Essays On the Impact of Competition Policies in the United States

By

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Abstract

The research topics of my dissertation focus on studying the impact of three competition policies in the United States – used car lemon laws, Apple's alternative iPhone financing policy, and net neutrality rules. The results of my research work in this regard have aimed to contribute to the existing body of knowledge in these areas. I found evidence that, the implementation of the alternative payment plan induced competition in the wireless communication industry and resulted in a reduction in average plan price – the carrier's average revenue per user fell by 5.9%. Also, my results reveal that the absence of net neutrality leads to a decrease in both maximum and average download speeds of 39.5 and 68.14, respectively, and increases average monthly charge by $9.53. A decrease in download speed (quality) contradicts the argument that the absence of net neutrality will incentivize ISPs to increase investment which will intend improve the quality of internet service to the end-users. Lastly, my results affirm the theoretical assertion of warranty provision as a remedy to information asymmetry in a secondary market. I found evidence that warranty provision, by reducing transaction cost, positively influence demand for used cars in the United States.

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Chapter 1

Assessing Apple iPhone Financing Program: A Look at Competition and Price effects in US Wireless Carrier Industry

Abstract

I examine the effects of a new iPhone financing program implemented by Apple as an alternative payment plan for the users of wireless communication services who wish to own an iPhone. The alternative iPhone payment plan offers potential customers the opportunity to purchase an unlocked iPhone which reduces switching cost and facilitates easy mobility between carriers. This induces competition in the wireless communication industry and puts downward pressure on a carrier's average plan price. By estimating a difference-in-difference model using carrier level panel data, I found evidence that, the implementation of the alternative payment plan induced competition in the industry and resulted in a reduction in average plan price. The introduction of this plan reduced carrier's average revenue per user by 5.9%.

Keywords: Alternative payment, wireless, carriers, switching cost, competition, network.

JEL Classification: L0, L1, L5.

1. Introduction

The wireless communication industry has become increasingly important to many households and individuals. Apart from providing communication services, the industry has also served as a source of internet connectivity to many individuals in the US. According to Pew Research Center, about 96 percent of Americans owned cellphones of some kind, and 81 percent of Americans owned smartphones at the end of 2018. Also, in a survey conducted by Pew Research Center in 2019, about 17 percent of Americans relied solely on their smartphones as a source of internet connectivity. Due to the immense importance of the wireless communication industry, government antitrust authorities have tried to keep the industry as competitive as possible. For example, in 2011, the US Department of Justice blocked merger between two of the four largest service providers in the industry - AT&T and T-Mobile.

The US wireless communication industry, as described in Federal Communication Commission (FCC) annual reports from 2013 to 2019, is highly concentrated and saturated. The top five largest carriers - AT&T, Verizon Wireless, T-Mobile, Sprint and US Cellular – control about 98 percent of the industry's total revenue and subscribers. High levels of market concentration may raise concerns that the industry is not competitive, however, this may not necessarily be true as one must consider multiple factors, including investment, innovation, and barriers to entry, to evaluate competition in a market. The FCC, in their reports on the state of competition in the industry, has pointed out subscribers' inability to easily switch between carriers - caused by the presence of huge switching costs - as the main cause of concentration and the resultant lack of competition in the market.

Switching costs, in the wireless telephone industry, can be actual or perceived costs associated with the process of moving from one carrier to another. Examples of these costs include early termination fees for canceling an existing contract, the cost of new cell phone because of lack of compatibility among carriers, and the time and effort needed to inform one's contacts of a new number because of the discontinued use of the old number. These costs are substantial, as Park (2011) estimated that, in addition to early termination fee ($50 - $350), consumers in this industry also face other forms of switching (or hassle) cost ranging from $32 to $140. Park (2011) also assessed the impact of mobile number portability (MNP) on competitive outcome in the industry. The MNP increases competition by reducing switching cost and facilitates easy mobility of customers between carriers.

Similarly, this paper seeks to assess how an iPhone financing or alternative payment plan has contributed to improving competition in the wireless communication industry by reducing switching costs. Specifically, I seek to answer the question: does the reduction in switching cost, through the purchase of an unlocked phone, influence competition and price outcome in the market for wireless telephone communication?

In September 2015, Apple announced a new iPhone financing or alternative payment plan, with zero interest, for its customers. With this plan, customers could buy and make monthly installment payments for their iPhones over a period of 24 months. An important benefit or feature of this payment plan to customers is that they also purchase the phone unlocked which offers them the flexibility of using the same phone with any network of their choice. I exploit this feature in assessing the competitive impact of this payment plan in the wireless communication industry. The ability to purchase an unlocked smartphone by customers has the potential to reduce switching cost in the wireless communication industry and consequently induce competition.

Another feature of the Apple iPhone payment plan requires a customer to have a plan with either AT&T, T-Mobile, Sprint, or Verizon to be eligible. These four carriers form the treatment group for my empirical analysis. Thus, to evaluate the causal impact of the policy, I use a difference-in-difference technique.

The results from my empirical analysis show that there is a negative treatment effect from the new payment plan. That is, the new payment plan led to a reduction in the average plan price in the wireless communication industry, an indication that there is an increase in competition in the industry induced by the new iPhone payment plan. In particular, I find that the introduction of the new payment plan reduced carrier's average plan price by $2.63. All things being equal, the payment plan will increase churn rates for carriers with higher prices. In response to these increased churn rates, carriers will reduce their prices to prevent further loss of customers. Some carriers may even reduce prices to the extent that they will attract additional customers. This appears to be the case among the largest four carriers, AT&T, T-Mobile, Sprint, or Verizon. Thus, I find that the introduction of the new payment plan also caused the market share of the largest four carriers to increase by 0.36 percentage points.

The rest of this paper will proceed as follow: Section 2 will proceed with a literature of previous research work in the area of switching cost and market competition. Section 3 discusses the data used in my estimation and presents a summary description of the dependent and other covariates used. Section 4.1 explains the estimation strategy employed in identifying the treatment effects of the new payment plan. Section 4.2 demonstrates, analytically and graphically, that the required assumption of parallel trend in the outcome variable between the treatment and the control groups before the payment plan was enacted can be reasonably implied. Section 5.1 discusses the results from the estimation of the model, section 5.2 highlights on the robustness of the results, and section 6 concludes the paper.

2. Literature Review

Several theoretical research works have studied and concluded that switching cost impedes competition in the market and keeps prices above competitive level. Klemperer (1995) is one of the early researchers who have studied welfare impact of switching cost in markets. He found evidence that the presence of switching costs in markets increases prices and causes deadweight losses.

Drawing on the limitations of Klemperer’s work, Lam (2017) developed a model useful for generalizing and extending beyond the traditional results in the switching cost and two-sided literature. The model proved that in a dynamic two-sided market, under strong external network effects, the standard U-shaped pricing does not emerge, and that the first period price decreases with switching costs as opposed to the static equilibrium pricing.

Switching costs have also been studied in relation to welfare effects of entry when firms maximize profits. Entry of new firms may affect welfare differently when switching costs are considered, Klemperer (1988), Gehrig, Shy and Stenbacka (2011). In the presence of switching costs, entry may be harmful to welfare and deterring entry will be justifiable. Quan, Ba’rcena-Ruiz and Di’az-Benito (2017) extended Klemperer (1988) to analyze how switching costs affect managerial firms and market structure. They allowed the entrant to be partially foreign-owned and assumed consumers incur switching costs when buying from the entrant and the entrant has to compensate the consumers for those switching costs.

While empirical research papers found evidence that a reduction in or elimination of switching costs would increase consumer welfare and that firms directly benefit from the presence of switching costs, some theoretical papers have argued that consumers can actually benefit from the presence of switching cost. For example, Cullen, Schutz and Shcherbakov (2020), argued that, theoretically, when wireless carriers choose endogenously whether to apply early termination fee (component of switching cost) or not, there exists an equilibrium where carriers benefit without early termination fee, and that forward-looking consumers can benefit from the presence of switching cost.

Empirically, Park (2011) studied and estimated the impact of the introduction of Mobile Number Portability on consumer welfare in US wireless communication industry. By estimating a non-linear least-square model using panel data, he found that the introduction of number portability resulted in increased competition and a fall in the average plan price. The paper argued that the ability of individuals to keep their number after switching carriers will induce switching and promote competition in the industry.

Wei and Zhu (2018) extended the study of the impact of mobile number portability (MNP) to market competition in customer-centric and technology-intensive service industries. They constructed a duopoly model with heterogeneous switching cost which predicts that the market share of the largest firms will shrink after MNP due to increased competition. Using a panel dataset of 218 wireless operators in 52 countries over 6 years, their empirical analysis concluded that, by allowing customer information to be transferable among service providers, MNP may help reduce switching cost and promote competition in the industry.

The extent of the impact of switching cost depends on the presence of network effects (Chen 2016). Network effects, as broadly defined by researchers, exist in a market when the utility to a consumer increases with the number of other consumers, Katz and Shapiro (1985), Farrell and Klemperer (2007). As network effects affect the utility of the users of wireless services, it will have direct influence on the pricing of these services and will also impact on the distribution of users and market share among carriers in the industry. For example, Chen (2016) developed a dynamic duopoly model of price competition to study the effects of switching cost on market outcomes. He concludes that the extent of the impact of switching cost depends on the network effects and the availability of an outside option and that the presence of switching cost generally raises prices by limiting competition.

Also, when historical data on certain platforms like Facebook, Google or Amazon are useful to their users and there is no digital tool for retrieving this data whenever needed it makes switching to other platforms costly. Tucker's (2019) research work studied digital data on these platforms to evaluate whether they decrease concerns about network effects and switching cost. Her analysis led to a conclusion that there are reasons to be optimistic that the processes of digitalization would lead to the weakening of network effects and switching cost.

I will highlight a few research work on the impact of network effects on competition, thus, the extent to which they can limit the impact of policy-induced reduction in switching cost on price. Maicas and Sese (2011) provided an overview of the impact of network effects on wireless communication industry and categorized these network effects into personal and direct network effects. They also emphasized that when network or installed base of users is large, users derive utility from it and their willingness to pay increases. Thus, in the presence of network effects, users will be less willing to switch carriers for a given policy-induced reduction in switching cost. This will result in less induced competition and less price reduction.

In no uncertain terms, some researchers have characterized the IT markets, including the mobile telecommunication, as network markets, Shapiro and Varian (1998), Shervani and Srivastava (2003), Shankar and Bayus (2003), etc.

Network effects, where they exist, play an important role since the base of users create benefits, in the form of reduced uncertainty and transfer of information, for existing and potential users. The higher the network effects to a user, the higher his/her willingness to pay for the good or service. The presence of network effects in the wireless communication industry reduces the full impact of Apple alternative payment plan for an iPhone in the market. Thus, any policy aiming at improving competition in this market must consider the impact of network effects, and the extent to which they can erode the gains from the policy.

3. Data

The data to be used in the estimation of my model outlined in the next section is panel data. This data contains quarterly carrier level variables, including market and external factors that influence demand in the US wireless mobile industry. The main source of the data is Statista and span the period from 2013 to the first quarter of 2017. Data on external variables is sourced from the U.S. Bureau of Labor Statistics. The main dependent variable is average revenue per user (ARPU). ARPU is used as a proxy for price in the industry. Other covariates in the data include the number of subscribers (NSUB), per capita disposable income (PCIncome), and ratio of young people (aged 15-24) in the population (YPOP).

There are eleven individual carriers in the data. Five of these carriers do not have any missing observations. For the other six carriers, each one has at least one missing observation in every variable so omitting missing observations will eliminate these six carriers from my data completely and significantly reduce the sample size. The conventional method of imputation used to replace missing value will not give a good representation of my sample. The method of imputation replaces missing values with either mean or median of that variable.

Given the relatively large sizes of the four main carriers (ATT, T-Mobile, Sprint, and Verizon), the mean or median of any variable may not be representative of any of the other smaller carriers. In this case, replacing a missing value for smaller carrier with the mean for that variable will be misleading. So, I estimate my model with an unbalanced panel. Table 1 below is the summary statistics of the variables used in my empirical analysis. The sample size for all variables is 187. Given $TREG_i$ as the treatment group indicator - (ATT, T-Mobile, Sprint, and Verizon), and $TREG_i$ as the post-treatment period indicator – September 2015 and beyond, AP represents the interaction ($TREG_i * TREP_t$) of two dummy variables. The mean value of 0.13 for AP means about 13 percent of the observations occurred both in September 2015 and beyond and for carriers in the treatment group.

Table1: Summary Statistics

Variable	No. of Obs	Mean	Sd	Min	Max
ARPU	187	47.56	7.23	11.13	60.92
AP	187	0.13	0.34	0	1
PCIncome	187	42016	1677.12	39143	44438
YPOP	187	0.12	0.00	0.11	0.12
MKTSHARE	187	19.08	12.74	1	35.40
GRateARPU	159	-0.01	0.09	-0.74	0.36

Source: Statista and U.S. Bureau of Labor Statistics

4.1. Theory and Estimation Strategy

Theoretically, when it becomes less costly for customers to switch between firms, it puts pressure on firms to offer cheap and affordable services to their existing customers. Wireless carriers that charge relatively high prices for their plans, all other things being equal, will lose customers to their competitors.

When a customer, who is locked in a long-term contract, of a particular wireless carrier is considering switching, he or she is faced with switching cost associated with either early termination fee, losing existing number and/or losing the use of a locked phone they have already made partial payment on. This switching cost, to some extent, will discourage customers from switching. This denies them the benefits associated with having varieties to select from. Also, wireless carriers can take advantage of customers' inability to switch and charge higher prices. Thus, Apple's alternative payment plan for an iPhone, which offered customers the opportunity to purchase unlocked smartphones, will facilitate switching between carriers by reducing switching cost and thereby signal to wireless carriers that their existing customers could easily switch carriers if they charge relatively higher prices. Also, with more people buying directly from Apple, wireless carriers will not need to charge an early termination fee since this fee is to a large extent dependent on a customer buying a discounted phone.

On the other hand, since mobile phone and wireless services are complements, if Apple's financing program is very appealing and leads to an increase in the number of new and first-time mobile phone owners, it could lead to increased demand for wireless communication service. Increase in demand for wireless services, for a given supply or capacity, will cause average price for plans to rise. So, the overall impact of this program depends on relative decrease in price, due to increase in competition because of the decrease in switching cost, and the increase in price due to relative increase in demand for wireless services. My expectation is that the former will outweigh the latter, thus, the program will lead to a decrease in average plan price and therefore increase consumer surplus and welfare in the industry. This is because, as indicated in FCC 2019 annual report on competition in the industry, the industry has experienced massive investment in innovation and technology in recent years. With improved technology and innovation, supply is relatively elastic, and that is the basis of my expectation.

To estimate the competitive effects of Apple's iPhone financing program on average plan price, I will estimate a difference-in-difference model. One key requirement to qualify for iPhone financed by Apple is that a customer must have a plan with any of these four eligible wireless carriers, T-Mobile USA, AT&T, Verizon, and Sprint. These eligible carriers define my treatment group. The program was launched in September 2015. So, the treatment period of interest is September 2015 and beyond. My dependent variable (plan price) is the *ARPU*. I also controlled for other covariates that could influence variations in *ARPU*.

The mathematical form of the model estimated is:

$$Y_{it} = \alpha_i + \delta Q_t + \rho W_i + \beta X_{it} + \gamma TREG_i * TREP_t + \varepsilon_{it}$$

Where ARPU is individual *i* carrier's average revenue per user at time *t*, X is a set of other control variables. $TREG_i$ is a dummy for being in the treated group and $TREP_t$ is a dummy for quarters after treatment went into effect (September 2015 and beyond).

$TREG_i * TREP_t$ would take a value equal to 1 if an observation occurred within the treatment period and for an individual within the treatment group and 0 otherwise. α, and β are set of parameters to be estimated. Q_t and W_i are quarter and carrier dummies which account for time and carrier fixed effects, respectively. The parameter of interest in my estimation is γ because it captures the treatment effect. While my expectation is that it takes on a negative sign, because of the increase in competition induced by lower switching cost, it could also take a positive sign because the financing program could lead to an increase in the number of first-time smartphone owners that would result in an increased demand for wireless services and, thus, cause ARPU to rise.

The variables in the set X_{it} include per capita disposable income (*PCIncome*) and the ratio of young people (aged 15-24) in the population (*YPOP*). I expect a positive coefficient for *PCIncome*. An increase in per capita income in the economy will result in higher demand for wireless services and holding other things constant will result in *ARPU* or plan price. Younger people tend to use more wireless service as they spend more time on social media to keep contact with their social network. As a result, an increase in the ratio of young people in the population will increase demand for wireless services and cause average plan prices to increase. So, I expect a positive coefficient for *YPOP*.

4.2. Parallel Trend Assumption

In this section, I seek to explain and demonstrate that the critical assumption of parallel trend can be applied: that the pre-policy intervention trends in the outcome variable are the same between the treated and the control groups. This assumption requires that in the absence of the policy (alternative payment plan), the difference in the outcome variable is constant between the group that is affected by policy (treatment group) and the group that is not (control group). Failure to reasonably meet this assumption will result in biased estimates from applying the difference-in-difference method. Table 2 test this assumption by using F-test.

The null hypothesis is that pre-policy difference in the outcome variable (ARPU) is constant between treatment and control groups. In carrying out the F-test, I estimated two simple linear models. The first is the overall model, which uses ARPU as dependent variable. Independent variables include the interaction of the treatment group indicator ($TREG_i$) with the pre-treatment and post-treatment periods indicators. The second model also uses ARPU as dependent variable but with only the interaction of treatment group indicator ($TREG_i$) and post-treatment period indicator as independent variable. Both models controlled for seasonality. The mathematical representation is as follows:

$$ARPU_{it} = \alpha_i + \pi TREG_i * POST_t + \mu TREG_i * TREP_t + \varepsilon_{it}$$

Eq.1

$$ARPU_{it} = \alpha_i + \tau TREG_i * POST_t + + \varepsilon_{it}$$

Eq.2

The two models are then compared using Analysis of Variance or ANOVA. This leads to the results in table 2 below. The p-values in the parentheses suggest that we do not reject the null hypothesis, and thus, parallel trend can be assumed.

Table 2: F-test for parallel trend

ARPU	log(ARPU)	ARPU	log(ARPU)
0.391	0.351	1.026	1.049
(0.947)	(0.963)	(0.426)	(0.409)
Carrier and time effects		Time fixed effects	

** p-values for the F-statistics are in the parentheses

Note: These are the test statistics of the hypothesis that prior to the implementation of the iPhone payment plan by Apple average revenue per user for treatment and control carriers move together

Figure 1:

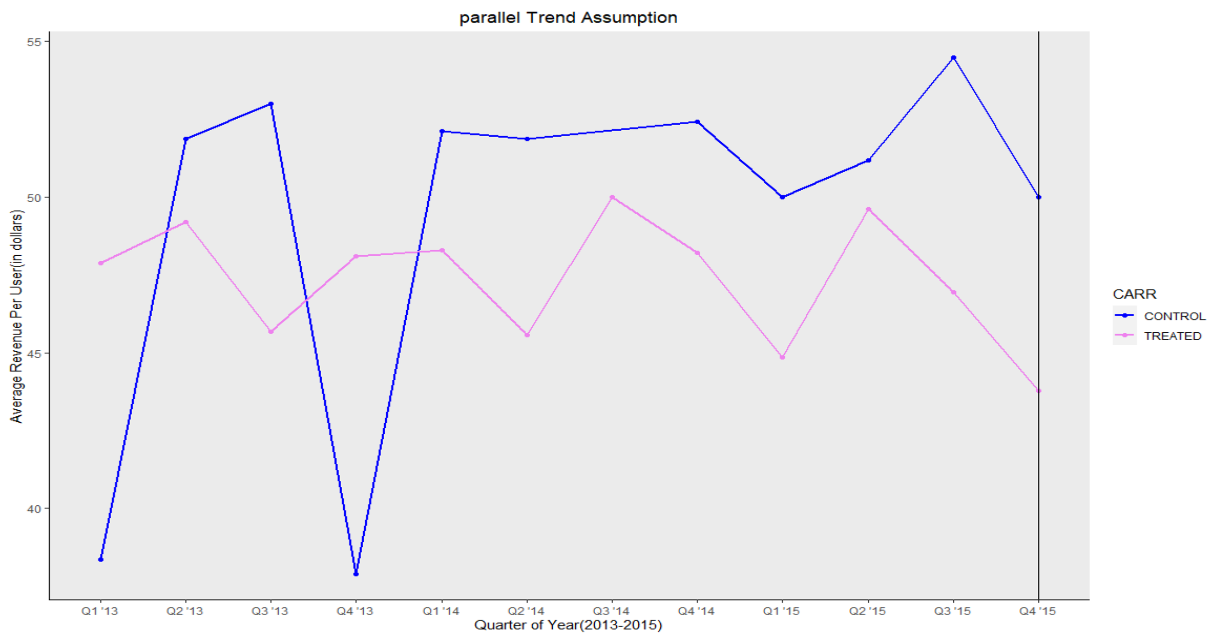
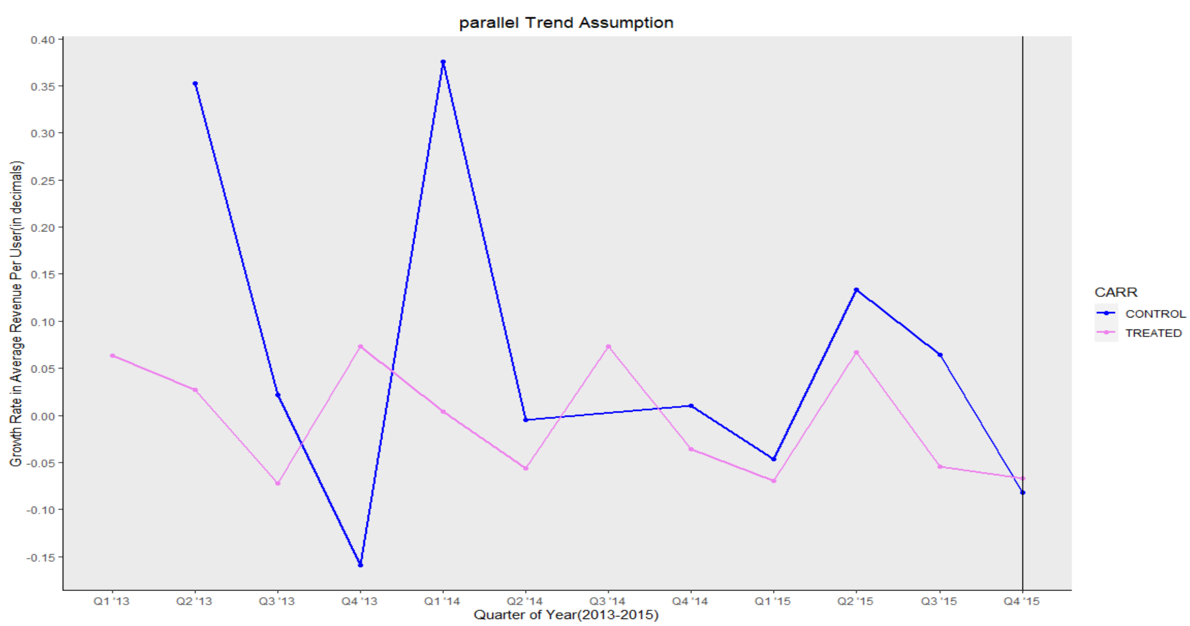


Figure 2:



In figure 1, I used the actual ARPU for treatment and control groups. In figure 2, I computed the quarterly growth rates. Both graphs suggest that ARPU for carriers in the treatment and control groups were moving together before the new iPhone payment plan was enacted in 2015.

Both the F-tests from table 2 and the graphical examination of the outcome variable for the carriers suggest that I can reasonably make the parallel trend assumption as a requirement for estimating a difference-in-difference model.

5.1. Results and Discussion

In Table 3, I conduct a preliminary analysis of the treatment effects of the payment policy on the outcome variable (ARPU). I computed ARPU for each quarter for the two groups (treated and control). Then, for each group, I computed average ARPU for pre-policy and post-policy periods. Applying the concept of difference-in-difference, I arrived at a statistically significant reduction in ARPU by $2.833

Table 3: Preliminary analysis of treatment effects

	Treatment Group	Control Group	Treatment Effect
Pre	48.526	48.780	
Post	45.661	48.748	
			-2.833
Diff	-2.865	-0.032	(0.000)

Note: figure in parenthesis is p-value for treatment effects

.

In Table 4, I compare the market shares of carriers in the treatment and control groups between the pre- and post-policy periods. The post-policy average market share of carriers in the treatment group increased by 0.36 percentage point while the post-policy average market share of carriers in the control group decreased by 0.53 percentage point.

Table 4: Post-Policy Market Share Changes

	Treatment Group	Control Group
Pre	24.36	1.580
Post	24.72	1.05
	0.36	-0.53
Diff	(0.000)	(0.000)

Note: figures in parentheses are p-values

In Tables 5 and 6, *AP* is the variable that captures the treatment effect of the new iPhone payment plan. The tables differ by time-trend and quarter-year fixed effects. In table 5, I estimated a difference-in-difference model with two other control variables, while in table 6 I did not control for other variables. The results in these tables shown negative treatment effects of about -2.63 in the model specifications with ARPU as dependent variable. This represents a post-policy induced fall in average revenue per user by $2.63. This effect is statistically significant at 10 percent significance level.

Differences in carrier specific (as shown by carrier dummies) attributes have significant contribution to the differences in carriers' ARPU. Some carriers have positive carrier-fixed effects relative to AT&T while others have negative carrier-fixed effects. For example, relative to AT&T, Verizon's average ARPU is $5.37 higher, and $0.11 higher for log (ARPU) as a dependent variable. Also, US Cellular's average ARPU is about \$7.5 higher relative to AT&T while Sprint's average ARPU is \$3.20 lower relative to AT&T's average ARPU.

The US wireless communication industry is highly concentrated with AT&T being the second largest carrier. A possible explanation for the positive or negative sign for carrier-fixed effects relative to AT&T is due to the way *ARPU*, a proxy for plan price, is computed. ARPU is total revenue from wireless telephone services divided by the total number of subscribers. AT&T may charge higher plan prices than carriers that have positive carrier-fixed effects and still be able to retain their subscribers or even attract new subscribers due to network effects. This implies that the carrier may have increases in their total revenue because of higher prices being charged, but if there is corresponding more than proportionate increases in the number of subscribers due the positive network effects, the result will be lower *ARPU* compared to other carriers. This is likely the case in this situation. Alternative explanation could be that AT&T increased market share by charging lower competitive plan prices that resulted in lower average ARPU relative to other carriers.

The coefficient for *YPOP* is positive as expected and statistically significant at 5 percent significance level. An increase in the ratio of young people by one percentage point, all things being equal, will increase average revenue per user by \$2.98. Also, a dollar increase in per capita income (PIncome) will cause *ARPU* to increase by \$0.98.

Specification 4 in tables 5 and 6 represents results for alternative model specifications. In this specification, I used growth rates in average revenue per user as dependent variable. The negative treatment effect in specification (4) further confirms that a policy-induced reduction in switching cost will increase competition and cause average plan price to fall.

Table 5: Results from Diff-in-Diff

Variable	(1) ARPU	(2) ARPU	(3) log(ARPU)	(4) GRateAR
Intercept	47.341***	46.446***	3.833***	0.019
	(1.203)	(1.125)	(0.023)	(0.016)
AP	-2.543*	-2.310*	-0.050*	-0.020
	(1.134)	(1.092)	(0.002)	(0.017)
PCIncome		0.976	0.021	0.007
		(1.050)	(0.022)	(0.012)
YPOP		2.982**	0.061**	0.009
		(0.976)	(0.020)	(0.011)
Carrier fixed effects:				
	-0.823	-3.509	-0.073	0.084***
CinBell	(2.571)	(2.327)	(0.048)	(0.025)
Clearwire	-33.710***	-38.983***	-1.491***	0.016
	(3.702)	(3.589)	(0.074)	(0.037)
Leapwire	1.254	-5.781	-0.117	-0.012
	(4.435)	(4.438)	(0.091)	(0.051)
MPC	-1.971	-10.317	-0.221	0.029
	(6.172)	(5.993)	(0.123)	(0.065)
Ntelos	8.646	0.535	0.011	-0.009
	(6.732)	(6.402)	(0.132)	(0.081)
Shentel	7.923	-0.004	-0.001	0.109
	(8.081)	(7.663)	(0.158)	(0.096)
SPRIN	4.403	-6.714	-0.145	0.035
	(9.248)	(8.969)	(0.185)	(0.111)
TMOB	9.693	-3.012	-0.064	0.031
	(10.543)	(10.229)	(0.211)	(0.127)
Uscell	17.306	3.068	0.049	0.028
	(11.861)	(11.468)	(0.236)	(0.142)
VER	16.238	0.357	0.002	0.041
	(13.139)	(12.755)	(0.263)	(0.158)
Time-Trend	-0.064	-0.030	0.001	-0.000
	(0.077)	(0.075)	(0.002)	(0.000)
R-Squared	0.73	0.80	0.91	0.35
Number of observations	187	187	187	159

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

Table 6: Results from Diff-in-Diff

Variable	(1) ARPU	(2) ARPU	(3) log(ARPU)	(4) GRateAR
Intercept	46.445***	47.658***	3.855***	0.0.15
	(1.058)	(1.667)	(0.034)	(0.023)
AP	-2.634*	-2.716*	-0.060	-0.019
	(1.145)	(1.695)	(0.034)	(0.021)
Carrier fixed effects:				
CinBell	-1.936	-3.920	-0.079	0.078***
	(2.240)	(2.132)	(0.044)	(0.020)
Clearwire	-35.554***	-36.569***	-1.440***	0.003
	(3.023)	(3.023)	(0.060)	(0.020)
Leapwire	-1.969	-3.671	-0.072	-0.031
	(2.240)	(2.141)	(0.044)	(0.020)
MPC	-5.485	-6.698	-0.143	0.003
	(4.164)	(3.996)	(0.082)	(0.020)
Ntelos	3.233	2.514	0.055	-0.041*
	(1.671)	(1.667)	(0.034)	(0.020)
Shentel	1.360	2.961	0.064	0.071***
	(1.671)	(1.667)	(0.031)	(0.020)
SPRIN	-3.203*	-3.203*	-0.068**	-0.010
	(1.372)	(1.246)	(0.026)	(0.020)
TMOB	1.001	1.001	0.023	-0.021
	(1.372)	(1.246)	(0.026)	(0.020)
Uscell	7.506***	7.486***	0.146***	0.030
	(1.398)	(1.308)	(0.027)	(0.020)
VER	5.373***	5.373***	0.112***	-0.025
	(1.372)	(1.246)	(0.026)	(0.020)
Quarter-Year Effects:				
Q2_13		0.293	0.007	0.002
		(1.941)	(0.040)	(0.025)
Q3_13		1.803	0.041	0.019
		(2.059)	(0.042)	(0.025)
Q4_13		1.316	0.031	-0.006
		(2.059)	(0.179)	(0.025)
Q1_14		1.371	0.029	-0.000
		(2.042)	(0.042)	(0.025)
Q2_14		0.947	0.020	-0.001
		(2.042)	(0.042)	(0.025)
Q3_14		1.037	0.022	0.005
		(2.042)	(0.042)	(0.025)
Q4_14		1.185	0.026	0.007
		(2.042)	(0.042)	(0.025)
Q1_15		0.403	0.013	0.009
		(2.321)	(0.048)	(0.026)
Q2_15		-0.149	0.003	0.002
		(2.321)	(0.048)	(0.026)
Q3_15		-1.356	-0.022	-0.009
		(2.321)	(0.048)	(0.026)
Q4_15		-1.966	-0.036	0.004
		(2.321)	(0.048)	(0.026)
Q1_16		-3.004	-0.056	0.017
		(2.035)	(0.042)	(0.025)
Q2_16		-3.079	-0.057	-0.005
		(2.099)	(0.043)	(0.025)
Q3_16		-3.874	-0.074	-0.010
		(2.099)	(0.043)	(0.025)
Q4_16		-4.367*	-0.084	-0.006
		(2.099)	(0.043)	(0.025)
Q1_17		-5.026*	-0.099	-0.009
		(2.099)	(0.043)	(0.025)
R-Squared	0.73	0.80	0.91	0.36
Number of observations	187	187	187	159

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

5.2. Robustness

The results from my estimations have been tested to be valid and consistent. I have estimated different specifications of difference-in-difference model. I used ARPU and log(ARPU) as dependent variables. In all these specifications, the coefficient estimates shown to be consistent in both signs and absolute values. There are no huge variations in the estimates.

Additionally, in tables 7 and 8, I split the treatment effects into four for each of the carriers in the treatment group. The results are largely consistent with the estimates in tables 5 and 6 and confirm that the estimates from the model are robust. Apart from Sprint, the model produced negative treatment for all the other three carriers. This means that they responded to the policy by reducing plan price. AT&T had the largest and statistically significant treatment effect of -$7.50. This is because AT&T has a large customer base, and for it to be able to prevent customers from switching, it will have to reduce average plan price by a greater amount than the rest of the carriers. The results in tables 7 and 8 also account for heterogeneity in response to the new payment plan. For example, the incentive to keep a larger customer base and to benefit from network effects will cause larger carriers to lower their prices in response to the new payment plan. This is supported by the relatively large negative treatment effect of about -$7.50 from AT&T.

Table 7: Results - Robustness

Variable	(1) ARPU	(2) ARPU	(3) log(ARPU)	(4) GRateAR
Treatment Effects:				
	48.563***	47.667***	3.862***	0.025
Intercept	(1.257)	(1.151)	(0.023)	(0.018)
	-0.657	-0.434	-0.005	-0.017
POST_VER	(2.209)	(1.964)	(0.040)	(0.033)
	-7.735***	-7.501***	-0.170***	-0.043
POST_ATT	(2.209)	(1.964)	(0.040)	(0.033)
	0.400	0.633	0.014	-0.005
POST_SPRIN	(2.209)	(1.964)	(0.040)	(0.033)
	-2.181	-1.948	-0.040	-0.017
POST_TMOB	(2.209)	(1.964)	(0.040)	(0.033)
Controlled Variables:				
		0.976	0.021.	0.007
PCIncome		(1.011)	(0.021)	(0.012)
		2.983**	0.061**	0.009
YPOP		(0.940)	(0.019)	(0.011)
Carrier fixed effects:				
	-2.045	-4.731*	-0.101*	0.078**
CinBell	(2.549)	(2.275)	(0.046)	(0.026)
	-			
	34.931***	-40.204***	-1.519***	0.010
Clearwire	(3.640)	(3.478)	(0.071)	(0.038)
	0.032	-7.003	-0.145	-0.017
Leapwire	(4.351)	(4.293)	(0.087)	(0.051)
	-3.193	-11.539*	-0.249*	0.023
MPC	(6.040)	(5.785)	(0.118)	(0.066)
	7.425	-0.686	-0.017	-0.015
Ntelos	(6.585)	(6.178)	(0.126)	(0.081)
	6.702	-1.226	-0.029	0.104
Shentel	(7.899)	(7.391)	(0.150)	(0.097)
	2.489	-8.628	-0.188	0.026
SPRIN	(9.055)	(8.662)	(0.176)	(0.113)
	8.386	-4.319	-0.094	0.025
TMOB	(10.314)	(9.873)	(0.201)	(0.128)
	16.084	1.846	0.021	0.023
Uscell	(11.583)	(11.053)	(0.225)	(0.143)
	14.573	-1.308	-0.037	0.034
VER	(12.843)	(12.302)	(0.250)	(0.160)
	-0.064	0.030	0.001	-0.000
Time-trend	(0.075)	(0.072)	(0.001)	(0.000)
R-Squared	0.75	0.80	0.92	0.35
Number of observations	187	187	187	159

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respective

Table 8: Results - Robustness

Variable	(1) ARPU	(2) log(ARPU)	(3) GRateAR
Treatment Effects:			
Intercept	48.879***	3.883***	0.020
	(1.655)	(0.034)	(0.024)
POST_VER	-0.830	-0.015	-0.015
	(2.378)	(0.048)	(0.036)
POST_ATT	-7.907**	-0.179***	-0.041
	(2.378)	(0.048)	(0.035)
POST_SPRIN	0.228	0.005	-0.003
	(2.378)	(0.048)	(0.035)
POST_TMOB	-2.353	-0.050	-0.016
	(2.378)	(0.048)	(0.035)
Carrier fixed effects:			
CinBell	-5.141*	-0.107*	-0.072***
	(2.092)	(0.042)	(0.022)
Clearwire	-37.790***	-1.468***	-0.002
	(2.824)	(0.057)	(0.022)
Leapwire	-4.892*	-0.100*	-0.036
	(2.100)	(0.043)	(0.022)
MPC	-7.919*	-0.171*	-0.002
	(3.867)	(0.079)	(0.022)
Ntelos	1.292	0.027	-0.047*
	(1.655)	(0.034)	(0.022)
Shentel	1.740	0.036	-0.065**
	(1.655)	(0.034)	(0.022)
SPRIN	-5.117***	-5.111***	-0.019
	(1.371)	(0.028)	(0.023)
TMOB	-0.306	-0.006	-0.027
	(1.371)	(0.028)	(0.023)
Uscell	6.265***	0.118***	-0.035
	(1.323)	(0.027)	(0.022)
VER	3.708**	0.073*	-0.031
	(1.371)	(0.028)	(0.023)
Quarter-Year Effects:			
Q2_13	0.293	0.007	0.002
	(1.868)	(0.038)	(0.025)
Q3_13	1.803	0.041	0.020
	(1.982)	(0.040)	(0.025)
Q4_13	1.316	0.031	-0.006
	(1.982)	(0.040)	(0.025)
Q1_14	1.371	0.029	-0.000
	(1.966)	(0.040)	(0.025)
Q2_14	0.945	0.020	-0.001
	(1.966)	(0.040)	(0.025)
Q3_14	1.037	0.022	0.005
	(1.966)	(0.040)	(0.025)
Q4_14	1.185	0.026	0.008
	(1.966)	(0.040)	(0.025)
Q1_15	0.403	0.013	0.009
	(2.234)	(0.045)	(0.026)
Q2_15	-0.149	0.003	0.002
	(2.234)	(0.045)	(0.026)
Q3_15	-1.356	-0.022	-0.009
	(2.234)	(0.045)	(0.026)
Q4_15	-1.966	-0.036	0.004
	(2.234)	(0.045)	(0.026)
Q1_16	-3.004	-0.056	0.017
	(1.958)	(0.040)	(0.025)
Q2_16	-3.079	-0.057	-0.005
	(2.020)	(0.041)	(0.025)
Q3_16	-3.874	-0.074	-0.010
	(2.020)	(0.041)	(0.025)
Q4_16	-4.367*	-0.084*	-0.006
	(2.020)	(0.041)	(0.025)
Q1_17	-5.026*	-0.099*	-0.009
	(2.020)	(0.041)	(0.025)
R-Squared	0.83	0.92	0.36
Number of observations	187	187	159

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

6. Conclusion

Wireless service providers, through the sale of locked phones, increase switching cost and create exiting barriers to their existing customers from switching to other providers. This has the potential of limiting competition in the industry and leads to higher average plan price. With higher than competitive prices, consumer surplus is lower. Consumers are also worse off if their ability to choose from large variety of providers is limited by a purchase of a locked phone. Several policies, including Mobile Number Portability in 2003, aimed at reducing switching cost, have been implemented in the industry to increase competition and drive plan price down. The competitive impacts of this policy have been studied by Park (2011).

In this paper, I have added to the body of existing knowledge by empirically examining the competitive and price effect of Apple's iPhone financing policy that incentivizes consumers of smartphones to buy and own unlocked phones. Buying an unlocked smartphone facilitates easy switching between wireless carriers, increases competition and puts downward pressure on the average plan price. With a decrease in average plan price, consumer welfare, as measured by consumer surplus, will increase. The policy has resulted in a reduction in a carrier's average revenue per user by $2.63, an indication that the policy caused average plan price to fall.

Additionally, the results reveal that AT&T may be able to charge higher plan prices than carriers that have positive carrier-fixed effects and still be able to retain their subscribers or even attract new subscribers due to network effects.

While number portability policy is a consumer protection policy, deliberately implemented to influence outcomes in the wireless service industry, Apple's iPhone financing policy is a marketing policy implemented by a private firm in one industry (smartphone) which may have spillover effects on market outcome in a related industry (wireless telephone service). Thus, the findings from this paper have further shed light on how these markets are related.

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Chapter 2

The Effect of Net Neutrality Rules on the Cost of Internet Service to Consumers: A Case Study of Net Neutrality Rules in the United States.

Abstract

In this paper, I apply difference-in-difference approach to estimate the competitive effects of net neutrality rules on market outcomes in the internet service industry. In 2015, net neutrality was enforced in all fifty states in the United States. In June 2018, net neutrality was terminated in all but ten states. I exploit this exogenous variation to estimate its effects on average price and quality of internet service in the industry. The results of my estimation reveal that the absence of net neutrality results in a decrease in both maximum and average download speeds of 39.5 and 68.14 megabytes per second, respectively. Also, average monthly charge increases by $9.53. A decrease in download speed (quality) contradicts the argument that the absence of net neutrality will incentivize ISPs to increase investment which will in turn improve the quality of internet service to the end-users.

Keywords: Net Neutrality, Internet Service Provider, prioritization, download speed, investment.

JEL Classification: L0, L1, L5

1. Introduction

Up until 2015, the internet service industry, comprising of Internet Service Providers (ISPs), end-users (businesses and household) and content providers (Google, Netflix, Facebook, etc), was classified under Title I. This exempted the industry from being regulated by the Federal Communications Commission (FCC) – the regulatory body responsible for the regulation of communication industry. The industry, being free from regulation, has both positive and negative consequences, and the debate over whether it should be regulated raises the question of whether ISPs should be able to charge different prices depending on the consumer.

The debate over net neutrality in the United States has been contentious and dates several years back until April 2015, when the FCC made a move that seek to enforce net neutrality rules in the internet service industry. In April 2015, the court ruled in favor of the FCC allowing internet services to be classified under Title II of the communications act of 1934. Title II service providers, unlike Title I service providers, are rigorously subjected to regulation and specific standards. Thus, reclassification of internet services under Title II gave the FCC the authorization to implement and enforce net neutrality rules. Net neutrality rules forbid internet service providers (ISPs) from discriminating by charging differential prices based on user or content. Also, net neutrality rules mandate internet service providers to provide disclosure on blocking, paid prioritization, congestion management, and security rules. Additionally, the ISPs must provide explanation for slowing down or speeding up specific data.

The FCC, in 2015, argued that, by creating a fair level ground for all businesses, net neutrality will help new and small businesses to survive. Thus, net neutrality will facilitate growth in the number of new and small businesses and increase employment. One another hand, the opponents of net neutrality rules based their argument on the anticipated negative effects on innovation and incentives to invest by internet service providers. Their argument is that the internet service providers can only optimize and recover the cost of research and development if they are allowed to charge varying prices based on content and users. Providers are incentivized to increase investment and drive innovation if they can charge higher prices to big content firms and to users who are willing and able to pay extra for high-speed internet. Thus, the enforcement of net neutrality rules will drive down investment in the industry, and consequently, the quality of internet services will deteriorate in the future.

The existing literature on net neutrality has largely focused on its impact on investment. While the enforcement of net neutrality rules may disincentivize ISPs from increasing investment, it may also affect the average price of internet service for all end users. This is because, theoretically, the profit maximizing firm will choose the level of investment, price, and quality to maximize profit. While, theoretically, it is expected that an increase in investment will increase quality, and consequently, cause price to rise since consumers must pay the higher prices for higher quality, the existence of market power for each ISP makes it feasible to charge lower prices for higher quality service at even a constant or higher fixed cost.

An ISP facing a downward sloping demand curve can, in order to maximize profit, choose an optimal price or number of subscribers. The downward sloping demand curve implies a trade-off between price and subscribers. In choosing a price, an ISP is implicitly choosing the number of subscribers if they know the shape of their demand curve. Therefore, with net neutrality, to increase revenue in equilibrium to cover for investment cost, ISPs, facing a downward sloping demand curve, can either increase prices or increase their subscriber base. A unilateral increase in price by an ISP will decrease its number of subscribers, and for a relatively elastic demand, the impact of which on revenue may outweigh the impact of the increase in price.

The research questions of interest are whether net neutrality rules caused households to pay high prices for internet service and what effects does net neutrality have on the quality of internet service. In order to answer these two, but, related questions, I exploit the exogenous variation created when several states (control states) issued executive orders and subsequently passed regulation, following the end of net neutrality in the United States in May 2018, to continue to enforce net neutrality rules in their states. Using this source of exogenous variation, I estimate the impact of net neutrality on the market outcomes – price and quality - using a difference-in-difference approach. Since net neutrality rules were enforced in all the fifty states in 2015 and then switched off in all but nine states, I treat the states that switched off net neutrality rules as treatment states in my estimation strategy and treat those that continued to enforce net neutrality as the control states.

The results from the estimation of difference-in-difference model reveal that the absence of net neutrality results in an increase in the number of providers, and a decrease in both maximum and average downloads of 39.5 and 68.14 megabytes per second, respectively. Also, average monthly charge increases by $9.53, and average charge per MB decreases by $0.04 as a result of switching away from net neutrality rules. A decrease in download speed (quality) contradicts the argument that the absence of net neutrality will incentivize ISPs to increase investment which will in turn improve the quality of internet service to the end-users.

The rest of the paper is outlined as follow: Section 2 will proceed with a literature review of previous research work on net neutrality and market competition. Section 3 discusses the data used and presents a summary description. Section 4.1 explains the estimation strategy employed in identifying the treatment effects of net neutrality rules. Section 4.2 presents a graphical demonstration of the required assumption of parallel trend in the outcome variable between the treatment and the control groups before net neutrality rules were discontinued in some states. Section 5 discusses the results from the estimation, and lastly, section 6 concludes the paper.

2. Literature

In the twenty-first century, promoting free and easy flow of information, which will lead to the promotion of competition and innovation among existing firms while creating an equal level ground for new businesses to survive, has become a key policy focus for most countries.

Many countries, including the United States, have approached this goal by imposing net neutrality rules against the outcry that these regulatory rules may in the long run have anti-competitive effects in the industry. The argument against net neutrality in the US has been centered around its effects investment in the industry. It has been argued that net neutrality will disincentivize ISPs from increasing investment which will, consequently, affect the quality of internet service in the future. Based on argument, the FCC reviewed several empirical research works on the effects of net neutrality rules on investment after it was passed in 2015.

While some of these empirical studies - Brake (2017), Singer (2017), Turner (2017), etc - found evidence that net neutrality did not have negative effects on investment and innovation, others - Ford (2017a), Ford (2018), Hooton (2017), etc - found that the enforcement of net neutrality in the United States caused a decline in investments by ISPs. The conclusion of the FCC review was in favor of work that found evidence of decline in investment by ISPs. Consequently, in May 2018, net neutrality was reversed.

Some theoretical researchers have also studied net neutrality rules from the perspective of anti-trust and price differentiation. For example, Choi and Kim (2010), Reggiani and Valletti (2016) and Krämer and Wiewiorra (2012) focus on net neutrality as it prevents the ISPs from offering differentiated access qualities to content providers, and how net neutrality affects investment incentives of ISPs.

Lee and Wu (2009), Economides and Tag (2012) on another hand studied net neutrality as a zero-pricing rule and its implications on investment incentives of internet service providers. Net neutrality, as zero-pricing rule, prevents ISPs from charging content providers for accessing final consumers. Economides and Tag (2012), by studying the implications of net neutrality as zero-pricing rule in a two-sided market, concluded that, theoretically, net neutrality leads to lower prices for content providers and higher prices for end users. Other researchers, such as Musacchio et al. (2009) and D'Annunizio and Russo (2015) have studied net neutrality as a zero-pricing rule, and the conclusions have been similar.

In summary, the literature on the effects of net neutrality rules have been largely theoretical. The few empirical research papers have focused on the impact on investment of ISPs. This paper seeks to add to the existing literature by looking at the effects on price and quality of internet service.

3. Data

The data used in estimating the model is sourced from the Federal Communication Commission (FCC) and covers the period from 2014 to 2020. The dataset is state-level panel data and include variables such as number of providers in each census block, maximum download per time, average download per minute, average monthly charge for internet service access, and average charge per MB. For number of providers, maximum download, and average download per minute, the FCC requires all facilities-based broadband providers to file data with the commission twice in a year – June and December - (form 477) on where they do or can offer internet access services at speeds exceeding 200kbps. For other variables such as average monthly charge, and average charge per MB, the data is collected once in a year. Thus, there are thirteen and seven periods for the two groups of variables, resulting in 650 and 350 number of observations, respectively.

The following states continued enforcing net neutrality rules after it was terminated in May 2018: Colorado, Hawaii, Maine, Montana, New Jersey, New York, Oregon, Rhode Island, Vermont, and Washington. Thus, observations for internet service providers (ISPs) in these states constitute the control group. Observations for all other states constitute the treatment group. Treatment is the switching-off of net neutrality rules. In May 2018, net neutrality in the United States came to an end when the Senate voted to overrule its enforcement in 2015. Therefore, the treatment period is from May 2018 to 2019. Pre-treatment period is from April 2015 to May 2018. Table 1 below contains the summary statistics of the outcome variables used in estimating the model – difference-in-difference. On average, the average monthly charge for broadband subscription, within the sample period – 2014-2020, is about $92.65, while the while the charge per MB is about $0.96. Also, on average, the average and maximum download speeds are 375.19 and 443.73 per minute, respectively.

Table1: Summary Statistics

Variable	No. of Obs	Mean	Sd	Min	Max
NumProviders	650	1.14	0.27	0.30	1.86
MaxDL	650	443.73	289.48	10.46	2224.32
AveDL	650	375.19	245.67	9.95	1356.13
Av_Monthly_Charge	350	92.65	20.47	49.99	184.99
Av_Charge_perMB	350	0.96	0.52	0.10	2.80

Source: Federal Communication Commission (FCC)

4.1. Estimation Strategy

The estimation strategy of this paper draws insight from some of the propositions and key points in Economides and Tag (2012). One of the propositions of this paper states that, under a reasonable model of household (end-user) behavior, the welfare evaluation of net neutrality compared to any other system (tiering, or prioritization schema) can be reduced to an assessment of which system will permit the greatest flow of content. A key outcome variable relevant to this proposition is maximum or average household download per time. For net neutrality to be welfare superior to any system that allows prioritization or discrimination, net neutrality should result in an increase in maximum or average household download – a measure of the flow of content. Other key points from this reference paper include:

1. Each ISP has some market power for its differentiated internet service. That is, the market for internet service is oligopolistic. The fewer the number of ISPs the greater the market power to each ISP.
2. With each ISP facing a downward sloping demand curve for their internet service, the ISP has incentives to reduce price in equilibrium for a given set of parameter

values. The intuition is that in monopoly, consumers benefit from lower subscription price since ISP has incentives to attract more consumers to generate extra revenue. If lowering price would increase profits, they will do that until it won't increase profit anymore.

The relevance of these keys points to this paper is that it makes it possible, theoretically, for ISPs to continue to choose a profit-maximizing price based on the demand curve of the end users even after net neutrality rules are enforced.

I expect net neutrality rules to result in a decrease in the number of providers because ISPs are the main opponents to net neutrality rules, and if they are at liberty to withdraw their services in states that continue enforcing net neutrality, they will do so. Consequently, a decrease in the number of providers (a decrease in competition) will result in higher prices. Also, an increase in average or maximum download (quality) is consistent with an increase in price since, theoretically, superior quality must be paid for in the form of higher prices.

Another argument is that net neutrality is expected to increase competition for existing ISPs. This is because, without the ability to price-discriminate, an existing ISP has two ways of increasing revenue to recover their investment cost – increase price for existing subscribers or increase the number of subscribers. Since an ISP faces the possibility of subscribers switching to other competitors (that may outweigh gains from increase in price) if they increase their price unilaterally, it could reduce their profits. Thus, the remaining ISPs will compete to increase their customer base by reducing prices or increasing quality. A superior strategy will be to increase quality at a reduced price.

Given the above possibilities, this paper applies difference-in-difference estimation strategy to panel data to identify the impact of net neutrality rules on internet service market outcomes - maximum or average household download, number of providers (ISPs), average monthly charge, and average charge per MB. Mathematically, the difference-in-difference estimation strategy is presented as follows:

$$Y_{it} = \alpha_i + \gamma D_T + \delta(Treat_i * Post_t) + \varepsilon_{it}$$

Where Y_{it} is the outcome variable(s) (Number of Providers, Maximum Download, Average Download, Average Monthly Charge, or Average Charge Per MB), α is constant term and captures unobserved state level heterogeneity. D_T is a vector of time dummies, (June and December of each year from 2014 – 2020 for number of providers and download speed outcome variables, and yearly dummies from 2014-2020 for price/average charge variables). The coefficient, δ, of the interaction term, $Treat_i * Post_t$, is effect of treatment. The variable Post is 0 for pre-treatment period and 1 for post-treatment period. Treat = 0 for an individual state in a control group, and Treat = 1 for an individual state in treatment group.

Note, in this estimation, the treatment is the switching-off of net neutrality after it was overruled in May 2018. Thus, all states, apart from the ten states that continue to enforce net neutrality, constitute treatment group in the estimation strategy. The ten states that continued to enforce net neutrality rules will constitute control group.

4.2. Parallel Trend Assumption

This section focuses on graphically demonstrating the assumption of parallel trend. The parallel trend assumption states that the pre-policy intervention trends in the outcome variable are the same between the treated and the control groups. This assumption requires that in the absence of net neutrality rules, the difference in the outcome variable(s) is constant between the states that are affected by the change to net neutrality rules (treatment states) and the states that are not (control states). The figures below reasonably show that the parallel trend assumption can be made. From figure 1, we can see that there is a constant trend in the average charge per MB for the treated and control groups up until YR_2018 – when the net neutrality rules were terminated in the treatment states. This parallel trend is also seen all the other figures – figures 2-5.

Figure 1: Comparison of Average Price per MB

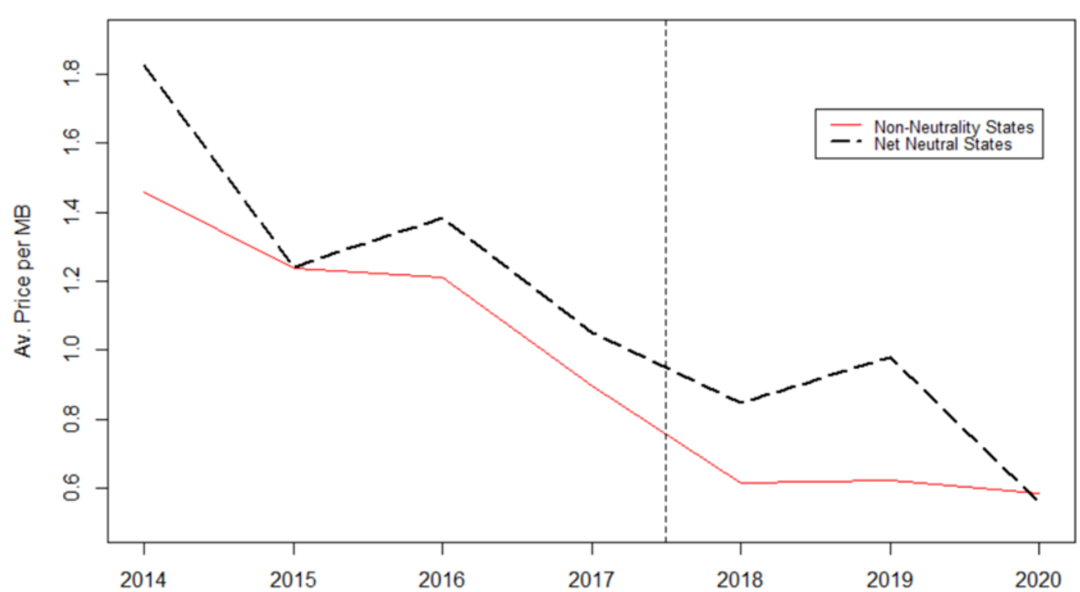


Figure 2: Comparison of Average Monthly Price ($)

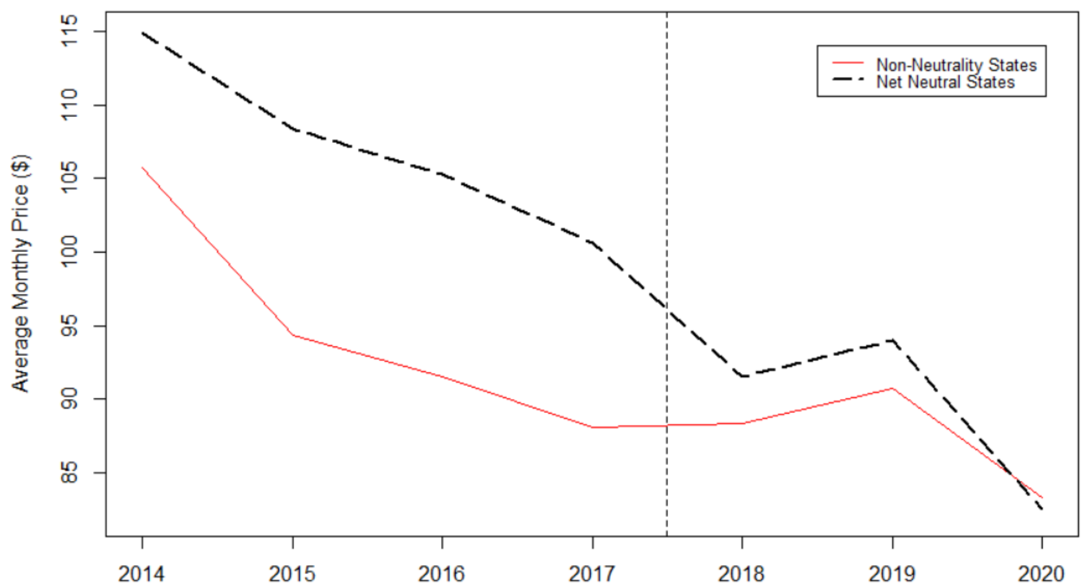


Figure 3: Comparison of Total Providers per Block Group

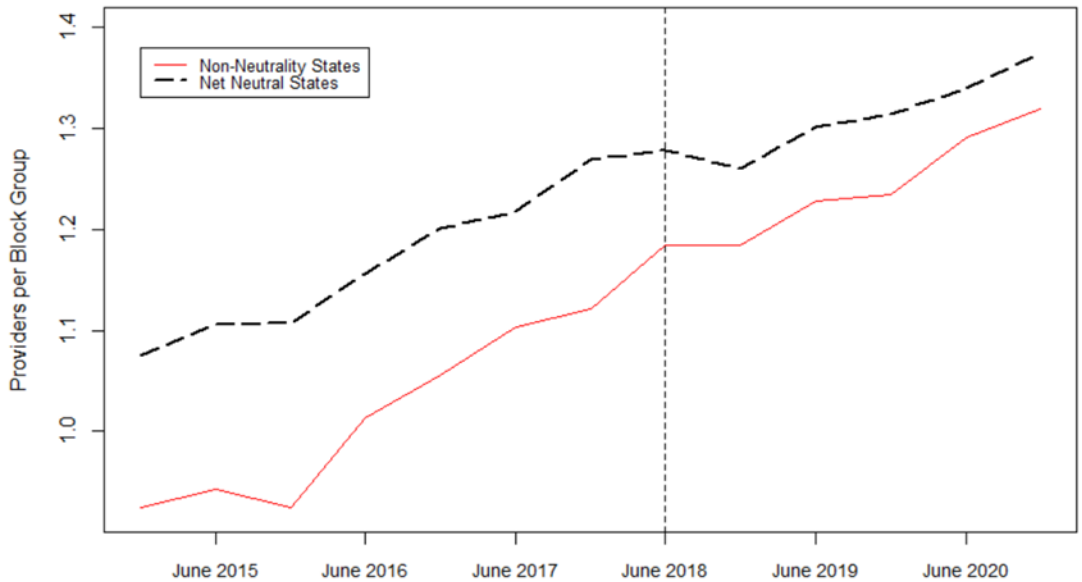


Figure 4: Comparison of Maximum Available Download Speed

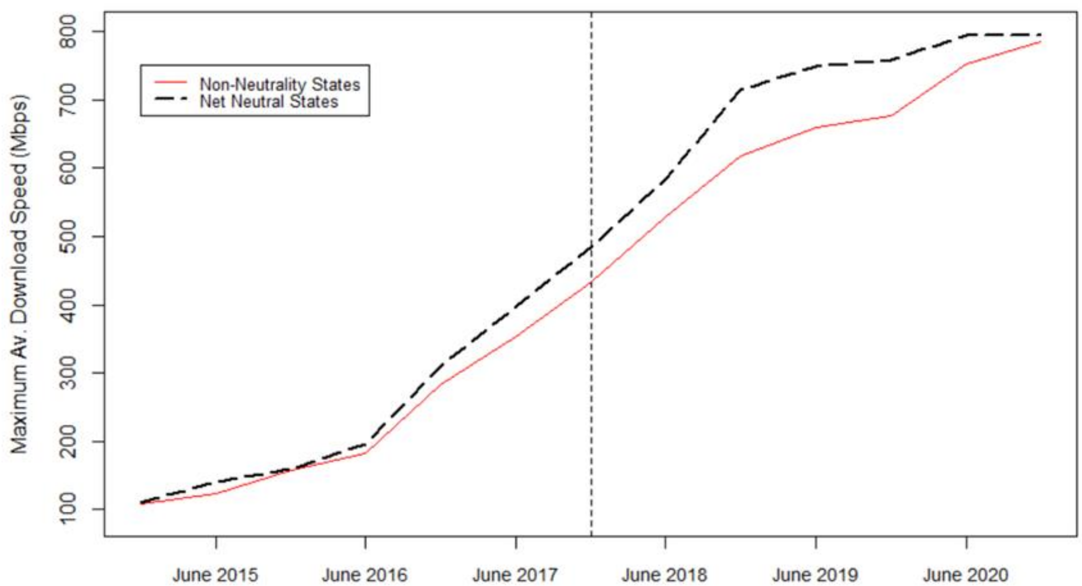
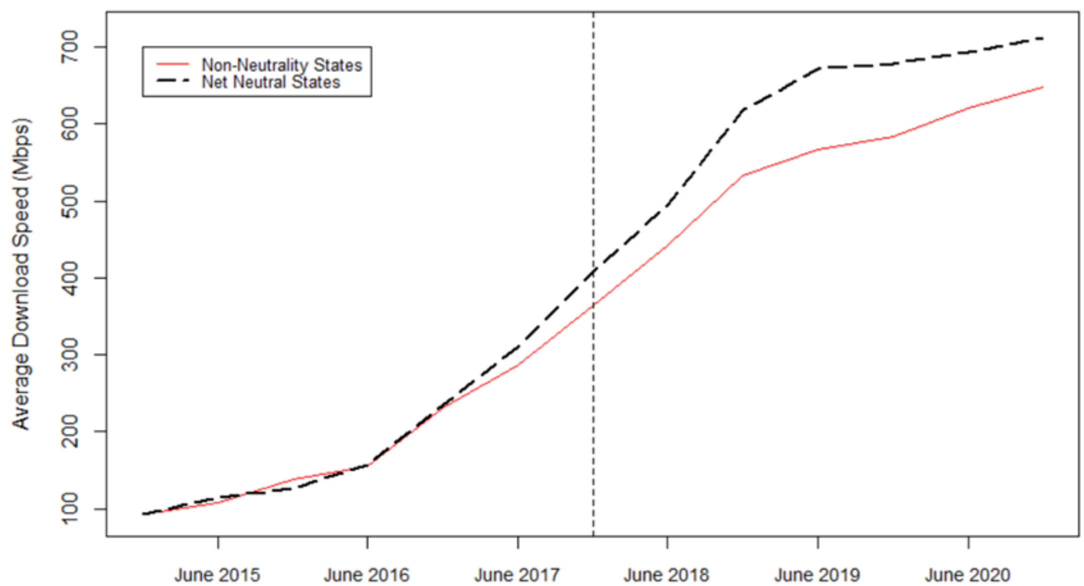


Figure 5: Comparison of Average Available Download Speed



5.1. Results and Discussion

To start with, I applied the concept of difference-in-difference estimation strategy in a preliminary analysis. Table 2 above summarizes the results from the preliminary analysis of the treatment effects of net neutrality rules on the market outcome variables – number of providers, maximum and average downloads, average monthly charge, and average charge per MB. This analysis is carried out by comparing averages of the outcome variables for the treatment and control groups in the pre- and post-periods. The results are similar, in magnitude and sign, to the results from the actual estimation in tables 3 and 4 below. That is, the removal of net neutrality rules in some states resulted in increases in the number of providers and average monthly charge by about the same magnitude in table 2 – 0.08 and $9.53, respectively. Also, average, maximum, and average charge per MB decreased by about 68.14, 39.50 and $0.04, respectively.

Table 2: Preliminary Analysis of Treatment Effects

TREAT

	NumProviders	MaxDL	Av_DL	Av_Monthly_Charge	Av_Charge_perMB
Pre	1.01	234.32	196.46	94.54	1.19
Post	1.24	670.29	565.72	87.34	0.61
Diff	0.23	435.97	369.26	-7.20	-0.58

CONTROL

	NumProviders	MaxDL	Av_DL	Av_Monthly_Charge	Av_Charge_perMB
Pre	1.16	257.050	206.52	107.23	1.37
Post	1.31	732.51	643.91	89.05	0.78
Diff	0.15	475.46	437.39	-18.18	-0.59

Treat_Effect

	NumProviders	MaxDL	Av_DL	Av_Monthly_Charge	Av_Charge_perMB
	0.08	-39.49	-68.13	10.98	0.01
	(0.005)	(0.000)	(0.000)	(0.000)	(0.293)

Table 3: Results: Difference-in-Difference (within estimator)

Variable	(1) Num of Providers	(2) Max Download	(3) Average Download
DiD (Post*TRGR)	0.08**	-39.50	-68.14**
	(0.02)	(31.31)	(24.91)
Month_Year Effect:			
Dec_2015	0.09***	18.60	15.61
	(0.02)	(23.66)	(18.41)
Jun_2016	0.13***	49.50*	42.25*
	(0.02)	(23.66)	(18.41)
Dec_2016	0.17***	76.44**	61.40***
	(0.02)	(23.66)	(18.41)
Jun_2017	0.20***	180.21***	138.25***
	(0.02)	(23.66)	(18.41)
Dec_2017	-0.13***	254.50***	198.17***
	(0.02)	(23.66)	(18.41)
Jun_2018	-0.13***	335.64***	280.24***
	(0.02)	(23.66)	(18.41)
Dec_2018	-0.09***	-247.63***	-207.24***
	(0.02)	(23.66)	(18.41)
Jun_2019	-0.08***	-149.14***	-109.96***
	(0.02)	(23.66)	(18.41)
Dec_2019	-0.03***	-108.92***	-72.08***
	(0.02)	(23.66)	(18.41)
Jun_2020	-0.08	-93.82***	-56.97**
	(0.02)	(23.66)	(18.41)
Dec_2020	-0.03***	-25.67	-25.33
	(0.02)	(23.27)	(18.41)
R-Squared	0.61	0.83	0.85
Number of observations	650	650	650

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

Table 4: Results: Difference-in-Difference (within estimator)

Variable	(4) Av.Monthly Charge	(5) Av.Charge Per MB
DiD (Post*TRGR)	9.53*	-0.04
	(4.74)	(0.11)
Year_Effect:		
Year_2014	31.32***	0.91***
	(5.11)	(0.12)
Year_2015	22.14***	0.63***
	(5.11)	(0.12)
Year_2016	18.84***	0.63***
	(5.05)	(0.12)
Year_2017	15.34**	0.32**
	(5.09)	(0.12)
Year_2018	6.09	0.10
	(3.19)	(0.08)
Year_2019	7.91*	0.10
	(3.25)	(0.07)
R-Squared	0.20	0.50
Number of observations	350	350

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

The FCC terminated net neutrality rules, which was passed in 2015, based on concerns by its opponents that it may have negative impact on investment by ISPs. The empirical findings on the impact of net neutrality on investment did not all point in one direction – negative effect – as expected by those opposing net neutrality. The findings from my estimation did not also support the argument advanced by the opposing side. For example, turning off net neutrality – which is the treatment in this estimation – results in a negative impact on download speed/quality. Although the change in maximum download is not statistically significant, both maximum and average downloads decrease by 39.50 and 68.14, respectively. Theoretically, if the absence of net neutrality caused or incentivized ISPs to increase their investment, as argued by the opponents of net neutrality, then we would expect quality, measured by download speed, to increase. However, the results indicated a decrease in quality.

Also, the price effects of net neutrality did not support the negative impact on investment argument. Again, increase in investment should either increase quality or lower marginal cost. Since quality does not seem improve, one might expect efficiency to improve, and consequently, result in lower prices for end-users of internet service. However, in table 4, the results indicate that the absence of net neutrality results in a statistically significant increase in the average monthly charge or price of $9.53. This contradicts the expected impact on price if we expect investment to increase by the removal of net neutrality rules. While there is negative effect of 0.04 on average charge per MB, this decrease is not statistically significant.

Additionally, the statistically significant increase in price/average monthly charge of $9.53 is not consistent with a decrease in competition as suggested by the increase in the number of providers by 0.08 (as a result of turning off net neutrality).

5.2. Robustness

Tables 5 and 6 presents the results from testing the robustness of my estimation. In order to test the consistency of the results, I used the log of each outcome variable in the difference-in-difference specification. While there are slight variations, in terms of the absolute values of the estimates, in terms of the signs, the results of these specifications are consistent with the original specifications in section 5.1. However, taking log of average monthly charge resulted in a non-statistically significant treatment effect. Overall, there are no huge variations in the estimates, and therefore, my conclusion is that the estimates from the model specification are robust.

Table 5: Results: Difference-in-Difference (within estimator)

Variable	(6) log(Num of Providers)	(7) log(Max Download)	(8) log(Average Download)
DiD (Post*TRGR)	0.07***	-0.10	-0.16**
	(0.02)	(0.05)	(0.05)
Month_Year Effect:			
Dec_2015	0.03	0.20	0.19***
	(0.02)	(0.05)	(0.05)
Jun_2016	0.01	0.42***	0.40***
	(0.02)	(0.05)	(0.05)
Dec_2016	0.10***	0.55***	0.51***
	(0.02)	(0.05)	(0.05)
Jun_2017	0.14***	0.98***	0.90***
	(0.02)	(0.05)	(0.05)
Dec_2017	0.18***	1.23***	1.15***
	(0.02)	(0.05)	(0.05)
Jun_2018	0.21***	1.44***	1.41***
	(0.02)	(0.05)	(0.05)
Dec_2018	-0.11***	-0.40***	-0.41***
	(0.02)	(0.05)	(0.05)
Jun_2019	-0.11***	-0.21***	-0.19***
	(0.02)	(0.05)	(0.05)
Dec_2019	-0.07***	-0.14*	-0.12*
	(0.02)	(0.05)	(0.05)
Jun_2020	-0.07	-0.11*	-0.09
	(0.02)	(0.05)	(0.05)
Dec_2020	-0.02***	-0.04	-0.05
	(0.02)	(0.05)	(0.05)
R-Squared	0.59	0.89	0.89
Number of observations	650	650	650

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

Table 6: Results: Difference-in-Difference (within estimator)

Variable	(9) log(Av.Monthly Charge)	(10) log(Av.Charge Per MB)
DiD (Post*TRGR)	0.07	-0.03
	(0.05)	(0.11)
Year_Effect:		
Year_2014	0.29***	0.98***
	(0.05)	(0.12)
Year_2015	0.21***	0.72***
	(0.05)	(0.12)
Year_2016	0.18***	0.77***
	(0.03)	(0.12)
Year_2017	0.14**	0.48***
	(0.05)	(0.12)
Year_2018	0.07*	0.17*
	(0.03)	(0.08)
Year_2019	0.09**	0.10
	(0.03)	(0.08)
R-Squared	0.18	0.54
Number of observations	350	350

Note: Standard errors are in parentheses. *, **, *** indicates 0.10, 0.05, and 0.01 significaance levels respectively.

6. Conclusion

In 2015, by reclassifying ISPs to fall under Title II of the communication act, the FCC implemented net neutrality rules nationwide that prohibited ISPs, among other things, from blocking online content or creating “fast lanes” and “slow lanes” on the internet. In 2018, the rules were reversed based on concerns that net neutrality will negatively affect investment in the industry and consequently, affect the quality of internet services. While the conclusions from research work on investment impact of net neutrality did not point in the same direction, the FCC made the determination to reverse net neutrality after an assessment of some empirical research work that found negative impact of net neutrality on investment. Following the reversal in June 2018, some ten states indicated their resolution to continue to enforce net neutrality.

By exploiting the exogenous variation created by the discontinuation of net neutrality in some states while other states continue to enforce it, this paper finds evidence that net neutrality may not have negative impact investment by ISP. This conclusion is arrived at based on the theoretical relationship between price, investment, and quality. As firms, theoretically, select equilibrium levels of price, investment, and quality, one will expect that a decrease in quality to be consistent with decreases in price and investment. I find evidence that quality, measured by download speed, decreases while average price increases as a result of removing net neutrality rules. This is not consistent with the expectation that the absence of net neutrality rules will lead to increases in investment by ISPs. If investment by ISPs is expected to increase in the absence of net neutrality, the theoretical expectation is that quality will increase, and other things being equal, or average price for internet service will decrease, or both, if the increased investment results in lower marginal cost. However, the results do not suggest a link between net neutrality and reduced investment.

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Chapter 3

The Signaling Effects of Warranty Provision in a Secondary Market: Evidence from US Automobile Market

Abstract

In this paper, I empirically tested Akerlof's (1970) theoretical assertion of warranty provision as a remedy to information asymmetry in a secondary market, specifically the US market for used cars. Warranty provision signals to potential buyers the quality of the used car and reduces transaction costs in the market. The reduction in transaction costs will lead to an increase in demand and potential increase in quantity of used cars sold. Using data from the National Highway Traffic Safety Administration, I estimated logistic regression, and the results indicate that warranty provision has a positive impact on demand and quantity of used cars sold. A positive marginal effect of 0.06 is evidence that individuals in states with used car lemon laws are 0.06 percentage point more likely to buy a used car than.

Keywords: Warranty, used car, lemon laws, information, transaction costs.

JEL Classification: D80, D82

1. Introduction

Akerlof (1970), in his paper, "Market for Lemons," modeled how quality uncertainty and the market mechanism in secondary markets lead to adverse selection; that is, 'lemons', or bad used cars, drive good used cars out of the market. In this secondary market, there exists information asymmetry about the quality of used cars. Sellers of used cars have prior knowledge of the quality of the cars they want to sell. Buyers on the other hand usually do not have prior knowledge of the quality of these cars. They only find out about the quality of a car after a purchase is made. Their purchase decisions of used cars and therefore the price they are willing to pay are made based on their estimation of average quality in the market.

As Akerlof stated, the price that prevails in the market is equal to the average quality. Hence, sellers of used cars with qualities less than average quality are willing and happy to sell at this price, while good used cars (with qualities greater than average) owners hold on to their cars. Consequently, lemons or bad cars are adversely selected into the market. The key point here is that the presence of information asymmetry about the quality of used cars leads to inefficient outcome in secondary markets.

Akerlof's model reiterated one of the key requirements for optimal performance in a competitive market – perfect information. Information is a key ingredient for efficiency in every market. The lack of information or whenever it is costly to obtain means that outcomes in a specific market are suboptimal. Akerlof, however, suggested ways through which the problem of information asymmetry can be eliminated, though not entirely. One of his solutions to information asymmetry is the provision of warranties, which is the focus of this paper.

Following Akerlof's paper, a number of researchers have, theoretically and empirically, tested and found that, there exists a relationship between quality and warranties in primary markets. For example, Cooper and Ross (1985) and Spence (1977) both concluded that there exists a relationship between the extensiveness of warranty protection and quality in primary markets. There has been little research work to test this relationship in the markets for used goods or secondary markets. Thus, by empirically estimating the impact of warranty provision, made mandatory by the enactment of lemon laws in six of the states in US, as solution to information asymmetry in secondary markets, I seek to add to the existing literature by testing whether or not such relationship exists in secondary markets too.

By the year 1994, all fifty States had enacted lemon laws for new cars, according to Shaffer and Ostas (2001). By this, manufacturers of new cars are mandated to provide warranty protection to buyers of new cars. The intention of mandatory warranty for consumers is to shield them from any unexpected future financial burden that could result from buying a defective car.

In addition to lemon laws for new cars, six states have also passed lemon laws for used cars. For example, the state of New Jersey, in 1996, passed a used car lemon law, which makes it mandatory for used cars dealers to explicitly provide some warranty protection for buyers of used cars. New York, Massachusetts, Minnesota, Hawaii and Rhode Island are among the six states that have passed lemon laws for used cars. I have listed these states again in table 2 with the years in which each state enacted a used car lemon law.

The warranty provides protection for some minimum number of months or miles, whichever comes first and may cover specific part(s) or a full refund if the car is still defective after a reasonable number of attempts to repair the car have failed.

While any dealer in all fifty states can provide some sort of warranty protection for buyers of used cars, it is not mandatory to do so. Therefore, the enactment of lemon law by six states in the United States provides an exogenous variation for assessing the impact of warranties on the performance in the used car market. By observing the provision of warranties for used cars in these six states as mandatory and not mandatory in the rest of the states, induces differences in search costs between used car buyers in the states with lemon laws and used cars buyers in states without lemon laws, and therefore a source of variation to be exploited in estimating the impact of warranty provision on outcome in the used car market.

To fully understand how lemon laws and warranties will impact outcome (price and quantity) in the used car market, we need to know how mandatory warranty provision will impact demand and supply in this market. As in any market, transaction cost is incurred in the used car market to facilitate exchange. Search and information costs are examples of transaction costs, and are incurred in determining the availability, price and quality of the good in the market. By making warranties mandatory, lemon laws for used cars reduce transaction costs for buyers in this market. Warranties signal to buyers that a particular used car is of high quality, thereby reducing uncertainty in the market, which results in a reduction in search cost. Thus, on the demand side, the introduction of lemon laws is expected to boost or increase demand in the used car market.

Also, unlike new car warranties, where manufacturers bear the cost of warranties, in the case of used car warranties, used car dealerships bear the cost of providing warranties to their customers. Dealers would like to keep quality complaints as low as possible in order to keep their customers satisfied and keep warranty related repair costs low. This will lead to an increase in efforts by used car dealers to improve the quality of used cars they put in the market. The result is an increase in cost of supplying good used cars and therefore a decrease in supply of used cars in the market.

The combined result of increased demand and decreased supply is an unambiguous rise in the average price of good used cars and an ambiguous change in quantity of good used cars sold in the states that passed lemon laws for used cars. Since, theoretically, the effect on price is unambiguous, and due to lack of price information, I will focus on estimating the impact on the quantity. A positive impact (increase) on quantity is an indication that the effect from the increase in demand for used cars outweighs the effect from the decrease in supply of used cars.

I will estimate logistic regression model. The results of the logistic regression determine the impact of warranty provision on demand. Individuals living in states with lemon laws will be more likely to buy used cars relative to those in states without lemon laws.

A positive coefficient of 0.23 for individuals in the states with lemon laws is an indication that individuals in these states are more likely to purchase used cars, relative to those states without lemon laws. Thus, warranty provision will result in increased demand for used cars, all other things being equal.

In the ensuing parts of this paper, section 2 will review previous literature on information and market performance, and warranty provision and quality. Section 3 will discuss the data and provide a table of summary statistics for the variables used for estimations. Section 4 will explain the models estimated. Section 5 will proceed with discussion of the results from estimations and section 6 will conclude with a summary of the paper.

2. Literature Review

In a market highly characterized by information asymmetry, any policy that will increase the amount of information to participants will have an impact on market outcome. The used car market is faced with a problem of adverse selection, whereby bad quality cars are more likely to be selected into the market. Sellers of good quality used cars can avoid this problem by offering warranties to signal the quality of their cars to potential buyers.

In other markets, empirical research has shown that increasing information in a market affects consumers' choices. For example, Jin, G.Z, and Leslie P (2002) and Bollinger, Leslie, and Sorensen (2011), have studied the impact of increase in information on consumer choice and market outcome for hospitals and restaurants, respectively. Similarly, this paper seeks to study the increase in information, through warranty provision, on consumer choices in the used car market.

The relationship between warranty and market outcomes in primary or new goods markets has been studied by several researchers.

Cooper and Ross (1985) developed a model of warranty and quality where moral hazard played a central role. They observed three key characteristics of warranties: 1. They provide less than full insurance against unsatisfactory performance, 2. They are provided by the seller of the product rather than by independent insurance agencies, 3. The extent of warranty protection bears no general relation to the in-built-quality of the good. The model, with warranty and quality being endogenous, is consistent with all three characteristics. They stated that, a seller of less quality product can offer less or more extensive warranty than a seller with a more quality product and vice versa. Cooper and Ross also mentioned that there is a possibility for a negative relationship between warranty and quality for exogenous quality.

When quality is unobservable, warranty plays a key role in signaling to consumers the quality of a good, (Spence, 1977). Sellers of high-quality goods use extensive warranties to signal the quality of their goods. Spence (1977) recognized a positive relationship between warranty and quality, which is at variance with Cooper and Ross's third characteristic of warranty (there is no general relationship between the two).

Douglas, Glennon and Lane (1993) theoretically extended Cooper and Ross's theory to include price and the cost of servicing warranty. In their model, price, quality and warranty are simultaneously and noncooperatively determined by the producers and buyers as they seek to maximize profits and utility respectively. Their theory aimed at explaining the observed negative relationship between warranties and quality (durability) in the US automobile market. Theoretically, they postulated that, manufacturers (US car manufacturers) who have a cost advantage in providing and servicing warranties, due to an extensive dealership network, will choose to offer lower quality cars with extensive warranties.

Similarly, buyers with higher cost of efforts in maintaining cars will seek out sellers with higher quality cars. They empirically tested their theory by answering the question of whether the relationship between warranty and quality is positive or negative and whether the observed relationship is due to differences in cost of providing network or due to differences in consumer preferences for quality. They found that the relationship between warranty and quality is positive when network cost and consumer preferences are controlled. Also, they concluded that, the relationship between warranty and quality is cost driven.

Emons and Sheldon (2009), reiterated Akerlof's (1970) lemon model. Their paper studied the behavior of both sellers and buyers, testing for adverse selection by sellers and quality uncertainty by buyers. Using data from Swiss Canton of Basle City, from 1985 – 1991, they found evidence that adverse selection and quality uncertainty is still a problem in the used cars market. Additionally, they found that vehicles which are privately sold are more likely to be defective than a randomly chosen vehicle.

Lemon laws fall under consumer legislation, which could be driven by public concern for efficiency or by interest groups with political power. Shaffer and Ostas

(2001), identified three affected interest groups of new car lemons laws – consumers, dealers and manufacturers – and assessed the role each played in the passage of lemon laws in the fifty States. In the case of lemon laws, they found that, both political power and efficiency concern played a role, and that there is no reason to believe one explanation excludes the other.

3. Data

Data for estimation in this paper is cross-sectional individual data. This is survey data collected by the National Highway Traffic Safety Administration in 2017 and includes characteristics and demographics that affect households travel demands. The years in which each state enacted a lemon law were taken into consideration such that I excluded from my data any vehicle that was purchased (in a state with used car lemon law) before the law was enacted. This is to ensure that the households in the data (from 2017) made their purchasing decisions while the law was enacted.

The dependent variable is an indicator for whether an individual owns a used vehicle, and it is constructed from the difference between the age of the vehicle and the number of years an individual has owned the vehicle. The vehicle is considered used if the age of the vehicle is at least two years more than the number of years the individual has owned it.

The main explanatory variable is an indicator for whether an individual resides in a state with a used car lemon law (TreState). Other variables that may influence an individual's decision to buy a used car are controlled for. These variables include the individual household income, age, sex, education attainment, race, and indicators for whether they reside in urban or rural city, and whether they own a home or not. The table below summarizes these variables.

Table 1: Summary Statistics

Variable	Mean	Sd	Min	Max
TreState	0.15	0.36	0	1
used	0.51	0.5	0	1
AGE	49.05	17.22	14	92
SEX	0.52	0.5	0	1
EDUC	3.39	1.14	1	5
HHIncome	6.68	2.51	1	11
urban	0.74	0.44	0	1
OWNHOME	0.79	0.41	0	1
RACE	1.31	0.96	1	6
HISPANIC	0.07	0.25	0	1

Number of Observation: 32111

Table2: Summary Statistics by TreState

	All obs	TreState	Not-in-TreState	p-value
n	32111	4896	27215	
ave. Income	6.68	6.78	6.66	0.00
ave. % of used	0.51	0.46	0.52	0.00
ave. AGE	49.05	50.37	48.81	0.00
ave. EDUC	3.39	3.45	3.38	0.00
ave urban	0.74	0.65	0.76	0.00

Note: p-values are for differences in averages between TreState and Not-in-TreState

From table 1, about 51 percent (mean of 0.51) of individuals in the sample own used cars. However, only about 15 percent (mean of 0.15) of the individuals in the sample reside in states with used car lemon laws. Table 2 seeks to compare the treatment and control groups. Individuals in these groups appear to have the same average income. These groups are also similar in terms of age, education and percentage living in urban areas.

4. Estimation Strategy

The enactment of lemon law by six states in the United States, which made it mandatory for used car dealers to provide warranties to buyers of used cars, provides an exogenous variation for estimating the signaling effects of warranties. In order to causally identify the impact of used car lemon laws on demand for used cars, I will estimate logistic regression model, controlling for other variables that could affect the probability of an individual buying a used car.

Logit Model:

My dependent or outcome variable (y) is an indicator for whether an individual owned a used car or not. My main independent variable is an indicator for whether an individual lived in a state with used car lemon laws or not. Additionally, I controlled for other individual characteristics that might influence their decision to buy a used car. These other variables include household income, age, education attainment, race, and whether the individual lives in an urban area.

The equations below identify the effects of these variables on the probability of an individual buying a used car. My expectation is that individuals who live in the states with used car lemon laws will be more likely to buy used cars. This is because mandatory provision of warranties increases information about quality of used cars and thus, reduces search cost in used car markets. Information asymmetry, which is the problem in this market, is reduced, if not eliminated. The effect is an increase in the probability that an individual will buy a used car.

For variables controlled for, I expect negative signs for parameters for household income and age. That is, households in higher income brackets will be less likely to buy or own used cars. Individuals who do not own homes are less likely to buy used cars since they may have fewer financial responsibilities in terms of mortgage payments on their homes, thus, can afford new cars.

Since higher education attainment increases individuals' earning potentials, I expect negative coefficient for education attainment. That is, relative to no education, individuals' probability of buying used cars should decrease as they get higher education.

Given that:

$$pr(y_i = 1) = pr(x_i'\beta + \varepsilon_i > 0) = \Phi(x_i'\beta)$$

$$pr(y_i = 0) = pr(x_i'\beta + \varepsilon_i \leq 0) = 1 - \Phi(x_i'\beta)$$

Where $y_i = 1$ means individual *i* purchased a used car and $y_i = 0$ means individual *i* did not purchase a used car.

The log likelihood function to be optimized is given as:

$$logL = \sum_i \{y_i log[\Phi(x_i'\beta)] + (1 - y_i) log[1 - \Phi(x_i'\beta)]\}$$

5. Results and Discussion.

Tables 3 and 4 present coefficient estimates and marginal effects for the logistic regression respectively. Each column presents estimates for different model specification. Results in column (1) are for the linear model, while the remaining columns are results for non-linear specifications.

Table 3: Logistic regression

variable	(1)	(2)	(3)	(4)	(5)
(Intercept)	-3.79***	-3.81***	-3.07***	-3.21***	-2.49***
	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
TreState	0.23***	0.23***	0.23***	0.23***	0.23***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
HH_income	0.21***	0.21***		0.21***	
	(0.01)	(0.01)		(0.01)	
AGE	0.03***	0.03***	0.03***		
	(0.00)	(0.00)	(0.00)		
AGEsq		0.00			
		(0.00)			
HH_Income Quartiles:					
2nd Quartile			0.63***		0.63***
			(0.03)		(0.03)
3rd Quartile			0.97***		0.97***
			(0.04)		(0.04)
4th Quartile			1.24***		1.25***
			(0.04)		(0.04)
AGE Dummy:					
30-40				0.51***	0.54***
				(0.05)	(0.04)
40-50				0.66***	0.67***
				(0.05)	(0.05)
50-60				0.82***	0.82***
				(0.04)	(0.04)
60-70				1.30***	1.29***
				(0.04)	(0.04)
70-80				1.67***	1.65***
				(0.05)	(0.05)
80-90				1.89***	1.87***
				(0.09)	(0.09)
>90				1.56***	1.51***
				(0.26)	(0.26)
Male	-0.5***	-0.50***	-0.48***	-0.50***	-0.48***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
High School Graduate or GED	0.62***	0.62***	0.62***	0.72***	0.71***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
Some college or associates degree	0.8***	0.79***	0.81***	0.89***	0.89***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Bachelor's degree	1***	1.00***	1.03***	1.09***	1.11***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Graduate or professional degree	0.98***	0.98***	1.03***	1.06***	1.10***
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
URBAN	0.2***	0.21***	0.21***	0.19***	0.21***
	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)
OWNHOME	0.08*	0.08*	0.14***	0.09**	0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Black or African American	-0.27**	-0.27***	-0.31***	-0.26***	-0.30***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Asian	0.57***	0.57***	0.56***	0.55***	0.53***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
American Indian	-0.12	-0.12	-0.13	-0.13	
	(0.16)	(0.16)	(0.16)	(0.16)	-0.14 (0.16)
Native Hawaiian	0.16	0.16	0.14	0.18	
	(0.24)	(0.24)	(0.25)	(0.24)	0.16 (0.25)
Multiple race	-0.23**	-0.23**	-0.24***	-0.24**	-0.26***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
HISPANIC	0.24***	0.23***	0.23***	0.22***	0.22***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	32111	32111	32111	32111	32111
Null Deviance	44498	44498	44498	44498	44498
Residual Deviance	39531	39531	39750	39562	39779
AIC	39565	39567	39788	39608	39829
Pseudo R-squared	0.11	0.11	0.11	0.11	0.11
p-value	0.00	0.00	0.00	0.00	0.00

Note: Standard errors are in parentheses. *, **, and *** indicate 0.10, 0.05, and 0.01 significance levels respectively

Table 4: Marginal effects (dF/dx)

variable	(1)	(2)	(3)	(4)	(5)
TreState	0.06***	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HH_income	0.05***	0.05***		0.05***	
	(0.00)	(0.00)		(0.00)	
Age	0.01***	0.01***	0.01***		
	(0.00)	(0.00)	(0.00)		
AGEsq		0.00***			
		(0.00)			
HH_Income Quartiles:					
2nd Quartile			0.16***		0.16***
			(0.01)		(0.01)
3rd Quartile			0.23***		0.23***
			(0.01)		(0.01)
4th Quartile			0.30***		0.30***
			(0.01)		(0.01)
AGE Dummy:					
30-40				0.14***	0.13***
				(0.01)	(0.01)
40-50				0.16***	0.17***
				(0.01)	(0.01)
50-60				0.20***	0.20***
				(0.01)	(0.01)
60-70				0.31***	0.31***
				(0.01)	(0.01)
70-80				0.36***	0.36***
				(0.01)	(0.01)
80-90				0.38***	0.38***
				(0.01)	(0.01)
>90				0.33***	0.33***
				(0.04)	(0.04)
Male	-0.12***	-0.12***	-0.12***	-0.12***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High School Graduate or GED	0.15***	0.15***	0.15***	0.18***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Some college or associates degree	0.20***	0.20***	0.20***	0.22***	0.22***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Bachelor's degree	0.24***	0.24***	0.25***	0.26***	0.27***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Graduate or professional degree	0.24***	0.24***	0.25***	0.26***	0.26***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Urban	0.05***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ownhome	0.02*	0.02*	0.03***	0.02**	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black or African American	-0.10***	-0.07***	-0.08***	-0.06***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	0.14***	0.14***	0.14***	0.13***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
American Indian		-0.03	-0.03	-0.03	-0.03
	-0.03 (0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Native Hawaiian	0.04	0.04	0.04	0.04	0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Multiple race	-0.06**	-0.06**	-0.06***	-0.06**	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hispanic	0.06***	0.06***	0.06***	0.06***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note: Standard errors are in parentheses. *, **, and *** indicate 0.10, 0.05, and 0.01 significance levels respectively

The coefficients for TreState and Males from the results of the logistic regression in table 3 have signs that are consistent with my expectations, but others do not. For example, the positive coefficient sign for individuals in treatment states (TreState) means that, relative to individuals living in states without lemon laws, individuals residing in states with lemon laws are more likely to buy or own used cars. This means that, the enactment of used car lemon laws resulted in increased demand for used cars. Apart from the coefficients for American Indians and Native Hawaiian, all coefficient estimates are statistically significant.

Now I will focus discussion on marginal effects in table 4. In column (1), a marginal effect of 0.06 for TreSate means, relative to individuals in sates without lemons laws and mandatory warranty provision for used car buyers, individuals in states with lemon laws for used cars are 0.06 percentage point more likely to purchase and own a used car. Thus, the empirical evidence supports the theoretical assertion by Akerlof that warranty provision will reduce information asymmetry.

For other covariates, the results show that, older people are more likely to buy used cars. In column (1) of the linear specification, an increase in age by one more year means an individual is 0.01 percentage point more likely to buy a used car. This is still true even with individuals in different age categories. Relative to individuals less than 30 years, the probability of buying a used car increases with age. Those in 30-40 and 40-50 categories are about 0.14 and 0.16 percentage points more likely to buy used cars respectively. Intuitively, older folks may have other financial responsibilities, like paying student loans and home mortgages, which are more pressing to them than buying a new car. As they even get older, they begin to save more towards retirement, which further increases their probability of buying used cars.

Interestingly, education attainment is positively related to the probability of buying used car. That is, relative to individuals without a GED, the probability of buying a used car increases with education attainment. For example, people with a GED, associates and bachelor's degrees are 0.15, 0.20 and 0.24 percentage points, respectively, more likely to buy used cars relative to people with no education. While higher educational attainment may increase earning potentials, it may also increase one's debt in terms of student loans. This may explain why probability of buying a used car increases with education attainment.

Urban residents and individuals who own homes are also more likely to buy used cars relative to non-urban residents and individuals living in rented apartments, respectively. They are 0.20 and 0.08 percentage points, respectively, more likely to buy used cars. While those living in urban areas may be earning more than those in non-urban areas, urban areas have a higher cost of living than non-urban areas. Also, people who owned houses may have the extra financial burden of a mortgage payment, hence, the need to buy used and cheaper cars.

Robustness

To check for robustness, I run different specifications of the logistic regression model. Columns 2 to 5 of tables 3 and 4 are results of non-linear specifications of the model. The results are robust to these specifications. The coefficient estimates in these specifications are pretty much the same. Also, the pseudo-R-squared from these different specifications do not differ significantly from each other, signifying that no specific specification gives a better explanation than the other.

6. Conclusion

The paper, primarily, seeks to estimate the signaling effects of warranty provision on demand for used cars by exploiting the exogenous variation in information on quality of used cars in states with lemon laws and states without lemon laws. The mandatory provision of warranty, through signaling quality to potential buyers, has the effect of reducing transaction costs in the market for used cars, thereby positively influencing individuals' choice decisions in a used car market. The results from the logistic regression led to a conclusion that warranty provision in a used car market will have a positive impact on demand for used cars. Therefore, a conclusion can be drawn that warranty provision increases information about product quality in secondary markets and solve the problem of asymmetric information that exists in these markets.

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