmetrically to fuel price increases and decreases. If so, price increases should be separated from price decreases. Because the elasticity of mileage demand may be larger in periods of rising energy prices, if a symmetric model is assumed instead of allowing for the possibility of asymmetry, the rebound effect may be overestimated.

Following Frondel and Vance (2013) this paper uses the price decomposition first put forth by Tweeten and Quance (1969). In their 1969 paper, Tweeten and Quance create dummy variables for periods of increasing and decreasing prices, then multiply said variables by the price level, as below.

$$p_{it}^{-} = p_{it} \ if \ p_{it} < p_{i(t-1)}; 0 \ otherwise$$

$$p_{it}^{+} = p_{it} \ if \ p_{it} \geq p_{i(t-1)}; 0 \ otherwise$$

This results in two variables with values that are positive or equal to zero and that sum up to the current price level. Wolffram (1971) criticized this method for implying a discontinuity in the demand curve, and suggested the use of a cumulative price change decomposition, adding price increases to the initial price to create a price increase variable and subtracting price decreases from the initial price to create a price decrease variable.

The literature on asymmetry has since built on this cumulative decomposition, with a notable extension coming from Traill et al. (1978), who allow for a distinction between historical price maxima and price increases below the maximum, referred to as price recoveries. They argue that drivers are not asymmetric in their response to price decreases and price recoveries, only to price maxima.

Any of the models that are based on Wolffram (1971) have the unexpected result of indicating that higher price volatility leads to higher output, as detailed by Griffin and Schulman (2005, p. 7). By including an additional constant term for the case of price increases, the price asymmetry causes a change in either the intercept or the slope of the regression equation, thus correcting for the initial criticism offered by Wolffram (1971). Modifying Equation 2.1 based on this approach yields the regression equation used in this paper, found in Equation 2.2.

$$ln(Miles_{it}) = \alpha_0 + \alpha_0^- D_{it}^- + \alpha_0^{rec} D_{it}^{rec} + \alpha_{p^{max}} D_{it}^{max} ln(p_{it}) + \alpha_{p^{rec}} D_{it}^{rec} ln(p_{it}) + \alpha_{p^-} D_{it}^- ln(p_{it}) + \alpha_{MPG} ln(MPG_{it}) + \alpha_x x_{it} + \xi_i + \nu_{it}$$

(2.2)

where D_{it}^- is equal to one if $p_{it} < p_{i(t-1)}$ and is zero otherwise, D_{it}^{rec} and D_{it}^{max} are defined similarly, x_{it} is a matrix of control variables discussed below and ξ_i are household fixed effects. Due to complications arising from intervehicle substitution in multivehicle households, this paper restricts the sample to single-vehicle households; thus i represents both household and vehicle. This regression equation allows for the testing of four null hypotheses as follows.

$$H_0 : \alpha_{p^{rec}} = \alpha_{p^-} \tag{2.3a}$$

$$H_0 : \alpha_{p^{max}} = \alpha_{p^-} \tag{2.3b}$$

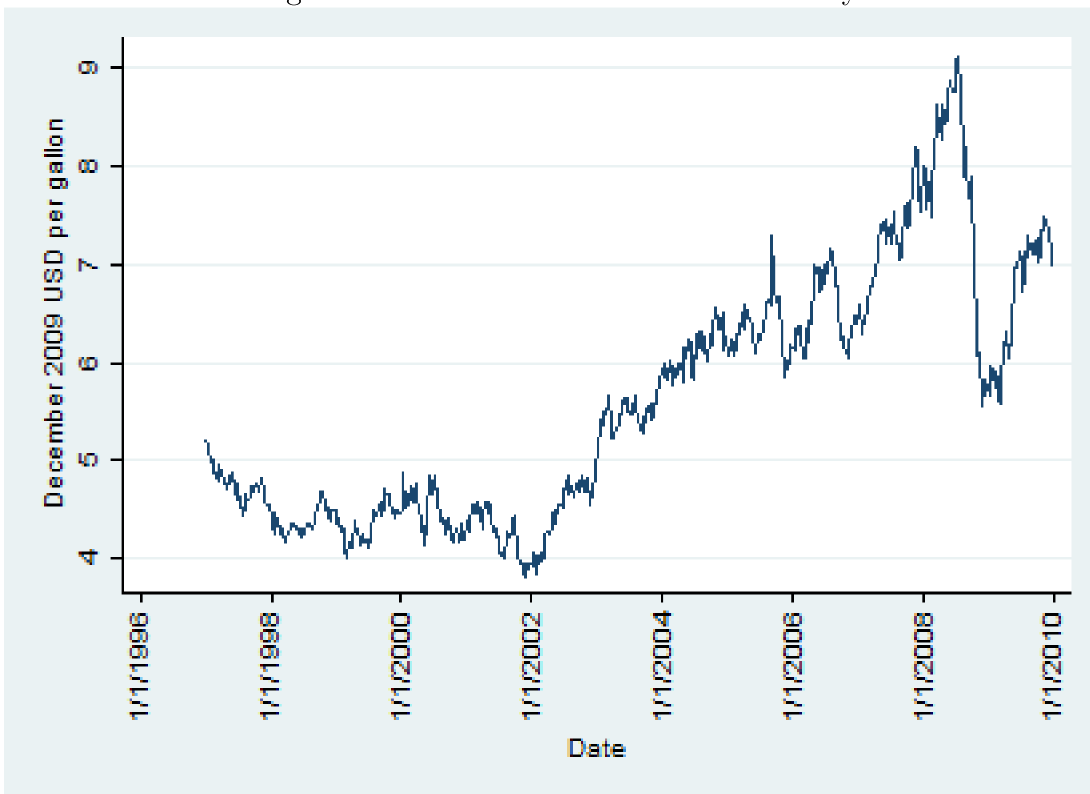
$$H_0 : \alpha_{p^{max}} = \alpha_{p^{rec}} \tag{2.3c}$$

There are a variety of explanations for the source of the price asymmetry in a transportation context. One is asset fixity. Long periods of high or increasing prices may induce an industry-wide technological change which is irreversible. Another explanation for price asymmetry is the different information regarding price changes. Falling prices rarely make headlines, while major price increases can be sensational. Dargay and Gately (1997, p. 72) propose that the concept of addiction asymmetry, or the "tendency to acquire habits to consume more easily than to abandon them," may be driving the asymmetric response. In other words, if a driver alters his or her behavior to consume less fuel in response to increasing gasoline prices, he or she is unlikely to revert to the earlier driving behavior when prices fall.

Habit formation theory suggests that utility is based on both current and past consumption, thus pushing rational consumers to consider future prices when making current consumption decisions. Because of this non-separability of preferences over time, an increase in consumption in the current period leads to further increases in the future. Although this theory does not directly imply asymmetry, it does show that influences beyond current prices impact consumer decisions, and it creates inertia that may be difficult to reverse. For example, Scott (2012) finds that consumers respond more strongly to fuel tax increases, viewed as permanent changes in gasoline prices, than to market fluctuations, viewed as temporary changes. It is possible that consumers during the sample period used in this work perceive price increases as more likely to recur, while price decreases may be viewed as more temporary. This seems plausible given the overall trend of increasing real gasoline prices evident in Figure 2.1. If this does represent German consumer expectations, then the asymmetry may be explained by habit formation theory.

It should be noted that other factors, such as transaction costs, can appear in the data to be similar to habit formation. Because of the time and financial costs involved in purchasing a new vehicle, increases in gasoline prices may induce a household to purchase a more fuel efficient vehicle, while a decrease in gasoline prices is unlikely to cause the household to return to the previous level of fuel economy, given the durable nature of automobiles. The rapid depreciation of automobiles creates additional disincentives to dispose of and purchase new vehicles frequently. Because the vehicle fleet is held constant in this study, these issues of transaction costs and durable decisions do not play a role in the results.

Figure 2.1: Real Gasoline Price in Germany



All of these theories indicate that the response to price increases may be larger than the response to decreases, which, if true, would lead to a biased estimate of the fuel price elasticity of mileage based on an assumption of a symmetrical response. For example, if a gas price elasticity of mileage were obtained using data from a period of overall rising gas prices but the author assumed symmetry, then the estimate would overestimate the elasticity that would be found in a period of declining prices. Because price falls have the same impact on the cost per mile as the improvements in fuel economy caused by regulation such as the CAFE standards, it is the response to gasoline price decreases that could estimate the relevant fuel economy elasticity of mileage, should these elasticities be equivalent.

Hypotheses 2.3a through 2.3c provide a basis for the test of price asymmetry. If these restrictions are correct, prices need not be decomposed into periods of increasing and decreasing prices in order to get unbiased estimates of fuel price elasticities of mileage. If these hypotheses are rejected, however, then α_{p^-} is the appropriate proxy for a fuel economy elasticity in a discussion of regulation intended to improve fuel economy or decrease emissions; if so, papers which do not use this decomposition will present upwardly biased estimates.

Because this paper holds vehicle stock constant, evidence of asymmetry will not be the result of technological change or asset fixity, two common explanations for the presence of asymmetry. Instead, the rejection of any of Hypotheses 2.3a through 2.3c will speak to either a difference in information regarding fuel price changes, to a more psychological phenomenon of addiction asymmetry, the tendency for individuals to hold onto their established habits unless pushed strongly to change, or to the economic theory of habit formation which states that consumers respond more strongly to price changes perceived as permanent due to their expected impact on future utility.

This paper tests for a difference in response to historical price maxima versus price increases below these historical maxima in addition to the gas price elasticity of price decreases calculated by Frondel and Vance (2013). Traill et al. (1978) assume that price rises above historical maxima have asymmetric effects while price rises below maxima do not. Their argument, however, focuses on asset fixity and changes in the vehicle stock.

Although this study does not deal with vehicle purchases by restricting the sample to households which do not change their vehicle fleet, the concept of addiction asymmetry supports the importance of looking separately at price maxima. It is possible that while increases in price cause changes in driving behavior, decreases are not large enough to push drivers to alter their habits. While I believe that subsequent price increases below the price maximum may alter driving behavior, making price recoveries more relevant than in the case of asset change, I do think that price maxima may create larger responses.

Griffin and Schulman (2005) propose instead that households may respond more strongly to price maxima because they *cannot* easily change the vehicle stock, thus preventing them from disinvesting in efficiency improvements. In papers that look at long-run situations, Griffin and Schulman (2005, pg. 2) argue that price asymmetry acts as a proxy for technical change rather than representing true asymmetry unless technical change is explicitly controlled for. Because my sample is restricted to households which do not change their vehicle fleet, any evidence of asymmetry is not the result of omitting technical change; instead the results of this paper will capture asymmetry resulting from changes in driving behavior.

$$H_0 : \alpha_{MPG} = -\alpha_{p^-} \tag{2.1}$$

Hypothesis 2.1 allows for the testing of the equivalence of the fuel price elasticity of mileage and the fuel economy elasticity of mileage. Note that the two coefficients are expected to have opposite signs. If Hypothesis 2.1 cannot be rejected, then using price elasticities will provide unbiased estimates in studies on regulation regarding the CAFE standards and emissions standards. Recall that all of the theories discussed above—habit formation theory, addiction asymmetry, and media attention regarding price increases—suggest that households respond less strongly to decreasing fuel prices than to increasing prices; therefore, using a symmetric price model that does not decompose prices will estimate a price elasticity that is above the decreasing price elasticity and below the increasing price elasticity. Hence, if Hypothesis 2.1 is false, then studies using price data to add variation will likely estimate the consumer response to fuel economy with bias.

2.4 Data

This paper uses the German Mobility Panel, a rotating panel travel survey that follows the same household for up to three consecutive years, and covers the years 1997 through 2009. The dataset consists of two parts, one a trip diary that takes place every fall, and the other a refueling-based survey in which the household records fuel purchase decisions for up to two months the following spring. The latter requires making note of the total cost of fuel per each stop at a gas station to refuel, the quantity of fuel purchased, and the kilometers driven since the last refueling. Additionally, the dataset includes household information, individual-specific characteristics, and transportation-relevant data such as make, model, and model year of the vehicle, horsepower, engine size, fuel type, and the distance to public transit options.

The dependent variable, in my model daily kilometers driven, and the key independent variables, fuel price in Euros per liter and observed fuel economy in kilometers per liter, are computed from these refueling records. Additional controls include the number of children in the household, the number of part-time and full-time employed household members, real monthly household income in Euros, population density in hundreds of residents per km^2, the number of household members who changed jobs in the last year, vehicle age, the total number of household members, a dummy variable indicating that the vehicle was used for the purpose of taking a vacation during the survey period, [21] and the number of household members with an "Abitur", an advanced high school diploma.

The scope of this study is restricted to single-vehicle households to prevent the complications of vehicle substitution in multicar households. This study uses each refueling as an observation, in sharp contrast with Frondel and Vance (2013), who use one observation per household per year.

Observed fuel economy is of course influenced by the manufacturer-specified, on-paper fuel economy of the vehicle, but is likely to vary with vehicle maintenance and driver behavior.[22] The EPA itself acknowledges that the purpose of the posted fuel economy is to allow car buyers to more easily compare the efficiency across several vehicles when shopping for a new vehicle. These numbers cannot account for changes in driving conditions that drivers face, including weather and road conditions. Different drivers also have different driving styles that will affect their actual

[21] Frondel and Vance (2013, p. 49) argue that "undertaking a vacation trip with the car crucially depends on factors other than current fuel prices, such as preferences for the vacation destination and the cost of alternative modes," so this variable is assumed to be exogenous.

[22] U.S. Environmental Protection Agency (2014a)

fuel economy, and over time a driver may have different on-road experiences that affect this driving style. In this study, the focus is on these behavioral changes in driving style as vehicle fleet is held constant, leaving driving behavior the only source of variation in fuel economy. Using a unique dataset capturing detailed driving data including speed, acceleration, and fuel consumption at ten second intervals, Langer and McRae (2015) document the high level of variation in fuel economy of different drivers with identical vehicles. They also show that within a single trip by a driver, fuel economy varies tremendously.

Due both to its short nature and to the lack of data on vehicle purchase decisions, the German Mobility Panel is not well suited to studying long-run responses to fuel price changes such as purchasing new vehicles or relocating closer to the place of work. This paper focuses on short-run responses and elasticities. Such short-run responses may include driving more slowly, accelerating more gradually, taking fewer unnecessary trips, or combining several trips into one trip. These behavioral changes can be easy to make and are more likely to occur during the days and weeks following a price change, as compared to the long-run responses described above which would likely take place after several months of increasing prices. Annual averages would be unlikely to capture everyday behavioral responses as accurately as shorter time periods.

Theoretically, people should drive fewer miles or they should drive more efficiently by altering driving speed and acceleration after price increases. Dargay and Gately (1997) show that households will not revert to driving more miles or to driving less efficiently after a price decrease. This may be because this would involve giving up newfound savings and convenience; if a behavioral change induced by the price increase included combining errands into one trip and therefore reducing mileage over running each errand separately, this would give the driver more leisure time, as less time will be wasted with unnecessarily repetitive mileage. Addiction asymmetry theory indicates that individuals are resistant to change, as though altering behavior comes with a transaction cost; although price increases may push them beyond this resistance and institute a change in behavior, the habit becomes set, and price decreases do not provide enough incentive to overcome the aversion to altering behavior. Therefore, there should be little change in behavior following price decreases, while a price increase should cause a decrease in miles driven and/or an increase in fuel economy.

As an example, if prices on average fall over the course of the year, a yearly observation would then suggest that driving behavior should not change; however, that annual average belies the potential for several price increases to have taken place over the course of the year. Addiction asymmetry theory thus suggests that there could have been a change in behavior following each increase, with subsequent decreases having little reverse effect. Yearly observations cannot capture the large variation in gasoline prices that take place over the course of the year; using observations taken daily allows me to observe more of the variation and to take the frequency of price increases or decreases into consideration rather than just the average size and direction of the change over the past year. When such short-run effects are the subject under investigation, therefore, it is important to use observations over as short a period as possible.

In this particular case of the German Mobility Panel, which follows households for up to three consecutive years, the calculation of price changes necessary for evaluation of asymmetry reduces the number of observations per household to a maximum of two. This makes for a very short panel, and does not allow for the inclusion for a price maximum variable in the work of Frondel and Vance (2013). By using each trip to the gas station as an observation, the observations available increases from 1100 to 12,180. There are a total of 1,552 households, with an average of 200 households in any given wave. This also allows me to test for the possibility of a higher consumer response to historical price maxima.

Summary statistics based on this sample are presented in Table 2.2. Sample means and standard deviations weighted based on the number of days between refuelings are included for comparison in Table 2.3. The weighted summary statistics should be representative of the average household in the population, whereas the unweighted summary statistics are representative of the average refueling and thus skewed towards households which drive more and therefore refuel more. More detailed statistics are given on the variation in fuel prices and fuel economy in Table 2.4. There is more variation within households than between households in the fuel economy variable, but there is ample variation of both types. Most of the variation in fuel prices, however, comes from between household variation.

In cases where multiple refuelings were made on the same day, these observations were aggregated into one observation. Liters of fuel purchased and kilometers

[23] The median number of days between refuelings was 8; the mean was slightly higher at 10.30 due to a small number of outliers at the high end of the spectrum. While these households certainly seemed unusual, it was not clear that these outliers were the result of measurement error, so they were included in the regression sample.

Table 2.2: Summary Statistics N=12,180

	Mean	Std. Dev.	Min	Max
daily km[23]	75.52	99.38	0.25	1368.00
price max (€)	1.06	0.16	0.52	2.03
price recovery (€)	1.00	0.16	0.48	1.39
price drop (€)	0.99	0.16	0.05	1.37
fuel economy (km/L)	13.10	5.64	0.06	55.61
number of children	0.44	0.83	0.00	4.00
net real monthly income (thousands of €)	2.08	0.66	0.22	3.86
number of employed household members	0.92	0.79	0.00	4.00
job change (dummy)	0.14	0.39	0.00	4.00
car vacation (dummy)	0.27	0.44	0.00	1.00
population density (residents per km^2)	0.87	1.02	0.04	4.27
car age (years)	6.41	4.31	0.00	35.00
household size	2.30	1.15	1.00	7.00
education	0.59	0.74	0.00	5.00
average rainfall since last refueling (mm)	20.38	21.18	0.00	300.67
average snow depth since last refueling (mm)	0.01	0.33	0.00	30.00
average high temperature since last refueling (degrees Celsius)	19.54	5.49	-0.07	34.60
average low temperature since last refueling (degrees Celsius)	8.99	3.19	-2.40	18.97

Table 2.3: Summary Statistics Weighting Based on Days Between Refuelings

	Mean	Std. Dev.
daily km	41.45	44.22
price max (€)	1.06	0.15
price recovery (€)	1.00	0.16
price drop (€)	0.98	0.16
fuel economy (km/L)	13.33	5.53
number of children	0.42	0.81
net real monthly income (thousands of €)	2.06	0.65
number of employed household members	0.85	0.79
job change (dummy)	0.12	0.37
car vacation (dummy)	0.23	0.42
population density (residents per km^2)	0.89	1.03
car age (years)	6.47	4.34
household size	2.25	1.12
education	0.57	0.73
average rainfall since last refueling (mm)	21.11	16.86
average snow depth since last refueling (mm)	0.01	0.21
average high temperature since last refueling (degrees Celsius)	20.38	3.48
average low temperature since last refueling (degrees Celsius)	9.32	2.62

Table 2.4: Panel Summary Statistics for Fuel Economy and Fuel Prices

Variable		Mean	Std. Dev.	Min	Max
fuel economy (km/L)	overall	13.10	5.639175	0.063291	55.61224
	between		3.205011	1.031746	34.15054
	within		4.889142	-8.0248	57.57192
price max (€)	overall	1.06	0.155642	0.522413	2.027411
	between		0.152074	0.524974	1.605716
	within		0.05164	0.565798	1.56015
price recovery (€)	overall	1.00	0.163447	0.483193	1.387828
	between		0.156271	0.516593	1.331169
	within		0.048289	0.513836	1.310115
price drop (€)	overall	0.99	0.161551	0.054604	1.371178
	between		0.151496	0.511668	1.325758
	within		0.062598	0.061561	1.428838

driven are the summation of the multiple fillups, and the price is the average price of the multiple fillups. These observations constitute a small portion of the overall sample, less than 3%.

In cases where households did not completely fill the tank, fuel economy was created as the average fuel economy between complete tank fillups. Observations in which fuel economy is higher than 56 km per liter are dropped, although the results presented below are robust to the inclusion of observations with outlier values. This number was chosen as the cutoff because it was the highest three-observation average fuel economy.

2.5 Empirical Results

The data described above are applied to Equation 2.2 and yield the results shown in Table 2.5.

Some might argue that endogeneity could be biasing these results because expected demand for miles may influence the choice of fuel economy in a new vehicle, but these should be captured in the fixed effect. [24] If an individual expects to drive long distances, he or she may purchase a high-efficiency vehicle to reduce costs, or he or she may buy a large vehicle that is more comfortable than a small vehicle but also likely less efficient. Drivers with pro-environmental beliefs are more likely to buy fuel efficient vehicles as well as making an effort to limit mileage. Living in an urban environment can decrease necessary mileage through the close proximity of work and errand destinations as well as increased access to alternative forms of transportation. At the same time, people in cities may buy more fuel efficient vehicles if they opt for alternative fuel vehicles which operate better in the city than on the highway, or the decreased expected mileage may cause city-dwellers to purchase less fuel efficient vehicles. These factors are time-invariant in the short-run and, as the model used in this paper holds vehicle fleet constant, are therefore not present in the fixed effect model. As a result, this is the model this paper will focus on.[25]

The fixed effect results show fuel price elasticity estimates ranging from -0.048

[24] As a robustness check, the model was run excluding fuel economy. See Table A.1 in Appendix A for the price elasticity estimates.

[25] Results are also highly robust to time fixed effects. See Table A.2 in Appendix A

for price decreases to -0.289 for price recoveries. These estimates are lower than the results found by Frondel and Vance (2013) and are in line with the literature, only slightly higher than the -0.22 to -0.23 estimates supported by several studies. [26] Although the price decrease estimate is statistically insignificant, the small size of both the estimated coefficient and the standard error rules out a large elasticity. It is reasonable to assume that this is a precisely estimated zero, and consumers show a completely inelastic response to fuel prices during periods of decreasing prices, because the standard error on the fixed effect specification estimate of the price drop variable is quite low, indicating that the lack of significance may come more from the diminutive size of the coefficient.

As seen in the hypothesis test results displayed at the bottom of Table 2.5, there is not evidence of a statistically different response to price maxima versus price increases below historical maxima in any specification. This indicates that it may be sufficient to decompose prices into price increases and price decreases, rather than separating price increases into recoveries and maxima. There is ample evidence of asymmetry, however; the coefficients on price decreases are significantly different from both types of price increases in all specifications. The mileage elasticity with respect to decreasing fuel prices is around 0.20 lower than the mileage elasticity with respect to increasing fuel prices in the OLS and fixed effect specifications. Therefore, studies using a symmetric price model will show biased estimates. Although drivers have an inelastic response to price decreases, an increase in the price of fuel, such

[26] Haughton and Sarkar (1996); Greene et al. (1999); Small and Van Dender (2007); Gillingham (2014)

Table 2.5: Asymmetric Results

	Dependent Variable: ln(Daily KM driven)	
	Pooled OLS	Fixed Effects
price_max	-0.357***	-0.262**
	(0.099)	(0.104)
price_rec	-0.365***	-0.289***
	(0.114)	(0.104)
price_drop	-0.212***	-0.048
	(0.082)	(0.077)
ln(fuel economy)	0.542***	0.533***
	(0.025)	(0.027)
# children	-0.020	0.031
	(0.022)	(0.056)
income	0.065***	0.039
	(0.025)	(0.026)
# employed	0.089***	-0.013
	(0.019)	(0.031)
job change	0.054*	0.034
	(0.031)	(0.038)
car vacation	0.307***	0.272***
	(0.024)	(0.029)
population density	-0.023	0.151*
	(0.014)	(0.078)
car age	-0.013***	-0.009
	(0.003)	(0.005)
hh size	-0.010	-0.012
	(0.021)	(0.043)
education	0.065***	0.012
	(0.019)	(0.037)
rain	-0.004***	-0.004***
	(0.001)	(0.000)
snow	-0.016	-0.012
	(0.026)	(0.023)
temp min	0.048***	0.054***
	(0.005)	(0.004)
temp max	-0.078***	-0.077***
	(0.003)	(0.003)
p_rec	0.061***	-0.005
	(0.016)	(0.015)
p_max	-0.147***	-0.101***
	(0.018)	(0.016)
Constant	3.521***	3.482***
	(0.093)	(0.141)
Adj. R-squared	0.282	0.258
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.0873	0.0044
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.1473	0.0158
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.9500	0.8052
$H_0 : \alpha_{MPG} = -\alpha_{price\_drop}$	p=0.0002	0.0000

Robust standard errors clustered at the household level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Observations: 12,108. Number of Households: 1,552

as would be caused by a fuel tax increase, would reduce miles driven.

Based on the theory of habit formation, the relatively inelastic consumer response to decreasing prices may be resulting from expectations that the price decreases are temporary. As seen in Figure 2.1, for the first six years of my sample, gas prices remained fairly stable in Germany, but in the second half of the sample prices were on an overall upward trend, with the exception of a sizeable price fall in late 2008. It is not unreasonable, therefore, to think that consumers would expect gasoline prices to increase, or at least for increasing prices to be more persistent than decreasing prices. If price increases are expected to be permanent, while decreases are considered temporary, consumers would show a larger change in behavior following a price increase.[27]

The lack of asymmetry between price maxima and price recoveries may be an indication that consumers do not pay any additional attention to price maxima than they do to any other price increase, but it may also be resulting from the restriction of vehicle stock. My sample includes only households that do not alter their vehicle stock, but when Traill et al. (1978) initially included a price maximum variable it was with the argument revolving around purchasing new factors of production, in this case an automobile. It would be interesting to see if Hypothesis 2.3c still fails to be rejected in a study that can account for changes in the vehicle stock, as it seems possible that this distinction between different types of price increases may matter more for the extensive margin of travel demand than in the intensive margin studied here.

[27] Scott (2012)

The fuel economy elasticity of mileage is robust across specifications, hovering around 0.535. This is significantly higher than the fuel price elasticity of mileage during periods of decreasing prices. Therefore, if a study's sample period includes decreases in fuel prices, the fuel price elasticity of mileage demand will underestimate the effect of fuel economy policy such as the CAFE standards. The estimate is closer to the fuel price elasticity of mileage during periods of increasing prices, although the difference is significant at the 5% level in the fixed effect specification.

Because the vehicle fleet is held constant, the variation in fuel economy in this paper comes from different sources than that present in most papers modeling fuel economy through vehicle choice. Rather than fuel economy changing as households purchase new vehicles, fuel economy varies with driver behavior and environmental factors such as road conditions. Although these sources of variation are free from the endogeneity problem associated with vehicle choice being associated with expected miles driven, they are also potentially endogenous. Some of these sources of fuel economy variation, such as weather conditions, may be controlled for through inclusion in the regression equation. Others can be controlled for through the inclusion of fixed effects, such as a driver's innate driving style. Others are harder to control for, such as current road conditions, route attributes, and vehicle maintenance. [28]

Traffic conditions may influence fuel economy in that idling or travelling at very low speeds both decrease fuel economy. Drivers may also choose to drive less during

[28]The only data available on vehicle maintenance in the German Mobility Panel is whether or not the vehicle was in the shop during the survey period. It does not specify if this is the result of vehicle damage or if it is for routine maintenance, and there are very few observations in which any type of maintenance occurs, less than 3%. Inclusion of this variables has almost no effect on the results.

periods of dense traffic to save time; on the other hand, rush hour traffic is slow precisely because most drivers must travel to and from their places of work at certain times of day, in which case drivers may be more likely to drive during periods of dense traffic. To the extent that a household's commute is time-invariant, this issue will be controlled for through the inclusion of fixed effects. The commute is most likely to change following a change in job, which is explicitly included in the regression. As a result, changes in traffic conditions over time are expected to have minimal endogeneity bias in this regression. There is still the matter of changes in the make-up of the miles driven on a given refueling. If a consumer puts more commuting miles between fillups, there will be lower fuel economy, assuming commuting takes place during rush hour with heavier traffic. This decrease in fuel economy will induce a smaller number of miles driven between these fillups. Therefore, commuting may create correlation between the fuel economy and miles driven, resulting in an upward bias.

Route attributes such as the number of stop signs on a trip may have similar effects on fuel economy, but are less likely to affect the mileage decision directly. There may still be correlation between route attributes and miles traveled, however, in that higher fuel economy is achieved on highways than in urban environments and drivers typically use highways to travel longer distances than urban roads. The population density of the area helps to control for this, but to the extent that endogeneity bias remains this will cause an upward bias in the fuel economy coefficient.

Vehicle maintenance is required more frequently when more miles are driven, and some types of maintenance improve fuel economy. Similarly, if there is a problem with the vehicle, the fuel economy may be decreased, and the driver may be less inclined to drive the vehicle. This is therefore another potential source of upwardly biasing endogeneity, indicating that the estimated fuel economy elasticity may be an upper bound.

To instrument for these sources of endogeneity, this study would require a variable that affects the observed fuel economy of the vehicle but which does not impact miles driven directly. Such an instrument is almost impossible to find as most sources of fuel economy variation are endogenous; as just discussed both maintenance problems with the vehicle and the type of road on which the vehicle is driven impact both fuel economy and mileage. Weather, too, could affect both fuel economy and mileage, largely through precipitation but also through extreme temperatures. Drivers may be less likely to take extraneous trips in extreme weather. Precipitation could also cause drivers to drive more defensively, potentially increasing fuel economy, as well as decreasing the grip of the tire treads on roadways, decreasing fuel economy. Cold temperatures also decrease fuel economy.[29]

Although fuel prices are usually assumed to be exogenous, the actual prices paid by drivers may be endogenous. This paper assumes them to be exogenous, but a robustness check is run using state average fuel prices found in the German Mobility Panel to instrument for local fuel prices. Although the point estimates for price elasticities do not change much, the standard errors increase enough to remove significance. Fuel economy results are unchanged. These results can be found in

[29] U.S. Energy Information Administration (2014)

Table A.3. [30]

There is some concern about the endogenous sampling that occurs when each refueling is used as an observation; households which drive more miles will need to refuel more often and will therefore appear more often in the dataset. If the model is well-specified, the expectation of the coefficient should be the same regardless of weight used to correct for this problem. One can argue about the correct way to weight, but weighting based on the estimated number of times a household would refuel, the total number of liters purchased by a household, and leaving the sample unweighted yields essentially the same results; the results of the key hypothesis tests are unchanged and the magnitudes of the estimated coefficients are similar. Under the argument for doing estimation at the level for which data is available, this paper focuses on the unweighted results. The results from the weighted models appear in Appendix A in Tables A.4 and A.5.

It would be interesting to explore the possibility that households respond differently to large fuel price changes or persistent price changes. This would require a larger dataset, however; in the German Mobility Panel, by far the vast majority of price changes that took place during this period were small price changes of short duration. This is not surprising given the volatility in fuel prices, and a very large number of observations would be required to have enough long-trending or large price changes to have any power in estimating these effects.

Results using a symmetric model are included for comparison in Table 2.6.

[30] National level oil prices are also used to instrument, but make for bad instruments. These results are also included in Table A.3.

The coefficient on fuel price is much closer to the price increase coefficients from the asymmetric results than to the price decrease coefficient. The fuel economy estimate remains unchanged around 0.46. Although the symmetric price coefficient is higher than the price decrease coefficient in the asymmetric model, the fixed effect results still show a statistically significant difference in the price elasticity and the fuel economy elasticity of mileage demand. Table 2.6 also shows results using a fuel cost per mile variable, fuel price divided by the fuel economy. The fuel cost per mile coefficients are very close to the negative of the fuel economy coefficients, indicating that the fuel cost variable in this sample is identified primarily by the variation in fuel economy rather than fuel price variation.

These results indicate that estimating the effect of a price increase, such as a gas tax increase, using a symmetric model would slightly underestimate the effect of the price increase. Using the symmetric model price results to discuss regulation which improves fuel economy, such as the CAFE standards or emissions standards, would result in an underestimation of the effect of this regulation. This assumes that the fuel economy estimate is not available, thus necessitating the use of the price elasticity as a proxy, or that there is insufficient variation in the fuel economy data available, such that fuel prices are combined with fuel economy in a price per mile. When the fuel economy variable is excluded, the fixed effect estimate drops 0.09, though still remains well above the asymmetric estimate at 0.179.

Table 2.6: Symmetric Results

	Dependent Variable: ln(Daily KM driven)			
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
price	-0.367***	-0.269***		
	(0.075)	(0.087)		
ln(fuel economy)	0.528***	0.521***		
	(0.025)	(0.027)		
ln(fuel cost per mile)			-0.507***	-0.513***
			(0.024)	(0.027)
# children	-0.021	0.033	-0.022	0.031
	(0.022)	(0.057)	(0.022)	(0.058)
income	0.061**	0.035	0.054**	0.033
	(0.026)	(0.027)	(0.026)	(0.027)
# employed	0.092***	-0.014	0.093***	-0.013
	(0.019)	(0.031)	(0.019)	(0.031)
job change	0.057*	0.036	0.059*	0.033
	(0.031)	(0.039)	(0.031)	(0.039)
car vacation	0.314***	0.275***	0.314***	0.278***
	(0.025)	(0.029)	(0.025)	(0.029)
population density	-0.024*	0.150**	-0.025*	0.164**
	(0.014)	(0.075)	(0.014)	(0.066)
car age	-0.012***	-0.008	-0.012***	-0.007
	(0.003)	(0.006)	(0.003)	(0.006)
hh size	-0.010	-0.009	-0.010	-0.011
	(0.021)	(0.043)	(0.021)	(0.043)
education	0.069***	0.016	0.073***	0.018
	(0.019)	(0.037)	(0.019)	(0.037)
rain	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.000)	(0.001)	(0.000)
snow	-0.016	-0.011	-0.015	-0.010
	(0.027)	(0.024)	(0.027)	(0.023)
temp min	0.054***	0.057***	0.054***	0.057***
	(0.005)	(0.004)	(0.005)	(0.004)
temp max	-0.080***	-0.078***	-0.080***	-0.078***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	3.522***	3.468***	3.577***	3.477***
	(0.094)	(0.140)	(0.092)	(0.136)
Adj. R-squared	0.274	0.254	0.273	0.253
$H_0 : \alpha_{MPG} = -\alpha_{price}$	p=0.0419	0.0043		

Robust standard errors clustered at the household level in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Observations: 12,180. Number of Households: 1,552

2.6 Conclusions

This model shows that there is asymmetry in the consumer response to prices, and when it is allowed for, consumers show a much lower response to price decreases than price increases. The paper also finds that households do not respond to price decreases in an equal and opposite way as they do to improvements in fuel economy; instead households seem to respond to improvements in fuel economy at the same magnitude at which they respond to price increases. The magnitudes of these elasticities imply that fuel economy policy is less effective at influencing mileage and oil consumption than increases in the gas tax.

When fuel prices go up, households decrease their miles driven by one quarter to one half the size of the change in fuel prices. An increase in the gas tax would therefore result in a decrease in miles driven that is smaller than the required amount to maintain the same expenditure on transportation. Although drivers will decrease miles, there is a degree of inelasticity such that they will pay more to continue to drive considerable distances.

Based on the fuel economy elasticity of mileage estimated in this paper, an improvement in fuel economy resulting from strengthening the CAFE standards or emissions standards common in Europe will increase miles driven by just under half the size of the change in fuel economy. If the fuel economy variable used here is endogenous however, then researchers can use the negative of the response to a decrease in fuel prices, which is significantly lower, to provide insight into responses to changes in fuel economy.

Carbon dioxide emissions are linearly related to fuel consumption, the inverse of fuel economy.[31] The EU recently passed regulations limiting CO_2 emissions from vehicles to 95 g/km by 2021, down from the target of 130 g/km in 2015,[32] a 27% change. The fuel tax in Germany is currently €0.6545, while Tscharaktschiew (2014) finds that the optimal tax is €0.96, a 47% increase. My model predicts that a 27% improvement in fuel economy, equivalent to the 27% decrease in emissions currently regulated, will result in a 12.7% to 13.0% increase in miles driven. Similarly, if the proposed tax change were implemented, there would be an 11.3% to 23.7% decrease in miles driven.

This suggests that the true change in mileage resulting from the above policy changes would be twice as high as the literature would predict based on a 0.22 elasticity. The model predicts a smaller change in mileage than Frondel and Vance (2013) predict, as low as two-thirds the size in the case of the emissions regulation and one-third the size in the case of the tax increase.

If the goal of these policies is to decrease oil consumption or miles driven, then fuel economy or emissions regulation may be inferior to gasoline taxes as the increase in mileage following an improvement in fuel economy is of a considerable size, while the *decrease* in mileage following an increase in fuel prices is at least as high, if not higher, than the overall consensus in the literature. If endogeneity is expected to be biasing the fuel economy estimate, however, then the price decrease variable is a better estimate of the impact of these policies, in which case the increase

[31] U.S. Environmental Protection Agency (2015b)

[32] Mock (2014)

in mileage following an improvement in fuel economy is much smaller, and may in fact be zero. In this case, although the gas tax would yield a *decrease* in miles driven, fuel economy or emissions policy may be an acceptable alternative if there is insurmountable political difficulty associated with a tax increase.

This model shows that there may be more to adjustments in fuel economy than just a desire to influence cost per mile. This may be the result of external forces such as weather and road conditions, or from indirect driver behavior such as running late causing the driver to alter his or her driving style. It is also possible that this is the result of conscious alterations to driver behavior which then form a new and sticky habit, a new norm for the individual that is hard to change.

Because this model is designed to explore the question of an asymmetrical response to prices in a simple context, the sample is restricted to single vehicle households to avoid complications from intervehicle substitution in multivehicle households. More significantly, there is a lack of data on vehicle choice options, which causes the sample to be further restricted to households which do not alter their vehicle fleet.

Although every attempt has been made to adequately control for endogeneity regarding the inclusion of fuel economy in the equation, it is possible that there remains bias in this estimated coefficient. In general, when a household is purchasing a vehicle, the expected mileage plays a role in the weight given to a variety of vehicle characteristics, including the fuel economy of the vehicle. This study could not capture these effects because there is very little information that could provide insight into the vehicle choice decision made by the household. Even with the year the vehicle was purchased an attempt could be made at constructing a feasible choice set, but this variable was not made available until 2012. There is potential for future research on this if a dataset can be created with adequate information on the vehicle purchase. This could then be used to build a structural model which could both control for endogeneity and allow for changes in the vehicle fleet, providing insight into long term responses to fuel prices.

Future work should also attempt to clarify the cause of the asymmetry. In this study several possible explanations are put forward to explain an asymmetric response to prices and the lack of equivalence between the price and fuel economy elasticities of mileage demand, however it is not clear which of these stories are the true cause. Welfare analysis results are complicated by the assumptions relaxed here and would vary depending on the expected cause of the asymmetry. In order to conduct an adequate welfare analysis, a clearer picture of why this asymmetry occurs is necessary.

Chapter 3: Does the Rebound Effect Vary With Income? A Micro-data Study

3.1 Introduction

Motor vehicles use a large amount of oil; in 2010 the transportation sector accounted for 71% of U.S. petroleum consumption, and motor gasoline made up two thirds of that consumption.[1] Oil imports create a national security concern while the use of fossil fuels generates pollution.[2] There are several regulations in place to deal with this problem, many of which attempt to do so by regulating fuel economy. The effect of these policies may not be as straightforward as the policymakers intend, however. As fuel economy improves, the cost of driving a mile decreases, holding fuel prices constant. The consumer response to the lower cost is known as the rebound effect, and this study attempts to estimate the magnitude of this effect.

The literature on the rebound effect can be divided into two separate categories: those studies that use aggregate data and those that use disaggregate data. There is a fair amount of consensus among studies that use aggregate data; most

[1] Energy Information Adminstration (2011)

[2] National Highway Traffic Safety Administration (2016)

notably Haughton and Sarkar (1996) and Small and Van Dender (2007) converge on a long run estimated effect of 22%. The disadvantage of aggregate data is the smoothing of variation that occurs when averages are used. Disaggregate data includes the variation that comes from looking at individual households, but at a cost; because this data is at the individual decision level, variables that are exogenous at the aggregate level may become endogenous, as discussed below. The focus on household level data within a given survey year that has been most common in rebound effect studies results in a loss of inter-temporal variation. Studies relying on disaggregate data have a broader range of estimates, with short run estimates ranging from 0% to 87%. A notable exception is Greene et al. (1999), which uses the Residential Transportation Energy Consumption Survey and finds a long run rebound effect of 23%, consistent with the aggregate data papers. Few of these papers deal with the effect that income level may have on the rebound effect.

Greene (1992) finds that estimation of a linear model suggests that the elasticity of cost per mile should be decreasing over time as vehicle miles traveled increases. A Chow test of structural change only weakly supports a change in parameter values over time; however, cost per mile and income, measured as gross national product, were the only regressors to show any difference across periods. The Chow test for stability of the elasticity of cost per mile alone could not reject the null hypothesis of no change over time. Greene et al. (1999) looks at separate models for households with different numbers of vehicles. The finding that households respond similarly to fuel prices and fuel economy across ownership levels provides some evidence against a relationship between income and the rebound effect, in that the number of vehicles owned is strongly correlated with income; if high vehicle ownership implies high income but no difference in the rebound effect, this suggests that the rebound effect does not vary with income. The impact of income on the rebound effect is not explicitly tested, however, and the quality of the income data used is poor. Small and Van Dender (2007) allow the rebound effect to vary with time, income, and the degree of urbanization through the use of interaction terms. They find evidence that the rebound effect declines with income, where income is defined as real personal income per capita. This is the technique I will use to explore the effect of income on the rebound effect using household income data from the Consumer Expenditure Survey. Most recently, Gillingham (2014) uses California data and finds that the rebound effect *increases* with income, based on separate regressions for different income brackets. He believes this result to come out of intervehicle substitution in multi-vehicle households, which he cannot directly observe as each vehicle is a separate observation with no household identifier available. Gillingham (2014) also estimated a fuel price elasticity of mileage rather than the fuel economy elasticity used in this paper.

In this study, I use panel data from U.S. households over the period of 1997 to 2003 to estimate the rebound effect. I instrument to correct for and test likely endogeneity. Because expected demand for miles may influence the choice of fuel economy in a new vehicle, there is likely correlation between the fuel economy variable and the error term. If an individual expects to drive long distances, he or she may purchase a high-efficiency vehicle to reduce costs, or he or she may buy a large vehicle that is more comfortable than a small vehicle but also likely less efficient.

Drivers with pro-environmental beliefs are more likely to buy fuel efficient vehicles as well as making an effort to limit mileage. Living in an urban environment can decrease necessary mileage through the close proximity of work and errand destinations as well as increased access to alternative forms of transportation. At the same time, people in cities may buy more fuel efficient vehicles if they opt for alternative fuel vehicles which operate better in the city than on the highway, or the decreased expected mileage may cause city-dwellers to purchase less fuel efficient vehicles. By using the instrumenting for the efficiency decision, this endogeneity should be controlled for.

This study explores the potential for the rebound effect to vary with income. It is likely that driving becomes an inferior good after a certain level of income, so that low income groups for whom mileage is a normal good will take back more of the fuel efficiency improvements. Income may also affect the rebound effect via the proportion of total driving costs associated with fuel. If wage rates increase faster than energy costs, time costs will play a progressively larger role in the overall rebound effect relative to fuel costs.

The model predicts a rebound effect of 17.8% to 23.6% if there is no correlation between income and the effect. When an interaction term between income and fuel cost is included, the results imply that the rebound effect decreases with income. The effect may be large enough to induce not only an increase in mileage, but also an increase in gasoline consumption for low income households.

Section 3.2 provides more information on fuel economy regulation in the United States. Section 3.3 explains the theoretical model from which the empirical model is derived and explains two common definitions of the rebound effect that are employed in the relevant literature. This section also discusses the different models that are derived from these definitions and the assumptions required for the resulting models to be equivalent. Section 3.4 describes the data; section 3.5 reports the results; and section 3.6 discusses the limitations of the study and planned future work.

3.2 Fuel Economy Regulation in the United States

For decades there have been laws requiring manufacturers to meet fuel economy standards. The Corporate Average Fuel Economy (CAFE) standards, introduced in 1975, require car manufacturers' annual fleets to meet a minimum harmonic mean fuel economy.[3] The Energy Act of 1978 requires manufacturers to pay a Gas Guzzler Tax on all cars sold that are below a certain fuel economy, currently 22.5 miles per gallon.[4] More recently, there have been many regulations encouraging the use of alternative fuel vehicles which achieve high mile per gallon of gasoline equivalent. The American Recovery and Reinvestment Act of 2009 (ARRA) introduced several energy related tax credits that provide incentive to improve energy efficiency, including a credit for electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs).[5]

According to the National Highway Traffic Safety Administration (2012) "the purpose of [the] CAFE [standards] is to reduce energy consumption by increasing

[3] U.S. Environmental Protection Agency (2015a)

[4] U.S. Environmental Protection Agency (2014b)

[5] Internal Revenue Service (2011)

the fuel economy of cars and light trucks." If the Jevons paradox holds for personal automotive transport and the rebound effect is greater than 100%, as proposed by Brookes (1990) and Khazzoom (1980), then improvements in energy efficiency can only increase fuel consumption. Even if this backfire does not occur and the rebound effect is less than but close to 100%, improved fuel economy may create a sufficiently large increase in VMT that policies encouraging improved fuel economy, such as the CAFE standards, become an ineffective way to address issues of oil consumption relative to other demand reducing policies.

Increased driving causes not only increased fuel consumption, but also pollution and congestion, implying further problems resulting from a high rebound effect. As driving becomes cheaper with improvements in fuel economy, individuals may take more trips or drive farther. There may also be substitution from public transportation if the cost per mile drops below the equivalent transit fare. Hymel et al. (2010) find that congestion increases 11% in the long run after a 1% improvement in fuel economy. Therefore, it is important to understand the magnitude of the rebound effect in terms of miles driven as well as gasoline consumed.

3.3 Model

3.3.1 Definitions

Many definitions of the rebound effect are employed in the literature. The most scientifically accurate definition of the rebound effect is the fuel economy elasticity of the demand for mileage. Fuel economy is defined as $MPG = \frac{S}{E}$, where S is miles and E is a unit of fuel; most commonly MPG is miles per gallon of gasoline, though in the case of an alternative fuel vehicle it can be standardized to miles per gallon of gasoline equivalent. The first definition of the direct rebound effect is then

$$\eta_{MPG}(S) = \frac{\partial S}{\partial MPG} * \frac{MPG}{S} = \frac{\partial lnS}{\partial lnMPG}$$

If $\eta_{MPG}(S) > 0$, then an improvement in fuel economy will result in an increase in miles driven. This does not mean, however, that energy consumption will increase. Note that $E = \frac{S}{MPG}$, so $lnE = lnS - lnMPG$. Then

$$\eta_{MPG}(E) = \frac{\partial lnE}{\partial lnMPG} = \frac{\partial lnS - \partial lnMPG}{\partial lnMPG} = \frac{\partial lnS}{\partial lnMPG} - 1 = \eta_{MPG}(S) - 1 \quad (3.1)$$

Equation (3.1) shows how the fuel economy elasticity of the demand for mileage, $\eta_{MPG}(S)$, also provides information on the effect of a fuel economy policy on fuel consumption. It is only if demand for miles is elastic ($\eta_{MPG}(S) > 1$) that energy consumption will increase ($\eta_{MPG}(E) > 0$); i.e. if the elasticity of miles with respect to fuel economy is less than one, fuel economy policies will reduce energy consumption.

Another definition of the rebound effect that is often used in the literature is the negative price elasticity of demand for mileage. Let the fuel cost per mile be defined as $P_S = \frac{P_E}{MPG}$. Note that a decrease in the price of fuel when fuel economy is constant should have the same effect on fuel cost per mile as an increase in fuel economy holding the price of fuel constant. This second definition of the rebound effect is

$$-\eta_{P_S}(S) = -\frac{\partial S}{\partial P_S}\frac{P_S}{S} = \frac{\partial lnS}{\partial lnP_S}$$

Recall that the demand for miles is a function of fuel and maintenance, subject to a budget constraint. If income and the price of maintenance is held constant, the demand for miles is solely a function of the fuel cost per mile; $S = s(P_s)$. Then as long as the price of fuel is independent of fuel economy,

$$\frac{\partial E}{\partial MPG} = \frac{\partial P_S}{\partial MPG}\frac{\partial S}{\partial P_S}\frac{1}{MPG} - \frac{s(P_S)}{MPG^2}$$

Thus

$$\eta_{MPG}(E) = \frac{\partial E}{\partial MPG}\frac{MPG}{E} = (\frac{P_E}{MPG^2}\frac{\partial S}{\partial P_S}\frac{1}{MPG} - \frac{s(P_S)}{MPG^2})\frac{MPG}{\frac{S}{MPG}} = -1 - \frac{\partial S}{\partial P_S}\frac{P_S}{S} = -1 - \eta_{P_S}(S)$$

Therefore, $-\eta_{P_S}(S)$ can function as a proxy for $\eta_{MPG}(S)$. This second definition, $\eta_{P_S}(S)$, is often used in place of $\eta_{MPG}(S)$ because many data sets lack sufficient variation in fuel economy, MPG. The additional variation given by P_E gives greater efficiency to the estimate of the rebound effect in such works.

In the long run, technological improvements in fuel economy may induce a household to change their vehicle stock, but the short nature of the panel data used in this study puts this outside the scope of this work; instead, only short run changes in utilization as measured by miles driven by a vehicle are explored here.

3.3.2 Theory

According to Becker's (1965) household production model, individuals do not derive utility directly from energy commodities, such as gasoline. Instead the demand for energy comes from the demand for energy services, such as transportation, which is made up of the quantity of services consumed as well as the quality of those services. Transportation services are therefore composed of miles traveled, S, and the attributes of transportation service, A. These attributes can include performance characteristics, e.g., speed and acceleration, as well as factors such as the prestige associated with the brand and the comfort of the ride. Fuel economy, MPG, is one of these attributes. Historically, fuel economy affected demand for transportation only through its affect on the budget constraint via fuel costs. In the past decade, however, high levels of fuel economy have become valuable in their own right as being "green," has become a consumer preference. Therefore an individual will maximize a utility function such as

$$U = u(c, S, MPG) \ s.t. \ I \geq P_c c + P_S S + P_{MPG} MPG \tag{3.2}$$

where c is a composite good and I is income. The cost per mile is represented as P_S, and can be divided into the fuel cost per mile and the operating cost per mile. The fuel cost per mile is $\frac{P_E}{\frac{S}{E}}$, where E is the quantity of fuel consumed and P_E is the price of fuel; in general this fuel will be gasoline, but I refer to it in this general way to account for alternative fuels. The operating cost per mile is $\frac{P_O}{\frac{S}{O}}$, where O is the maintenance required to keep the household's vehicles running. Substituting this into the budget constraint, the consumer's optimization problem becomes

$$maxU = u(c, S, MPG) \ s.t. \ I \geq P_c c + (P_E E + P_O O) + P_{MPG} MPG \tag{3.3}$$

where the consumer is choosing the quantity of other goods he or she will purchase, the amount of fuel he or she will consume, the amount he or she is willing to spend on maintenance, and the fuel economy of his or her vehicle(s). Miles driven is then a function of fuel and maintenance, restricted by the cost of purchasing a car with that level of fuel economy.

Higher fuel economy typically comes at a higher vehicle cost due to the technological improvements that go into the development of the vehicle. Therefore, it is possible that the fuel cost reduction could be matched or even outweighed by the increase in vehicle purchase price; however, the consumer may place value on the increase in fuel economy independent of the financial benefits, because of self-satisfaction at helping the environment, a desire to stop for gas less often, or praise from society for making such a purchase. In this case, the consumer may purchase a vehicle for which the purchase price outweighs the fuel savings. If owning a vehicle with that level of fuel economy is a source of pride to the consumer, they may drive more to show off the vehicle. Or if the individual is truly of an environmental mind, they will drive less than a consumer who is otherwise similar. The price of fuel economy is really representing the price of new vehicles and therefore the price of all attributes of the vehicle. Although other attributes are not included in the base specification, some vehicle attributes are included in a robustness check, shown in Table B.5.

The demands for mileage and fuel economy are separate but related. Households base the use decision on the price per mile, expected gas prices, income, the price of maintenance, and household characteristics. This results in the vehicle utilization model found in Equation (3.4).

$$S_{ht} = f(\frac{P_{E_{ht}}}{MPG_{ht}}, P_{E_{h,t-s}}, I_{ht}, P_{O_t}, X_{ht}) \tag{3.4}$$

where S_{ht} is the miles driven by household h in period t, $P_{E_{ht}}$ is current gas prices faced by household h in period t, $P_{E_{h,t-s}}$ is a vector of lagged gas prices which give the household a sense of the trend of future gas prices, P_{O_t} is the price of maintenance in period t and is treated as exogenous, and X_{ht} is a vector of household characteristics. The definition of fuel economy, MPG_{ht}, is less clear in this context; in the case of a single vehicle household, this will just be the fuel economy of the vehicle, but in a multi-vehicle household, fuel economy could be measured as a use-weighted household composite fuel economy.

This study treats fuel economy as a continuous variable. Although a discrete vehicle choice model would be a more complete representation of the efficiency decision, this paper only estimates the short run rebound effect, and short run adjustments to fuel economy are likely to involve changes in driving behavior, such as driving at slower speeds and accelerating more gradually, and frequency of maintenance, both of which treat efficiency as continuous. This results in the fuel economy model given in Equation (3.5).

$$MPG_{ht} = f(P_{E_{ht}}, P_{E_{h,t-s}}, S_{ht}, I_{ht}, P_{NV_t}, X_{ht}) \tag{3.5}$$

where P_{NV_t} is the price of new vehicles in period t, which controls for the decision to sell a vehicle and replace it with a new vehicle. The price of new vehicles therefore serves as the excluded instrument and controls for the endogeneity inherent in the system.

3.3.3 Empirical Utilization Model

Because the first definition, $\eta_{MPG}(S)$, represents the direct influence of fuel economy on travel, it is a more accurate definition of the rebound effect than $\eta_{P_S}(S)$, which includes the price of fuel. The latter definition is equivalent only if households respond in the same way to changes in fuel economy as to changes in fuel prices, an assumption which often does not hold when explicitly tested[6] and which does not appear to hold in the results presented later in this paper. Therefore, the former elasticity should be used to estimate the rebound effect if the data is available to do so. This can be achieved by regressing the natural log of miles traveled by vehicle i owned by household h in period t, $ln(S_{it})$, against the natural log of fuel economy, $ln(MPG_{it})$, as shown in Equation (3.6). The price of fuel, $ln(P_{E_{iht}})$ and a number of household characteristics, X, serve as controls.

$$ln(S_{it}) = \alpha_0 + a_{MPG} ln(MPG_{it}) + \alpha_{P_E} ln(P_{E_{iht}}) + \alpha_{MPGy}(ln(y_{ht}) \times ln(MPG_{it})) + \alpha_y ln(y_{ht}) + \alpha_{P_O} P_{O_{ht}} + \alpha_X X_{ht} + \nu_{ht}$$

(3.6)

In Equation (3.6), $\alpha_{MPG} + \alpha_{MPGy} ln(y)$ is the estimate of the rebound effect. The control matrix X includes urban/rural fixed effects; dummy variables for race, gender, and various levels of education; the number of children under the age of 18; the total number of people in the household; and the age of the household head. Each vehicle is treated as a separate observation; if a new vehicle is purchased, that vehicle is added to the sample, and if a vehicle is sold, the vehicle leaves the sample. This increases the number of observations, but does not allow for exploration of

[6] Wheaton (1982); Small and Van Dender (2007); Linn (2013)

substitution between vehicles in a multivehicle household. Although the vehicle purchase and scrappage decisions are relevant to the rebound effect, they are more likely to play a role in the long run rebound effect and are beyond the scope of this work.

Income is interacted with fuel economy because theory suggests that the rebound effect should fall as income rises. After a threshold level of income driving is likely to become an inferior good, which should therefore decrease the rebound effect from fuel economy improvements. Any increase in mileage resulting from improvements in fuel economy should be small once household mileage passes the satiation point. Because low-income households are farther from this threshold, direct rebound effects will be higher among low income groups. Higher opportunity costs associated with time for high income individuals may also cause the rebound effect to decrease with income. Because energy forms a larger portion of the total expenditure of low income groups, they are more responsive to energy prices. Thus, excluding income from the rebound effect results in an overestimation of the direct rebound effect for higher income groups. Interacting fuel economy and income allows the response to changes in fuel economy to vary with income by taking into account the negative correlation between time efficiency and energy efficiency.

Vehicle level fuel economy may be a poor regressor if there is insufficient variation over time; however, a similar model can be achieved by regressing the natural log of miles traveled by household h in period t, $ln(S_{ht})$, against the natural log of household composite fuel economy, $ln(\frac{total\ household\ miles}{total\ household\ fuel\ expenditure}) = ln(MPG_{ht})$. This model would require that $ln(S_{ht})$ be solved out of the right hand side of the equation. For reasons discussed in Section 3, this work focuses on single vehicle households, so this method is not used.

An alternative setup involves the second definition, $\eta_{P_S}(S)$, which uses the natural log of the fuel cost per mile, $ln(P_{S_{it}})$, as the key explanatory variable. Because the fuel cost per mile, P_S, involves energy prices there is ample variation over time. Variation in fuel costs allows P_S to vary over time, so there is no need to aggregate to the household level. This specification assumes that households respond equally to changes in fuel economy and fuel prices, which does not appear to be the case in the data used here, so this method is not used in this paper.

3.3.4 Empirical Efficiency Model

Fuel economy is likely correlated with the error term in the mileage equation. Vehicle utilization depends on the efficiency of the vehicle since the fuel economy affects the fuel cost per mile; at the same time, the choice of efficiency will depend on the expected use of the vehicle. An empirical model of fuel efficiency is given in Equation (3.7). Instrumenting for fuel economy controls for the endogeneity in the system. The price of new vehicles is used as the excluded instrument.

$$ln(MPG_{iht}) = \delta_0 + \delta_{P_E} P_{E_{ht}} + \delta_{P_{E_{t-s}}} P_{E_{ih,t-s}} + \delta_S S_{iht} + \delta_y y_{ht} + \delta_{P_{NV}} P_{NV_t} + \delta_X X_{ht} + \mu_{ht} \tag{3.7}$$

3.4 Data

This study uses the Consumer Expenditure Survey (CEX) data from 1997 to 2003. This is a rotating panel that interviews households for five consecutive quarters, with one fifth of the sample from the preceding quarter being replaced by a new set of households every quarter. This survey collects information on household characteristics, as well as detailed information on vehicle characteristics including make, model, model year, number of cylinders, and type of transmission, which are then used to merge fuel economy data from the website fueleconomy.gov, which is jointly run by the Department of Energy and the EPA. Although the rotating panel of this length does not equate to a true panel over the years included in the study, it includes both cross-sectional and time-series variation, giving an advantage over studies looking at only one year of household level data.

There appears to be measurement error in the self-reported mileage variable included in the CEX. [7] For this reason, I am calculating mileage using household gas expenditure, state gas prices, and vehicle fuel economy. [8] Because gas expenditure is only available at the household level, it is impossible to know how multi-vehicle households divide the mileage across vehicles, so that this calculation cannot be done for multi-vehicle households. I explored weighting each vehicle using weights

[7]See Appendix B.1 for more information on the self-reported mileage variables, including summary statistics and results

[8]Because fuel economy appears in the calculation of miles driven, bias from measurement error may be exacerbated. If an observation has a fuel economy value that is lower than the true fuel economy, then the miles driven variable will also be lower, and vice versa. As a result, there may be correlation between miles driven and fuel economy that would present an upward bias, indicating that these results are an upper bound.

based off of the self-reported variable, but the noise in the self-reported variable was sufficient to make such weights unreliable. For the duration of this paper, I will focus on single vehicle households.

Single vehicle households account for 40.7% of vehicle-owning households in the CEX. It is possible that high income households with only one vehicle are fundamentally different from other one vehicle households due to differences in unobservable characteristics such as environmental preferences. Therefore, I restrict the estimation sample to one vehicle one adult households, because it is less unusual for a one adult household of any income to have only one vehicle. One adult households make up 54.8% of one vehicle households. Due to difficulty matching the EPA vehicle data with the CEX data, 17,004 observations, or 50.3%, are dropped out of the initial 33,833 observations.

Although households complete five interviews, only income data and basic durable information, such as how many vehicles the household owns, are collected in the first interview. Expenditure data is collected in the following four interviews, so that only four mileage observations are possible. Less than 1% of the remaining observations had to be dropped due to an inability to calculate the price of gas because of missing state data. Vehicles which are reported as being driven less than 100 miles during the quarter are excluded from the sample. Similarly, observations reporting more than 12,000 miles driven in a quarter are dropped from the sample. Overall, 3.8% of the remaining observations were dropped because they were outside of the accepted mileage range. Summary statistics of the remaining sample are found in Table 3.1.

Table 3.1: Summary Statistics for Estimation Sample Using Calculated Mileage

Variable	Observations	Mean	Std Dev	Min	Max
Quarterly miles driven	14,774	3181.39	1932.95	109.25	11992.22
Fuel economy (miles/gallon)	14,474	23.71	4.68	12	51
Household income before taxes ($)	14,474	28,535.15	26,745.65	1	483,288
National index of price of maintenance	14,474	181.32	11.58	161.23	198.3
Lagged expenditure on maintenance ($hundreds)	6,312	1.21	2.75	0	48
Price of gasoline ($)	14,474	1.36	0.21	0.79	1.93
White household head (dummy)	14,474	0.84	0.36	0	1
Children under the age of 18	14,474	0.30	0.77	0	7
Household in an urban location (dummy)	14,474	0.99	0.11	0	1
Age of household head	14,474	48.86	19.64	15.00	94.00
Female household head (dummy)	14,474	0.64	0.48	0	1
Number of household members	14,474	1.30	0.77	1	8
National index of price of new vehicles	14,474	141.35	2.39	136.63	145.40
Highest education of household head (dummies):					
High School	14,474	0.26	0.44	0	1
Some College	14,474	0.33	0.47	0	1
College	14,474	0.21	0.41	0	1
Graduate School	14,474	0.10	0.29	0	1

Summary statistics for all one vehicle households are presented in Table 3.2. Miles driven per quarter, fuel economy, income, and family size are significantly different from the estimation sample. One adult households drive fewer miles per quarter, have higher fuel economy, lower income, and smaller families than multi-adult one vehicle households. With fewer drivers, somewhat fewer miles are expected; it is drivers as well as vehicles that create constraints on mileage. The higher fuel economy could be explained by unobservable characteristics such as environmental beliefs or distance to work. It could also be explained by lower income if the improved fuel economy comes from owning fewer luxury vehicles or large SUVs. With only one adult, household income is understandably lower, and families are smaller. One adult households are also younger, more likely to be female, and more educated than multi-adult households.

Table 3.3 shows the summary statistics for the entire vehicle owning population in the CEX. Note that mileage could not be calculated for the multi-vehicle

Table 3.2: Summary Statistics for All One Vehicle Households Using Calculated Mileage

Variable	Observations	Mean	Std Dev	Min	Max
Quarterly miles driven	25,366	3577.09	2209.50	102.63	11,995.43
Fuel economy (miles/gallon)	25,366	23.32	4.57	12	51
Household income before taxes ($)	25,366	35,981.06	36,505.32	1	610,000
National index of price of maintenance	25,366	181.32	11.55	161.23	198.30
Lagged expenditure on maintenance ($hundreds)	10,996	1.23	2.78	0	48
Price of gasoline ($)	25,366	1.36	0.21	0.79	1.93
White household head (dummy)	25,366	0.84	0.37	0	1
Children under the age of 18	25,366	0.52	0.99	0	9
Household in an urban location (dummy)	25,366	0.99	0.12	0	1
Age of household head	25,366	49.30	19.33	15	94
Female household head (dummy)	25,366	0.53	0.50	0	1
Number of household members	25,366	2.03	1.33	1	12
National index of price of new vehicles	25,366	141.36	2.39	136.63	145.40
Highest education of household head (dummies):					
High School	25,366	0.28	0.45	0	1
Some College	25,366	0.31	0.46	0	1
College	25,366	0.19	0.39	0	1
Graduate School	25,366	0.09	0.29	0	1

households so mileage is not included here. All variables are significantly different in the total population as compared to one vehicle households. As expected, the general population has a higher income and larger families than one vehicle households. They also have lower fuel economy, which may result, again, from the higher income being used to purchase vehicles such as luxury vehicles and SUV's which are less efficient. The differences in the price of new vehicles and the price of maintenance represent a slight difference in distribution of households over time because they are national indices. Actual expenditure on maintenance is likely higher because of the higher income and number of vehicles. Larger families require more vehicles.

3.5 Results

If endogeneity is present, using instrumental variables should control for the endogeneity bias. The price of new vehicles is used to instrument for fuel economy

Table 3.3: Summary Statistics for Entire Vehicle Owning Population in CEX

Variable	Observations	Mean	Std Dev	Min	Max
Number of cars owned, including vans and trucks	139,399	2.47	1.32	1	18
Fuel economy (miles/gallon)	67,781	22.64	4.78	11	51
Household income before taxes ($)	139,399	59,035.48	51,061.81	1	812,601
National index of price of maintenance	139,399	179.93	11.17	161.23	197.20
Lagged expenditure on maintenance ($hundreds)	104,093	2.39	5.27	0	400.60
Price of gasoline ($)	139,133	1.35	0.20	0.79	1.93
White household head (dummy)	139,399	0.87	0.33	0	1
Children under the age of 18	139,399	0.78	1.11	0	10
Household in an urban location (dummy)	139,399	0.98	0.13	0	1
Age of household head	139,399	49.08	15.39	15	94
Female household head (dummy)	139,399	0.37	0.48	0	1
Number of household members	139,399	2.92	1.50	1	16
National index of price of new vehicles	139,399	141.62	2.28	136.63	145.40
Highest education of household head (dummies):					
High School	139,399	0.28	0.45	0	1
Some College	139,399	0.30	0.46	0	1
College	139,399	0.20	0.40	0	1
Graduate School	139,399	0.12	0.32	0	1

in the mileage equation, as the price of new vehicles will affect the vehicle purchase decision and therefore the fuel economy but is not likely to directly influence mileage. First stage results are presented in Table 3.4. The first column regresses the natural log of fuel economy on the national index of the price of new vehicles, income, current and lagged gas prices, all taken as natural logs, as well as lagged maintenance expenditure and a series of household control variables. The second column replaces lagged maintenance expenditure with the national index of the price of maintenance. The instrument is not particularly strong, but endogeneity is rejected in each specification. Although this may be due to the weakness of the instrument, without a better instrument at hand, IV estimation will not provide reliable results, so I assume that fuel economy is exogenous and use median regressions in all future specifications. Median regression is preferred to OLS in this work because it minimizes the impact of outliers present in these data.

The results of the median regression estimation are presented in Table 3.5.

Table 3.4: IV First Stage Results

	(1)	(2)
F statistic	5.7505	0.0165
Observations	6,312	14,474
Partial R-squared	0.0017	0.0000
Durbin-Wu-Hausman test reject null of exogeneity?	NO	NO

Columns (1) uses lagged maintenance expenditure to control for maintenance prices. Column (2) replace this variable with a national index of maintenance prices. The results in these specifications indicate that the rebound effect is between 17.8% and 23.6%, which is in line with the literature in which 10% to 30% is a common range and several papers report estimates around 22%. When the interaction is included in Columns (3) and (4), the response to a change in fuel economy for households with very low income rises to 80.3% to 105.0%, indicating a potential increase in gasoline consumption. These results indicate that there may be substantial takeback in mileage in response to an improvement in fuel economy for low income households. The interaction term shows the expected sign; the rebound effect appears to decrease with income. All specifications includes gas prices lagged one, two, three, and four quarters, as well as the full set of controls shown in Table 3.1, although they are not displayed in the table.

The same specifications are then run with the inclusion of an interaction of income with fuel prices. Inclusion of this variable has little effect on the results, outside of understandably increasing the magnitude of the fuel price elasticity estimates. The results indicate that low income households respond more strongly to changes in fuel prices than high income households, likely due to the higher percent-

Table 3.5: Median Regression Estimates

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.236***	0.178***	1.050***	0.803***
	(0.049)	(0.033)	(0.378)	(0.294)
ln(income)	0.070***	0.076***	0.334***	0.271***
	(0.010)	(0.006)	(0.118)	(0.093)
ln(income)× ln(mpg)			-0.083**	-0.062**
			(0.037)	(0.029)
ln(price of gas)	-0.811***	-0.712***	-0.845***	-0.718***
	(0.123)	(0.084)	(0.119)	(0.079)
ln(price of gas lagged)	0.224	0.306***	0.257	0.291**
	(0.177)	(0.117)	(0.174)	(0.114)
lagged maintenance expenditure	0.016***		0.016***	
	(0.003)		(0.003)	
maintenance price index		0.001		0.001
		(0.001)		(0.001)
Constant	6.774***	6.776***	4.166***	4.799***
	(0.218)	(0.191)	(1.225)	(0.940)
Pseudo R^2	0.1088	0.0926	0.1093	0.0928
Observations	6,312	14,474	6,312	14,474

Standard errors clustered at the household level and presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1

age of the cost per mile that these fuel costs make up. The rebound effect estimates remain quite high when the interaction of income and fuel economy is included, although there is no longer an indication of backfire.

Table 3.6: Income Interacted with Fuel Prices

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.233***	0.181***	0.918**	0.797***
	(0.047)	(0.032)	(0.406)	(0.277)
ln(income)	0.047***	0.056***	0.273**	0.248***
	(0.018)	(0.013)	(0.132)	(0.087)
ln(income)× ln(mpg)			-0.069*	-0.061**
			(0.040)	(0.028)
ln(price of gas)	-1.616***	-1.403***	-1.418***	-1.429***
	(0.504)	(0.374)	(0.441)	(0.345)
ln(income)× ln(price of gas)	0.080	0.067*	0.058	0.070**
	(0.050)	(0.036)	(0.045)	(0.033)
ln(price of gas lagged)	0.237	0.311***	0.254	0.298***
	(0.175)	(0.113)	(0.176)	(0.115)
lagged maintenance expenditure	0.017***		0.016***	
	(0.003)		(0.003)	
maintenance price index		0.001*		0.001
		(0.001)		(0.001)
Constant	7.012***	6.930***	4.767***	4.985***
	(0.272)	(0.212)	(1.328)	(0.884)
Pseudo R^2	0.1090	0.0928	0.1095	0.0931
Observations	6,312	14,474	6,312	14,474

Standard errors clustered at the household level and presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robustness checks are included in Appendix B.2.

3.6 Conclusion

Using median regressions to minimize the effects of outliers and including an interaction of income and fuel economy, the estimate of the rebound effect is allowed to vary with income. The rebound effect may be anywhere between 17.8% and 105.0%, which is large enough for the consumption of gasoline to increase. In every specification in which it is included, the interaction between income and fuel economy is negative, implying that the rebound effect decreases with income as expected; however, the interaction is insignificant in some robustness checks.

Inclusion of additional vehicle attributes increases the estimated rebound effect, while dropping the highest and lowest 10% of income has little effect on the estimates independent of income and reduces significance when the interaction is included. This seems to indicate that the lowest income decile dries most of the results. Including regional dummies makes almost no difference in the results. By using current consumption in place of income, the results again increase somewhat, at 26.7% to 27.9% when no interaction is included and 69.6% to 138.3% when it is included.

If the rebound effect is larger than 100%, policies that support fuel economy improvements will actually increase fuel consumption, and even if the rebound effect is lower, if it is sufficiently close to 100% such policies are ineffective methods of reducing oil use and pollution. A decline with income would mean that the rebound effect is lower in more developed countries, making fuel economy policies an effective tool in the developed world. It is also possible that certain types of fuel economy policies will have differential effects. A scrappage program focusing on older vehicles may help low income families get a better vehicle, but it may also increase oil consumption, congestion, and pollution. A subsidy for an alternative fuel vehicle on the other hand is likely to target consumers that are driving about as many miles as they would want to, so that they will not increase mileage very much upon purchasing an alternative fuel vehicle. The nationwide, manufacturer focused CAFE standards likely falls somewhere in the middle of these options.

In the future, I would like to try to better capture the comfort and prestige of driving certain vehicle models as these are the most likely factors that would influence the mileage decision. I would also like to look at the equivalence of the definition of the rebound effect using fuel economy. Recall that a similar model could be estimated using the elasticity of mileage with respect to the cost per mile as the estimate of the rebound effect. The fuel prices inherent in this definition provide more variation, however this definition may not be as accurate as that used in Equation (3.6) because there is an assumption implicit in this estimation of the rebound effect. Using $P_S = cost\ per\ mile = \frac{P_E}{mpg}$ implies that cost-minimizing consumers respond equally to an decrease in the price of gas as to an increase in fuel economy. If $\alpha_{MPG} \neq -\alpha_{P_E}$, then Equation (3.6) is equivalent to an equation using cost per mile. In the literature, cost per mile is used more often than fuel economy because of the greater variation in fuel prices as compared to fuel economy. Two studies, Greene et al. (1999) and Schimek (1996), test and find that consumers do respond to increases in fuel economy in a equal and opposite way to decreases in fuel prices; however, Small and Van Dender (2007) test and find that $\eta_{MPG}(S) \neq \eta_{P_E}(S)$.

In their specification, $\eta_{P_S}(S)$ is found to be closer to $\eta_{P_E}(S)$ rather than the more accurate $\eta_{MPG}(S)$. Based on these results, studies which use the fuel cost definition may have biased estimates of the rebound effect.

Chapter 4: Historical Cost of Consumer Credit, Interest Rate Stickiness and Salience: Evidence from Mail Order Catalogs

4.1 Introduction

Credit card rates, as opposed to the rates of many other forms of credit, were extremely sticky in the 1980s.[1] From 1981 to 1991, the yield on the 3-month Treasury Bill decreased by 9 percentage points. Over the same period, average finance rates on 48-month new auto loans and 24-month personal loans issued by commercial banks decreased by 5 and 3 percentage points, respectively. On the other hand, average rates on credit cards issued by commercial banks stayed relatively flat at around 18% APR.[2] The insensitivity of credit card issuers to decreasing cost of funds as well as evidence of their earning supranormal profits implies that they held market power. However, such market power is puzzling given low entry barriers and concentration of the industry.[3] In light of this, researchers have proposed several explanations for credit card rate stickiness including search costs, switching costs and adverse selection.

[1]For good overviews of credit card rates in the 1980s, read Ausubel (1991) and Calem (1992).

[2]Rates retrieved from FRED Economic Data from the Federal Reserve Bank of St. Louis and Federal Reserve Bank Annual Statistical Digest, accessed through FRASER, Federal Reserve Archive.

[3]See Ausubel (1991) for evidence of credit card issuer profits.

In order to further investigate drivers of rate stickiness and their implications for current credit card holder behavior, this paper looks historically at the adoption of this style of credit as a popular means for purchasing small dollar retail goods. Because cost and term information was not systematically collected in the United States until the 1970s, we create a new dataset of credit terms from credit plans offered in the major U.S. mail order catalogs of the 20th century.[4] As a result, this study uses a time series of finance rates offered by major creditors of small dollar loans from the late 1920s to the early 1990s.

Mail order catalogs, as well as other retailers, initially offered credit in the form of installment plans, a type of "closed-ended" credit. To purchase a good on credit, a "carrying" charge was added to the cash price of the good and households paid off this summed amount (minus a down payment) in equal payments over several months. Between the late 1950s and the early 1960s, catalogs added or completely switched to "revolving" credit plans. These plans are very similar to today's credit cards. Goods purchased with these plans did not incur credit costs if the outstanding balances were paid off within a specified number of days. After that, purchasers had to make a minimum monthly payment and incurred an interest charge, both based on outstanding balance size.

This work calculates finance rates on both installment and revolving credit plans for varying good prices based on required payment streams. Rates on installment plans that covered all goods in the catalogs ranged from an equivalent of [5]

[4] "Rates on Consumer Instalment Loans", September 1973 Federal Reserve Bulletin.

[5] Because APR was not provided until the 1960s, the IRR is referred to as the APR, while the APR is referred to as the "published APR."

10% and 60% APR.[6] There are instances when installment plan finance rates decreased even without major decreases in interest rates in the general economy. Upon adoption of a revolving credit plan, each retailer charged 18% APR and held that rate for at least a decade. Revolving credit was initially cheaper than installment credit for small purchases; however, with additions of minimum fees and changes in outstanding balance calculations, pricing between the two types of credit became comparable. On the other hand, the 18% APR credit price on medium to large purchases was much higher than those on installment plans.

This paper investigates possible reasons revolving credit rates seemed sticker than their installment credit counterparts, arguing that several previous explanations of credit card rate stickiness in the 1980s—including switching costs, search costs, and adverse selection—are not as applicable in explaining revolving credit rate stickiness in mail order catalogs. This study also argues that the 18% sticky revolving credit rate was not simply a story of market power or binding usury ceilings, instead it proposes that revolving credit, as compared to installment and other closed-ended credit, is more effective in diminishing the salience of interest costs in the price of goods. This work finds evidence of shrouding of credit costs over time in the catalogs as well as noting that the method of cost disclosure used for revolving credit requires more cognitive effort to incorporate into a good's total costs. Hence rate stickiness can be explained by theoretic models of shrouding prices or profitably deceptive equilibriums, in which it is optimal for firms to hide or diminish costs rather than compete on them. Such models offer explanations not only for the

[6]Rates above 18% were only typical of smaller purchases.

observed revolving credit rate stickiness in the mail order catalog setting, but also for retailer preference of revolving credit to installment credit and for the decision of some retailers to concurrently offer installment and revolving credit.

If revolving credit reduces the salience of costs, then, all else being equal, consumers purchase more goods with revolving credit access than with access to equally priced closed-ended forms of credit. Also, holders of revolving credit instruments, like bank credit cards, may have more difficulty assessing whether the benefits of switching to slightly lower interest credit card outweighs any switching costs. These consumers, therefore, will appear less responsive to small price changes.

The remainder of the paper is organized as follows. Section 4.2 provides background on the general merchandise mail order catalog industry and its use of credit. Section 4.3 reviews previous explanations for interest rate stickiness. Section 4.4 describes the constructed data set. Section 4.5 presents the stylized facts found in the data, assesses the applicability of previous explanation of interest rate stickiness to the mail order setting, and proposes a new explanation. Section 4.6 discusses the implication of the findings and concludes.

4.2 Background

Unlike consumers in the late 20th century who could make small purchases on credit by use of bank credit cards, consumers in the early 20th century depended on retailers for credit. Retailers used credit to facilitate sales and promote customer loyalty.[7] Among retailers that strongly embraced the use of credit were general merchandise mail order catalogs such as Sears, Montgomery Ward and Spiegel. Examples of items sold on installment can be seen in the catalogs from the early 1900s. Installment tables that offered credit for categories of goods were published in catalogs in the late 1920s. Eventually, mail order catalog retailers offered credit plans for all goods in their catalogs in the 1930s. Many retailers, including mail order, also offered customers access to charge accounts which allowed customers a window of time (e.g. 30 days) to pay for a good without incurring any penalties. Often customers were given charge plates or cards that contained the identifying information of a customer's charge account. Eventually, retailers offered revolving credit in the 1950s and 1960s.

In the installment credit market as a whole, commercial banks remained the biggest lenders of installment credit, which included automobile financing and personal loans. However, retailers grew as creditors, contributing to about one fifth of the total installment credit extended in the 1970s, as seen in Figure C.1.[8] Retailers, on the other hand, were the dominant issuers of charge and revolving credit. However, bank issued credit cards expanded tremendously in the late 1960s, with 19% growth in 1969 and 25% growth in 1970, as seen in Figure C.2. In any case, at the beginning of the 1970s, retail stores had more cards outstanding and more credit balances owed than any other type of credit card, making them the leaders in revolving credit.[9]

[7] Mandell (1990)

[8] All figures for this paper may be found in Appendix C.

[9] Mandell (1990)

In 1973 54% of the credit cards in use were retail cards, while bank cards made up only 11% of the total credit cards in use.[10] By 1978, however, 52 million Americans had at least two bank credit cards and they accounted for 31% of total credit card spending versus 34% on retail cards.[11] Table C.1 shows the use of retail cards from the "big three" retail companies in 1975; at that time Sears had more active cardholders than any other credit card source.[12] Table C.2 shows the market penetration of the top five cards in the credit card industry in 1979.

Throughout the 1980s, large retail stores issued far more cards than the banks, with Sears leading the industry.[13] Although retail cards remained more common than bank cards, the spending and debt on retail cards was lower than that on bank cards. Spending and debt accumulation on bank cards increased throughout the 1980s, but they peaked in the middle of the decade for retail credit cards.[14] By 1988, 12.6% of total consumer spending for all goods and services was charged to credit cards in the U.S., and the top four card issuers in the U.S. were all retailers, led by Sears.[15]

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[10] Mandell (1990)
[11] Mandell (1990)
[12] Mandell (1990)
[13] Mandell (1990)
[14] U.S. Bureau of the Census (1989)
[15] Mandell (1990)

4.3 Explanations of Rate Stickiness

4.3.1 Search Costs, Switching Costs and Adverse Selection

Ausubel (1991) and Calem and Mester (1995) offer several possible explanations for the observed credit card rate stickiness of the 1980s. In this section, this study reviews these explanations. Section 4.5 examines their applicability for the mail order catalog setting and suggests another explanation based on the observations presented in that section.

Ausubel (1991) proposes three reasons for credit card rate stickiness: 1) search costs, 2) switching costs, and 3) consumer over optimism concerning balance repayment behavior combined with adverse selection. Search costs could arise if it takes time and effort to find banks issuing credit cards at different rates. Switching costs can come from several sources, such as the time and effort expended in filling out an application, the emotional toll of receiving a rejection, the annual fee associated with some credit cards, and the perception that one builds a stronger credit rating or receives higher credit limits by holding the same credit card longer.

If search costs are present in the mail order industry, credit information should be difficult to obtain from the retailers studied in this paper. If switching costs are contributing to interest rate stickiness, we should see long and complicated credit applications, the presence of annual fees, indication of improved credit terms for longstanding accounts, and a potential of being denied credit.

Lastly, Ausubel proposes the existence of three types of credit card users:

credit card users who never incur interest with their usage because they pay off their balances before the end of the "Grace Period," low-default credit card users who think that they are the first type of credit card users but end up borrowing and incurring interest, and high-default credit card users who know they will be borrowers and search for the lowest cost credit. The low-default credit card borrowers ignore credit card interest rate information because they do not think they will incur interest. In this setup, if credit card issuers compete on interest rates, they will disproportionately attract the less desirable high-default type borrowers over the more desirable low-default type borrowers. Hence, credit card issuers do not compete on interest rates due to this adverse selection problem. This theory would predict that retailers would avoid attracting liquidity constrained consumers, for example by maintaining moderate down payments and monthly payments.

Calem and Mester (1995) add to these explanations three possibilities that involve search or switch costs leading to adverse selection. They first posit that consumers with high search costs also tend to hold high balances. This could occur if those who are unwilling to devote time for search because of their preference for leisure also are impatient and value current consumption over future consumption. Hence, if credit card issuers lower interest rates, they would disproportionately attract individuals with lower search costs and who also will hold less profitable low credit card balances. This could occur in the mail order industry if credit information is difficult to obtain, requiring time and effort to locate the appropriate payment tables and fee information.

Second, they propose that creditworthy customers are offered favorable credit limits by their current creditors based on private information. Hence, these customers would face higher switching costs than their less creditworthy counterparts. Credit card issuers who lower rates would more easily attract the less desirable customers. If this theory holds in the mail order industry, retailers should show signs of extending or restricting credit limits based on private credit information on past credit transactions. This would indicate that the mail order companies use private information, such as the frequency with which a consumer pays on time or runs over their credit limit, to influence future credit transactions.

Finally, Calem and Mester propose that individuals with high credit card balances have more difficulty switching to credit cards because credit card issuers cannot identify if individuals are simply moving their current balances to the new credit card or are planning to accumulate even higher debts, making them higher risk customers. Due to this asymmetric information problem, credit card issuers reject potentially more profitable higher balance individuals and accept less profitable lower balance borrowers. Hence, credit card issuers are less motivated to compete for customers, but keep rates high for their captive clientele. As with Ausubel's adverse selection theory, this would indicate that retailers in the mail order industry should want to avoid attracting liquidity constrained customers by keeping down payments and monthly payments relatively high.

4.3.2 Salience of Revolving Credit Costs

Theorists conjecture that a shrouded prices equilibrium, in which firms do not compete on the total price of a good, can be supported if there exist consumers who themselves neglect to consider the full price of a good. Gabaix and Laibson (2006) model a setting in which base goods come with add-ons (e.g. a printer and printer cartridges or a bank account and overdraft services). If some customers do not consider the cost of these add-ons when making their purchase decision on the base good, then it may be optimal for firms to not compete on the price of the add-on feature. This would occur if unshrouding leads newly educated customers to become less profitable to the unshrouding firm by their avoiding of the add-on feature (and potentially the base good all together). This model predicts that the cost of credit, an add-on to the retail merchandise, will be overlooked by consumers. As a result, these costs will become more and more obscured in the mail order industry, either through more complicated interest rate disclosure or through a simple lack of information provided openly to the consumer.

In a related model, Heidhues et al. (2016) describe a setting in which a good's total price is made up of upfront prices that are understood by all and other prices that could be ignored by naïve consumers unless unshrouded (e.g. credit cards with upfront annual fees but more shrouded interest rate costs). Firms compete on the upfront price, which has a price floor. If the price floor is binding, then firms will only compete on the shrouded prices if the good is not socially wasteful (i.e. production costs of the good is below the value people have for the good). However, firms will not unshroud if the good is socially wasteful because consumers will not purchase the good once they are able to see the total price. So, perversely, socially wasteful goods are always sold in a profitably deceptive (shrouded) equilibrium. The model can also support an equilibrium in which sophisticated and naïve consumers each separate and purchase superior and relatively inferior goods, respectively, and the existence of the superior good reinforces a profitably deceptive equilibrium of the relatively inferior goods rather than unravels it. According to this theory, if the cost of credit is likely to be ignored by naïve consumers, retailers in the mail order industry should prefer a credit model in which interest rates are shrouded over one which states credit costs openly, though the model also suggests that it may be optimal to offer multiple plans at the same time to appeal to both sophisticated and naïve consumers.

4.4 Data

In this paper we construct a unique panel data set of credit terms from general mail order catalogs from the U.S. spanning decades of the 20th century. Data was collected from Sears, Aldens, Montgomery Ward, Spiegel, and J.C. Penney catalogs and spans Spring 1928 through Spring 1994, though no one company covers that entire range. We only collected credit data from catalogs when credit covered a category of goods versus being specific for each individual good. If there were several credit plans covering different categories of goods, we collected information from all of them. In the case of installment credit, information was usually disclosed in the form of down payment, carrying charge, and monthly payment tables that specified the named variables, respectively, for a given range of balance values; see Figure C.3. For revolving credit, usually only a minimum monthly payment table was disclosed along with information about monthly charges in fine print; see Figure C.4. Information from these disclosures allowed us to construct a stream of payments for varying balance sizes, from the down payment to the final monthly payment. For revolving credit, this study conducts analysis on a payment stream in which only the minimum required monthly payment is paid.

From this information we constructed a time series of five variables of interest: annualized internal rate of return (IRR), first minimum monthly payment requirement, interest cost divided by borrowed amount, down payment and APR. The internal rate of return is defined as the interest rate for which the net present value of the cash flows is zero; in other words, it is the interest rate such that the cost of the loan is equal to the expected cash flows. The equation used to calculate the IRR is shown in Equation 4.1. We multiply the IRR by 12 to annualize it.

$$0 = NPV = -\text{ Initial Investment } + \sum_{n=1}^{n} \frac{\text{Future Cash Flow}}{(1 + IRR^{n})} \tag{4.1}$$

The first minimum monthly payment will be equal to all monthly payments in the case of installment credit. This is not necessarily true with revolving credit as monthly payments are weakly decreasing with the outstanding balance. However, the first minimum monthly payment will necessarily be the highest monthly requirement that a borrower will have to fulfill for the duration of the loan.

Interest cost is equal to the carrying charge in the case of installment credit. To determine the interest cost for revolving credit, we add up all monthly payments in the payment stream and subtract out the cash price of the good. This interest cost could be thought of as the "carrying charge" equivalent for revolving credit. For the variable of interest, we divide the interest cost by the borrowed amount (cash price minus down payment).

Finally, the APR is a credit cost measure that was standardized by the TILA. This rate was not published in any of the catalogs until TILA became effective in 1969. However, the monthly percent charge that is applied to outstanding revolving credit balances is the APR divided by 12. Hence, this paper reports the monthly percent charge multiplied by 12 in the analysis to fill in the APR time series prior to TILA. IRR and APR should mostly coincide; however, fees and other details given in the fine print of these credit agreements could often cause the rates to diverge.

It should be noted that the IRR is impacted by loan terms other than the interest rate, such as the down payment and the loan term. These other terms complicate the comparison; the IRR may increase due to a decrease in monthly payments which leads to an increase in the length of the payment term. The increased rate may therefore be associated with an increased ability to pay for liquidity constrained consumers, so a consumer may be better off with loan terms with a higher IRR but lower monthly payments. The IRR remains the best single measure of the cost of credit available, but welfare arguments cannot be made with confidence based on the IRR alone.

4.5 Historical Cost of Consumer Credit

Several of the theories presented in Section 4.3 may be dismissed as explanations of credit rate stickiness in the mail order industry based off of some simple observations. Recall that search costs could be present if credit information is difficult to obtain from mail order companies, and switching costs could be present if there are long application processes, annual fees, private information between retailer and consumer, or a chance of being denied credit. Search costs should be relatively minimal in the mail order catalog setting as credit plan comparison would only require opening to the credit sections of the catalogs which themselves are received in the mail. In general, mail order catalog credit switching costs are also minimal. Credit applications in catalogs are typically very short (usually encompassing half a page) and many times are located on the other side of the product order form. Furthermore, no annual fees are associated with this type of credit. Unlike general-purpose credit cards, retailer credit was exclusive to the purchase of products sold by the retailer and it was not unusual for households to have access to multiple retailer credit accounts.[16] Hence, there would be less of a concern that purchasing a good on credit from different retailers would lead to a damaged credit record. Also, though this study does not have information on this, it is possible that retailers allotted greater "credit limits" to customers with longer (good) histories.[17]

[16] In 1980, 83 million Americans held 290.5 retail credit cards. That is, on average, 3.5 retail credit cards per retail credit card holder. (U.S. Bureau of the Census (1989))

[17] Since credit terms such as down payments (which were eventually equal to 0 in most catalogs) were the same for all borrowers, it is more likely that catalog companies offered greater "credit limits" by either completely approving the printed credit offer or completely denying it. At certain times, catalogs offered several credit plans with varying liberal terms. Thus, it is possible that cat-

However, again, there would be no impetus for customers to close one retail credit account, and with it a good credit relationship/history, in order to open another retail account. On the other hand, like general-purpose credit cards, there was still a chance of being denied credit by mail order catalog retailers for both revolving and installment plans.

Adverse selection resulting from consumer creditworthiness as private information, as argued by Calem and Mester (1995) can possibly be applicable to mail order catalogs in the sense that a customer who has built up a good credit history with one catalog retailer may be able to purchase more expensive items on credit from that retailer than from another with whom the customer has no history. In this way, the customer stays more loyal to that catalog. On the other hand, as previously mentioned, because retailer credit is exclusive to a specific retailer, households may already have credit accounts with various retailers at the same time, allowing them to more easily build credit histories than with general-purpose credit cards. Furthermore, there are no indications in the catalogs that once a customer had an approved open account (whether installment or revolving) that there could be individual restrictions on the maximum amount purchased unless it would lead to an outstanding balance that was above the maximum amounts printed in the catalog credit terms themselves.

alog companies could deny credit for one plan but offer the customer credit with more conservative terms.

4.5.1 Stylized Facts

To understand the applicability of other theories to the mail order industry requires a more in-depth analysis of the data set. Terms on mail order catalog credit plans varied with purchase size, typically with higher finance rates associated with smaller purchases. To simplify the exposition in this section, this paper focuses on a purchase amount of $300 in nominal dollars.[18] Stylized facts in the section are generalizable for most purchase amounts except for small purchases. Historical terms of credit for other purchase amounts can be provided upon request.

Figure C.5 presents the annualized internal rate of return for credit plans offered by mail order catalogs. Installment plans are in shades of red and revolving plans are in shades of blue. Plans that only covered appliances, furniture and other specified durable goods are symbolized by diamonds, while plans that covered all goods in the catalog are symbolized by circles. This study shows that costs of credit during the low-interest rate period of the 1930s and 1940s is comparable in magnitude to those found on credit cards during the equivalently low-interest rate period of the writing of this paper. For example, in 2015 the average interest rate on credit cards outstanding was 12.09% APR while the average 3-month Treasury yield was 0.05%. In comparison, the rates on installment plans offered by Sears and Montgomery Ward were 10.67% APR and 11.92% APR, respectively, when the 3-month Treasury yield was 0.05% in 1939.[19] Montgomery Ward and Sears started publish-

[18] Nominal dollars are used to ease comparison over consecutive years. Real dollar figures can be provided on request.

[19] For comparison, note that credit provided by mail order catalog retailers is secured by the underlying goods while that provided by general purchase credit cards is typically unsecured.

ing installment credit tables in 1928. Rates quickly dropped after the introduction of these tables. From 1928 to 1940, rates charged by Sears and Montgomery Ward dropped from 16.36% to 9.52% and 23.59% to 11.92%, respectively. In contrast, over the same time period, the 3-month Treasury bill yield dropped by only 1.75 percentage points from 1.79% to 0.04%. Figure C.6 and Figure C.7 show that the decreased installment credit rates are a result of retailers competing on monthly payment amounts, carrying charges or both. A decrease in either of these two variables holding the other constant will lower the cost of credit.

During WWII, the Federal Reserve enacted restrictions on consumer credit that included the setting of down payment floors and the limiting of the length of installment loans. As a result, Sears and Montgomery Ward did not offer installment credit for items above approximately $220. When restrictions were lifted at the end of the War, credit on more expensive items was again offered in catalogs and interest rates on credit experienced another falling episode. From 1945/1946 to 1954/1955, rates on installment plans in Sears, Montgomery Ward, Aldens, and Spiegel catalogs dropped from around 19.48% to 11.11%, 19.48% to 11.11%, 17.72% to 10.51% and 19.97% to 12.70%, respectively. In comparison, over the same time period, the yield on the 3-month Treasury bill increased from 0.38% to 1.73%. Figures C.6 and C.7 show that the rate drops are, again, driven by a mixture of monthly payment and carrying charge decreases.

As seen in Figure C.8, Spiegel started offering plans with no down payment at the end of 1945. The other mail order retailers charged down payments of 10% or more. Spiegel, in turn, required higher monthly payments than its competitors.

In the early 1950s, Sears started offering several plans on appliances and other durable goods with lower down payments and lower monthly payments. For the majority of the 1950s, neither Aldens nor Spiegel offered equivalently low monthly payment plans. Montgomery Ward, however, eventually followed suit by offering plans with lower down payments and monthly payments. Towards the end of the 1950s, both Sears and Montgomery Ward offered plans with zero down payment requirements. Sears and Montgomery Ward charged higher carrying charges on these more liberal credit plans. Eventually, carrying charges increased on all plans as interest rates rose for the economy as a whole. In 1959 and 1960, Spiegel and Aldens replaced their installment credit plans with revolving credit plans. As can be seen in Figure C.6, upon adopting revolving credit, Spiegel and Aldens started lowering the minimum monthly payment amounts to levels comparable to those of the liberal installment plans offered by Sears and Montgomery Ward. As seen in Figure C.7, Aldens and Spiegel correspondingly increased the potential amount of equivalent "carrying charge" under revolving plans. Sears and Montgomery Ward also added revolving credit plans to their suite of installment plans in 1959 and 1960. J.C. Penney entered the mail order business in the early 1960s, and when it started offering credit, it only offered revolving-style plans. By the early 1970s, all mail order catalogs, with the exception of Sears, only offered revolving credit. Sears retired installment plans in the late 1970s.

One striking feature of revolving credit is the stickiness of the rates. Figure C.9 shows that all mail order catalog retailers published a rate of 1.5% a month (18% APR) on their revolving credit plans upon their adoption in 1959 and 1960.

Revolving credit rates stayed at 18% APR or higher for the remainder of time the catalogs existed or credit terms were published in the catalogs.[20] In the case of Sears, this was a period of more than 30 years that included more than a decade of decreasing interest rates in the economy. In the next section, this paper will go more into depth about possible reasons for this rate stickiness.

To summarize:

1) Rates on installment plans decreased faster than the yield on 3-month Treasury bills during two episodes in the period of study, leading to a decrease in the spread between the two rates.

2) In the late 1950s and early 1960s, revolving credit was adopted by existing mail order retailers, and, by the end of the 1970s, none of the retailers offered installment credit plans.

3) Upon adopting revolving credit, firms that had not previously offered liberal terms under installment plans lowered their minimum monthly payment requirements to more competitive levels.

4) Rates on revolving credit were very sticky, unlike their installment credit counterparts. Rates on revolving credit were, generally, 18% APR or above, even over periods when most other interest rates in the economy were falling.

[20] Aldens charged a rates of 12% APR when outstanding balances were above $350. In the early 1960s and again in 1974, Montgomery Ward charged 12% APR when outstanding balances were above $500. From 1965 to 1973, J.C. Penney offered a revolving credit plan for durable goods that charged 14.4% APR for most outstanding balance amounts (though for a period they charged 18% APR when outstanding balances were lower than $90). From 1969 to 1973, J.C. Penney charged 12% APR on both revolving credit plans when outstanding balances were above $500. In a few states in the 1960s and more states in the 1970s, retail store credit fell under usury laws. Thus, in some states, rates on revolving credit plans were under 18% APR depending on the level of the state's usury ceiling.

4.5.2 Application of Adverse Selection Explanations

It seems unlikely that Ausubel's adverse selection explanation regarding the different types of credit card users applies in the mail order catalog setting. Recall that this theory predicts that retailers will avoid attracting liquidity constrained consumers; however, mail order catalog retailers lowered minimum monthly payment requirements on their revolving plans while maintaining the interest rate of 18% over significant periods of time. Lowering minimum monthly payment requirements could reasonably disproportionately attract more liquidity constrained individuals. On the other hand, it is true that if catalog retailers lowered interest rates, they would lose interest income on revolving credit customers who underestimate their probability of becoming borrowers. However, the 18% APR on revolving credit may discourage certain customers from borrowing (or even purchasing goods) who would have borrowed under the cheaper (though less liberal) terms of installment plans. These customers would realize that even if they pay the same (higher) monthly payments as required by the older installment plans, they would take longer to pay off their loans and they would incur a higher equivalent of a "carrying charge." Hence, mail order companies will not compete on interest rates if the gains from irrational revolving credit users outweigh the losses from low-default risk borrowers who find revolving credit too expensive.

Calem and Mester's argument regarding high balance users facing higher switching costs is also an imperfect fit in the mail order setting. This theory also suggested that retailers would avoid liquidity constrained consumers. It is unclear in this study period whether a customer's credit balance information with one retailer was accessible to other retailers.[21] In fact, with less accessible credit information, retailers would face larger asymmetric information obstacles than credit card issuers in the 1980s. However, as mentioned previously, retailers' behavior of setting down payments to 0 and lowering minimum monthly payments requirements would indicate that they were not trying to dissuade liquidity constrained (and potentially higher risk) individuals from applying for credit. Finally, all of Calem and Mester's explanations of rate stickiness should be just as applicable to installment credit as to revolving credit.

To summarize, search costs should have been minimal in the mail order catalog setting. Some types of switching costs possibly existed and could account for some of the credit cost stickiness in catalogs; however, since these costs would exist for both revolving and installment credit plans, they could not explain the variation of rate stickiness between the two credit types. Adverse selection explanations for rate stickiness seem to be at odds with retailers' offering of more liberal terms through time. On the other hand, consumer time-inconsistency or over-optimism concerning the level of debt that will be carried with revolving credit can explain mail order catalog retailer hesitancy to compete on credit costs.

[21] Credit reporting agencies did not get computerized until the 1970s, which is when they started to aggregate information nationally (Furletti, 2002).

4.5.3 Application of Salience Explanations

Along with the previous explanation, this paper proposes that revolving credit rates are stickier than those on closed-ended credit because revolving credit more successfully reduces the salience of credit costs in the price of goods.

The model presented by Gabaix and Laibson (2006) fits nicely in the mail order retailer setting in which credit is an add-on to the merchandise purchased. Recall that this model predicts that retailers will attempt to hide the cost of credit. There are signs of gradual shrouding of credit costs in the catalogs. Initially, when installment credit was introduced in catalogs, a cash price and a credit price were printed side by side (along with other credit terms) near the advertised product. Later, installment tables clearly featured the carrying charges that were to be added to order balances. In some early catalogs, customers had to add carrying charges to cash prices themselves when filling out the catalog order forms. In all these cases, credit costs were explicitly integrated into the price of purchased goods. Eventually, order forms stopped including an area for customers to do the previously mentioned calculation and instead only included a box that customers could check to indicate their desire to purchase on credit. Under revolving credit, costs of credit on the main catalog pages that explained credit plans became more obscured. Revolving credit tables in catalogs only emphasized “low” minimum monthly payment requirements for associated outstanding balance amounts and advertising in catalogs focused on the buying power of these plans. Information on costs, specifically the monthly percentage charge on outstanding balances, was now located in fine print of catalogs. At most, main text in the catalog alluded to "a low monthly charge" when referencing credit costs.

The model developed by Heidhues et al. (2016) presents an explanation of why mail order catalog retailers who were not offering the most competitive installment terms preferred switching to the more shrouded credit innovation of revolving credit over offering more transparent installment credit with higher carrying charges but lower monthly payments. This model predicts that firms will not compete on any delayed or hidden costs, such as the cost of credit on top of the cash price of the merchandise. It also suggested that multiple goods, in this case credit plans, could be offered if some consumers were sophisticated and others were not. If revolving credit plans were indeed relatively inferior to installment credit or if they were socially wasteful, then the implied necessary existence of a profitably deceptive equilibrium could explain why more firms adopted and replaced their installment credit plans with revolving credit plans. Furthermore, the model can also explain why Sears continued to offer both the superior installment plan, which could attract sophisticated customers, as well as revolving credit plans.

Other than the de-emphasis of credit costs in catalogs through use of fine print, diminished salience of credit costs with revolving credit can also come from the increased cognitive effort consumers must exert in order to translate the monthly or annual percentage charge into the total price of a good. Researchers have found instances when consumers are more responsive to all inclusive price postings than posts where parts of the price are quoted in percent form. This occurs even when costs associated with the percent quoting will be paid with certainty within minutes of the purchase decision.[22] In the mail order catalog setting, revolving credit posits a much more complicated computation with greater levels of uncertainty, balance-varying minimum payment constraints, and many possible streams of payments over longer periods of time. In fact, Gabaix and Laibson (2006, pg. 528) assume that, "consumers show a relatively muted response to complex, contingent, camouflaged, distant, or disaggregated costs."

4.5.4 Other Explanations

There are other possible explanations for the rate stickiness of revolving credit in the mail order catalog setting. Unlike the bank credit card market, the mail order catalog market did not include as many players and did potentially have high barriers to entry. Hence, price competition might be muted by market power. However, this study argues that enough competitive pressure existed in this setting to encourage some competition with installment credit prices. Furthermore, though some of the mail order retailers exited the market in the 1980s, it is exactly the time when bank credit cards emerged as strong alternatives to retail credit. Hence, this paper argues that a simple market power explanation does not completely explain the observed rate stickiness.

Another possible source of rate stickiness is binding usury ceilings. This certainly could have been the case in the late 1970s and early 1980s when interest rates in the economy were very high. However, the stickiness of revolving credit rates started almost 20 years earlier when this type of credit first appeared in the

[22] Chetty et al. (2009)

catalogs and when usury regulation was only beginning to be applied to it. As noted by Curran (1967), most states did not consider retail credit to be under usury regulation before 1957. This is because the courts viewed goods sold on credit as being sold at a different price than cash price, which was not illegal. However, with the prevalence of credit use, lawsuits emerged claiming usury violations that led to the enactment of stricter regulations on retail credit in some states throughout the 1960s. If these usury ceilings were in fact binding, then rationing of credit should occur. Though this study does not have information on credit application rejections or credit account closures for the mail order catalog retailers, there is information on credit terms. As seen in Figure C.6, in the 1960s, when retail credit regulation became more stringent and interest rates were not decreasing, revolving credit terms became more liberal while the posted rate stayed fixed at 18% APR. Since more liberal terms should attract more liquidity constrained individuals, it seems unlikely that firms were facing binding rate ceilings. Alternatively, firms could have used the newly applicable ceilings to facilitate tacit collusion.[23]

4.6 Discussion and Conclusion

If revolving credit reduces the salience of interest costs in the price of goods, then, all else being equal, consumers purchase more goods with revolving credit access than with access to equally priced closed-ended forms of credit. Hence, access to credit cards would lead to overconsumption even if consumers do not posses

[23]Knittel and Stango (2003)

present-biased preferences.

Another implication of low salience of revolving credit costs is that holders of revolving credit instruments, like bank credit cards, may have more difficulty assessing whether the benefits of switching to slightly lower interest credit cards outweigh any switching costs. Hence, these consumers will be less responsive to small price changes. This may explain some of the stickiness of bank credit card rates in the 1980s and as well as the popularity of credit card offers with extremely low introductory rates.

Regulators who want to minimize these impacts may want to increase the salience of credit card and other revolving credit costs. However, this task is not easy. For example, TILA mandated the disclosure of APR. It also mandated the disclosure of interest costs at the initiation of the contract for closed-ended credit. However, no equivalent disclosure of interest cost was mandated for revolving credit, at least at the initiation of the contract. Hence, for revolving credit customers, the TILA led to the disclosure of almost no new information, other than an annualized versions of their monthly quoted rate. As a result, Figure C.9 shows that there were no large changes to the APR of revolving credit plans at the time of TILA.[24]

The 2009 Credit Card Accountability Responsibility and Disclosure Act (CARD) mandated the disclosure of interest rate costs for a credit card holders outstanding balance if only the minimum payments are paid for the duration of the loan as well as the interest rate costs if current balances are paid off in 36 months. This type of

[24] In fact, for smaller balances there was an increase in revolving credit costs at the time of TILA due to adoption of minimum interest fees and changes in the way monthly outstanding balances are calculated.

disclosure is addressing revolving credit cost salience issues more directly than those in the TILA. Consumers can more clearly see how interest rate costs add up in two examples on their statement.[25] However, these disclosures are presented after the purchase decision has already been made. Policy that can increase salience of the cost of revolving credit at the point of purchase would potentially be more effective.

[25] Agarwal et al. (2014) and Wang and Keys (2014) find that 36-month payment amount creates an anchor effect. Keys and Wang present evidence that some consumers who were paying their full balance end up paying the 36-month payment. Furthermore, this disclosure itself might be shrouded for credit card customers who pay their bills and view their credit card activity online. These customers would need to open an electronic version of their paper statement in order to view the disclosure as it is not required to be displayed elsewhere.

Appendix A: Robustness Checks for Chapter 2

When the fuel economy variable is excluded, the estimated elasticities change slightly in the fixed effects results, with the price increase estimates ranging from -0.188 to -0.257, while the price decrease variable increases only very slightly to -0.080. There is still no statistically significant difference between the price maximum and price recovery, and the difference between the price recovery and price drop is significant at the 5% level. The difference between the price maximum and price drop coefficient are no longer statistically significant, making the asymmetry results inconclusive. These results can be found in Table A.1.

The results—including price and fuel economy point estimates, standard errors, and hypothesis test results—are highly robust to the inclusion of season fixed effects. Including month fixed effects decreases the estimated coefficient on price maxima by 0.06; this results in a lack of significance in the difference between response to price maxima and the response to price decreases. The asymmetry results are therefore ambiguous, as there is still no significant difference between the two types of price increases and there is still a significant difference between price recoveries and price decreases. The results using a yearly time trend brings the price increase and price decrease coefficients closer together, but the asymmetry test re-

Table A.1: Exclusion of Fuel Economy

Dependent Variable: ln(Daily KM driven)	Pooled OLS	Fixed Effects
price_max	-0.348***	-0.189*
	(0.105)	(0.108)
price_rec	-0.412***	-0.256**
	(0.117)	(0.111)
price_drop	-0.301***	-0.078
	(0.083)	(0.082)
# children	-0.023	0.028
	(0.023)	(0.062)
income	0.046*	0.036
	(0.026)	(0.029)
# employed	0.091***	-0.029
	(0.019)	(0.034)
job change	0.069**	0.030
	(0.033)	(0.047)
car vacation	0.312***	0.277***
	(0.025)	(0.030)
population density	-0.032**	0.169*
	(0.014)	(0.095)
car age	-0.017***	-0.010*
	(0.003)	(0.006)
hh size	-0.024	-0.002
	(0.022)	(0.046)
education	0.086***	-0.012
	(0.020)	(0.041)
rain	-0.004***	-0.004***
	(0.001)	(0.000)
snow	-0.010	-0.006
	(0.027)	(0.026)
temp min	0.048***	0.054***
	(0.005)	(0.005)
temp max	-0.074***	-0.074***
	(0.003)	(0.003)
p_rec	0.113***	0.049***
	(0.017)	(0.016)
p_max	-0.076***	-0.036**
	(0.018)	(0.016)
Constant	4.846***	4.712***
	(0.071)	(0.153)
Adj. R-squared	0.208	0.167
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.2478	0.0461
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.6527	0.2194
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.6325	0.5473

Robust standard errors clustered at the household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Observations: 12,108. Number of Households: 1,552

sults remain strong, and the fuel economy estimates remain the same. Finally, time fixed effects decrease all price elasticity estimates, bringing the price decrease estimate very close to zero, while standard errors increase only very slightly. Fuel economy results remain unchanged. These time effect results can be found in Table A.2.

Table A.2: Time Effects

	Dependent Variable: ln(Daily KM driven)							
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
price_max	-0.345***	-0.248**	-0.291***	-0.207**	-0.696***	-0.236**	-0.992***	-0.230*
	(0.099)	(0.104)	(0.098)	(0.103)	(0.109)	(0.106)	(0.124)	(0.122)
price_rec	-0.345***	-0.271***	-0.327***	-0.278***	-0.647***	-0.268**	-0.923***	-0.234*
	(0.115)	(0.104)	(0.115)	(0.104)	(0.123)	(0.106)	(0.133)	(0.120)
price_drop	-0.199**	-0.035	-0.177**	-0.031	-0.445***	-0.032	-0.678***	-0.000
	(0.082)	(0.077)	(0.082)	(0.077)	(0.094)	(0.078)	(0.112)	(0.093)
ln(fuel economy)	0.545***	0.534***	0.549***	0.538***	0.532***	0.533***	0.537***	0.536***
	(0.025)	(0.027)	(0.025)	(0.027)	(0.025)	(0.027)	(0.025)	(0.027)
# children	-0.019	0.031	-0.019	0.031	-0.015	0.030	-0.015	0.041
	(0.022)	(0.056)	(0.022)	(0.057)	(0.021)	(0.056)	(0.021)	(0.056)
income	0.067***	0.040	0.068***	0.040	0.071***	0.038	0.074***	0.039
	(0.025)	(0.026)	(0.025)	(0.027)	(0.024)	(0.026)	(0.024)	(0.026)
# employed	0.087***	-0.011	0.087***	-0.009	0.092***	-0.015	0.094***	-0.022
	(0.019)	(0.031)	(0.018)	(0.031)	(0.018)	(0.031)	(0.018)	(0.030)
job change	0.054*	0.033	0.054*	0.030	0.044	0.038	0.035	0.044
	(0.031)	(0.038)	(0.031)	(0.038)	(0.030)	(0.039)	(0.029)	(0.040)
car vacation	0.308***	0.272***	0.309***	0.272***	0.308***	0.273***	0.298***	0.272***
	(0.024)	(0.029)	(0.024)	(0.029)	(0.024)	(0.029)	(0.024)	(0.028)
population density	-0.022	0.155*	-0.022	0.153*	-0.017	0.140*	-0.017	0.135*
	(0.014)	(0.080)	(0.014)	(0.078)	(0.014)	(0.080)	(0.014)	(0.072)
car age	-0.013***	-0.009	-0.013***	-0.010*	-0.014***	-0.008	-0.013***	-0.007
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.006)
hh size	-0.011	-0.013	-0.011	-0.014	-0.016	-0.013	-0.018	-0.002
	(0.021)	(0.043)	(0.021)	(0.043)	(0.020)	(0.044)	(0.020)	(0.043)
education	0.065***	0.009	0.065***	0.009	0.056***	0.012	0.048***	0.001
	(0.019)	(0.036)	(0.019)	(0.036)	(0.019)	(0.037)	(0.018)	(0.036)
rain	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
snow	-0.016	-0.012	-0.024	-0.019	-0.011	-0.012	-0.009	-0.011
	(0.025)	(0.023)	(0.028)	(0.025)	(0.024)	(0.023)	(0.023)	(0.022)
temp min	0.058***	0.058***	0.064***	0.064***	0.052***	0.054***	0.044***	0.051***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
temp max	-0.080***	-0.078***	-0.081***	-0.080***	-0.080***	-0.077***	-0.079***	-0.077***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p_rec	0.062***	-0.004	0.065***	-0.002	0.061***	-0.003	0.072***	-0.006
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.017)	(0.015)
p_max	-0.153***	-0.105***	-0.155***	-0.109***	-0.140***	-0.105***	-0.154***	-0.115***
	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
Constant	3.426***	3.441***	3.673***	3.607***	3.404***	3.577***	3.389***	3.466***
	(0.095)	(0.144)	(0.097)	(0.143)	(0.098)	(0.172)	(0.100)	(0.166)
season fixed effect	yes	yes						
month fixed effects			yes	yes				
time trend					yes	yes		
year fixed effects							yes	yes
Adj. R-squared	0.284	0.258	0.287	0.261	0.287	0.258	0.299	0.261
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.1019	0.0051	0.0952	0.0035	0.0246	0.0051	0.0086	0.0054
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.1453	0.0165	0.2620	0.0470	0.0114	0.0214	0.0030	0.0106
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.9992	0.8292	0.7772	0.5103	0.6916	0.7637	0.5753	0.9671
$H_0 : \alpha_{MPG} = -\alpha_{price\_drop}$	p=0.0001	0.0000	0.0000	0.0000	0.3733	0.0000	0.2606	0.0000

Robust standard errors clustered at the household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Observations: 12,108. Number of Households: 1,552

The first two columns of Table A.3 show the results of 2SLS regression using national level Brent oil prices to instrument for fuel prices. These did not make for good instruments, as seen by the very large standard errors. The second two columns show the results of 2SLS regression using state average fuel prices as calculated from the self-reported prices in the German Mobility Panel. In the fixed effects results found in the last column, magnitudes have not changed much from the original results, but the standard errors have increased to two to three times their original size. This indicates that the state-level prices are also weak instruments. This is probably due to the decomposition of prices; a price maximum at the local level may not be a price maximum at the state level, for example. The fuel economy results are unchanged, however, and there remains a significant difference between the fuel economy elasticity of mileage demand and the fuel price elasticity of mileage demand during periods of decreasing prices.

I considered using frequency weights based on the number of days between fillups to control for the fact that households who refuel more often appear in the dataset more often; however, I feared that they would artificially increase significance of coefficients. Frequency weights, which give insight into what the typical household does on a typical day by treating each day equally, are less compatible with household fixed effects, and are thus not used in this study, although their inclusion make little difference to the OLS results.

In the specification using probability weights, in which the weight is the inverse of the estimated number of times the household refuels in the dataset, the fixed effect price elasticity estimates increase by 0.037 to 0.059. Standard errors increase

Table A.3: Instrumenting for Fuel Prices

	Dependent Variable: ln(Daily KM driven)			
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
price_max	-14.918	-48.627	-0.196	-0.299
	(18.930)	(285.104)	(0.170)	(0.198)
price_rec	23.258	99.233	0.084	-0.252
	(32.078)	(592.465)	(0.259)	(0.292)
price_drop	-1.307	20.167	-0.170	-0.077
	(4.627)	(119.109)	(0.134)	(0.141)
ln(fuel economy)	0.624***	0.760	0.544***	0.533***
	(0.122)	(1.498)	(0.025)	(0.027)
# children	-0.001	1.130	-0.018	0.031
	(0.069)	(6.489)	(0.022)	(0.056)
income	0.067	0.136	0.074***	0.039
	(0.068)	(0.826)	(0.025)	(0.026)
# employed	0.135	-0.140	0.087***	-0.012
	(0.094)	(1.060)	(0.019)	(0.031)
job change	0.109	1.364	0.053*	0.034
	(0.103)	(7.704)	(0.031)	(0.038)
car vacation	0.276***	0.039	0.307***	0.272***
	(0.081)	(1.208)	(0.024)	(0.029)
population density	-0.033	-3.552	-0.022	0.151*
	(0.042)	(22.279)	(0.014)	(0.077)
car age	-0.024**	-0.216	-0.014***	-0.009
	(0.012)	(1.240)	(0.003)	(0.005)
hh size	-0.033	0.436	-0.011	-0.012
	(0.065)	(2.607)	(0.021)	(0.043)
education	0.098	1.239	0.062***	0.013
	(0.081)	(7.505)	(0.019)	(0.037)
rain	-0.005**	-0.019	-0.004***	-0.004***
	(0.002)	(0.088)	(0.001)	(0.000)
snow	-0.070	-0.195	-0.017	-0.012
	(0.054)	(0.817)	(0.026)	(0.023)
temp min	0.082	0.236	0.048***	0.054***
	(0.062)	(1.128)	(0.005)	(0.004)
temp max	-0.085***	-0.107	-0.078***	-0.077***
	(0.024)	(0.235)	(0.003)	(0.003)
p_rec	0.347	0.466	0.066***	-0.004
	(0.479)	(2.948)	(0.018)	(0.016)
p_max	0.630	2.436	-0.157***	-0.099***
	(1.064)	(15.006)	(0.019)	(0.019)
Constant	3.183***	4.556	3.518***	3.481***
	(0.399)	(7.874)	(0.093)	(0.141)
Adj. R-squared			0.280	0.259
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.4957	0.8676	0.4353	0.5867
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.3909	0.8648	0.9067	0.3051
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.4523	0.8662	0.4015	0.8895
$H_0 : \alpha_{MPG} = -\alpha_{price\_drop}$	p=0.8813	0.8622	0.0067	0.0015

Robust standard errors clustered at the household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Observations: 12,108. Number of Households: 1,552

somewhat but significance remains the same or improves in the case of the price maximum variable. The fuel economy elasticity decreases slightly and the hypothesis test results are unchanged. These results are shown in Table A.4. The results are much the same when using the inverse of the liters of fuel purchased as the weight, although the price elasticity estimates increase slightly more, by 0.061 to 0.085. These results may be seen in Table A.5.

Table A.4: Probability Weights Using Estimated Number of Fillups

Dependent Variable: ln(Daily KM driven)	Pooled OLS	Fixed Effects
price_max	-0.427***	-0.299***
	(0.104)	(0.107)
price_rec	-0.423***	-0.328***
	(0.125)	(0.116)
price_drop	-0.253***	-0.107
	(0.087)	(0.075)
ln(fuel economy)	0.526***	0.505***
	(0.022)	(0.022)
# children	-0.032	0.045
	(0.023)	(0.062)
income	0.041	0.037
	(0.026)	(0.028)
# employed	0.103***	-0.004
	(0.019)	(0.034)
job change	0.071**	0.040
	(0.035)	(0.038)
car vacation	0.319***	0.262***
	(0.027)	(0.031)
population density	-0.032**	0.167**
	(0.014)	(0.081)
car age	-0.012***	-0.011**
	(0.003)	(0.005)
hh size	0.004	0.004
	(0.021)	(0.048)
education	0.051***	0.003
	(0.019)	(0.038)
rain	-0.004***	-0.004***
	(0.001)	(0.000)
snow	-0.028	-0.016
	(0.032)	(0.025)
temp min	0.047***	0.046***
	(0.005)	(0.005)
temp max	-0.076***	-0.072***
	(0.003)	(0.003)
p_rec	0.070***	-0.001
	(0.020)	(0.017)
p_max	-0.163***	-0.114***
	(0.019)	(0.017)
Constant	3.555***	3.472***
	(0.089)	(0.152)
Adj. R-squared	0.281	0.245
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.1049	0.0211
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.1016	0.0376
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.9787	0.8061
$H_0 : \alpha_{MPG} = -\alpha_{price\_drop}$	p=0.0029	0.0000

Robust standard errors clustered at the household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Observations: 12,145. Number of Households: 1,549

Table A.5: Probability Weights using Liters Purchased

	Dependent Variable: ln(Daily KM driven)	
	Pooled OLS	Fixed Effects
price_max	-0.452***	-0.347***
	(0.106)	(0.120)
price_rec	-0.304**	-0.350***
	(0.122)	(0.132)
price_drop	-0.160	-0.125
	(0.100)	(0.099)
ln(fuel economy)	0.519***	0.487***
	(0.027)	(0.023)
# children	-0.037	0.035
	(0.024)	(0.059)
income	0.046*	0.028
	(0.025)	(0.029)
# employed	0.105***	-0.018
	(0.021)	(0.034)
job change	0.056*	0.009
	(0.033)	(0.041)
car vacation	0.389***	0.306***
	(0.027)	(0.033)
population density	-0.044***	0.127
	(0.014)	(0.094)
car age	-0.011***	-0.015***
	(0.003)	(0.006)
hh size	0.036*	-0.003
	(0.020)	(0.045)
education	0.051**	0.016
	(0.020)	(0.046)
rain	-0.004***	-0.004***
	(0.001)	(0.001)
snow	-0.046	-0.021
	(0.039)	(0.026)
temp min	0.040***	0.046***
	(0.006)	(0.005)
temp max	-0.072***	-0.072***
	(0.004)	(0.003)
p_rec	0.095***	-0.003
	(0.022)	(0.019)
p_max	-0.173***	-0.123***
	(0.022)	(0.018)
Constant	3.273***	3.409***
	(0.094)	(0.152)
Adj. R-squared	0.275	0.229
$H_0 : \alpha_{price\_rec} = \alpha_{price\_drop}$	p=0.2487	0.0357
$H_0 : \alpha_{price\_max} = \alpha_{price\_drop}$	p=0.0139	0.0221
$H_0 : \alpha_{price\_max} = \alpha_{price\_rec}$	p=0.3084	0.9793
$H_0 : \alpha_{MPG} = -\alpha_{price\_drop}$	p=0.0008	0.0005

Robust standard errors clustered at the household level in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Observations: 12,180. Number of Households: 1,552

Appendix B: Appendix for "Does the Rebound Effect Vary With Income? A Microdata Study"

B.1 Self-Reported Mileage

The Consumer Expenditure Survey periodically gathers self-reported travel information; however, the miles driven as reported by the households are highly noisy, with several nonsensical responses. Table B.1 shows the summary statistics for the self-reported quarterly miles driven compared to the calculated variable that is used for analysis above. In both cases, the miles driven goes to unrealistically high levels, and for this reason the sample is restricted to vehicles which are driven fewer than 12,000 miles per quarter, but the self-reported mileage variable is clearly unreliable given the extreme maximum and the large number of observations (1,539) with an impossible, negative value. The summary statistics for these variables are repeated in Table B.2 using a sample restricted to the observations in which these variables take on values between 100 and 12,000. While this restriction in the sample requires dropping only 4.65% of the observations of the calculated mileage variable, wholly 26.74% of the observation of the self-reported mileage variable are dropped with this restriction. The clear flaws in the self-reported variable lead this paper to focus on the calculated mileage variable.

Table B.1: Summary Statistics for Mileage Variables for All One Vehicle Households

Variable	Observations	Mean	Std Dev	Min	Max
Self-reported quarterly miles driven	35,282	3056.702	33303.7	-1,600,000	1,603,000
Quarterly miles driven calculated from gas expenditure and fuel economy	30,128	3821.609	3130.738	0	69,842.98

Table B.2: Summary Statistics for Mileage Variables Restricted Sample

Variable	Observations	Mean	Std Dev	Min	Max
Self-reported quarterly miles driven	25,846	3120.64	2348.98	101	11961
Quarterly miles driven calculated from gas expenditure and fuel economy	28,728	3602.34	2208.52	102.6389	11995.43

For the sake of comparison, results using the self-reported mileage variable are given in Table B.4, with summary statistics for the estimation sample given in Table B.3. Almost none of the estimates are statistically significant and many show an unrealistic sign.

Table B.3: Summary Statistics for Estimation Sample Using Self-reported Mileage

Variable	Observations	Mean	Std Dev	Min	Max
Quarterly miles driven	7,263	3038.67	2274.31	105	11,500
Fuel economy (miles/gallon)	7,263	23.81	4.65	12	51
Household income before taxes ($)	7,263	29,690.08	27,192.56	3	483,288
National index of price of maintenance	7,263	180.93	11.52	161.23	198.30
Lagged expenditure on maintenance ($hundreds)	5,030	1.25	2.80	0	48
Price of gasoline ($)	7,263	1.36	0.21	0.79	1.93
White household head (dummy)	7,263	0.86	0.35	0	1
Children under the age of 18	7,263	0.26	0.71	0	7
Household in an urban location (dummy)	7,263	0.99	0.11	0	1
Age of household head	7,263	50.93	19.27	16	94
Female household head (dummy)	7,263	0.64	0.48	0	1
Number of household members	7,263	1.26	0.71	1	8
National index of price of new vehicles	7,263	141.42	2.38	136.63	145.40
Highest education of household head (dummies):					
High School	7,263	0.27	0.44	0	1
Some College	7,263	0.32	0.47	0	1
College	7,263	0.22	0.41	0	1
Graduate School	7,263	0.10	0.30	0	1

Table B.4: Results Using Self-Reported Mileage Variable

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	-0.102	-0.073	0.589	-0.103
	(0.063)	(0.056)	(0.719)	(0.728)
ln(income)	0.065***	0.069***	0.273	0.060
	(0.014)	(0.012)	(0.217)	(0.217)
ln(income)×ln(mpg)			-0.067	0.003
			(0.070)	(0.070)
ln(price of gas)	-0.020	0.030	-0.038	0.031
	(0.191)	(0.145)	(0.176)	(0.161)
ln(price of gas lagged)	-0.213	-0.146	-0.170	-0.155
	(0.247)	(0.199)	(0.230)	(0.209)
lagged maintenance expenditure	0.012**		0.013**	
	(0.006)		(0.006)	
maintenance price index		0.000		0.000
		(0.001)		(0.001)
Constant	7.973***	7.822***	5.819**	7.910***
	(0.279)	(0.340)	(2.261)	(2.291)
Pseudo R^2	0.1022	0.1000	0.1023	0.1000
Observations	5,030	7,263	5,030	7,263

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.2 Robustness Checks

As a robustness check, I run the same four specifications adding in five vehicle attributes: a dummy for a sunroof, a dummy for a turbocharged engine, a dummy for a two-door vehicle, a dummy for a convertible, and a dummy for air conditioning. Results are presented in Table B.5. The inclusion of additional attributes increases the estimate of the rebound effect, except in Column (4), in which the estimate decreases very slightly. The same pattern remains in that the rebound effect is much higher when the interaction between income and fuel economy is included and the rebound decreases with income. Gas prices remain the main driver of the mileage decision. The signs on the control variables remain unchanged. Drivers of vehicles with sunroofs and air conditioning drive more, while vehicles with turbocharged engines drive less. Very few vehicles in the sample had turbocharged engines, which may be affecting this estimate.

Another robustness check involves dropping the bottom and top 10% of income. Results are presented in Table B.6. This has little effect on the estimate of the rebound effect. Independent of income, it ranges from 18.3% to 21.1%. Again, the rebound effect appears to decrease with income, although the rebound estimates become insignificant when the interaction is included, indicating that the households in the lowest decile drive the majority of the results in Table 3.5. It is not unprecedented to find an insignificant rebound effect; Goldberg (1998) also found this estimate to be insignificant and concluded that the rebound effect may be zero. It is also possible that this specification is overspecified.

Table B.5: Inclusion of Vehicle Attributes

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.386***	0.326***	1.410**	0.797**
	(0.061)	(0.040)	(0.563)	(0.372)
ln(income)	0.062***	0.069***	0.391**	0.217*
	(0.010)	(0.007)	(0.174)	(0.117)
ln(income)$\times$ ln(mpg)			-0.101*	-0.046
			(0.054)	(0.037)
ln(price of gas)	-0.950***	-0.859***	-0.937***	-0.850***
	(0.130)	(0.089)	(0.120)	(0.090)
ln(price of gas lagged)	0.235	0.423***	0.287	0.414***
	(0.192)	(0.132)	(0.181)	(0.133)
lagged maintenance expenditure	0.017***		0.017***	
	(0.004)		(0.003)	
maintenance price index		0.001		0.001
		(0.001)		(0.001)
Constant	6.259***	6.294***	2.933	4.780***
	(0.249)	(0.239)	(1.833)	(1.211)
Pseudo R^2	0.1172	0.1002	0.1179	0.1003
Observations	5,033	11,490	5,033	11,490

Standard errors clustered at the household level and presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.6: Dropping Top and Bottom 10% of Income

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.211***	0.183***	0.435	0.471
	(0.062)	(0.036)	(1.059)	(0.696)
ln(income)	0.187***	0.195***	0.262	0.285
	(0.021)	(0.013)	(0.334)	(0.218)
ln(income)×ln(mpg)			-0.024	-0.029
			(0.106)	(0.069)
ln(price of gas)	-0.760***	-0.659***	-0.764***	-0.658***
	(0.136)	(0.085)	(0.131)	(0.091)
ln(price of gas lagged)	0.161	0.276**	0.169	0.269**
	(0.194)	(0.117)	(0.197)	(0.124)
lagged maintenance expenditure	0.014***		0.015***	
	(0.004)		(0.003)	
maintenance price index		0.001		0.001
		(0.001)		(0.001)
Constant	5.860***	5.776***	5.145	4.875**
	(0.290)	(0.227)	(3.357)	(2.219)
Pseudo R^2	0.1200	0.1055	0.1200	0.1055
Observations	5,025	11,444	5,025	11,444

Standard errors clustered at the household level and presented in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.7 presents results in which regional fixed effects are added to all specifications. This has very little effect on the estimates, so that they range from 19.1% to 23.5% when the interaction term is not included, to 75.6% to 102.1% for low income households. Again the coefficient on the interaction term is negative. The estimates appear to be robust to the inclusion of regional fixed effects.

Table B.7: Inclusion of Regional Fixed Effects

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.235***	0.191***	1.021**	0.756**
	(0.050)	(0.033)	(0.425)	(0.302)
ln(income)	0.067***	0.075***	0.317**	0.248***
	(0.010)	(0.007)	(0.133)	(0.096)
ln(income×ln(mpg)			-0.079*	-0.055*
			(0.042)	(0.030)
ln(price of gas)	-0.777***	-0.648***	-0.755***	-0.658***
	(0.108)	(0.079)	(0.107)	(0.077)
ln(price of gas lagged)	0.249	0.304***	0.207	0.306***
	(0.165)	(0.107)	(0.163)	(0.110)
lagged maintenance expenditure	0.015***		0.016***	
	(0.003)		(0.003)	
maintenance price index		-0.000		-0.000
		(0.001)		(0.001)
Constant	6.723***	6.960***	4.219***	5.175***
	(0.213)	(0.194)	(1.357)	(0.984)
Pseudo R^2	0.1121	0.0960	0.1125	0.0962
Observations	6,312	14,474	6,312	14,474

Standard errors clustered at the household level and presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, current household expenditure is used in place of income. Results are presented in Table B.8. This results in somewhat higher estimates of the rebound effect, at 26.7% to 27.9% when no interaction is included and 69.6% to 138.3% when the interaction term is included. The interaction is negative, once again indicating that the rebound effect declines with income, though it is insignificant with the standard errors having approximately doubled. Using consumption, the model is slightly better at predicting mileage, as evidenced by the pseudo R^2.

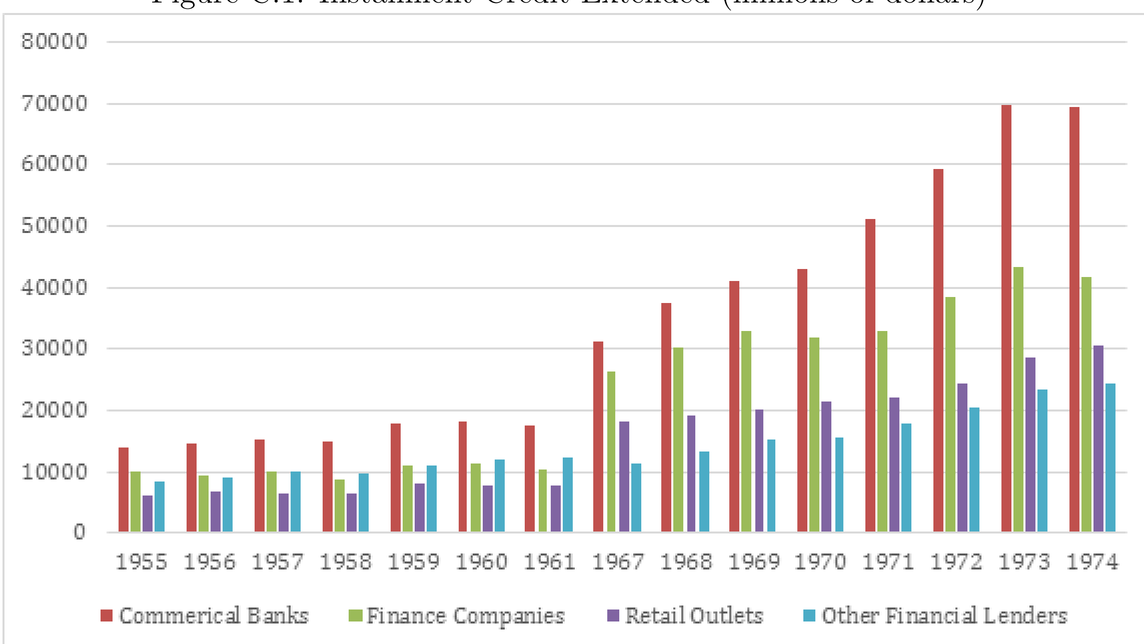
Table B.8: Current Consumption Instead of Income

VARIABLES	(1)	(2)	(3)	(4)
ln(mpg)	0.279***	0.267***	1.383**	0.696
	(0.043)	(0.031)	(0.695)	(0.424)
ln(expenditure)	0.360***	0.326***	0.755***	0.484***
	(0.019)	(0.011)	(0.248)	(0.158)
ln(expenditure)×ln(mpg)			-0.127	-0.050
			(0.080)	(0.050)
ln(price of gas)	-0.868***	-0.793***	-0.867***	-0.793***
	(0.101)	(0.060)	(0.101)	(0.065)
ln(price of gas lagged)	0.264**	0.346***	0.266*	0.345***
	(0.135)	(0.086)	(0.141)	(0.091)
lagged maintenance expenditure	0.009***		0.009***	
	(0.003)		(0.003)	
maintenance price index		0.001		0.001
		(0.001)		(0.001)
Constant	4.636***	4.788***	1.131	3.426**
	(0.211)	(0.181)	(2.171)	(1.353)
Pseudo R^2	0.1428	0.1215	0.1431	0.1215
Observations	7,021	16,331	7,021	16,331

Standard errors clustered at the household level and presented in parentheses
*** p<0.01, ** p<0.05, * p<0.1

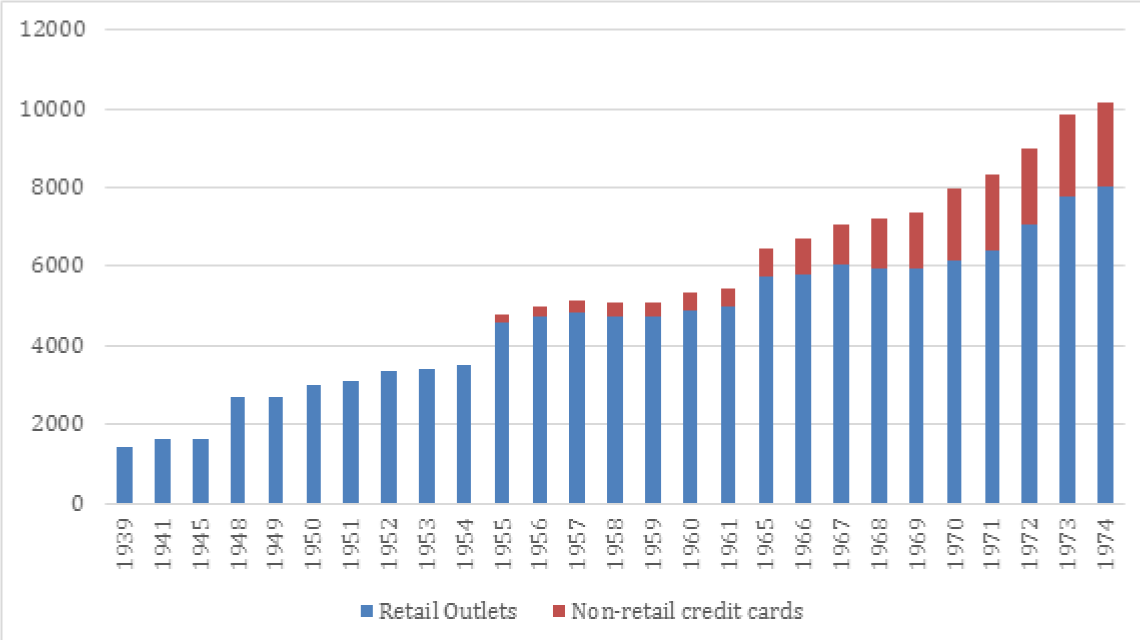
Appendix C: Figures and Tables for "Historical Cost of Consumer Credit, Interest Rate Stickiness and Salience: Evidence from Mail Order Catalogs"

Figure C.1: Installment Credit Extended (millions of dollars)



Source: Federal Reserve Bulletins, August 1962 and December 1975

Figure C.2: Charge Account Credit (millions of dollars)



Source: Federal Reserve Bulletins, August 1962 and December 1975

Table C.1: Retailer Credit Cards in 1975

Retailer	Active Cardholders (millions)	Cards Outstanding (millions)	Charge Volume ($billions)
Sears	21.6	33	7.9
J.C. Penney	10.5		2.7
Montgomery Ward	6.5		2.1

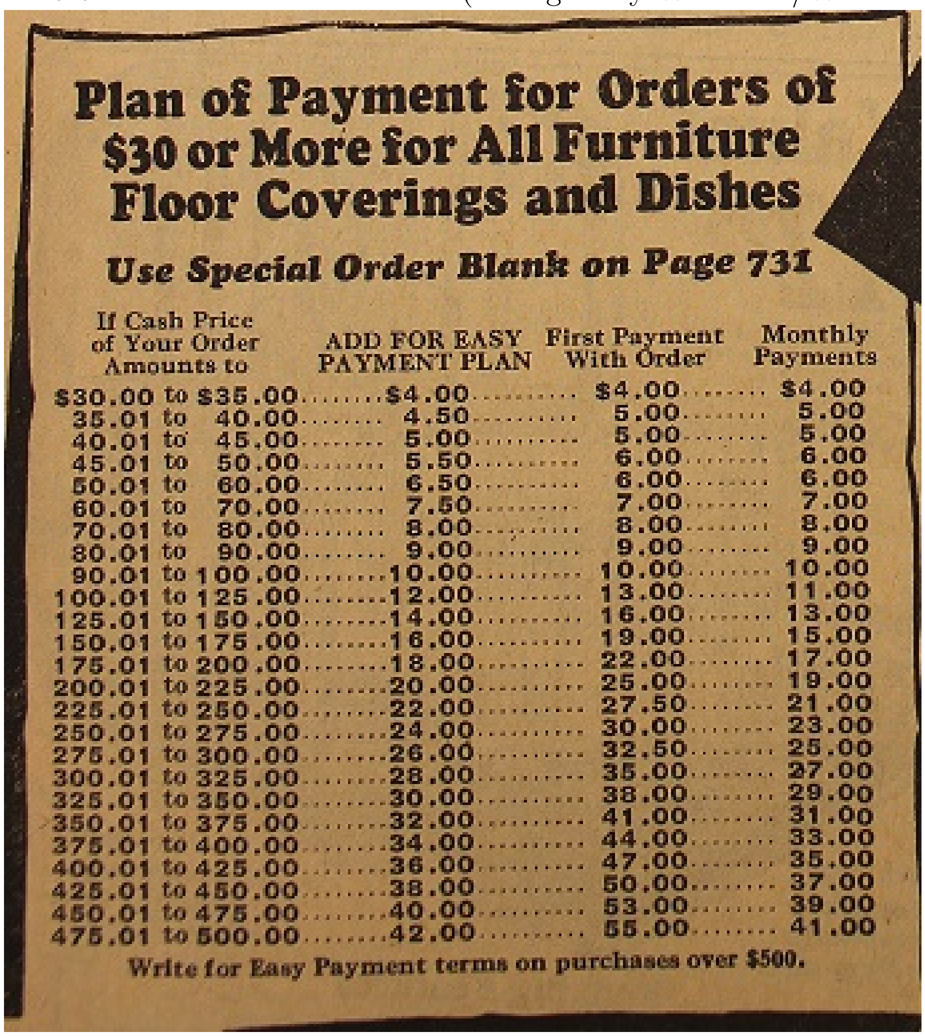
Source: Mandell (1990)

Table C.2: U.S. Households with at Least One Card in 1979

Sears	57%
Visa	53%
MasterCard	47%
J.C. Penney	39%
Montgomery Ward	27%

Source: Mandell (1990)

Figure C.3: Installment Terms Table (Montgomery Ward Fall/Winter 1928)



Plan of Payment for Orders of $30 or More for All Furniture Floor Coverings and Dishes

Use Special Order Blank on Page 731

If Cash Price of Your Order Amounts to	ADD FOR EASY PAYMENT PLAN	First Payment With Order	Monthly Payments
$30.00 to $35.00	$4.00	$4.00	$4.00
35.01 to 40.00	4.50	5.00	5.00
40.01 to 45.00	5.00	5.00	5.00
45.01 to 50.00	5.50	6.00	6.00
50.01 to 60.00	6.50	6.00	6.00
60.01 to 70.00	7.50	7.00	7.00
70.01 to 80.00	8.00	8.00	8.00
80.01 to 90.00	9.00	9.00	9.00
90.01 to 100.00	10.00	10.00	10.00
100.01 to 125.00	12.00	13.00	11.00
125.01 to 150.00	14.00	16.00	13.00
150.01 to 175.00	16.00	19.00	15.00
175.01 to 200.00	18.00	22.00	17.00
200.01 to 225.00	20.00	25.00	19.00
225.01 to 250.00	22.00	27.50	21.00
250.01 to 275.00	24.00	30.00	23.00
275.01 to 300.00	26.00	32.50	25.00
300.01 to 325.00	28.00	35.00	27.00
325.01 to 350.00	30.00	38.00	29.00
350.01 to 375.00	32.00	41.00	31.00
375.01 to 400.00	34.00	44.00	33.00
400.01 to 425.00	36.00	47.00	35.00
425.01 to 450.00	38.00	50.00	37.00
450.01 to 475.00	40.00	53.00	39.00
475.01 to 500.00	42.00	55.00	41.00

Write for Easy Payment terms on purchases over $500.

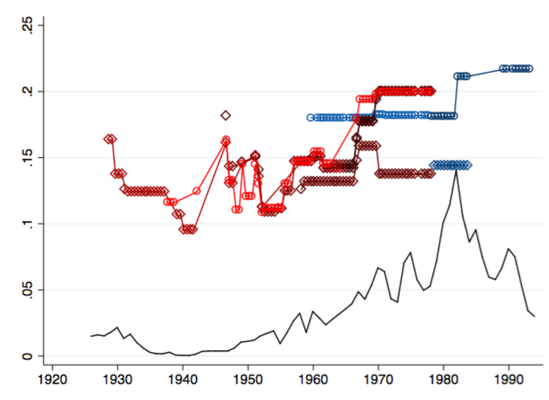
Figure C.4: Revolving Terms Table (Aldens Fall/Winter 1964)

For a Monthly Payment of:	Your Account Balance Can Be:
$ 4	$ 75
5	120
6	145
7	170
8	190
9	215
10	240
11	265
12	290
13	310
14	335
15	360
16	385
17	410
18	430
19	460

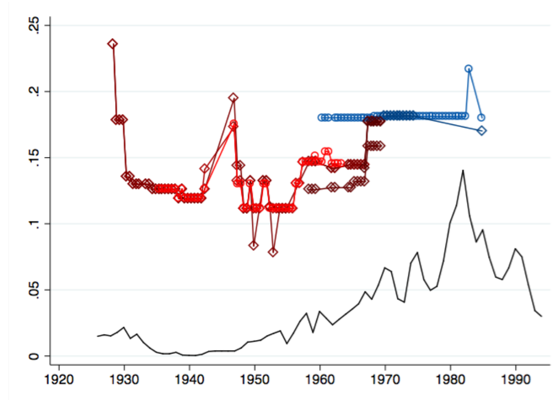
FOR PURCHASES OVER $460, to increase your Credit Reserve Fund, or your special credit problems, write to Aldens: Attention: Mr. Charles Arthur.

SERVICE CHARGE. A small service charge of **1½%** is added to your Account each month based on amount owing as of last statement (minimum charge of **50c**). As your monthly balance decreases, service charge is reduced. No other carrying charges.

Figure C.5: Internal Rate of Return for $300 Purchase



((a)) Sears



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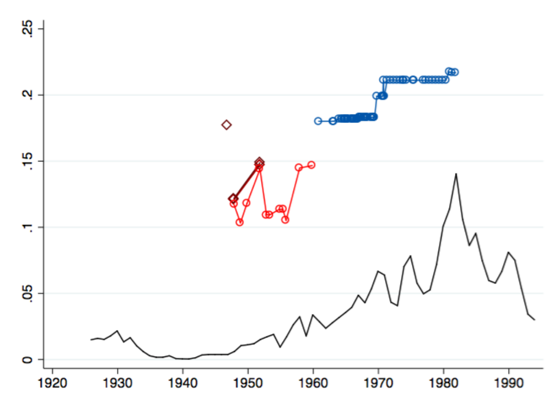

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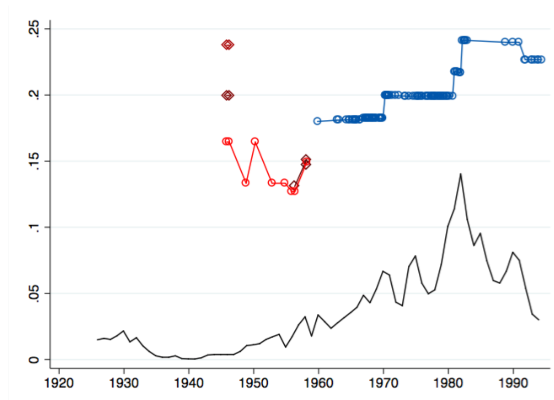

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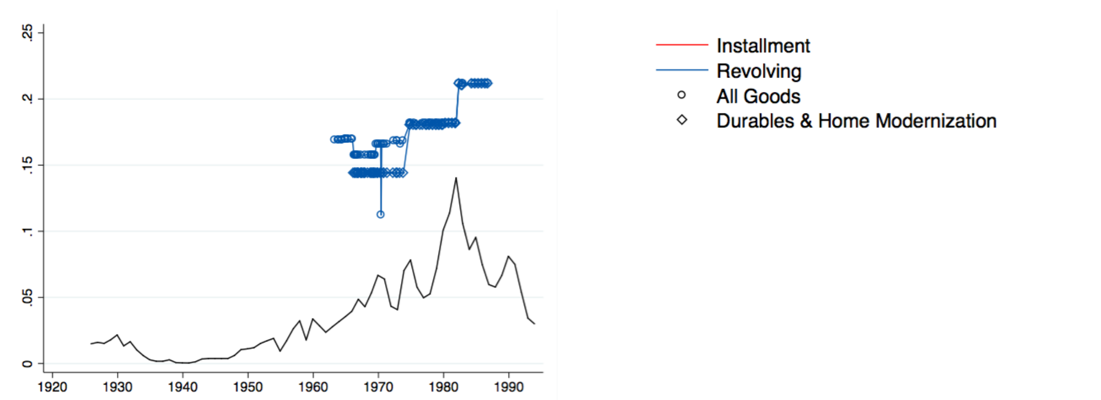
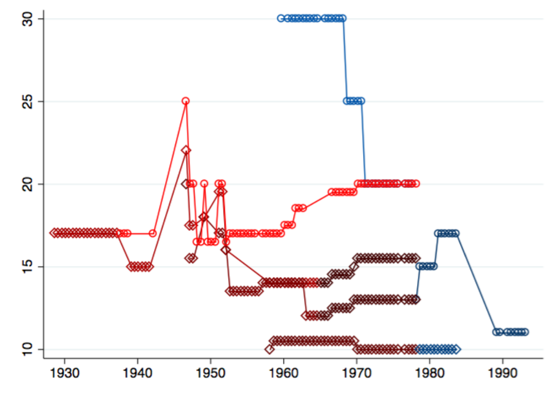


((e)) J.C. Penney

Note: Solid black line represents the rate on a 3-month Treasury bill.

Figure C.6: First Minimum Monthly Payment for $300 Purchase



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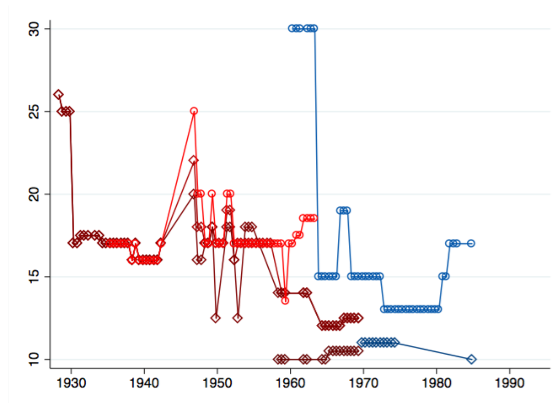

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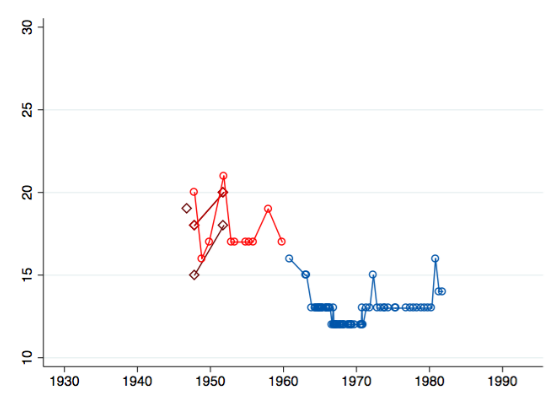

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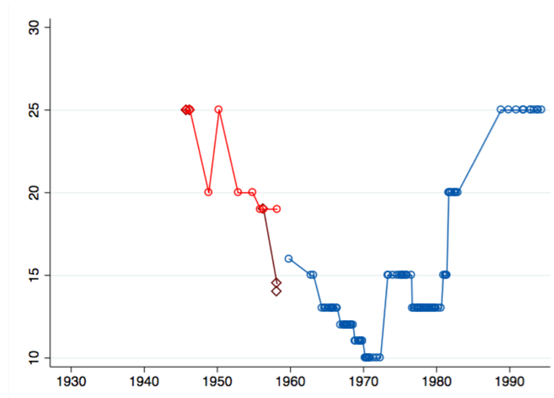

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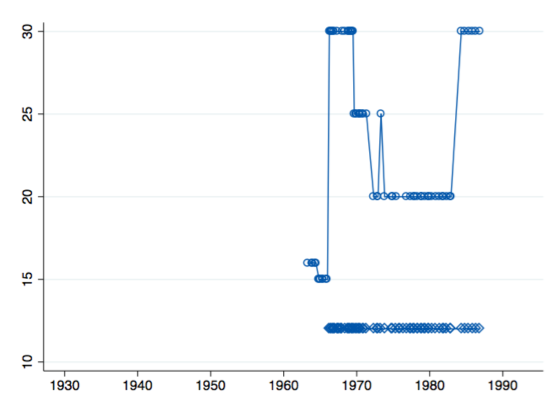


((e)) J.C. Penney

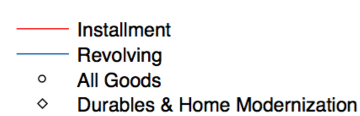
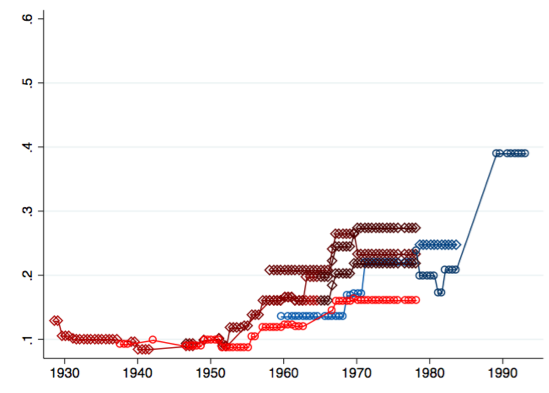
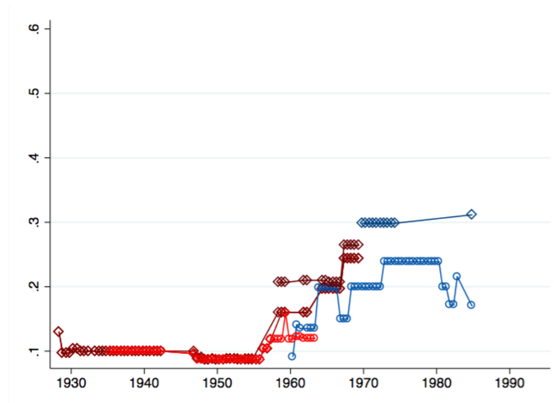


Figure C.7: Interest as a Percentage of Loan Amount for $300 Purchase



((a)) Sears



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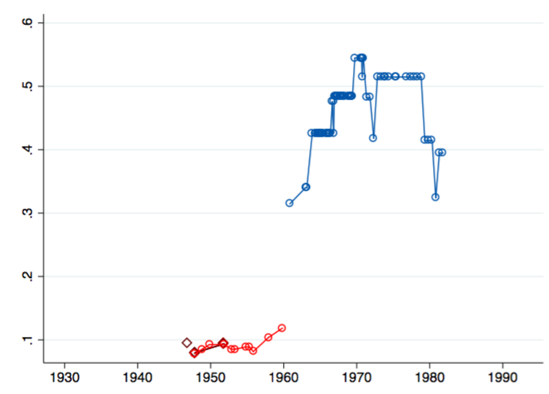

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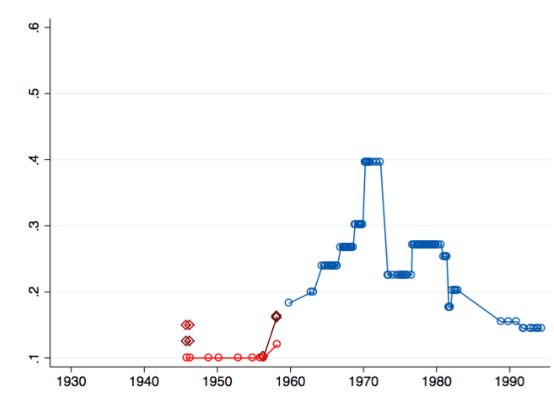
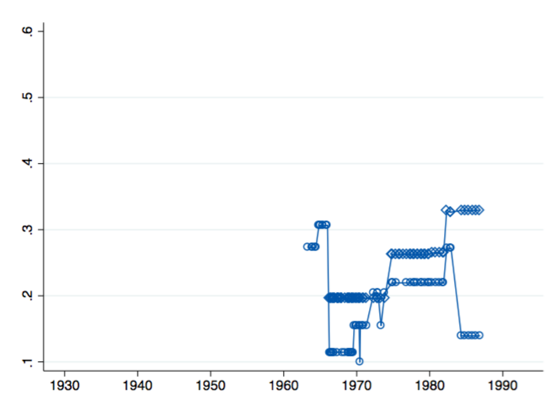


((d)) Spiegel



((e)) J.C. Penney

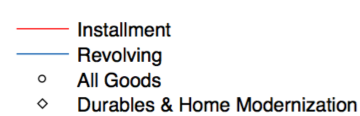
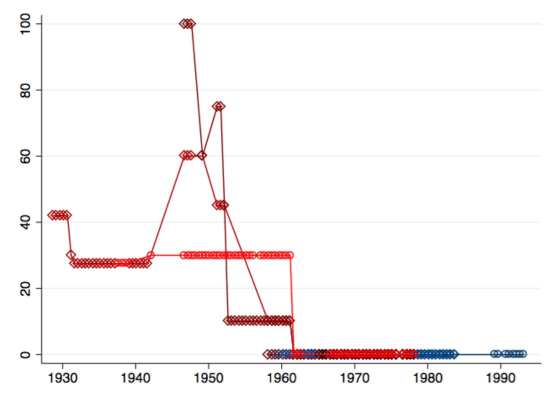


Figure C.8: Down Payment for $300 Purchase



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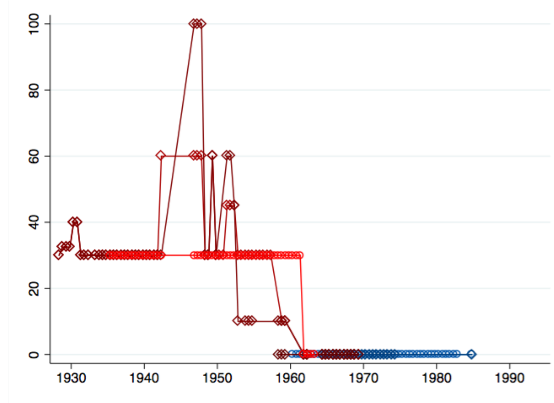

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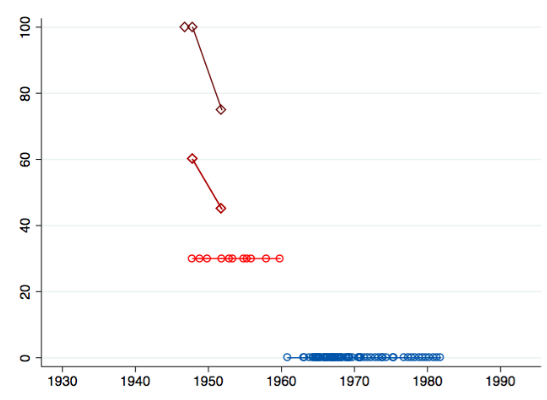

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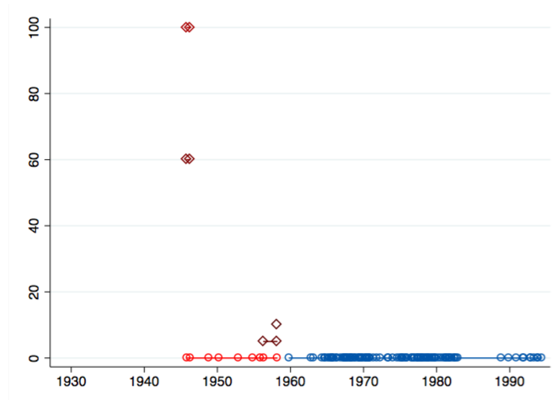

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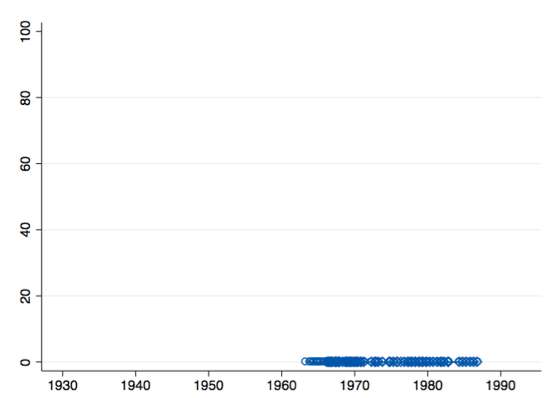

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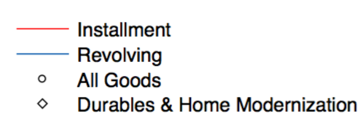
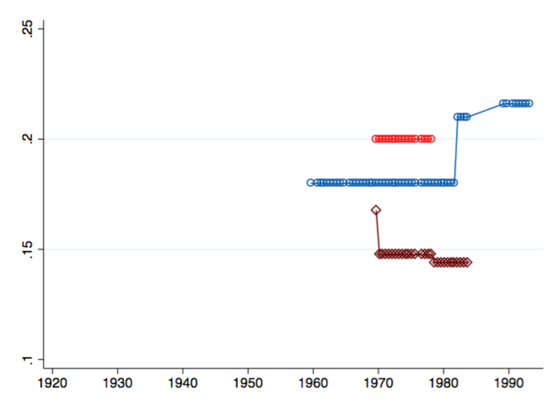


Figure C.9: Annual Percentage Rate for $300 Purchase



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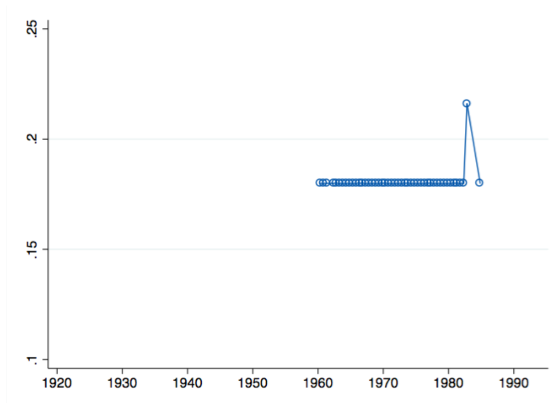

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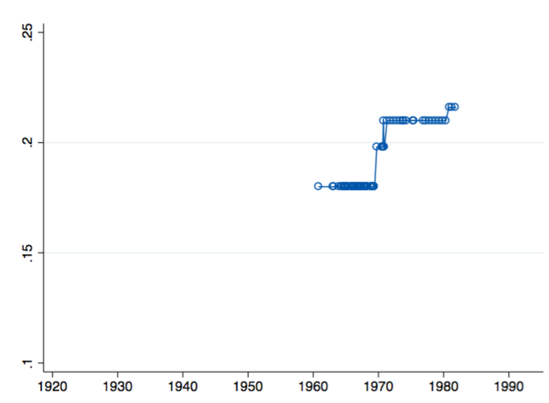

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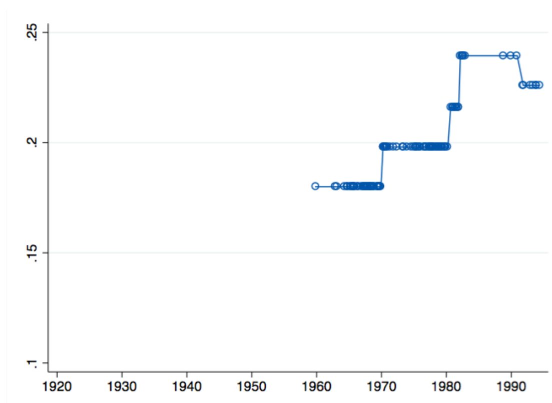

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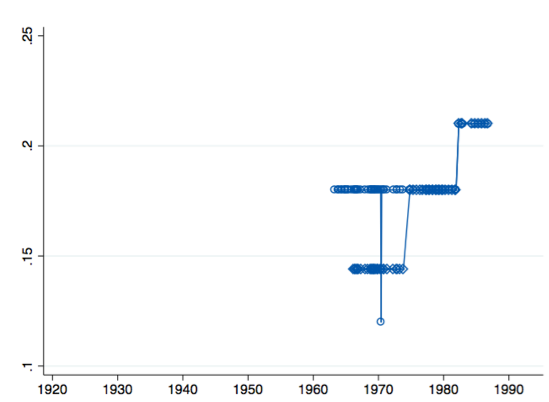

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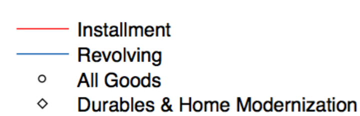

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