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

Samuel Fraiberger Arun Sundararajan

December 19, 2014

Abstract

We develop a new dynamic model of peer-to-peer Internet-enabled rental markets for durable goods in which consumers are heterogeneous in their price sensitivity and asset utilization rates. We analyze the welfare effects of introducing such a market when consumers may also trade the durable assets they own in (traditional) secondary markets, while transaction costs and depreciation rates vary with self-utilization and rental intensity. We characterize the stationary equilibrium of the model. We then calibrate the model by combining data about US automobile ownership and usage with 2 years of transaction-level data we have obtained from a large peer-to-peer car rental marketplace. Our calibration allows us to project the longer-run welfare and distributional effects of this kind of 'sharing economy'. Counterfactual analyses show that peer-to-peer rental markets change the allocation of goods significantly, may diminish asset trade volumes, but increase consumers' surplus. The increase in consumer surplus is about three times larger for households in the top decile of the price sensitivity distribution than for households in the bottom decile, which suggests that lower-income consumers will capture the greater fraction of eventual welfare gains from the sharing economy. (JEL D4, L1, L81)

*Fraiberger: Department of Economics, New York University, 19, West 4th Street, New York, NY 10012 (email: samuel.fraiberger@nyu.edu). Sundararajan: Leonard N. Stern School of Business, New York University, 44, West 4th Street, New York, NY 10012 (email: digitalarun@nyu.edu). We thank Anmol Bandhari, Andrew Caplin, Natalie Foster, Lisa Gansky, Anindya Ghose, John Horton, John Lazarev, Alessandro Lizzeri, Romain Ranciere, Justin Rao, David Rothschild, Shachar Reichman and Marshall Van Alstyne for helpful comments and discussion.

I Introduction

In recent years, we have witnessed the emergence of a number of Internet and smartphone enabled peer-to-peer marketplaces for the short-term rental of durable goods. Examples include Getaround and RelayRides (which enable car owners to rent their vehicles to peers in their neighborhood), Snapgoods and Yerdle (which are rental marketplaces for household appliances), Airbnb (which allows consumers to rent their living space to others for short periods) and Rente-vous (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 individuals for a variety of services, from urban transportation (Lyft, Sidecar, Uber), dining (Kitchit, EatWith) and assorted labor services (Taskrabbit, Zaarly) to inter-city transit (carpooling.com) and travel planning (Vayable), which are collectively being referred to as creating a new 'sharing economy' (Sundararajan (2013)).

Such marketplaces differ from earlier Internet-based secondary marketplaces like eBay[1] because they focus on facilitating recurring short-term rental rather than occasional resale. 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*, rather than between an individual and a firm created to provide such a rental service.[2] In particular, the first set of motivating examples we highlighted (Getaround, Relayrides, Airbnb, Snapgoods, Yerdle) are marketplaces whose stated purpose is to facilitate the 'secondary' ad-hoc rental of goods by consumers who otherwise own these goods for their personal consumption.[3]

This new form of exchange is still emergent but is growing very rapidly. Last month, Airbnb indicated that they were intermediating the booking of over 375,000 stays per night, making them

[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 which rental rather than ownership is an option, but continue to do so using a firm-to-consumer supply model. Thus, our model does not represent the entire 'sharing economy', but focuses specifically on the effects of peer-to-peer marketplaces.

[3] A series of recent studies by Airbnb indicates that over 80% of their hosts participate by renting out either their primary or secondary (vacation) residences.

comparable in transaction volume to the world's largest hotel brands[4]. Airbnb was valued at over $10 billion in early 2014, higher than many established hotel brands like Wyndham and Hyatt. The urban transportation platform Uber, which introduced its service in New York City in 2011, is now the city's largest non-taxi car service with an estimated 9000 active vehicles in the city,[5] and was valued at $18 billion dollars in mid-2014. 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.

Will this rapid growth of the sharing economy have positive welfare effects? 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, 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 is eventually an empirical question, and may vary across product categories, depending on the nature of preferences and the magnitude of marketplace transaction costs.

Our paper will have two main contributions. We develop the first dynamic model with a rental market for durable goods among consumers who have heterogeneous price sensitivity, goods' utilization rate and preference shocks. We characterize the stationary equilibrium when consumers are allowed to trade in a (traditional) secondary marketplace in addition to the (new) peer-to-peer rental marketplace, incorporating transaction costs from selling, as well as depreciation rates which vary with vehicle usage. In addition to this theoretical contribution, we will calibrate our model using new data from large peer-to-peer car rental marketplaces (supplemented with the appropriate data about vehicle ownership, secondary market trade and patterns of vehicle usage) to provide the first empirical assessment of the welfare implications of Internet-based peer-to-peer marketplaces. Our

[4]For comparison: the Marriott Hotels brand, the world's third largest hotel brand, has a little over 200,000 rooms worldwide.

[5]There are about 13,000 yellow cabs in New York City.

counterfactual analysis already suggest that the 'sharing economy' may be inequity reducing in its welfare impacts, and our eventual analysis will project what the broader economic impact of the sharing economy might be.

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 pertinent prior literature. Section 3 presents our model and characterizes its equilibrium. Section 4 summarizes our data, preliminary analysis, and outlines plans for further research.

II Peer-to-Peer Markets: Economic Effects

Buying a durable good provides value to a consumer during multiple periods. In an idealized frictionless world, consumers could freely adjust their holdings of durables at any time to match their current needs. In practice, however, durable goods are illiquid and the transaction costs associated with replacing them are often large. This costly adjustment gives rise to inertial behaviors: consumers purchase durable goods and hold on to them until they depreciate sufficiently to make it worthwhile to replace them. Much like the effect of a secondary market for the resale of durable goods, the presence of a rental market for durable goods among consumers makes products of differing vintages available to consumers, thus making a single-product market a multi-product market with vertical differentiation. All things being equal a consumer with a higher price sensitivity will choose a vintage of lower quality.

There are large time series and cross-sectional variations in consumers' intensity of utilization of durable goods. The average automobile in the United States is used only 5% of the time [6]. This heterogeneity in utilization rate is an important force which can explain the gains from trade in peer-to-peer rental markets. [7]. Owners can temporarily supply the unutilized capacity of their durable goods; in parallel, others whose average utilization levels are too low (or their price sensitivity too

[6] Source: National Household Transportation 2009 Survey (NHTS).

[7] Other important forces can explain the gains from trades in peer-to-peer rental markets, such as idiosyncratic income or preference shocks.

high) to justify ownership can temporarily rent these durable goods from owners. Consequently, the introduction of peer-to-peer rental markets will affect the value of the associated underlying assets.

There are significant and distinct costs associated with rental. Depreciation cost is the most important cost associated with vehicle ownership; it represents around 40% of the lifetime costs of ownership [8]. Supplying rental service increases vehicle's mileage which directly impacts its resale value and scrappage age. In addition the owner of a durable good holds it over an extended period of time, and factors this into the usage and care of the asset. Someone who rents for a shorter period is unlikely to treat the asset with the same level of care: despite a variety of technological advances for monitoring and the emergence of sophisticated online reputation systems, moral hazard cannot be fully mitigated. Rental will therefore affect the expected lifetime of a vehicle as well as the transaction costs incurred in the resale market. We model these forces by making the depreciation rate and resale transaction costs depend on durables utilization rate [9].

Finally, although peer-to-peer rental platforms have been growing rapidly in the past few years they still affect a small fraction of durable goods markets. Consumers who own a durable good can access it without cost over its lifetime. In contrast, while Internet-enabled marketplaces do lower the transaction costs associated with search and with matching, these are still non-zero, and there are additional costs associated with product assessment and with the process of taking physical possession of the product. As we discuss in the following section, we model the fact that only a fraction of the population can access rental markets at this point; for consumers who have access to rental markets, we introduce a matching parameter which represents the likelihood of meeting a trading partner. In our counterfactual analysis we will measure the effects caused by varying the level of access and frictions in rental markets.

While their has been considerable interest in analyzing Internet-enabled rental markets for digital goods over the last decade (see, for instance Varian (2000) for an early theoretical treatment and

[8] Source: National Automobile Dealer Association Guide (NADA).

[9] In principle, vehicles' expenditure such as maintenance, repairs and insurance costs can also be affected by rental. We chose to keep the period cost of ownership constant for now since they are of an order of magnitude less important than depreciation costs. Making vehicles' expenditure depend on utilization rate will constitute a minor extension of the model.

Rao (2011) for a more recent empirical analysis), this paper is the first (to our knowledge) to focus on Internet-enabled peer-to-peer rental of durable goods among consumers. However, our model rests on a varied literature that considers different equilibrium effects of secondary markets for durable goods (Rust (1985), Anderson and Ginsburg (1994), Hendel and Lizzeri (1999a), Hendel and Lizzeri (1999b), 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 (1999b) show that firms can benefit from resale markets through indirect price discrimination. Hendel et al. (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 Stolyarov (2002) by adding a rental market for durable goods among consumers.

There has been a number of empirical analyses of secondary markets for cars (Porter and Sattler (1999), 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 (forthcoming)). [10] Porter and Sattler (1999) studies the consumer replacement problem in partial equilibrium with no resale market. 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

[10] Other analysis of secondary markets for durable goods in the literature include aircrafts (Gilligan (2004) Gavazza (2011a) Gavazza (2011b)), 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)).

costs and goods depreciation. [11] Gavazza et al. (forthcoming) 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 et al. (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.

III Model

A Consumers

Time is discrete and the is no aggregate uncertainty. There is a continuum of infinitely lived consumers of unit mass. Agents are expected utility maximizers and discount future utility flows at rate β. Each consumer is characterized by his price sensitivity $\theta \geq 0$ and his utilization rate $\rho \in [0,1]$, and his propensity to match in the rental market $\gamma \in [0,1]$[12]. 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 [13].

B Goods

Goods are indexed by $a \in \{0,1,2\}$. $a = 0$ represents a new good, $a = 1$ a used good and $a = 2$ the outside option of holding 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 $\rho x_a - \theta \kappa_a + \epsilon_a$

[11] 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.

[12] The parameter γ captures in a reduced form fashion factors such as population density at the consumer's location, attractiveness of the consumer's location, etc ... We are planning on putting more structure to this friction in future iterations.

[13] We are exploring the possibility of letting consumers hold more than one good in every period. 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. The reason we are restricting the choice set for now is that allowing consumers to hold more than one good greatly complicates the resolution of the model.

from consuming the good. The persistent utility component x_a is constant across consumers and across time. Newer goods have higher utility flows associated with them:

$$x_0 > x_1 > x_2 = 0.$$

κ_a represents the period's expenditure spent on a good of vintage $a \in \{0, 1\}$[14]. We set $\kappa_2 = 0$ for an "outsider" (consumer holding the outside option) and $\kappa_0 = \kappa_1 = \kappa$ for an owner.

The idiosyncratic component $\epsilon_{\theta\rho\gamma} = (\epsilon_{\theta,\rho,\gamma,0}, \epsilon_{\theta,\rho,\gamma,1}, \epsilon_{\theta,\rho,\gamma,2})$ introduces horizontal differentiation. In each period, a new ϵ_θ is drawn from a type 1 extreme value distribution. $\epsilon_{\theta,\rho,\gamma,a}$ is assumed to be i.i.d. across $(\theta, \rho, \gamma, a)$[15].

C Markets

Trade takes place every period. New goods are supplied at a constant and exogenous price p_0[16]. There is a rental market (the peer-to-peer 'sharing economy' marketplace) where good a can be rented at price r_a. An owner (outsider) of type γ will match a fraction γ_s (γ_d) of the flow he supplies (demands) in the rental market. [17]. There is also a resale market (the traditional secondary market) where good a can be purchased at price p_a. A seller of a good faces transaction costs in the resale market which are explained below. 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 $p_2 = r_2 = 0$.

D 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 his preference shocks $\epsilon_{\theta,\rho,\gamma}$. Trade occurs

[14] Vehicle's expenditures include maintenance, insurance and repairs. Expenditures on gas are included in x_a.

[15] The preference shocks ϵ are introduced to generate interesting dynamics on the demand side of the peer-to-peer rental market. Having an exogenous utilization rate ρ already generates interesting dynamics on the supply side of the peer-to-peer rental market. We are planning on making ρ endogenous in future iterations.

[16] We will run the analysis with different types of supply curves for the new good.

[17] We assume that (γ_s, γ_d)=(0,0) for people who do not have access to (or are not yet aware of the existence of) peer-to-peer rental markets.

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 his unutilized service flow $(1-\rho)$ in the rental market – since only a fraction γ_s will be matched, he will receive a service flow of $\gamma_s(1-\rho)\theta r_a$ from supplying rental – or (b) leave his unutilized capacity idle. His decision rule is given by [18]:

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

Correspondingly, each outsider decides whether or not to rent a flow ρ of his preferred good $\hat{b} \in \{0,1,2\}$. He will only access a fraction γ_d of the flow he chooses; thus his net service flow is given by :

$$u^o_{\theta,\rho,\gamma,\epsilon}\big[a=2\big] = \gamma_d \max_{\hat{b}\in\{0,1,2\}} \left\{ \rho x_{\hat{b}} - \theta\rho r_{\hat{b}} + \epsilon_{\hat{b}} \right\} \tag{1}$$

Using the properties of type 1 extreme value distributions, the fraction of renters of type (θ,ρ,γ) who demand vintage $\hat{b} \in \{0,1,2\}$ in the rental market is given by :

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

We are therefore assuming that during any given period, each consumer is either a supplier, or a buyer, or neither, **but not both**, in the rental market. Each owner can only choose whether or not to rent the full amount of unutilized capacity it owns [19]. Each renter pays a cost $\rho r_{\hat{b}}$ which is proportional to the usage he will have of his preferred vintage, instead of paying the fixed cost of ownership $\kappa_{\hat{b}}$.

[18] In the empirical section we proxy utilization rate with the fraction of time spent driving per year. In future iterations we will add a buffer time between driving periods and rental periods to simultaneously match the distribution of usage time reported in the survey and the distribution of availability observed on the peer-to-peer platform.

[19] In practice owners would choose their desired level of rental supply somewhere on the interval $[0, 1-\rho]$ rather than make the binary choice described here. We will treat the continuous case in an extension.

Following this "consumption" phase, rental markets then close. Each good of vintage $a \in \{0,1\}$ stochastically depreciates to the vintage $a+1$. The probability of depreciation of a durable of vintage a held by a consumer of type $\left(\theta,\rho,\gamma\right)$ is given by:

$$\delta_{\rho,\gamma}\left[a;b\right] = \begin{cases} 1 & \text{if} \quad a=0, \\ \delta\left[\rho+(1-\rho)\gamma_s b\right] & \text{if} \quad a=1, \\ 0 & \text{if} \quad a=2. \end{cases} \tag{3}$$

In other words, each new good becomes a used good after one period, each used good becomes worthless with probability $\delta\left[\rho+(1-\rho)\gamma_s b\right]$, and the outside option does not depreciate.

Resale markets then open. Each consumer decides whether to retain ownership of his current good, or to replace it with his favorite vintage for the next period. His optimal replacement rule is given by $a^*_{\theta,\rho,\gamma}\left[a \in \{1,2\}, b \in \{0,1\}\right] \in \{0,1,2\}$. A seller of type $\left(\theta,\rho,\gamma\right)$ who owns a durable which has just depreciated to vintage $a \in \{1,2\}$ faces a transaction cost which is given by [20]:

$$\tau_{\rho,\gamma}\left[a;b\right] = \begin{cases} \tau\left[\rho+(1-\rho)\gamma_s b\right]p_a & \text{if} \quad a=1, \\ 0 & \text{if} \quad a=2. \end{cases} \tag{4}$$

These different features are summarized in the following consumers' problem [21].

E The Consumers' Problem

Let $V_{\theta,\rho,\gamma,\epsilon}$ be the value function for a consumer of type $\left(\theta,\rho,\gamma\right)$ who arrives at the beginning of the period with a good of vintage $a \in \{0,1,2\}$. The Bellman Equation for a consumer who owns a durable of vintage $a \in \{0,1\}$ is given by:

[20] We will also run the analysis with a transaction cost which is not proportional to the resale price.

[21] Having a stochastic depreciation rate is a convenient way to computationally simplify the model while keeping the interesting dynamics associated with durability. However, as we show in our empirical section, we have access to a very rich dataset of prices of used vehicles for different mileage and age, to empirically estimate equation (4). On the other hand, it is more difficult to obtain good quality data on replacement / scrappage rates as a function of usage to estimate equation (3). In part to benefit from the richness of the transaction costs data available, we are exploring an extension of the model with more than 2 vintages.

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

The expectation of his value function is given by:

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

His continuation value is given by:

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

Note that in a stationary equilibrium the owner of a good which has not depreciated has no incentive to replace it. Due to the transaction costs in the resale market, owners may choose to wait until their good has depreciated enough to make it worthwhile to go back to their preferred vintage. However a consumer who chooses to own a good would never let it depreciate to the point where he would enter a new period with the outside option.

The Bellman Equation for an outsider is given by:

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

where the net service flow $u^o_{\theta,\rho,\gamma,\epsilon}\big[a = 2\big]$ is given by equation (1). In the continuation value of equation (7), we have set $b = 0$ since an outsider cannot supply service flow to the rental market. In a stationary equilibrium a consumer who chooses to hold the outside option at the beginning of

a period will always find it optimal not to hold any good.

Using the properties of type 1 extreme value distribution, equation (7) becomes:

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

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 unutilized capacity; however if his utilization rate is too low he will be better off holding the outside option.

F Stationary Distribution

Now let's consider the stationary distribution $\lambda\big[a'\in\{0,1,2\}|\theta,\rho,\gamma\big]$ of holdings of durables for a consumer of type $\big(\theta,\rho,\gamma\big)$. We omit the indices $\big(\theta,\rho,\gamma\big)$ for simplicity. It is defined recursively by:

$$\begin{aligned}\lambda\big[a'\in\{0,1,2\}|\theta,\rho,\gamma\big]&=\Big(1-\delta\big[a';b^*[a']\big]\Big)\mathbb{1}\Big\{a'\neq 2\Big\}\lambda\big[a'|\theta,\rho,\gamma\big]+\mathbb{1}\Big\{a'=a^*\big[2,0\big]\Big\}\lambda\big[2|\theta,\rho,\gamma\big]\\&+\sum_{a=0}^{1}\delta\big[a;b^*[a]\big]\mathbb{1}\Big\{a'=a^*\big[a+1,b^*[a]\big]\Big\}\lambda\big[a|\theta,\rho,\gamma\big]\end{aligned} \tag{9}$$

The first term on the right hand side of equation (9) corresponds to the fraction of consumers of type $\big(\theta,\rho,\gamma\big)$ who were holding in the previous period a good of vintage $a'\in\{0,1\}$ which has not depreciated. The second term corresponds to consumers who were holding the outside option and decide to replace it with a'. Finally the last term corresponds to the flows of purchases from owners whose goods have just depreciated and optimally decide to replace it with vintage a'.

G Market Clearing Conditions

Now let's turn to the characterization of the 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.

G.I Rental Market

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

$$\int q_S\big[a \in \{0,1\}|\theta,\rho,\gamma\big]\,dF_1\big[\theta\big]\,dF_2\big[\rho\big]\,dF_3\big[\gamma\big] = \int q_D\big[a \in \{0,1\}|\theta,\rho,\gamma\big]\,dF_1\big[\theta\big]\,dF_2\big[\rho\big]\,dF_3\big[\gamma\big] \tag{10}$$

where the supply of rental for a consumer of type $\big(\theta,\rho,\gamma\big)$ is given by:

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

and the demand for rental for a consumer of type $\big(\theta,\rho,\gamma\big)$ is given by:

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

Notice that consumers who are holding the outside option in equilibrium are the ones generating the demand for rental of new and used goods.

G.II Resale Market

The market clearing condition in the resale market for used goods is given by:

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

where the supply of used good for a consumer of type $\left(\theta,\rho,\gamma\right)$ is given by:

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

where the demand for used good for a consumer of type $\left(\theta,\rho,\gamma\right)$ is given by:

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

In a stationary equilibrium the supply of used goods is generated by consumers who used to own a new good which has just depreciated and who optimally choose to replace it with a new good. The demand for used good is created by consumers who used to own a used good which has just become worthless and optimally choose to replace it with a used good. The market for new goods is assumed to be perfectly competitive and any quantity demanded is supplied at price p_0.

With all these elements in place we can now characterize the stationary equilibrium.

H Stationary Equilibrium

A stationary equilibrium consists of a vector of rental prices (r_0,r_1), a vector of resale prices (p_0,p_1), 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. Each consumer of type (θ,ρ,γ) chooses the decision rules which 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) is verified.

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

IV Data and Calibration

A Data

Our initial empirical context will be the US peer-to-peer automobile rental marketplace [22]. The high levels of per-capita automobile ownership coupled with a large product variety and the low levels of asset utilization make it an especially promising industry for peer-to-peer rentals. A number of peer-to-peer rental marketplaces for cars have emerged internationally in the last 5 years. For example, Getaround, founded in 2011, now operates in U.S. cities that include San Francisco, Portland, Chicago, Austin and San Diego, and has raised over $19 million in venture financing. RelayRides, founded in 2009, offers its peer-to-peer rental service in over 100 U.S. cities. Drivy in France claims to have over 15,000 vehicles available for peer-to-peer rental.

We have started to estimate empirical counterparts to the model quantities. The parameters which cannot be estimated directly from the data will be calibrated to match some aggregate features of the data.

[22] We plan to extend our analysis to France and the Netherlands. We are in the process of acquiring the data of the largest peer-to-peer rental marketplaces of both countries.

A.I Peer-to-Peer Automobile Rental Marketplace

We have partnered with an internet based marketplace and obtained data about each peer-to-peer automobile rental transaction in San Francisco conducted through this marketplace during the period July 2012 through July 2014[23]. 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.' [24].

Figure (1) illustrates the cross section of car availability on the peer-to-peer rental marketplace:

[Figure 1 about here.]

As illustrated, there is considerable variation in the extent to which individuals renting their vehicles out in the marketplace reserve them for personal use – over half the users seem to treat the vehicle almost exclusively as an asset they are supplying to the marketplace, while the availability fractions of the others suggest a pattern of usage reflective of combining personal driving with marketplace supply.

Table (1) presents moment conditions estimated using data from the peer-to-peer rental marketplace and their counterparts in the model:

[Table 1 about here.]

On the supply side on the rental marketplace, we have estimated the average fraction of time suppliers make their vehicle available each year, how much of this supply actually gets rented and

[23]Since our initial peer-to-peer rental dataset covers the city of San Francisco, the additional data we present in the rest of the section focuses on the state of California. We chose to focus on California as a first approximation to balance concerns about sample size and restrictions on granularity. We will extend to the rest of the country as we get more data from our partners in the next couple of months.

[24]This is unlike some other peer-to-peer marketplaces like Airbnb: there is no 'approval' step by the supplier after a vehicle is requested

the average revenue generated by suppliers. On the demand side, we have computed the average amount of time per year during which users rent vehicles on the rental marketplace, as well as the average payments they make.

In section (B.II), we will show how the moment conditions presented in table (1) can be used to calibrate the distribution of matching frictions in the rental markets γ_s and γ_d.

A.II Estimate of Vehicle's Utilization Rate

In our model, the cross section of rental supply is driven by variations in consumer's utilization rate. We proxy utilization rate with the fraction of time a consumer would drive a vehicle for personal use each year if he was to own one. We have access to a sample of utilization rates for vehicle owners in California reported in the NHTS 2009 Survey. The distribution of utilization rates in our sample is described in figure (2) [25]:

[Figure 2 about here.]

For each household in our sample we extract the number of miles driven per year using their most recently acquired vehicle [26]. We convert miles into usage time using each vehicle's average driving speed [27].

Figure (2) illustrates the low level at which vehicle owners use their vehicle: the average vehicle is used 5.59% of the time with a standard deviation of usage time equal to 3.84%.

A.III Estimation of Transaction Costs, Depreciation Rates and Vehicle Expenditures

Table (2) summarizes all the parameters estimates we describe in this section [28]:

[25] In other words we can estimate the distribution of utilization rates conditional on owning a vehicle. In the next section we will calibrate the unconditional distribution of utilization rates by matching some moments of the joint distribution of ownership and utilization rate reported in the NHTS 2009 Survey.

[26] According to the NHTS 2009 Survey, households hold 1.9 vehicles on average. Since in this initial version of the model households are allowed to hold at most one vehicle, we measure utilization rates by only considering the most recent vehicle they have purchased.

[27] In our sample the average driving speed is 25.88 mph.

[28] Our estimates are calculated for 2009, the latest year for which the NHTS Survey is available. Since 2009 was the worse year of the latest financial crisis, we will compare our results with estimates obtained using the NHTS 2001 Survey.

[Table 2 about here.]

The largest cost of ownership comes from depreciation which is directly impacted by vehicles' mileage. Since rental affects mileage the largest cost associated with rental is likely to come from depreciation. This will affect the resale price of a vehicle as well as its scrappage age. Our estimation of the transaction costs function $\tau[\rho]$ given by equation (4) is described in figure (3):

[Figure 3 about here.]

In equation (4), the transaction costs function represents the percentage difference between the retail price and the trade-in price of a used vehicle, as a function of utilization. To estimate the transaction costs function, we use data from the NADA Guide. For each of the 5 most popular vehicles in California, [29] we compute the percentage difference between the retail price and the trade-in price, for different used car mileages and different vehicle ages. We convert yearly mileage into usage time by using an average driving speed in California of 25.88 mph reported in the NHTS 2009 Survey. We take the transaction costs function for the average vehicle age [30] and we fit a polynomial to the data. We then use the fitted polynomial for our calibration exercise.

As we can see in figure (3), the transaction costs function increases with age for a given usage level [31]. 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 vehicle owners (5.59%) are reported in table (2). They are equal to 36.55% 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$. These values are also reported in table (2).

The rate of stochastic depreciation is related to the rate at which used cars are replaced. By fixing $\gamma = (0, 0)$ (which is equivalent to assuming that rental markets are closed), the demand for

[29] We use the 5 following models: Toyota Prius, Honda Civic, Honda Accord, Toyota Camry and Toyota Corolla.

[30] The average vehicle age in our sample is 7 years.

[31] The transaction costs function is defined as a percentage of the used price of a vehicle. Since prices of used vehicles decrease with age, transaction costs actually decrease with age.

used cars simplifies to:

$$Q_D\left[a=1|\theta,\rho,\gamma=(0,0)\right]=\delta_{\rho,\gamma=(0,0)}\left[1;0\right]\lambda\Big[1|\theta,\rho,\gamma=(0,0),1=a^*\left[2,0\right]\Big]$$

So the depreciation rate function in equation (3) can be written:

$$\delta\left[\rho\right]=\int\frac{Q_D\left[a=1|\theta,\rho,\gamma=0\right]}{\lambda\Big[1|\theta,\rho,\gamma=(0,0),1=a^*\left[2,0\right]\Big]}dF_1\Big[\theta\Big] \tag{12}$$

Equation (12) implies that the depreciation rate function corresponds to the rate at which households replace used cars by used cars at a given utilization rate. Our estimate of the depreciation rate function given by equation (12) is described in figure (4):

[Figure 4 about here.]

Using data from the NHTS 2009 Survey we can estimate the fraction of households who purchased a used car in the past 12 months, and divide it by the fraction of households who are holding a used car which they have purchased when it was already used [32]. By computing this ratio for different utilization rates observed in the data, we obtain an empirical estimate of $\delta\left[\rho\right]$. We then fit a polynomial to the data, which we use for our calibration exercise [33].

As shown in figure (4), the fitted depreciation rate function increases from 11.5% for a utilization rate close to zero, to 16% when the utilization rate reaches 14%. At the average utilization rate of 5.59% the fitted depreciation rate function is equal to 13.89%. This value for the depreciation rate implies an approximate vehicle age of 7.3 years, which is equal to the average vehicle age of 7 years observed in our sample.

[32] We again select the most recent vehicle for households who possess more than one vehicle.

[33] In the baseline calibration we fitted a linear function to our estimates of the depreciation rate function. We will also run the analysis by fitting a higher order polynomial to the data.

Finally we estimate the average vehicle expenditures using the 2009 Consumer Expenditure Survey [34]. We compute the average household expenditures 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 950$ which we report in table (2).

B Calibrated Parameters

B.I Car Ownership Parameters

The remaining parameters cannot be directly estimated from the data. We assume that θ follows a log normal distribution with parameters $(\mu_\theta, \sigma_\theta)$ and that ρ follows a Beta distribution with parameters $(\alpha_\rho, \beta_\rho)$. We first calibrate the parameters which determine the distribution of car ownership $\left(x_0, x_1, \mu_\theta, \sigma_\theta, \alpha_\rho, \beta_\rho\right)$. We set $\gamma = (0, 0)$ for the calibration of these parameters, which corresponds to closing rental markets [35].

Table (3) presents the moments of the distribution of households car ownership that we have used in our calibration procedure, and the corresponding moments obtained from the model :

[Table 3 about here.]

The parameters were calibrated by minimizing the sum of the squared percentage difference between moments estimated using the NHTS 2009 Survey and their counterparts in the model. These results show that the model matches the moments of the distribution of households car ownership very well [36]. Table (4) presents the values for the calibrated parameters:

[Table 4 about here.]

[34] Expenditures per vehicle are essentially constant across vintages. We do not have good estimates of how expenditures vary with utilization. However since expenditures are of an order of magnitude smaller than depreciation costs as a share of ownership costs, we believe that assuming constant expenditures across utilization levels will not affect our results significantly.

[35] We assume that the peer-to-peer rental market was small enough in 2009 not to impact the calibration of the quality index x, price sensitivity parameter θ and utilization rate ρ.

[36] We believe that the calibration can be further improved by incorporating some of the refinements discussed in section (III), in particular the increase in the number of vintages available.

B.II Rental Market Parameters

We now reopen rental markets. At this stage we are only presenting a back of the envelop calibration procedure for the matching frictions γ_s and γ_d [37].

We assume for now that γ_s and γ_d are constant across the consumers who have access to rental markets. The average supply of rental time reported in table (1) is equal to 69.97% and the average supply which gets rented is equal to 6.93%. By assuming that γ_s is constant, we get $\gamma_s \approx 10\%$.

To compute γ_d, we take a partial equilibrium approach as a first step. The average payment that renters make on the peer-to-peer platform is equal to 336$ per year. The average fraction of time renters use rented cars is 1.06% per year. This implies an average yearly rental rate of $r \approx 336/0.0106 \approx 31,800$$ per year. Given the distribution of outsiders characteristics obtained in section (B.I), we can compute the average utilization time the model predicts that these outsiders would demand in the rental market, at an average yearly rental price equal to r. We obtain an average fraction of rental time demanded equal to 1.45%. Given that the average fraction of time that consumers use rented cars reported in table (1) is equal to 1.06%, we can get an estimate of $\gamma_d \approx 0.0106/0.0145 \approx 73\%$. We choose $\gamma_d \approx 70\%$ to be conservative.

We can now use these parameters in the counterfactuals analyses presented below.

V Counterfactuals (Work in Progess)

We can use the model as a stripped-down "laboratory" to conduct some counterfactual analyses. Our primary focus will be on understanding how automobile consumption will change as the fraction of consumers who have access to peer-to-peer rental marketplaces increases, and the role of matching frictions in peer-to-peer rental markets.

Given the parameters obtained in section (B) we can compute the equilibrium using the following algorithm:

[37] In future iterations we will calibrate the model to simultaneously match the moment conditions described in table (1) and (3). We will do so by adding more structure to the matching frictions γ_s and γ_d such as information on consumers' location available in the dataset.

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

2. Draw N = 1000 consumers of type $\left(\theta_i, \rho_i\right)$.

3. For each consumer compute its 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 cars $\lambda_i\left[a \in \{0,1,2\}\right]$ 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 10^{-3}.

A Counterfactual 1: Increase in Access to Peer-to-Peer Rental Markets

Currently, only a very small fraction of the U.S. population is aware of the existence of peer-to-peer car rental markets [38], and these are just starting to become a viable alternative to car ownership for drivers in a couple of U.S. cities.

Table (5) presents variations in equilibrium quantities as we increase the percentage of households who have access to peer-to-peer rental markets:

[Table 5 about here.]

These results show that as access increases, consumers start switching from owning a used vehicle to not owning a vehicle. As a result, prices of used vehicles go down. Sales of new and used vehicles also diminish. Consumers are better off: consumer surplus increases by more than 6% when the level of access goes from zero to 40%.

Figure (5) shows how changes in consumer surplus (relative to relative to having no access to rental market) are distributed across households with different price sensitivities, as we increase the level of access to peer-to-peer rental markets:

[38] According to Google Consumer Surveys, only 17.4% of people in California are currently aware of the existence of peer-to-peer rental markets for automobiles.

[Figure 5 about here.]

Figure (5) shows that as the level of access to peer-to-peer rental markets increases, households in the top half of the distribution of price sensitivities (i.e. below median income households) enjoy a higher increase in consumer surplus than households in the bottom half. They essentially correspond to consumers who choose to switch from owning a good which they use infrequently to being occasional renters. When 40% of the population has access to peer-to-peer rental markets, this preliminary simulation shows that the consumer surplus of the top decile of the price sensitivity distribution is over three times as large as the consumer surplus of the bottom decile.

VI Future work

These counterfactual results are promising; however they are still preliminary. For instance, there is no reason to think that the level of frictions is or will stay constant as more people have access to rental markets. We have presented these results to illustrate the power of the framework we have developed.

Moving forward, we will incorporate the refinements which have been described in the text. As we get more data from other countries we will improve our estimates of the frictions that consumers face when using rental markets, and the join distribution of these frictions with consumers' price sensitivities, utilization rates and ownership rates. We will also refine our calibration to simultaneously match some of the aggregate features observed on peer-to-peer rental marketplaces and moments of the distribution of car ownership. We are also investigating ways in which we might incorporate the existence of traditional car rental companies, as well as of competing marketplaces.

References

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

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

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

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

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

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

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

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

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

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

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

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

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

___ **, Alessandro Lizzeri, and Nikita Roketskiy**, "A Quantitative Analysis of the Used-Car Market," forthcoming. American Economic Review.

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

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

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

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

___ **and** ___ , "Adverse Selection in Durable Goods Markets," *American Economic Review*, 1999, *89* (5), 10971115.

___ **and** ___ , "Interfering with Secondary Markets," *The RAND Journal of Economics*, 1999, *30* (1), 1–21.

___ **and** ___ , "The Role of Leasing under Adverse Selection," *Journal of Political Economy*, 2002, *110* (1), 113–143.

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

Hideo, Konishi and Michael T. Sandfort, "Existence of Stationary Equilibrium in the Markets for New and Used Durable Goods," *Journal of Economic Dynamics and Control*, 2002, *25*, 1029–1052.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 1: Peer-to-Peer Rental Marketplace Estimates

	Estimates	Model Quantities
Fraction of time supplied cars are available (in % per year)	69.97	$E\left[(1-\rho)\vert b^*[a]=1\right]$
Fraction of time supplied cars get rented (in % per year)	6.93	$E\left[\gamma_s(1-\rho)\vert b^*[a]=1\right]$
Suppliers' revenue (in 10,000$ per year)	$*.**$	$E\left[\gamma_s(1-\rho)r_a\vert b^*[a]=1\right]$
Fraction of time renters use rental cars (in % per year)	1.06	$E\left[\gamma_d\rho\vert\hat{b}^*\in\{1,2\}\right]$
Renters' payment (in 10,000$ per year)	$*.**$	$E\left[\gamma_d\rho r_a\vert\hat{b}^*\in\{1,2\}\right]$

Notes: This table presents the moment conditions used in the calibration procedure described in section (B.II). The numbers in the left column were computed using a representative sample of vehicles listed on the peer-to-peer marketplace. The right column describes their counterparts in the model. The averages were estimated using peer-to-peer transactions which occurred in the city of San Francisco over the period July 2012 to July 2014 and were then annualized. Suppliers' revenue and renters' payment are available upon request.

Table 2: Parameters' Estimates

	Estimates	Model Quantities
Price of new cars (in 10,000$)	2.90	p_0
Transactions costs (in %)	36.55	$\tau\big[\rho\big]$
Depreciation rate (in % per year)	13.89	$\delta\big[\rho\big]$
Vehicle expenditures (in 10,000$ per year)	0.10	κ

Notes: This table presents the parameters which were directly estimated from the data. The average price of new cars was taken from the 2009 NADA Guide. The transaction costs function was computed by taking the percentage difference between the retail and the trade-in prices for different utilization rates for the 5 most popular vehicles in the NADA Guide. We then fitted a polynomial to the transaction costs at the average vehicle age. The depreciation rate function was computed using formula (12), by estimating the fraction of used vehicles replaced by used vehicles for different utilization rates in the NHTS 2009 Survey. We then fitted a linear function to the data. We reported the values for the transaction costs function and the depreciation rate function at the average utilization rate of vehicle owners ($\rho = 5.59\%$). The annual amount of expenditures per vehicle was computed using the 2009 Consumers Expenditure Survey. We have summed households expenditures on maintenance, repairs and insurance, and computed expenditures per vehicle using an average of 1.9 vehicles per household.

Table 3: Moments Conditions

Consumer's type	Data	Calibration
Purchased a car in the past 12 months		
and are above median income (in %)	13.04	11.13
and are below median income (in %)	7.68	6.47
and use it above median driving frequency (in %)	11.73	11.46
and use it below median driving frequency (in %)	8.99	6.15
and chose a new car (in %)	7.75	8.00
and chose a used car (in %)	12.97	9.60
Do not own a car (in %)	7.56	7.60

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

Table 4: Calibrated Parameters

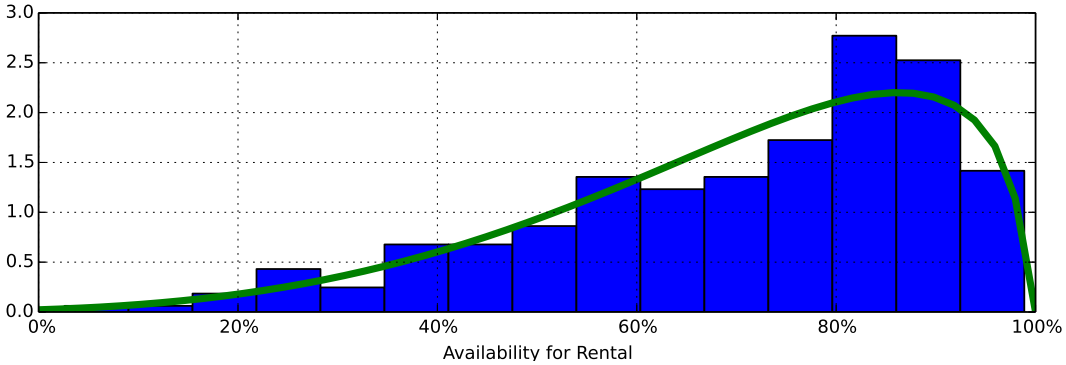
Model Quantities	Calibration
x_0	85.28
x_1	62.38
μ_θ	0.57
σ_θ	0.46
α_ρ	1.88
β_ρ	31.06

Table 5: Counterfactual 1: Increase in Access to Peer-to-Peer Rental Markets

	Access Level (in %)				
	0	10	20	30	40
Consumers who purchase a new car (in % per year)	10.83	10.71	9.73	9.24	8.25
Consumers who purchase a used car (in % per year)	7.94	7.38	7.33	6.87	6.39
Consumers who own a used car (in %)	79.77	74.49	69.67	65.36	60.15
Consumers who supply car rentals (in % per year)	0.00	1.93	4.36	5.72	7.83
Consumers who do not own a car (in %)	9.40	14.80	20.60	25.40	31.60
Consumers who demand car rentals (in % per year)	0.00	5.79	12.74	18.51	25.44
Purchase price of new cars (in 10,000$)	2.90	2.90	2.90	2.90	2.90
Purchase price of used cars (in 10,000$)	1.77	1.75	1.64	1.50	1.39
Change in consumer surplus (in %)	0.00	1.38	2.90	4.72	6.17

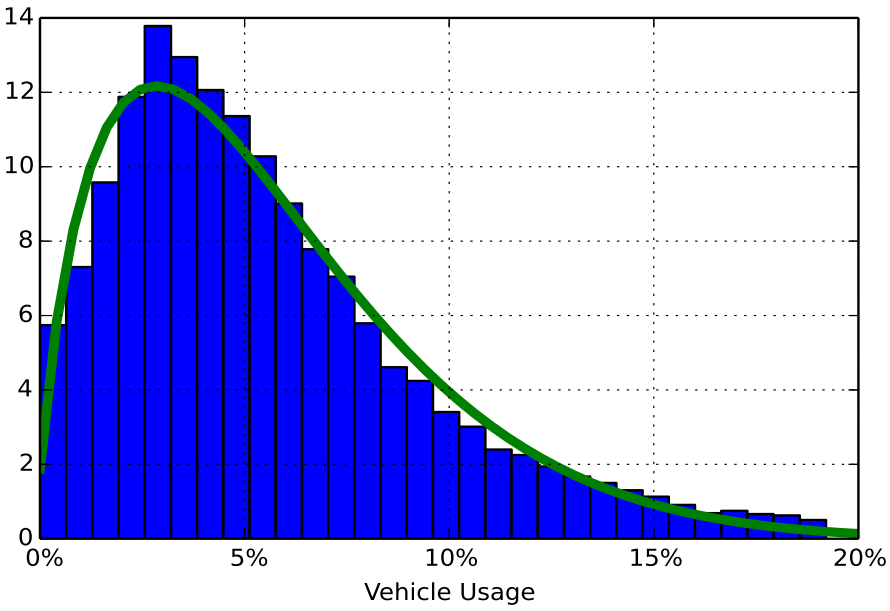
Notes: This table presents changes in equilibrium quantities as we increase the percentage of households who have access to peer-to-peer rental markets. As a first approximation, we have assumed that $\gamma_s = 10\%$*, which is the average level at which rental supply gets rented on the peer-to-peer platform. We have also assumed that* $\gamma_d = 70\%$*, which is calibrated using the procedure described in section (B.II).*

Figure 1: Distribution of Vehicle Availability for Rental



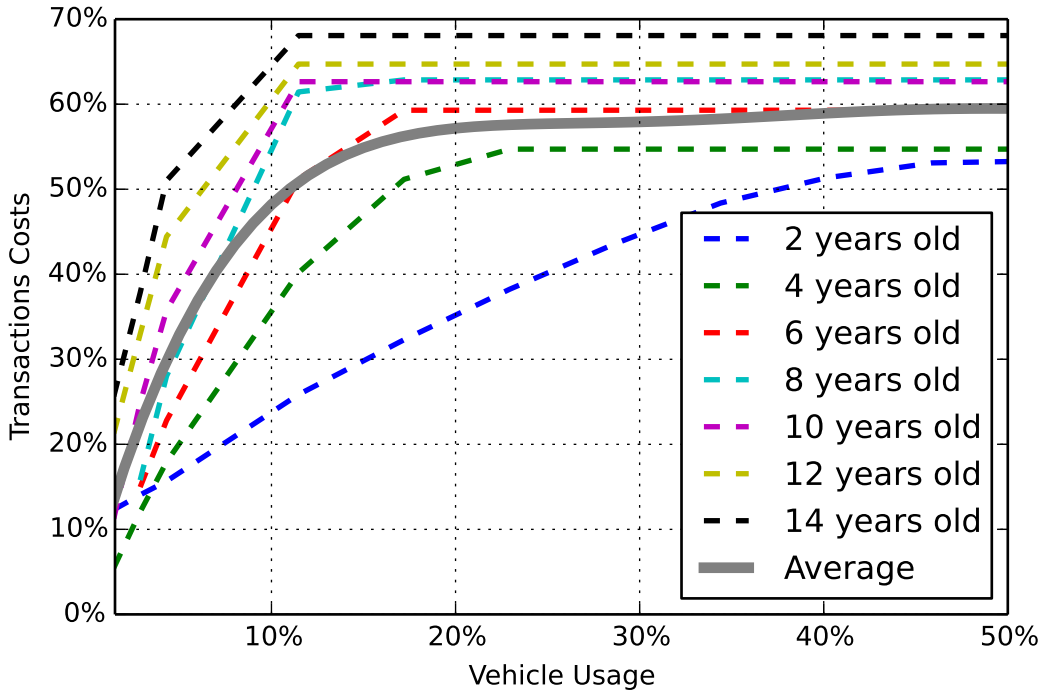
Notes: This figure shows the distribution of the fraction of time a representative sample of the vehicles listed on the peer-to-peer marketplace were available for rental. The horizontal axis measures the fractional availability of the vehicle, and the vertical axis measures the mass of vehicles in our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

Figure 2: Distribution of Vehicle Usage



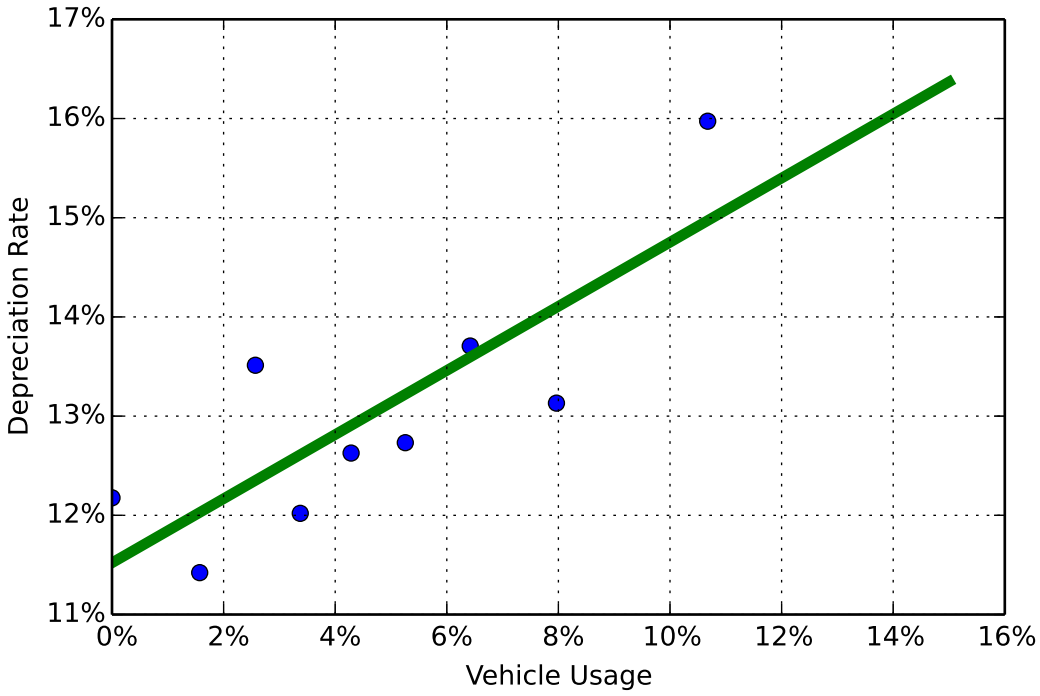
Notes: This figure shows the distribution of vehicle owner's yearly utilization of their automobiles in California. We convert yearly miles driven into the fraction of time that the primary vehicle of each household is being used per year, at its average driving speed. We fit a Beta distribution to the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

Figure 3: Transaction Costs Function



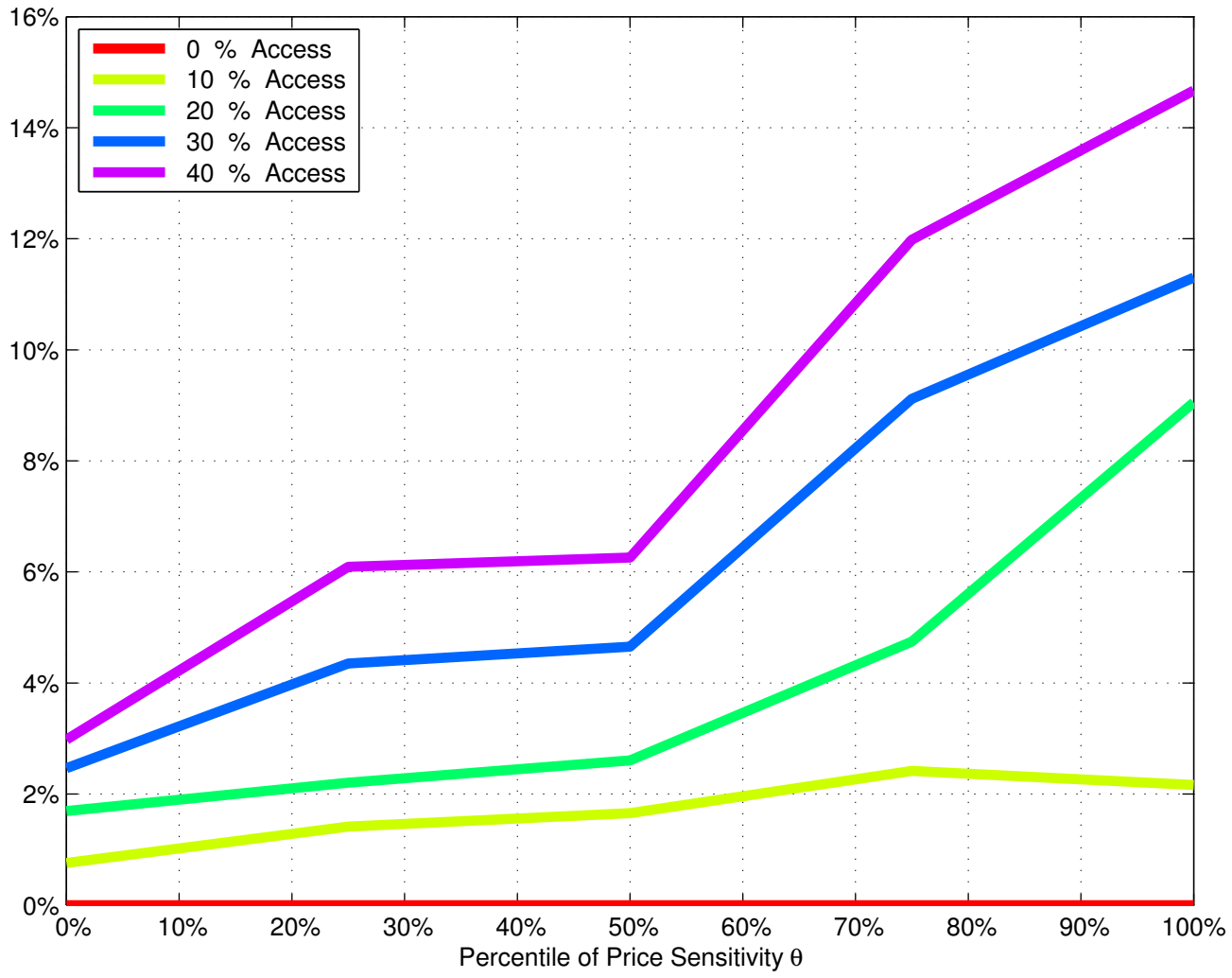
Notes: This figure shows estimates of the transaction costs incurred during the resale of a used vehicle as a function of its yearly utilization rate and its age (dotted lines). The transaction costs are computed as the difference between the retail and the trade-in price of the 5 most popular vehicles in California, for different mileage. We convert miles driven into usage time using an average speed of 25.88 mph reported in the NHTS 2009 Survey. We then fit a polynomial to the data for the average vehicle age (thick line) . (Source: NADA Guide).

Figure 4: Depreciation Rate Function



Notes: This figure shows estimates of the depreciation rate as a function of utilization rate (blue dots). The depreciation rate function is computed using equation (12). We convert miles driven into usage time using an average speed of 25.88 mph. We then fit a linear function to the data (green line). (Source: NHTS 2009 Survey).

Figure 5: Distribution of Changes in Consumer Surplus



Notes: This figure shows how changes is consumer surplus (relative to having no access to rental market) are distributed across households with different price sensitivities, as we increase the level of access to peer-to-peer rental markets. Each plot corresponds to an increasing fraction of the population who have access to rental markets.