Peer-to-Peer Rental Markets in the Sharing Economy*

By SAMUEL FRAIBERGER AND ARUN SUNDARARAJAN

To investigate whether peer-to-peer rental markets for durable goods are welfare-improving, we develop a new dynamic model of such markets in which users with heterogeneous utilization rates may also trade in secondary markets. We calibrate our model with US automobile industry data and transaction-level data from Getaround, a large peer-to-peer car rental marketplace. Counterfactual analyses illustrate significant shifts away from asset ownership as marketplace access grows. Used-good prices fall and replacement rates rise, while gains in consumer surplus range from 0.8% to 6.6%. The changes in consumption mix and the surplus increases are significantly more pronounced for below-median income consumers.

JEL: D4, L1, L81

* Fraiberger: Department of Economics, New York University (email: spf248@nyu.edu). Sundararajan: Leonard N. Stern School of Business, New York University (email: digitalarun@nyu.edu). We thank the executive team at Getaround (and especially Padden Murphy, Jessica Scorpio, Sam Zaid and Ranjit Chacko) for numerous helpful conversations and for providing access to their anonymized data. We thank Anmol Bandhari, Erik Brynjolfsson, Andrew Caplin, Natalie Foster, Andrey Fradkin, Lisa Gansky, Shane Greenstein, Anindya Ghose, John Horton, John Lazarev, Alessandro Lizzeri, Romain Ranciere, Justin Rao, David Rothschild, Shachar Reichman, Scott Stern, Marshall Van Alstyne, Joel Waldfogel, and seminar participants at Carnegie-Mellon University, the Federal Reserve Bank, New York University, the MIT/BU Platform Strategy Research Symposium, the NBER Digitization Workshop and the ZEW Center for European Economic Research for helpful discussions on preliminary versions of this work. Fraiberger gratefully acknowledges support from the NET Institute. Sundararajan gratefully acknowledges support from Google and the Ewing Marion Kauffman Foundation. Fraiberger and Sundararajan have no current or prior commercial relationship with Getaround. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2574337.

In recent years, a number of Internet enabled peer-to-peer marketplaces have emerged to facilitate the short-term rental of durable goods. Examples include Getaround, Turo and Drivy (which enable car owners to supply their vehicles as short-term rentals), Airbnb and onefinestay (which allows consumers to rent their living space to others for short periods) and StyleLend (which facilitates the peer-to-peer rental of apparel and accessories). These are specific examples of a much broader array of new platforms which facilitate market-based trade between private individuals for a variety of assets and services, from urban transportation (Lyft, Sidecar, Uber), dining (VizEat, Kitchit, EatWith) and intercity transit (BlaBlaCar, carpooling.com) to labor (TaskRabbit, Handy, Thumbtack), local delivery (Instacart, Postmates), and loans (Lending Club, Funding Circle), collectively sometimes referred to as creating a new 'sharing economy' ((Gansky 2010), (Botsman and Rogers 2010), (Sundararajan 2013)).

Such marketplaces differ from earlier Internet-based secondary marketplaces like eBay[1] because they focus on facilitating recurring short-term rental or service provision rather than occasional resale under which asset ownership is transferred; peer-to-peer rental marketplaces thus alter the incentives to invest in assets that are traditionally a source of dedicated supply for one individual. They are also distinct from long-standing short-term rental services for consumption involving durables (via, for example, traditional hotels or car rental companies) because the trade they facilitate is largely between individuals or *peer-to-peer* rather than between an individual and a firm created to provide rental services.[2]

[1]Much like eBay, most of these platforms have sophisticated consumer identity verification and feedback systems.

[2]A number of new 'sharing' services do follow the traditional firm-to-consumer model, While closely associated with the 'sharing economy', Zipcar is simply a new kind of firm-to-consumer car rental service. Others, like Rent the Runway, are expanding the categories of products for

In particular, the first set of motivating examples we highlighted are marketplaces whose stated purpose is to facilitate the 'secondary' ad-hoc rental of assets by consumers who otherwise possess these goods exclusively for their personal consumption.

This new form of peer-to-peer exchange is growing rapidly. In 2015, Airbnb indicated that they had over one million hosts on their site, and over the summer of 2015, indicated their hosts were accommodating over a million guests per night, making them comparable in inventory and transaction volume to the world's largest hotel brands.[3]

Will this rapid growth of the sharing economy be welfare-improving? We identify a number of potentially countervailing economic effects. New rental marketplaces can increase allocative efficiency by creating new gains from trade between consumers, may generate additional surplus for consumers who could not previously afford ownership, may shift consumption towards higher quality products, and might even increase manufacturer surplus by inducing new 'ownership for peer-to-peer rental supply.' On the other hand, increased rental can induce more rapid depreciation; besides, firms may be hurt by lower equilibrium production volumes as durable goods are used more efficiently.

This paper has two main contributions. First, we develop a new dynamic model of an economy with a peer-to-peer rental market for durable goods among con-

which rental rather than ownership is an option, but continue to do so using a firm-to-consumer supply model.

[3]For comparison: Intercontinental Hotel Group, the world's largest hotel chain by room count, has a little over 600,000 rooms worldwide. Other Internet-enabled peer-to-peer markets are also growing very rapidly. Uber, which introduced its service in New York City in 2011, is now the city's largest non-taxi car service with over 23,000 active vehicles in the city as of mid-2015. (There are about 13,000 yellow cabs in New York City.) Its largest competitor, Lyft reported giving over 7 million rides in the U.S. in October 2015. A recent industry survey of consumers in the United States, Canada and the United Kingdom ((Owyang and Samuel 2014)) suggests that about one in four respondents had used one or more of these 'collaborative economy' marketplaces in the last year.

sumers who have heterogeneous price sensitivity, utilization rates and preference shocks. We characterize the stationary equilibrium when consumers can own new products, or can trade owned assets in a (traditional) secondary marketplace in addition to the peer-to-peer rental marketplace. Our model incorporates both transaction costs and depreciation rates which vary with asset usage, as well as heterogeneous matching frictions that alter the rate at which rental supply and demand are fulfilled.

Second, we provide a calibration our model using transaction and survey data from Getaround, a leading large peer-to-peer car rental marketplace, and supplemented with data about vehicle ownership, secondary market trade and patterns of vehicle usage from the Bureau of Labor Statistics (BLS), the National Automobile Dealers Association (NADA) and the National Household Transportation Survey (NHTS). This yields the first empirical assessment of the welfare implications of Internet-based peer-to-peer rental marketplaces in the automobile industry.

A consistent finding across all our counterfactual analyses is that peer-to-peer markets improve consumer welfare. Increases in surplus grow with the fraction of the population that has access to the marketplace and the fraction of supply and demand requests that are fulfilled. Predicted consumer surplus gains in the automobile industry are substantial, ranging from 0.8% to 6.6%.[4]

Whose activity drives these gains? We find that there is an interesting contrast between the impact of peer-to-peer rental markets on the choices of below-

[4]To benchmark the scale of gains: there are over 200 million passenger vehicles in the US, and consumers spend about $1 trillion annually on the purchase of new and used vehicles. Estimates of current consumer surplus are harder to specify exactly, but are of the same order of magnitude. For example, (Chen, Esteban and Shum 2013) estimate an annual consumer surplus flow of $5000 per vehicle, which would translate into total consumer surplus of roughly $1 trillion. Thus, a 1% increase in consumer surplus corresponds to an additional flow on the order of $10 billion annually.

median income and above-median income consumers. Specifically, below-median income consumers contribute a higher fraction of demand, and are almost twice as likely (30% versus 18% in our baseline calibration) to give up ownership, driven in part by their greater propensity to avoid the period fixed costs of ownership when a peer-to-peer rental alternative exists. Additionally, a significantly higher fraction of below-median consumers choose to supply newer vehicles for peer-to-peer rental. Consequently, the percentage surplus gains enjoyed by below-median income consumers are significantly higher than those enjoyed by above-median income consumers.

A number of factors lead to these higher gains for the below-median income segment. One factor is greater inclusion: lower-income consumers who could not afford to own a car and were thus excluded from participation now consume through the peer-to-peer rental marketplace. A different fraction of below-median income consumers shift from being owners to being non-owner renters, realizing ownership cost savings, gains from greater usage efficiency and higher quality consumption. A small fraction of below-median income consumers switch from being non-owners to being owners, induced in part by lower used car prices, realizing surplus gains through their supply activity on the peer-to-peer rental marketplace.

The rest of this draft is organized as follows. Section 2 outlines the different economic effects induced by peer-to-peer rental marketplaces and connects our work to the literature. Section 3 presents our model and characterizes its equilibrium. Section 4 summarizes our data, describes our calibration. Section 5 provides the results of our counterfactual analyses. Section 6 concludes and discusses future work.

I. Potential Economic Effects of Peer-to-Peer Rental

The purchase of a durable good provides value to a consumer over an extended period of time. In a frictionless world, consumers would freely adjust their holdings of durable goods to match their current needs. In practice, however, durable goods are illiquid and the transaction costs associated with buying and selling them are often large. The prospect of costly adjustment gives rise to inertial behaviors: consumers purchase and keep durable goods until they have depreciated sufficiently to make replacement worthwhile. The introduction of a rental market creates the alternative of simultaneous access to (vertically differentiated) products of differing vintages for short periods of time.

Part of the potential gains from trade in a peer-to-peer rental market are induced by the widespread variation, both across consumers and across time, of the utilization of owned durable assets. There are also other potential sources of gains from trade. Ownership as a prerequisite to utilization may exclude a fraction of potential users. Idiosyncratic income or preference shocks may create additional possibilities for trade.

With access to sufficiently liquid peer-to-peer rental markets, owners of durable goods can temporarily supply their non-utilized capacity to others who may prefer to rent this capacity instead of owning their own asset because their average utilization levels or income levels are too low. Correspondingly, the prospect of future rental (much like the prospect of future resale created by secondary markets) might make consumers more willing to invest in asset ownership. The introduction of peer-to-peer rental markets will thus affect the value of the associated underlying assets.

There are also distinct costs associated with the rental activity itself. In the case of automobiles, depreciation costs, which represent about 40% of the lifetime costs of ownership, will change. The increase in mileage from renting out a vehicle directly impacts its resale value and the age at which one might scrap the vehicle. Similarly, renting out one's personal dwelling space on Airbnb leads to wear-and-tear, higher maintenance costs, and more rapid depreciation of the property's value.

The owner of a durable good holds it over an extended period of time, factoring future use into the usage and care of the asset. Someone who rents the same good for a shorter period is unlikely to treat it with the same level of care as an owner. Despite a variety of technological advances for monitoring and the emergence of sophisticated online reputation systems ((Sundararajan 2012)), moral hazard cannot be fully mitigated. Peer-to-peer rental therefore affects the expected lifetime of an asset as well as any transaction costs incurred during resale. We model these effects by making the depreciation rate and resale transaction costs explicit functions of the realized per-period asset utilization rate.

Finally, although the popularity of peer-to-peer rental platforms has been growing rapidly, their reach and liquidity are still limited. Consumers who own a durable good can access it costlessly and instantly over its lifetime. In contrast, search and matching costs in Internet-enabled marketplaces are still non-zero (see (Fradkin 2014) or (Horton 2013) for more detailed analyses of matching frictions in peer-to-peer marketplaces). An asset may not be available for rental when one wants it, and correspondingly, there is no guarantee that rental demand exists at all times that one's owned asset is listed as available for rental. There are also costs associated with product assessment and the process of taking physical possession of a rented asset. We therefore consider a scenario in which only a fraction of the population has access to peer-to-peer rental markets, and for those consumers who have access to rental markets, we use two matching parameters which capture the fraction of time a supplier or a renter will find a trading partner. These parameters are calibrated using both Getaround's marketplace data as well as using data from surveys we have done of their users. Our counterfactual analyses vary these parameters.

Related Literature: Internet-enabled rental markets for digital goods have been analyzed extensively over the last decade (see, for instance (Varian 2000) for an early theoretical treatment and (Rao 2011) for a more recent empirical analysis). However, our paper is the first (to our knowledge) to focus on Internet-enabled peer-to-peer rental of durable goods among consumers. Our model draws from and builds on a varied literature that considers different equilibrium effects of secondary markets for durable goods ((Rust 1985), (Anderson and Ginsburg 1994), (Hendel and Lizzeri 1999*a*), (Hendel and Lizzeri 1999*b*), (Hideo and Sandfort 2002), (Stolyarov 2002), (Hendel and Lizzeri 2002), (House and Leahy 2004) , (Hendel, Lizzeri and Siniscalchi 2005), (Johnson 2011)). (Rust 1985) shows that in a market with vertical differentiation across goods of different vintages and in the absence of transaction costs, consumers will costlessly return to their preferred vintage each period. Having a rental market in this setting would imply that the rental rate would equal the expected price depreciation of the durable good. (Anderson and Ginsburg 1994) and (Hendel and Lizzeri 1999*b*) show that firms can benefit from resale markets through indirect price discrimination. (Hendel, Lizzeri and Siniscalchi 2005) show that even in the presence of asymmetric information, an efficient allocation can be obtained when a monopolist offers a set of rental contracts to consumers. (Stolyarov 2002) solves for a stationary equilibrium with competitive primary and resale markets with heterogeneous consumers and exogenous transaction costs and shows that the equilibrium dynamics follow an (S,s) rule. We extend the kind of model developed by (Stolyarov 2002) by integrating a rental market for durable goods among consumers into a set up otherwise quite similar to his.

There have also been a number of empirical studies of secondary markets for cars ((Porter and Sattler 1999), (Adda and Cooper 2000), (Stolyarov 2002), (Aizcorbe, Starr and Hickman 2003), (Esteban and Shum 2007), (Wang 2007), (Cho and Rust 2010), (Shiraldi 2011), (Yurko 2012), (Chen, Esteban and Shum 2013), (Gavazza, Lizzeri and Roketskiy 2014)).[5] (Adda and Cooper 2000) analyze consumers' replacement problem to explore the impact of government subsidies on durable goods markets. (Cho and Rust 2010) explores the pricing strategy and replacement policy for a rental firm and shows that it behaves sub-optimally. (Shiraldi 2011) uses the dimensionality reduction proposed by (Gowrisankaran and Rysman 2012) to estimate the dynamic demand for automobiles in the presence of secondary markets, transaction costs and goods depreciation.[6] (Gavazza, Lizzeri and Roketskiy 2014) extends (Stolyarov 2002) by allowing consumers to hold 2 durables at a time; their model successfully explains resale patterns of the US and the French car market. Like (Chen, Esteban and Shum 2013), we allow durable goods to live for multiple periods by introducing a stochastic rate of depreciation and we allow consumers' valuation for the good to have both a persistent and a time-varying component.

We also add to a small literature that deals explicitly with economic issues relating to peer-to-peer 'sharing economy' marketplaces. For example, (Fradkin

[5]Other analysis of secondary markets for durable goods in the literature include aircrafts ((Gilligan 2004) (Gavazza 2011*a*) (Gavazza 2011*b*)), textbooks ((Chevalier and Goolsbee 2009)), digital goods ((Varian 2000), (Rao 2011), (Schiller 2012) (Gilbert, Randhawa and Sun 2013)) among others. There is also a literature in macroeconomics that uses transaction costs to explain the slow adjustment in the stock of durables ((Eberly 1994), (Attanasio 2000)).

[6]For recent papers on dynamic demand estimation see (Erdem, Susumu and Keane 2003), (Hendel and Nevo 2006), (Carranza 2012), (Shiraldi 2011), (Melnikov 2013), (Gowrisankaran and Rysman 2012)). Although classic demand estimation papers such as (Berry, Levinsohn and Pakes 1995) deal with durable goods, their demand estimation is static and typically does not include secondary markets.

2014) studies how a variety of design choices made by a peer-to-peer rental marketplace might affect the efficiency with which it matches buyers and suppliers. He identifies three primary mechanisms that induce inefficiency, relating respectively to a consumer having an incomplete consideration set, having insufficient knowledge of whether a listed supplier is actually willing to trade, and trading at the wrong time, and uses counterfactual analyses to shows how changing Airbnb's current ranking algorithms can increase the rate at which buyers and sellers match by up to 10 %. (Cullen and Farronato 2014) develop a model of matching in peer-to-peer labor marketplaces. Their estimation using data from TaskRabbit indicates highly elastic supply: demand increases are matched by corresponding increases in supply per worker with little or no price response. They also quantify welfare gains per transaction and document variations in activity across cities. (Zervas, Proserpio and Byers 2015) examine the effects of Airbnb on hotel consumption in Texas, showing that a 10% increase in Airbnb supply results in a 0.35% decrease in monthly hotel room revenue, documenting non-uniform incumbent impacts (with lower-priced and non-business hotels being affected more). (Hall and Krueger 2015) provides a detailed analysis of the average wage rates received by the drivers who supply transportation through the peer-to-peer platform Uber, providing evidence that these may be higher than corresponding BLS averages for taxi drivers, and showing that variations in the volume of supply per driver do not affect average wage rates significantly.

II. Model

Consumers: We model a continuum of infinitely lived consumers of unit mass. Time is discrete and there is no aggregate uncertainty. Agents maximize expected utility and discount future utility flows at rate β. Each consumer is characterized by her price sensitivity $\theta \geq 0$, her utilization rate $\rho \in [0,1]$, and her propensity to match in the rental market $\gamma \in [0,1]$.[7] The parameters (θ, ρ, γ) are distributed according to the distribution $F_1[\theta], F_2[\rho], F_3[\gamma]$ respectively. Each consumer possesses at most one good in every period.[8]

Goods: Goods are indexed by $a \in \{0,1,2\}$. $a = 0$ represents a newer good (for simplicity in what follows, the 'new good'), $a = 1$ an older good or 'used good' and $a = 2$ the outside option of owning no good. Agents have perfect information about the quality of each good. A consumer of type (θ, ρ, γ) who possesses a good of type a derives a period utility of $\rho x_a - \theta \kappa_a + \varepsilon_a$. The persistent utility component x_a is constant across consumers and across time. Newer goods have higher utility flows associated with them, so $x_0 > x_1 > x_2 = 0$.

κ_a represents the period expenditure on a good of vintage $a \in \{0,1\}$.We set $\kappa_2 = 0$ for a "non-owner" (consumer holding the outside option) and $\kappa_0 = \kappa_1 = \kappa$ for an owner.[9]

The idiosyncratic component $\varepsilon_{\theta\rho\gamma} = (\varepsilon_{\theta,\rho,\gamma,0}, \varepsilon_{\theta,\rho,\gamma,1}, \varepsilon_{\theta,\rho,\gamma,2})$ introduces horizontal differentiation. In each period, ε_θ is realized from a type 1 extreme value distribution. $\varepsilon_{\theta,\rho,\gamma,a}$ is assumed to be i.i.d. across $(\theta, \rho, \gamma, a)$.[10]

Markets: Trade takes place in each period. New goods are supplied at a constant and exogenous price p_0. There is a rental market (the peer-to-peer 'sharing economy' marketplace) where good a can be rented at price r_a, endogenously de-

[7] The parameter γ captures, in a reduced form, factors such as population density at the consumer's location, parking spaces available for rentals near the consumer's location, and so on.

[8] According to the NHTS 2009 survey, 7% of households do not own a car, 31% hold one car and 62% hold more than one car. We restrict the choice set for analytical tractability.

[9] Vehicle expenditures κ_a include maintenance, repairs and insurance; fuel expenditures are included in x_a. In principle, maintenance, repairs and insurance costs can also be affected by rental. We choose to keep period costs of ownership constant for simplicity. This simplification is unlikely to affect our simulation results as period expenditures are of an order of magnitude smaller than depreciation costs.

[10] The preference shocks ε introduce horizontal differentiation and capture the reality that often, one's need for an asset has a time-varying component.

termined at the level that matches rental supply and demand after accounting for matching frictions. An owner (non-owner renter) of type γ will match a fraction γ_s (γ_d) of the flow she supplies (demands) in the rental market.[11] There is also a resale market (the traditional secondary market) where good a can be purchased at price p_a, also endogenously determined. Transaction costs in the resale market are explained shortly. Let $r = (r_0, r_1, r_2)$ be the vector of rental prices and $p = (p_0, p_1, p_2)$ the vector of resale prices, where $p_2 = r_2 = 0$.

Timing: At the beginning of each period, a consumer of type (θ, ρ, γ) "arrives" with a good of vintage a, having observed the rental prices r, the resale prices p and her own preference shocks $\varepsilon_{\theta,\rho,\gamma}$. Trade occurs in the following sequence. First, the rental market opens, while the resale market is closed. Each owner of a good $a \in \{0,1\}$ chooses to either (a) supply her non-utilized service flow $(1-\rho)$ in the rental market (because only a fraction γ_s will be matched, she will receive a service flow of $\gamma_s(1-\rho)\theta r_a$ from supplying rental) or (b) leave her non-utilized capacity idle. Her decision rule is:

$$b^*_{\theta,\rho,\gamma}[a \in \{0,1\}] = \begin{cases} 1 & \text{if the residual capacity is rented,} \\ 0 & \text{otherwise.} \end{cases}$$

Correspondingly, each non-owner decides whether or not to rent a flow ρ of her preferred good $\hat{b} \in \{0,1,2\}$. She will only access a fraction γ_d of the service flow provided by her optimal vintage; thus her net service flow is:

$$u^o_{\theta,\rho,\gamma,\varepsilon}[a=2] = \max_{\hat{b} \in \{0,1,2\}} \left\{ \gamma_d \left(\rho x_{\hat{b}} - \theta \rho r_{\hat{b}} \right) + \varepsilon_{\hat{b}} \right\}. \tag{1}$$

It follows that the fraction of renters of type (θ, ρ, γ) who demand vintage $\hat{b} \in$

[11] For consistency, we set (γ_s, γ_d)=(0,0) for consumers who do not have access to or are not yet aware of the existence of peer-to-peer rental markets.

$\{0,1,2\}$ in the rental market is:

$$\pi_{\theta,\rho,\gamma}\left[\hat{b} \in \{0,1,2\}\right] = \frac{\exp\left(\gamma_d\left(\rho x_{\hat{b}} - \theta\rho r_{\hat{b}}\right)\right)}{\sum_{b=0}^{2} \exp\left(\gamma_d\left(\rho x_b - \theta\rho r_b\right)\right)}. \tag{2}$$

Thus, in any period, in the rental market, each consumer is either a supplier, or a buyer, or neither, but not both. Each owner can only choose whether or not to rent out the full amount of non-utilized capacity she owns. The amount a renter pays $\rho r_{\hat{b}}$ is proportional to the usage she will have of her preferred vintage.

Following this "consumption" phase, rental markets close. Each good of vintage $a \in \{0,1\}$ undergoes stochastic depreciates to the vintage $a+1$.[12]. The probability of depreciation of a durable of vintage a held by a consumer of type (θ,ρ,γ) is:

$$\delta_{\rho,\gamma}\left[a;b\right] = \delta\left[\rho + (1-\rho)\gamma_s b\right]. \tag{3}$$

Next, resale markets open. Each consumer decides whether to retain ownership of her current good, or to replace it with her preferred vintage for the next period. Her optimal replacement rule is denoted $a^*_{\theta,\rho,\gamma}\left[a \in \{1,2\}, b \in \{0,1\}\right] \in \{0,1,2\}$. A seller of type (θ,ρ,γ) who owns a good a faces a transaction cost:

$$\tau_{\rho,\gamma}\left[a;b\right] = \tau\left[\rho + (1-\rho)\gamma_s b\right] p_a. \tag{4}$$

The Consumer's Problem: Let $V_{\theta,\rho,\gamma,\varepsilon}$ be the value function for a consumer of type (θ,ρ,γ) who arrives at the beginning of the period with a good of vintage

[12]Having a stochastic depreciation rate is a convenient way to computationally simplify the model while keeping the interesting dynamics associated with durability.

$a \in \{0,1,2\}$. The Bellman Equation for a consumer who owns a durable of vintage $a \in \{0,1\}$ is given by:

$$V_{\theta,\rho,\gamma,\varepsilon}\big[a \in \{0,1\}\big] = EV_{\theta,\rho,\gamma}\big[a \in \{0,1\}\big] + \varepsilon_a,$$

where

$$EV_{\theta,\rho,\gamma}\big[a \in \{0,1\}\big] = \rho x_a - \theta k_a$$
$$+ \max_{b\in\{0,1\}} \Big\{ 1\{b=1\}\gamma_s(1-\rho)\theta r_a + \Big(1-\delta_{\rho,\gamma}[a;b]\Big)V^c_{\theta,\rho,\gamma}[a;b] + \delta_{\rho,\gamma}[a;b]V^c_{\theta,\rho,\gamma}[a+1;b]\Big\},$$
(5)

and with continuation value:

(6)
$$V^c_{\theta,\rho,\gamma}[a \in \{0,1,2\};b] = \max_{a'\in\{0,1,2\}} \Big\{ \beta EV_{\theta,\rho,\gamma}[a'] + 1\{a' \neq a\}\theta\Big(p_a - \tau_{\rho,\gamma}[a;b] - p_{a'}\Big)\Big\}.$$

In a stationary equilibrium the owner of a good that has not depreciated has no incentive to replace it. Due to transaction costs in the resale market, owners wait until their good has depreciated before replacing it with their preferred vintage. However, in a stationary equilibrium, a consumer who chooses to own a good does not let it depreciate to the point where she would enter a new period without replacement.

The Bellman Equation for a non-owner is given by:

$$V_{\theta,\rho,\gamma,\varepsilon}\big[a=2\big] = u^o_{\theta,\rho,\gamma,\varepsilon}\big[a=2\big] + V^c_{\theta,\rho,\gamma}\big[a=2;b=0\big], \tag{7}$$

where the net service flow $u^o_{\theta,\rho,\gamma,\varepsilon}\big[a=2\big]$ is as in equation (7), $b=0$ in equation

(1) since a non-owner cannot supply service flow to the rental market. In a stationary equilibrium a consumer who chooses to not own a good at the beginning of a period will always find it optimal to continue to not hold.

In expectation, equation (7) becomes:

$$(8)\quad EV_{\theta,\rho,\gamma,}\left[a=2\right]=\log\left(\sum_{\hat{b}=0}^{2}\exp\left(\gamma_d\left(\rho x_{\hat{b}}-\theta\rho r_{\hat{b}}\right)\right)\right)+V^{c}_{\theta,\rho,\gamma}\left[a=2;b=0\right].$$

All things being equal, a consumer with a higher price sensitivity will choose a vintage of lower quality. An owner with a lower utilization rate who chooses to supply rental flow to the rental market will provide more non-utilized capacity; however if her utilization rate is too low, she will hold the outside option.

Stationary Distribution: The stationary distribution $\lambda\left[a'\in\{0,1,2\}|\theta,\rho,\gamma\right]$ of holdings of durables for a consumer of type $\left(\theta,\rho,\gamma\right)$ is defined recursively by:

$$\lambda\left[a'\in\{0,1,2\}|\theta,\rho,\gamma\right]=\left(1-\delta\left[a';b^*[a']\right]\right)1\left\{a'\neq 2\right\}\lambda\left[a'|\theta,\rho,\gamma\right]$$
$$+1\left\{a'=a^*\left[2,0\right]\right\}\lambda\left[2|\theta,\rho,\gamma\right]+\sum_{a=0}^{1}\delta\left[a;b^*[a]\right]1\left\{a'=a^*\left[a+1,b^*[a]\right]\right\}\lambda\left[a|\theta,\rho,\gamma\right].$$

(9)

The first term on the right hand side of equation (9) corresponds to the fraction of consumers of type $\left(\theta,\rho,\gamma\right)$ who were holding a good of vintage $a'\in\{0,1\}$ in the previous period, and whose good has not depreciated. The second term corresponds to consumers who were non-owners and decide to switch to holding a'. (In equilibrium, no consumer chooses to do this.) The last term corresponds to the flows generated by owners whose goods have just depreciated and optimally decide to hold vintage a' in the next period.

Market Clearing Conditions: We now characterize supply and demand equations. Let q_S (q_D) represent the supply (demand) in the rental market and Q_S (Q_D) the supply (demand) in the resale market.

The market clearing conditions in the rental market for new and used goods are given by:

(10)
$$\int q_S\left[a\in\{0,1\}|\theta,\rho,\gamma\right]dF_1\left[\theta\right]dF_2\left[\rho\right]dF_3\left[\gamma\right]=\int q_D\left[a\in\{0,1\}|\theta,\rho,\gamma\right]dF_1\left[\theta\right]dF_2\left[\rho\right]dF_3\left[\gamma\right],$$

where the supply of rental for a consumer of type (θ,ρ,γ) is

$$q_S\left[a\in\{0,1\}|\theta,\rho,\gamma\right]=\gamma_s(1-\rho)1\left\{b^*\left[a\right]=1\right\}\lambda\left[a|\theta,\rho,\gamma\right],$$

and the demand for rental for a consumer of type (θ,ρ,γ) is

$$q_D\left[a\in\{0,1\}|\theta,\rho,\gamma\right]=\gamma_d\rho\pi\left[\hat{b}^*=a\right]\lambda\left[2|\theta,\rho,\gamma\right].$$

Notice that consumers who hold the outside option in equilibrium are the ones who generate the rental demand.

Resale Market: The market clearing condition in the resale market for used goods is

(11)
$$\int Q_S\left[a=1|\theta,\rho,\gamma\right]dF_1\left[\theta\right]dF_2\left[\rho\right]dF_3\left[\gamma\right]=\int Q_D\left[a=1|\theta,\rho,\gamma\right]dF_1\left[\theta\right]dF_2\left[\rho\right]dF_3\left[\gamma\right],$$

where the supply of used good for a consumer of type (θ,ρ,γ) is

$$Q_S\left[a=1|\theta,\rho,\gamma\right]=\delta\left[0;b^*[0]\right]1\left\{0=a^*\left[1,b^*[0]\right]\right\}\lambda\left[0|\theta,\rho,\gamma\right],$$

and the demand for used good for a consumer of type (θ,ρ,γ) is given by:

$$Q_D\left[a=1|\theta,\rho,\gamma\right]=\delta\left[1;b^*[1]\right]1\left\{1=a^*\left[2,b^*[1]\right]\right\}\lambda\left[1|\theta,\rho,\gamma\right].$$

In a stationary equilibrium, the supply of used goods is generated by owners of new goods that have just depreciated and who optimally choose to replace them with new goods. The demand for used goods is from owners of used goods that have just depreciated and who optimally choose to replace them with used goods. The market for new goods is assumed to be perfectly competitive. Any quantity demanded is supplied at price p_0.

Stationary Equilibrium: A stationary equilibrium consists of a vector of rental prices (r_0, r_1, r_2), a vector of resale prices (p_0, p_1, p_2), a stationary distribution of holdings of durables $\lambda\left[a\{0,1,2\}|\theta,\rho,\gamma\right]$, replacement rules $a^*_{\theta,\rho,\gamma}\left[a\{1,2\}\right]$, rental rules for owners $b^*_{\theta,\rho,\gamma}\left[a \in \{0,1\}\right]$ and rental rules for renters $\pi_{\theta,\rho,\gamma}\left[\hat{b}^* \in \{0,1,2\}\right]$ such that:

1) Consumers of type (θ,ρ,γ) decision rules satisfy the Bellman equations (5), (6) and (8).

2) The stationary distribution $\lambda\left[a|\theta,\rho,\gamma\right]$ verifies equation (9).

3) The rental markets clearing conditions for new and used goods given by equation (10) are satisfied.

4) The resale market clearing condition for used goods given by equation (11) is verified, and the supply of new good is perfectly elastic.

III. Data

Our empirical context will be the US automobile marketplace. High per-capita automobile ownership coupled with high product variety and low asset utilization make it an especially promising industry for peer-to-peer rentals.[13] Potential

[13]A number of peer-to-peer rental marketplaces for cars have emerged in the US and internationally in the last 5 years. For example, Getaround, founded in 2011, now operates in U.S.

economic impacts are also quite significant: spending on new and used vehicle purchases are about $1 trillion annually in the US alone.

We use data about each peer-to-peer automobile rental transaction conducted in San Francisco through Getaround during the period July 2012-July 2014.[14] Our data set includes hour-by-hour vehicle availability, the marketplace choice set made available to each consumer, the price per unit of time and duration of each completed transaction, the location of the vehicle at the time of rental, full-text feedback provided by the renter and supplier of the vehicle, along with vehicle features (model/make/year) and some limited consumer demographics. In this specific marketplace, if a vehicle is listed as being available, then any renter in the marketplace can rent it **'instantly'**.[15]

Figure (A1) in the Online Appendix illustrates a cross-section of car availability on the Getaround peer-to-peer rental marketplace. The availability fractions of many users suggests a pattern of usage reflective of combining personal driving with marketplace supply from time-to-time.

A. Estimated Parameters

Peer-to-Peer Rental: Table (1) presents estimates of moment conditions from the peer-to-peer rental marketplace, and their counterparts in the model:

On the supply side of the rental marketplace, we estimate the average fraction of time suppliers make their vehicle available each year, how much of this supply

cities that include San Francisco, Portland, Chicago, Austin and San Diego, and has raised over $43 million in venture financing. Turo, founded in 2009, offers its peer-to-peer rental service in over 100 U.S. cities. Other marketplaces that have significant activity concentrated in specific other countries include Drivy in France and Germany, SocialCar in Spain, and SnappCar in the Netherlands.

[14]Since our initial peer-to-peer rental data set covers the city of San Francisco, the additional data we present in the rest of the section is about the state of California.

[15]This is unlike some other peer-to-peer marketplaces like Airbnb: there is no 'approval' step by the supplier after a vehicle is requested. Thus, matching frictions of the kind involving post-request non-availability discussed by (Fradkin 2014) are not present.

Table 1—: Peer-to-Peer Rental Marketplace Estimates

	Estimates	Model Quantities
Fraction of time supplied cars are available (p.a.)	76.6%	$E\left[(1-\rho)\vert b^*[a]=1\right]$
Fraction of time supplied cars get rented (p.a.)	7.6%	$E\left[\gamma_s(1-\rho)\vert b^*[a]=1\right]$
Average supplier revenue (in $10,000 p.a.)	$*.**$	$E\left[\gamma_s(1-\rho)r_a\vert b^*[a]=1\right]$
Average renter payment (in $10,000 p.a.)	$*.**$	$E\left[\gamma_d\rho r_a\vert \hat{b}^* \in \{1,2\}\right]$

Note: This table presents moment conditions used in the calibration procedure described in section (III.B). Averages in the left column are estimated using peer-to-peer transactions which occurred in the city of San Francisco over the period July 2012 to July 2014. The right column describes their counterparts in the model. Suppliers' revenue and renters' payment are available upon request.
Source: Getaround.

actually gets rented and the average revenue of suppliers. On the demand side, we compute the average payments that renters make.

The moment conditions presented in table (1) are used to calibrate the distribution of matching frictions in the rental markets γ_s and γ_d in section III.B.

Vehicle Utilization Rates: A consumer's utilization rate is proxied by the fraction of time she would choose to use a vehicle for personal use each year if she were to own one. Our sample of utilization rates for vehicle owners is drawn from the 2009 NHTS Survey. The distribution of utilization rates in our sample is described in figure (A2) in the Online Appendix.[16] The average vehicle is used 4.6% of the time.

For each household in the sample, we measure the number of miles driven per year using their most recently acquired vehicle.[17] We convert miles into usage

[16]From the 2009 NHTS Survey, we can estimate the distribution of utilization rates conditional on owning a vehicle. In section III.B, we will use these estimates to calibrate the unconditional distribution of utilization rates.

[17]According to the 2009 NHTS Survey, households hold 1.9 vehicles on average. In our model, households are allowed to hold at most one vehicle, and we measure utilization rates by only considering the most recent vehicle they have purchased. We therefore report our eventual findings about, for example, vehicle age changes, as being about a household's first car.

times using the average driving speed.[18]

Transaction Costs, Depreciation Rates and Vehicle Expenditures

Table (2) summarizes all the parameters estimates described in this section:

Table 2—: Parameter Estimates

	Estimates	Model Quantities
Average price of new cars (in $10,000)	2.9	p_0
Average transactions cost	29.4%	$\tau\left[<\rho>\right]$
Average depreciation rate	17.6%	$\delta\left[<\rho>\right]$
Average car expenditures (in $10,000 p.a.)	0.1	κ

Source: National Automobile Dealer Association, National Household Transportation Survey and Consumers Expenditure Survey.

Our estimation of the transaction costs function $\tau\left[\rho\right]$ defined in equation (4) is presented in figure (A3) in the Online Appendix:

The average price of new cars is from the NADA Guide. The transaction costs function, defined in (4), is computed as follows. We use the percentage difference between the retail and the trade-in prices for the 10 most popular vehicles in California, obtained from the NADA Guide.[19] We convert mileage into usage time using our estimate of the average driving speed. We then fit a polynomial to the transaction costs at the median vehicle age.[20]

Overall the transaction costs function for a used car at the average age vary from approximately 10% for a vehicle which is never used, to 60% when the average usage rate reaches 20%. Transaction costs at the average usage rate of

[18]In our sample, the average driving speed is 25.8 mph. We compute average driving speed as the ratio of yearly mileage with total time spent on trips, then averaging across vehicles. This way, time spent parking (for instance) is included in usage time.

[19]We use the following ten models: Toyota Prius, Honda Civic, Honda Accord, Toyota Camry, Toyota Corolla, Ford F-150, Honda CR-V, Nissan Altima, Toyota Tacoma and BMW 3-Series.

[20]The median vehicle age in our sample is 7 years.

vehicle owners are reported in table (2), and is 29.4% of the price of a used vehicle. Using the NADA Guide, we can also estimate that the average price of a new vehicle is equal to $29,000.

The rate of stochastic depreciation is related to the rate at which new goods are replaced. Equation (9) in the case of new goods can be rewritten as

$$\delta\left[0;b^*[0]\right]\lambda\left[0|\theta,\rho,\gamma\right]=\sum_{a=0}^{1}\delta\left[a;b^*[a]\right]1\left\{0=a^*\left[a+1,b^*[a]\right]\right\}\lambda\left[a|\theta,\rho,\gamma\right].$$

The left hand side corresponds to the stock of new goods which has depreciated. The right hand side corresponds to the demand for new goods. In the absence of peer-to-peer rental markets and by integrating over θ, we obtain:

$$\delta_{\rho,\gamma=(0,0)}=\frac{Q_D\left[0|\rho,\gamma=(0,0)\right]}{\lambda\left[0|\rho,\gamma=(0,0)\right]} \tag{12}$$

The depreciation rate function can now be computed using formula (12). Using the 2009 NHTS survey data, we identify each vehicle owner by his most recently purchased vehicle. We define a new vehicle as a vehicle whose age is less than a median aged vehicle. We convert mileage into usage time using using the average speed of 25.8 mph (also from the NHTS data), then partitioning the range of usage rates into deciles. For each decile, we estimate the ratio of the flow of new cars to the stock of new cars. We fit a line to the data, shown in figure (A4) in the Online Appendix. The fitted depreciation rate function goes from 16.6% for a utilization rate close to zero, to 24.7% when the utilization rate reaches 10%. At the average utilization rate of 4.6% the fitted depreciation rate function is equal to 17.6%, the value used for our calibration exercise.

Finally we estimate average vehicle expenditures using the 2009 Consumer Expenditure Survey from the BLS.[21]. We compute the average household expen-

[21] Estimates of expenditures per vehicle are essentially constant across vintages.

ditures per vehicle on maintenance, repairs and insurance, using an average of 1.9 vehicles per household. We obtain an average level of household expenditures per vehicle equal to $1,100.

B. Calibrated Parameters

The remaining model parameters cannot directly be estimated from the data. We assume that θ follows a lognormal distribution with parameters $(\mu_\theta, \sigma_\theta)$ and that ρ follows a Beta distribution with parameters $(\alpha_\rho, \beta_\rho)$. We calibrate $(x_0, x_1, \mu_\theta, \sigma_\theta, \alpha_\rho, \beta_\rho)$ in the absence of rental markets.[22]

Table (3) summarizes the calibration exercise. The parameters were calibrated by minimizing the sum of the squared percentage difference between moments estimates and their model counterparts. These results show that the model matches the moments of the distribution of households car ownership very well. Table (A1) in the Online Appendix presents the values for the calibrated parameters.

Finally, we calibrate the frictions on the peer-to-peer platform γ_s and γ_d. We assume that γ_s and γ_d both follow a beta distribution. Based on a survey, we assume that 10% of the population are currently aware of or have access to peer-to-peer rental markets.[23] For consumers who are not aware of or do not have access to peer-to-peer rental markets, we set $\gamma = (0,0)$. We calibrate the parameters of the distributions for γ_s and γ_d by matching the moment conditions presented in table (1).

On the supply side, we obtain: $< \gamma_s > \approx 10\%$ which corresponds to the ratio of the fraction of time supplied cars are rented, to the fraction of time they are

[22]This is observationally equivalent to having $\gamma = (0,0)$ for all consumers. We assume that when the 2009 NHTS Survey was administered, the peer-to-peer rental market was too small to impact the calibration of the quality index x, price sensitivity parameter θ and utilization rate ρ.

[23]A Google Survey we conducted in 2014 suggested that 17.4% of people in California are currently aware of the existence of peer-to-peer rental markets for automobiles. We choose an estimate of 10% to calibrate the model to be conservative.

Table 3—: Moments Conditions

	Data	Calibration
Fraction of above median income household		
who purchased a new car	13.1%	11.1%
who own a car	98.0%	95.1%
Fraction of below median income household		
who purchased a new car	4.0%	4.4%
who own a car	84.0%	86.3%
Fraction of household who do not own a car	9.0%	9.3%
Average utilization rate	4.6%	4.6%
Standard deviation of utilization rate	3.5%	3.9%

Note: This table presents the moments conditions used to calibrate the parameters $(x_0, x_1, \mu_\theta, \sigma_\theta, \alpha_\rho, \beta_\rho)$. The left column shows estimates obtained using the 2009 National Household Transportation Survey. The right column presents their counterparts in the model.
Source: National Household Transportation Survey.

available. On the demand side, we obtain $< \gamma_d > \approx 60\%$. A survey of Getaround platform users we conducted in 2014 provides some validation for these numbers.[24]

IV. Counterfactual Analyses

We use the calibrated model as a stripped-down "laboratory" to examine how peer-to-peer rental markets might affect future economic activity, with a focus on consumption changes and surplus redistribution as peer-to-peer rental marketplace access increases across the population, and as the liquidity of the peer-to-peer rental marketplace changes.

[24] In the survey, we asked: "When you come to Getaround to choose and rent a vehicle, what is your success rate at finding one you're willing to rent?" : 'Less than 20% of the time', '20%-39% of the time', '40%-59% of the time', '60%-79% of the time', '80%-99% of the time', 'Every time'. Among 424 respondents and approximating each bucket by its midpoint, the average response was 85%, higher than the baseline $< \gamma_d >$ value we use, but perhaps reflecting a selection effect.

We use the parameters from the prior section to compute the model's equilibrium using the following algorithm:

1) Start with an initial vector of prices p and r.

2) Draw N = 5000 consumers of type $\left(\theta_i, \rho_i, \gamma_{s_i} \gamma_{d_i}\right)$.

3) For each consumer, compute the set of decision rules $b_i^* \left[a \in \{0,1\}\right], \pi\left[\hat{b}_i^* \in \{0,1,2\}\right], a_i^* \left[a \in \{1,2\}, b \in \{0,1\}\right]$ which satisfy (5),(6) and (8).

4) Find the corresponding stationary distribution of goods $\lambda_i\left[a \in \{0,1,2\}\right]$ which satisfies (9).

5) Search for the vector of prices which minimizes the excess supply in the resale market for used goods, as well as the excess supply in the rental markets for new and used goods.

6) Stop when the maximum relative excess supply is smaller than $\frac{1}{N}$.

As of the writing of this paper, only a fraction of the potential population is aware of the existence of peer-to-peer car rental markets, and perhaps an even smaller fraction have actual access. In addition, regulatory constraints restrict the development of these markets in some cities. With an eye on the future, we compute outcomes for levels of peer-to-peer marketplace access that are at $25\%, 50\%, 75\%$ and 100%. These are not levels of actual participation we are imposing: rather, these are the fractions of consumers who are *potential* renters and suppliers, and realized values of participation are lower.

Additionally, apart from the baseline average liquidity levels of $<\gamma_s>= 10\%$ and $<\gamma_d>= 60\%$, we examine two other cases: high liquidity ($<\gamma_s>= 15\%$ and $<\gamma_d>= 75\%$) and low liquidity ($<\gamma_s>= 5\%$ and $<\gamma_d>= 50\%$). [25] We

[25] We examined other levels as well, and the results o have the same directional flavor as those discussed below.

assume that all agents have access to the resale (secondary) market.

A. *Ownership and consumption patterns*

Table (4) summarizes variations in a range of outcomes as we increase the percentage of households who have access to peer-to-peer rental markets and vary the level of liquidity in the peer-to-peer rental marketplace:

The counterfactual analysis predicts fairly dramatic changes in automobile ownership levels. For example, in the baseline case, even when only 25% of a population has access to a marketplace like Getaround, new car ownership drops by 5% in equilibrium, used car ownership drops by 12%, and the fraction of the population who do not own a car almost doubles, increasing by 86.7%. Not surprisingly, these effects - a significant rise in everyday renters, and a reduction in the fraction of the population who chooses not to own a car - intensify as the fraction of the population who gain access increases, and as the efficiency of supply and demand matching increases.

Until we have further empirical data, our interpretation of these results will be conservative. However, even with levels of liquidity that match our empirical data of marketplace activity between 2012 and 2014, the economic significance of the projected shifts is quite striking. Consider that in 2014, over 16.5 million new vehicles were sold in the US, and over 40 million used vehicles were traded, operating on an installed base of over 200 million personal vehicles. If one assumes conservatively, for example, that *any* peer-to-peer car rental as a viable alternative to ownership is restricted to *just* urban centers of the US that have a population of at least 100,000 people and a population density of at least 2,100 residents per square mile (25 times the national average of 84 people per square mile), this would still create a potential market of over 153 million people, or over half the US population. Thus, in the long run, even the most conservative estimates (a 5% drop in newer car ownership and an older car ownership drop of 12%) would reflect reductions of millions of owned vehicles, and a shift towards non-ownership based-consumption for millions of people.[26]

Tables (5) and (6) unpack these consumption shifts in a little more detail by mapping out the switching behaviors of consumers measured when 50% of the population has access to a peer-to-peer rental market.

Consider the first set of results, corresponding to our baseline levels of marketplace liquidity. As one would anticipate, the shift away from ownership is more pronounced for below-median usage consumers: 13.1% of owners of newer cars and 33.2% of owners of older cars shift to peer-to-peer rental as their mode of consumption, in contrast with 3.9% and 13.3% respectively of newer car and older car owners above the median usage level. When one examines the contrast between below-median and above-median *income* users, however, some more subtle effects emerge. First, a substantial fraction of users keep doing what they were doing (the diagonal values). Next, newer car ownership is far more resilient among above-median income than below-median income consumers (88.3% versus 72.3%). However, comparable fractions of used-car owners shift to peer-to-peer rental across income brackets. Finally, the eventual total fraction of non-owners who fulfill any demand through the peer-to-peer rental market, is much higher among below-median income consumers (30.6%) than above-median income consumers (18.4%), a theme we return to later in this discussion.[27]

[26] We used data from the 2010 US Census to arrive at the estimate of 153 million.

[27] The same patterns persist with lower or higher liquidity, so we do not discuss these results in detail.

B. Asset usage efficiency and marketplace supply

Table (4) also illustrates an interesting shift in the usage intensity of vehicles. While the installed base of vehicles in the economy drops with an increase in peer-to-peer rental market access, the usage intensity of vehicles, and especially of older vehicles, grows significantly. The projected efficiency gains increase with access levels and marketplace liquidity. This highlights the need to distinguish between the installed base of cars, and the average number of ”cars on the road.” The drop in the former will be more pronounced than the drop in the latter. Total per-person usage levels remain relatively stable, driven in part by our model's focus on person-to-person car rentals rather than ride-sharing.

What population serves as the source of supply in the peer-to-peer rental market? Figure (1) illustrates that while the supply of older vehicles in the peer-to-peer marketplace comes from consumers that span the income spectrum, a significantly higher fraction of below-median income consumers (3 to 5 times the fraction of above-median income consumers) provide their newer vehicles for rent. Thus, this (below-median income) segment of consumers appears to play a dominant role in sustaining activity in the peer-to-peer market, driving both the supply of and the demand for vehicles.

C. Gains in consumer surplus

As summarized in Table 4, consumers enjoy positive welfare effects as access to peer-to-peer markets increases. In our baseline case, consumer surplus gains rise by 0.8% at an access level of 25%, and by 3.1% at an access level of 100%. Consistent with our prior results, the gains are greater for higher levels of access and greater marketplace liquidity. It is challenging to decompose these gains into specific components: these are simultaneously contributed to by more efficient consumption in rental markets, shifts in the consumption mix between new and used cars, and lower prices of used cars.[28]

How are these gains distributed across the population? As one would now anticipate given the consumption shifts discussed, figure (2) illustrates that below-median income households consistently see significantly higher percentage increases in surplus, roughly three-fold or so higher percentage increases. A higher fraction of below-median income consumers switch to consuming through the peer-to-peer rental marketplace, and a greater fraction of them supply capacity to the marketplace as well.

V. Conclusions and Ongoing Work

Towards assessing the welfare implications of the 'sharing economy,' we develop a first dynamic equilibrium model of an economy with peer-to-peer rental markets and forward-looking consumers who are heterogeneous in their price sensitivity and asset utilization rates. Our model allows consumers to also trade their durable assets in traditional secondary markets, includes transaction costs and depreciation rates that vary with usage intensity and admits heterogeneous marketplace matching frictions. We conduct counterfactual analyses on a calibration that uses data about the US automobile industry and from a leading peer-to-peer car rental marketplace. These analyses consistently show economically significant improvements in consumer welfare due to the availability of the 'sharing economy' marketplace, and significantly higher improvements for the below-median income segment. They also project fairly dramatic shifts away from automobile ownership as the popularity and efficiency of such marketplaces

[28] Note, however, that the actual marketplace revenues generated by peer-to-peer exchange do not directly contribute to this increase, since they are transfers between consumers, and we are not modeling commissions captured by Getaround.

grows.

Several extensions could enhance both the theoretical and empirical contributions of this study. Theoretical extensions include linking vehicle maintenance, repair and insurance expenditures to utilization rates; admitting ownership of multiple goods; endogenizing the utilization rate ρ; allowing non-binary rental supply decisions; increasing the number of vintages available; imposing more structure on the matching frictions; and developing a more sophisticated model of the outside option that could proxy for services like Zipcar, or alternatives like Lyft and Uber.

Empirically, as more data on peer-to-peer marketplaces become available, we hope to calibrate versions of our model that are specific to each of the major urban areas of the US (some of which already have fairly high fractions of non-owners), towards being able to make city-specific impact projections, as well as understanding international impacts and cross-country variations.

Perhaps the most important takeaway from our current findings, one we expect will persist with extensions and alternative calibrations, is that peer-to-peer rental marketplaces have a disproportionately positive effect on lower-income consumers across almost every measure. This segment is more likely to switch from owning to renting, provides a higher level of peer-to-peer marketplace demand, is more likely to contribute to marketplace supply, and enjoys significantly higher levels of surplus gains. We highlight this finding because it speaks to what may eventually be the true promise of the sharing economy, as an economic force that democratizes access to a higher standard of living. Ownership is a more significant barrier to consumption when your income or wealth is lower, and peer-to-peer rental marketplaces can facilitate inclusive and higher quality consumption, empowering ownership enabled by revenues generated from marketplace supply, and facilitating a more even distribution of consumer value. We hope our findings will inform policy makers as they formulate appropriate regulatory frameworks for this rapidly growing part of the economy.

REFERENCES

Adda, Jerome, and Russel Cooper. 2000. "Balladurette and Juppette: A Discrete Analysis of Scrapping Subsidies." *Journal of Political Economy*, 108(4): 778–806.

Aizcorbe, Ana, Martha Starr, and James T. Hickman. 2003. "The Replacement Demand for Motor Vehicles: Evidence from the Survey of Consumer Finances." Federal Reserve Board Working Paper.

Anderson, Simon P., and Victor A. Ginsburg. 1994. "Price Discrimination via Second-hand Markets." *European Economic Review*, 38(1): 23–44.

Attanasio, Orazio. 2000. "Consumer Durables and Inertial Behavior: Estimation and Aggregation of (S,s) rules for Automobile Purchases." *Review of Economic Studies*, 67: 667–696.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890.

Botsman, Rachel, and Roo Rogers. 2010. *What's Mine Is Yours: The Rise of Collaborative Consumption.* Harper Business.

Carranza, Juan Esteban. 2012. "Estimation of Demand for Differentiated Durable Goods." Mimeo, University of Wisconsin-Madison.

Chen, Jiawei, Susanna Esteban, and Matthew Shum. 2013. "When do Secondary Markets Harm Firms?" *American Economic Review*, 103(7): 2911–2934.

Chevalier, Judith, and Austan Goolsbee. 2009. "Are Durable Goods Consumers Forward-Looking ? Evidence from College Textbooks." *Quarterly Journal of Economics*, 124(4): 1853–1884.

Cho, Sung Jin, and John Rust. 2010. "The Flat Rental Puzzle." *Review of Economic Studies*, 77: 560–594.

Cullen, Zoe, and Chiara Farronato. 2014. "Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms." Mimeo, Stanford University.

Eberly, Janice C. 1994. "Adjustment of Consumers' Durables Stocks: Evidence from Automobile Purchases." *Journal of Political Economy*, 102(3): 403–436.

Erdem, Tulin, Imai Susumu, and Michael Keane. 2003. "Brand and Quantity Choice Dynamics under Price Uncertainty." *Quantitative Marketing and Economics*, 1(1): 5–64.

Esteban, Susanna, and Matthew Shum. 2007. "Durable Goods Oligopoly With Secondary Markets: the Case of Automobile." *Rand Journal of Economics*, 38: 332–354.

Fradkin, Andrey. 2014. "Search Frictions and the Design of Online Marketplaces." NBER Working Paper.

Gansky, Lisa. 2010. *The Mesh: Why The Future of Business Is Sharing.* Portfolio Trade.

Gavazza, Alessandro. 2011*a*. "Leasing in Secondary Markets: Theory and Evidence from Commercial Aircraft." *Journal of Political Economy*, 119(2): 325–377.

Gavazza, Alessandro. 2011*b*. "The Role of Trading Frictions in Real Asset Markets." *American Economic Review*, 101(4): 1106–1143.

Gavazza, Alessandro, Alessandro Lizzeri, and Nikita Roketskiy. 2014. "A

Quantitative Analysis of the Used-Car Market." *American Economic Review*, 104(11): 3668–3700.

Gilbert, Stephen, Ramandeep Randhawa, and Haoying Sun. 2013. "Optimal Per-Use Rentals and Sales of Durable Products and Their Distinct Roles in Price Discrimination." *Production and Operations Management*.

Gilligan, Thomas. 2004. "Lemons and Leases in the Used Business Aircraft Market." *Journal of Political Economy*, 112(5): 1157–1180.

Gowrisankaran, Gautam, and Marc Rysman. 2012. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy*, 120(6): 1173–1219.

Hall, John, and Allan Krueger. 2015. "An Analysis of the Labor Market for Ubers Driver-Partners in the United States." mimeo.

Hendel, Igal, Alessandro Lizzeri, and Marciano Siniscalchi. 2005. "Efficient Sorting in a Dynamic Adverse Selection Model." *Review of Economic Studies*, 72(2): 467–497.

Hendel, Igal, and Alessandro Lizzeri. 1999*a*. "Adverse Selection in Durable Goods Markets." *American Economic Review*, 89(5): 10971115.

Hendel, Igal, and Alessandro Lizzeri. 1999*b*. "Interfering with Secondary Markets." *The RAND Journal of Economics*, 30(1): 1–21.

Hendel, Igal, and Alessandro Lizzeri. 2002. "The Role of Leasing under Adverse Selection." *Journal of Political Economy*, 110(1): 113–143.

Hendel, Igal, and Aviv Nevo. 2006. "Measuring the Implication of Sales and Consumer Inventory Behavior." *Econometrica*, 74(6): 1637–1673.

Hideo, Konishi, and Michael T. Sandfort. 2002. "Existence of Stationary Equilibrium in the Markets for New and Used Durable Goods." *Journal of Economic*

Dynamics and Control, 25: 1029–1052.

Horton, John. 2013. "The Effects of Subsidizing Employer Search." Available at http://john-joseph-horton.com/papers/employer_search.pdf.

House, Christopher, and John Leahy. 2004. "An (s,S) Model with Adverse Selection." *Journal of Political Economy*, 112: 581–614.

Johnson, Justin P. 2011. "Secondary Markets with Changing Preferences." *The RAND Journal of Economics*, 42: 555–574.

Melnikov, Oleg. 2013. "Demand for Differentiated Products: The Case of the U.S. Computer Printer Market." *Economic Inquiry*, 51(2): 1277–1298.

Owyang, Jeremiah, and Alexandra Samuel. 2014. "Sharing is the New Buying." Available at http://www.visioncritical.com/collaborative-economy-report.

Porter, Robert H., and Peter Sattler. 1999. "Pattern of Trade in the Market for Used Durables: Theory and Evidence." NBER Working Paper.

Rao, Anita. 2011. "Online Content Pricing: Purchase and Rental Markets." Working Paper.

Rust, John. 1985. "Stationary Equilibrium in a Market for Durable Assets." *Econometrica*, 53: 783–805.

Schiller, Benjamin Reed. 2012. "Digital Distribution and the Prohibition of Resale Markets for Information Goods." Brandeis University Mimeo.

Shiraldi, Patricia. 2011. "Automobile Replacement: a Dynamic Structural Approach." *The RAND Journal of Economics*, 42(2): 266–291.

Stolyarov, Dimitry. 2002. "Turnover of Used Durables in a Stationary Equilibrium: Are Older Goods Traded More?" *The Journal of Political Economy*, 110: 1390–1413.

Sundararajan, Arun. 2012. "Why The Government Doesn't

Need to Regulate the Sharing Economy." *Wired*. Available at http://www.wired.com/2012/10/from-airbnb-to-coursera-why-the-government-shouldnt-regulate-the-sharing-economy/.

Sundararajan, Arun. 2013. "From Zipcar to the Sharing Economy." *Harvard Business Review*. Available at https://hbr.org/2013/01/from-zipcar-to-the-sharing-eco/.

Varian, Hal. 2000. "Buying, Selling and Renting Information Goods." *Journal of Industrial Economics*, 48(4): 473–488.

Wang, Yijia. 2007. "Empirical Investigation of Effects of Durability in the U.S. Automobile Market." New York University Mimeo.

Yurko, Anna V. 2012. "From Consumer Incomes to Car Ages: How the Distribution of Income Affects the Distribution of Vehicle Vintages." Mimeo, National Research University.

Zervas, Georgios, Davide Proserpio, and John Byers. 2015. "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry." Available at http://ssrn.com/abstract=2366898.

Mathematical Appendix

Table 4—: Economic Effects of an Increase in Access to Peer-to-Peer Rental Markets

	Fraction of Consumers with Peer-to-Peer Access			
	25.0%	50.0%	75.0%	100.0%
Baseline $:< \gamma_s >= 10\%, < \gamma_d >= 60\%$				
Percentage change in new car owners	-5.0%	-13.3%	-22.1%	-30.2%
Percentage change in used car owners	-12.0%	-19.6%	-27.7%	-35.3%
Percentage change in non-owners	86.7%	163.7%	246.0%	321.9%
Average used car price/Average new car price	23.9%	20.8%	17.1%	13.0%
Change in average car usage per consumer	-0.9%	-1.5%	-2.2%	-3.1%
Change in average usage intensity of new cars	5.8%	13.0%	21.8%	31.4%
Change in average usage intensity of used cars	9.2%	23.7%	43.8%	66.2%
Change in average car's age	-1.4%	-2.8%	-4.6%	-6.6%
Change in consumer surplus	0.8%	1.5%	2.4%	3.1%
Lower Liquidity $:< \gamma_s >= 5\%, < \gamma_d >= 50\%$				
Percentage change in new car owners	-2.0%	-7.5%	-13.5%	-18.5%
Percentage change in used car owners	-9.8%	-14.9%	-20.7%	-25.5%
Percentage change in non-owners	62.2%	113.1%	170.5%	218.3%
Average used car price/Average new car price	24.5%	22.2%	19.8%	17.5%
Change in average car usage per consumer	-0.7%	-1.1%	-1.7%	-2.1%
Change in average usage intensity of new cars	2.5%	6.3%	11.0%	14.7%
Change in average usage intensity of used cars	7.8%	17.4%	30.1%	43.8%
Change in average car's age	-1.0%	-1.8%	-2.9%	-4.0%
Change in consumer surplus	0.5%	1.0%	1.4%	1.9%
Higher Liquidity $:< \gamma_s >= 15\%, < \gamma_d >= 75\%$				
Percentage change in new car owners	-11.4%	-27.0%	-43.0%	-54.5%
Percentage change in used car owners	-16.7%	-29.7%	-42.6%	-57.1%
Percentage change in non-owners	140.2%	278.1%	416.8%	545.4%
Average used car price/Average new car price	23.6%	18.8%	12.3%	5.4%
Change in average car usage per consumer	-1.1%	-2.1%	-2.2%	-2.7%
Change in average usage intensity of new cars	14.4%	36.0%	70.1%	112.6%
Change in average usage intensity of used cars	12.9%	35.2%	73.1%	129.1%
Change in average car's age	-2.4%	-5.5%	-10.1%	-16.0%
Change in consumer surplus	1.7%	3.3%	5.0%	6.6%

Note: This table presents changes in equilibrium quantities as we increase the percentage of households who have access to peer-to-peer rental markets.

Table 5—: Changes in Ownership by Income Level

Baseline :				
$<\gamma_s>=10\%, <\gamma_d>=60\%$		own new	own used	do not own
Below median income consumer		16.8%	52.6%	30.6%
used to own new	21.1%	72.3%	23.3%	4.4%
used to own used	65.3%	2.4%	71.8%	25.8%
used to not own	13.6%	0%	5.9%	94.1%
Above median income consumer		52.9%	28.7%	18.4%
used to own new	59.3%	88.3%	6.3%	5.4%
used to own used	35.8%	1.6%	68.6%	29.8%
used to not own	4.9%	0%	8.1%	91.9%
Lower Liquidity :				
$<\gamma_s>=5\%, <\gamma_d>=50\%$		own new	own used	do not own
Below median income consumer		18.6%	56.2%	25.2%
used to own new	21.1%	78.6%	20.2%	1.1%
used to own used	65.3%	3.1%	78.7%	18.3%
used to not own	13.6%	0%	4.4%	95.6%
Above median income consumer		55.8%	29.8%	14.4%
used to own new	59.3%	92.7%	5.2%	2%
used to own used	35.8%	2.3%	73.7%	24%
used to not own	4.9%	0%	6.5%	93.5%
Higher Liquidity :				
$<\gamma_s>=15\%, <\gamma_d>=75\%$		own new	own used	do not own
Below median income consumer		13.1%	45.5%	41.4%
used to own new	21.1%	57.9%	22.3%	19.8%
used to own used	65.3%	1.4%	61%	37.6%
used to not own	13.6%	0%	7.3%	92.7%
Above median income consumer		45.5%	25.5%	28.9%
used to own new	59.3%	76.4%	7.2%	16.4%
used to own used	35.8%	0.7%	58.7%	40.6%
used to not own	4.9%	0%	5.7%	94.3%

Note: This table shows changes in ownership by income level (relative to having no access to peer-to-peer rental markets) when 50% of households have access to peer-to-peer rental markets. Column 1 shows ownership allocation when there is no access to rental markets. Column 2,3 and 4 shows how these allocations are split when access to peer-to-peer rental markets increase to 50%.

Table 6—: Changes in Ownership by Usage Level

Baseline :				
$<\gamma_s>=10\%, <\gamma_d>=60\%$		own new	own used	do not own
Below median usage rate consumer		7.3%	50.4%	42.3%
used to own new	10.7%	66.3%	20.5%	13.1%
used to own used	70.7%	0.3%	66.5%	33.2%
used to not own	18.6%	0%	6.5%	93.5%
Above median usage rate consumer		62.4%	30.9%	6.8%
used to own new	69.7%	86.8%	9.3%	3.9%
used to own used	30.3%	6.3%	80.4%	13.3%
Lower Liquidity :				
$<\gamma_s>=5\%, <\gamma_d>=50\%$		own new	own used	do not own
Below median usage rate consumer		8.5%	54.5%	37%
used to own new	10.7%	76.6%	18.2%	5.3%
used to own used	70.7%	0.5%	73%	26.5%
used to not own	18.6%	0%	4.9%	95.1%
Above median usage rate consumer		65.8%	31.5%	2.7%
used to own new	69.7%	90.9%	7.8%	1.3%
used to own used	30.3%	8.1%	86%	5.9%
Higher Liquidity :				
$<\gamma_s>=15\%, <\gamma_d>=75\%$		own new	own used	do not own
Below median usage rate consumer		5.3%	44.4%	50.3%
used to own new	10.7%	48.3%	21.3%	30.4%
used to own used	70.7%	0.2%	57.8%	42.1%
used to not own	18.6%	0%	6.9%	93.1%
Above median usage rate consumer		53.4%	26.6%	20%
used to own new	69.7%	75%	9.6%	15.3%
used to own used	30.3%	3.5%	65.7%	30.8%

Note: Notes: This table shows changes in ownership by usage level (relative to having no access to peer-to-peer rental markets) when 50% of households have access to peer-to-peer rental markets. Column 1 shows ownership allocation when there is no access to rental markets. Column 2,3 and 4 shows how these allocations are split when access to peer-to-peer rental markets increase to 50%.

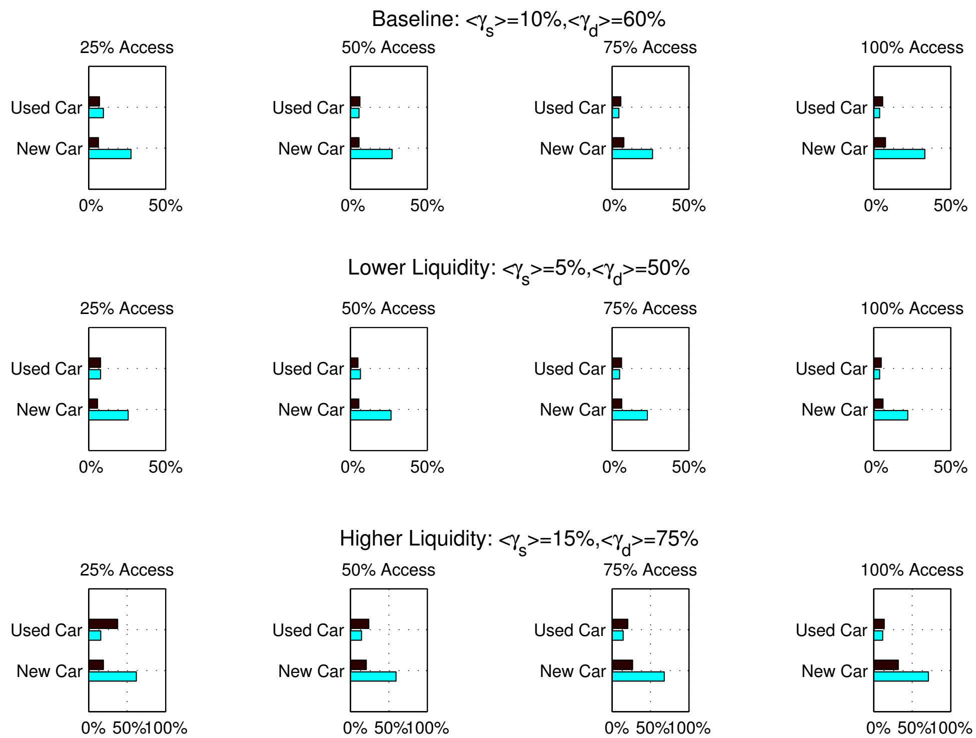

Figure 1. : How the Supply of Peer-to-Peer Rental Vehicles Varies With Income

Note: This figure shows the fraction of car owners with access to peer-to-peer rental markets who choose to supply rental, at different level of price sensitivity. The light bar corresponds to the fraction of below median income households, and the dark bar corresponds to the fraction of above median income households.

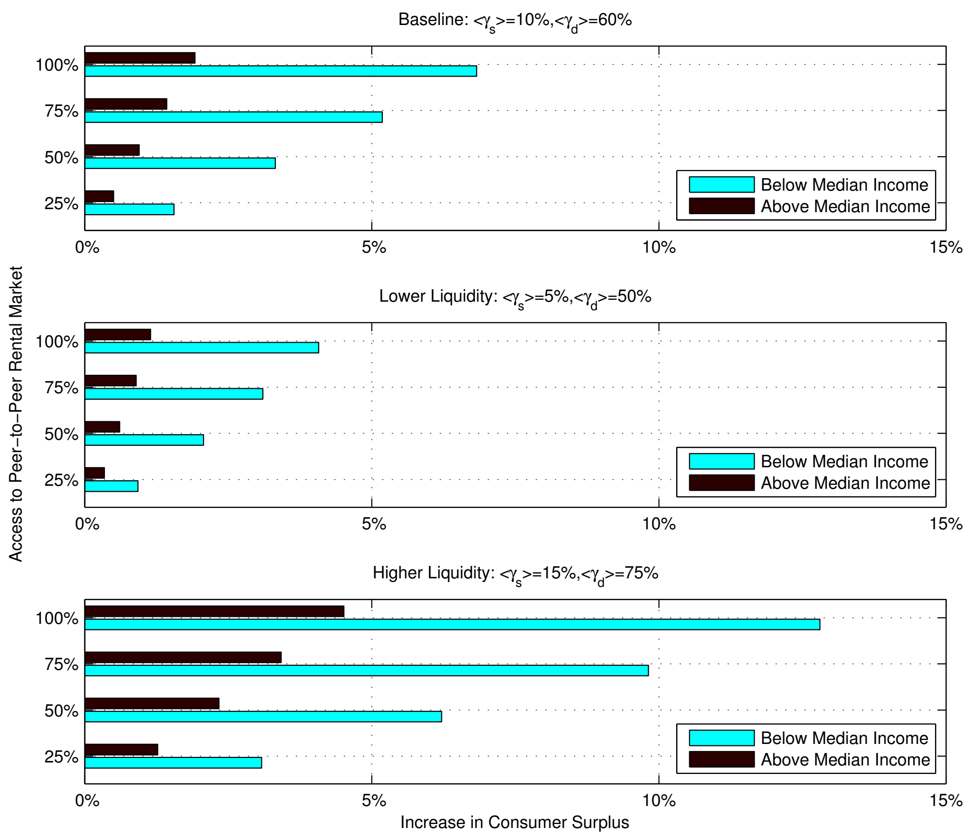

Figure 2. : Distribution of Changes in Consumer Surplus

Note: This figure shows how the percentage gains in consumer surplus (relative to the scenario of having no access to peer-to-peer rental market) are distributed across households with different price sensitivities, as access to peer-to-peer rental markets grows from 25% to 100% of the population.

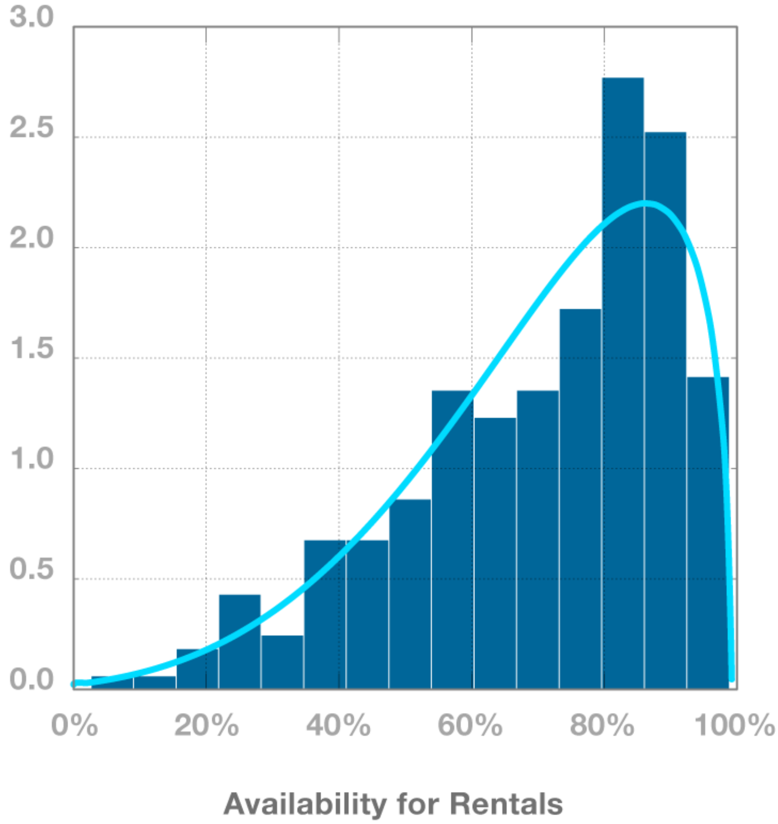

Figure A1. : Distribution of Vehicle Availability for Rental

Note: Notes: This figure shows the distribution of the fraction of time vehicles listed on the peer-to-peer marketplace were available for rental. The horizontal axis measures the fractional availability of the vehicle, and the vertical axis measures the fraction of vehicles in our sample that have that level of availability. The period is July 2012 through July 2014.
Source: Getaround.

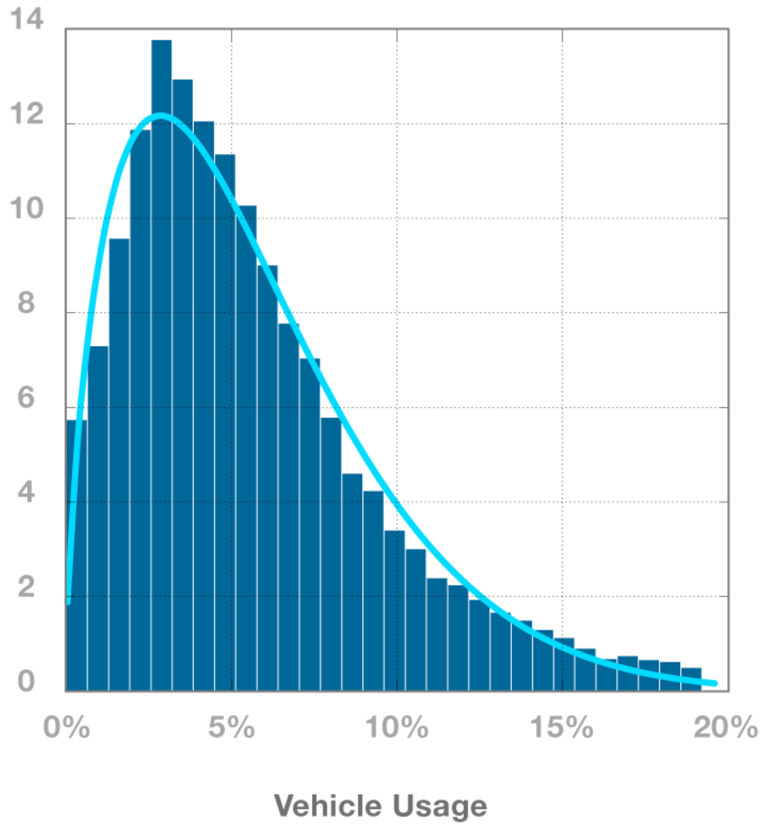

Figure A2. : Distribution of Vehicle Usage

Note: Notes: This figure shows the distribution of vehicle owner's yearly utilization of their automobiles in California. We convert yearly miles driven into the fraction of time that the primary vehicle of each household is being used per year, at the average driving speed (25.8 mph). We fit a Beta distribution to the data (light blue line).
Source: 2009 National Household Transportation Survey.

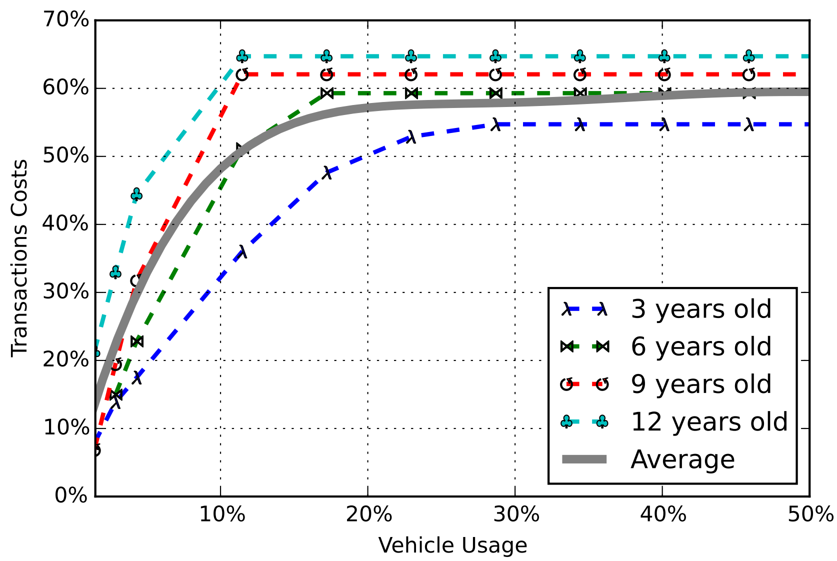

Figure A3. : Transaction Costs Function

Note: This figure shows estimates of the transaction costs incurred during the resale of a used vehicle as a function of its yearly utilization rate and its age (dotted lines). The transaction costs are computed as the difference between the retail and the trade-in price of the 10 most popular vehicles in California, across different mileages. We convert miles driven into usage time using the average speed of 25.8 mph estimated from the 2009 National Household Transportation Survey. We then fit a polynomial to the data at the median vehicle age (thick line).
Source: National Automobile Dealer Association and National Household Transportation Survey.

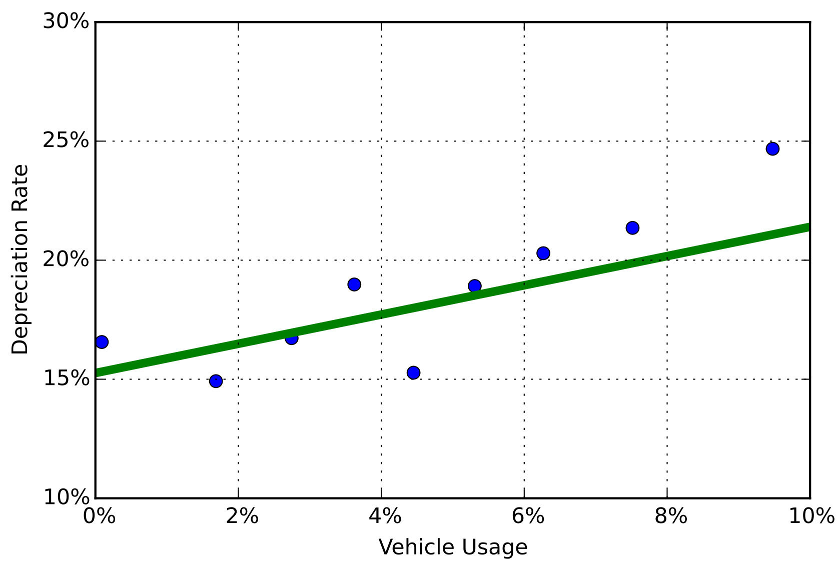

Figure A4. : Depreciation Rate Function

Note: This figure shows estimates of the depreciation rate as a function of utilization rate (blue dots). The depreciation rate function is estimated by taking the ratio of the flow of new cars to the stock of new cars as described by equation (12). We convert miles driven into usage time using the average speed (25.8 mph). We then fit a linear function to the data (green line).
Source: 2009 National Household Transportation Survey.

Table A1—: Calibrated Parameters

Quantity	Calibration Value
x_0	187.9
x_1	162.8
μ_θ	0.9
σ_θ	0.6
α_ρ	1.1
β_ρ	23.8
p_1	0.7

Note: This table shows the parameters calibrated using the moment conditions described in table (3).