

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

Samuel Fraiberger

Arun Sundararajan

This draft: March 6, 2015

## Abstract

We develop a new dynamic model of peer-to-peer Internet-enabled rental markets for durable goods in which consumers may also trade their durable assets in (traditional) secondary markets, transaction costs and depreciation rates may vary with usage intensity, and consumers are heterogeneous in their price sensitivity and asset utilization rates. We characterize the stationary equilibrium of the model. We analyze the welfare and distributional effects of introducing these rental markets by calibrating our model with US automobile industry data and 2 years of transaction-level data we have obtained from Getaround, a large peer-to-peer car rental marketplace. Our counterfactual analyses vary marketplace access levels and matching frictions, showing that peer-to-peer rental markets change the allocation of goods significantly, substituting rental for ownership and lowering used-good prices while increasing consumer surplus. Consumption shifts are significantly more pronounced for below-median income users, who also provide a majority of rental supply. Our results also suggest that these below-median income consumers will enjoy a disproportionate fraction of eventual welfare gains from this kind of 'sharing economy' through broader inclusion, higher quality rental-based consumption, and new ownership facilitated by rental supply revenues. (JEL D4, L1, L81)

---

\*Fraiberger: Department of Economics, New York University (email: samuel.fraiberger@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, Andrew Caplin, Natalie Foster, Lisa Gansky, Shane Greenstein, Anindya Ghose, John Horton, John Lazarev, Alessandro Lizzeri, Romain Ranciere, Justin Rao, David Rothschild, Shachar Reichman, Marshall Van Alstyne, and seminar participants at Carnegie-Mellon University, New York University and the 2014 MIT/BU Platform Strategy Research Symposium for helpful discussions on preliminary versions of this work. Fraiberger and Sundararajan have no current or prior commercial relationship with Getaround.

# I Introduction

In recent years, a number of Internet and mobile-device enabled peer-to-peer marketplaces have emerged to facilitate the short-term rental of durable goods. Examples include Getaround and RelayRides (which enable car owners to supply their vehicles as short-term rentals), Airbnb (which allows consumers to rent their living space to others for short periods) and StyleLend (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 (Kitchit, EatWith) and inter-city transit (BlaBlaCar, carpooling.com) to labor (TaskRabbit, Handy), local delivery (Instacart, Postmates), and short-term 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<sup>1</sup> 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.<sup>2</sup> In particular, the first set of motivating examples we highlighted (Getaround, Relayrides, Airbnb, StyleLend) 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 late 2014, Airbnb indicated that they had over one million listings on their site, and over the summer of 2014, indicated their hosts were accommodating over 375,000 guests per night, making them comparable in inventory and transaction

---

<sup>1</sup>Much like eBay, most of these platforms have sophisticated consumer identity verification and feedback systems.

<sup>2</sup>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 paper does not model the entire 'sharing economy,' focusing instead on peer-to-peer marketplaces.

volume to the world's largest hotel brands<sup>3</sup>. Airbnb was valued at \$20 billion in early 2015, higher than most established hotel brands. 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 over 15,000 active vehicles in the city as of the end of 2014,<sup>4</sup> and was valued at over \$40 billion dollars when raising its most recent round of financing. Its largest competitor Lyft reports having over 100,000 drivers in the U.S. as of 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 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. We develop the first dynamic model of an economy with a peer-to-peer rental market for durable goods among consumers 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 vehicle usage, as well as variable matching frictions that alter the rate at which rental supply and demand are fulfilled. Our model has been developed to be applicable to a range of settings in which peer-to-peer rental may expand consumption possibilities.

Our second contribution emerges from the 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 BLS, NADA

---

<sup>3</sup>For comparison: Intercontinental Hotel Group, the world's largest hotel chain by room count, has a little over 600,000 rooms worldwide.

<sup>4</sup>There are about 13,000 yellow cabs in New York City.

and the NHTS), which allows us to provide a first empirical assessment of the welfare implications of Internet-based peer-to-peer rental marketplaces in the automobile industry.

Our model yields a number of predictions. A consistent finding across all our counterfactual analyses is that peer-to-peer markets improve consumer welfare. These increases in surplus grow consistently with the fraction of the population who have access to the marketplace, and with the level of marketplace liquidity, or 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%, which corresponds to billions of dollars of value creation.<sup>5</sup>

Whose activity drives these gain? We find that there is an interesting contrast between the impact of peer-to-peer rental markets on the choices of below-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. For example, in our baseline calibration, as the fraction of consumers who have access to a peer-to-peer rental market increases from 25% to 100% of the population, average surplus gains for below-median income consumers grow from 1.56% to 6.82%, while corresponding average surplus gains for above-median consumers grow from 0.5% to 1.92%. This pattern is consistent across all our counterfactual analyses.

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

---

<sup>5</sup>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.

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 current geographical distribution of activity on Getaround across different neighborhoods in San Francisco are summarized in Figure 1, and seems consistent with our projections.

[Figure 1 about here.]

As illustrated in the figure, neighborhoods that have lower average income levels seem to be the ones with greater Getaround activity.

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 and current work. 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 summarizes ongoing work.

## **II Peer-to-Peer Markets: Economic Effects**

The purchase of a durable good provides value to a consumer over an extended period of time. In a frictionless world, consumers might freely adjust their holdings of durable goods at any time 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, in some ways, mirroring one of the economic effect of a secondary market for trading assets.

The potential gains from trade from a peer-to-peer rental market are induced in part by the widespread variation, both across consumers and across time, of the utilization of owned durable

assets. For example, the average automobile in the United States is used only 5% of the time <sup>6</sup>. This heterogeneity in utilization rate is one of many potential sources of gains from trade: ownership as a pre-requisite to utilization may exclude a fraction of potential users; idiosyncratic income or preference shocks may contribute further to gains from 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 (again, much like the prospect of future resale created by secondary markets) might make other consumers more willing to invest in asset ownership. Consequently, the introduction of peer-to-peer rental markets will 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, <sup>7</sup> will change. More specifically, if one rents out one's vehicle in a peer-to-peer market, the associated increase in mileage directly impacts the vehicle's resale value and the age at which one might scrap the vehicle. Similarly, if one rents out one's personal dwelling space on Airbnb, this increase in wear-and-tear could lead to higher maintenance costs, or more rapid depreciation of the property's value.

Furthermore, the owner of a durable good holds it over an extended period of time, and factors their future use 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 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. Rental will therefore affect 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.<sup>8</sup>

Finally, although the popularity of peer-to-peer rental platforms has been growing rapidly, their

---

<sup>6</sup>Source: National Household Transportation 2009 Survey (NHTS).

<sup>7</sup>Source: National Automobile Dealer Association Guide (NADA).

<sup>8</sup>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.

reach and liquidity are still limited. Consumers who own a durable good can access it costlessly at any time 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 (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 on a peer-to-peer marketplace. Further, there are costs associated with product assessment and the process of taking physical possession of a rented asset. As we discuss in the following section, we explicitly model a scenario in which only a fraction of the population has access to peer-to-peer rental markets, and even for those consumers who have access to rental markets, we mediate their gains using two matching parameters which capture the probability of finding a trading partner as a supplier and as a renter. 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 analysis measure the effects of varying both the breadth of access to and the level of matching frictions in peer-to-peer rental markets.

While there 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 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. 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 (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 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), Stolyarov (2002), Aizcorbe, Starr and Hickman (2003), Esteban and Shum (2007), Wang (2007), Cho and Rust (2010), Shiraldi (2011), Yurko (2012), Chen et al. (2013), Gavazza, Lizzeri and Roketskiy (2014)).<sup>9</sup> 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 costs and goods depreciation.<sup>10</sup> Gavazza et al. (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 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.

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

---

<sup>9</sup>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)).

<sup>10</sup>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.



of whether a listed supplier is actually willing to trade, and trading at the wrong time, and uses counterfactual analyses to show 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 and estimate it using data from TaskRabbit. Their estimation 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), and also providing evidence consistent with incumbent price reductions in response to increased Airbnb activity. 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.

### III Model

#### A Consumers

We model a continuum of infinitely lived consumers of unit mass. Time is discrete and there is no aggregate uncertainty. Agents are expected utility maximizers and discount future utility flows at rate  $\beta$ . Each consumer is characterized by her price sensitivity  $\theta \geq 0$  and her utilization rate  $\rho \in [0, 1]$ , and her propensity to match in the rental market  $\gamma \in [0, 1]$ <sup>11</sup>. The parameters  $(\theta, \rho, \gamma)$  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 <sup>12</sup>.

---

<sup>11</sup>The parameter  $\gamma$  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.

<sup>12</sup>An extension would allow consumers to own more than one product 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. Our restriction on the

## B 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 asset or '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  $(\theta, \rho, \gamma)$  who possesses a good of type  $a$  derives a period utility of  $\rho x_a - \theta \kappa_a + \epsilon_a$  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:

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

$\kappa_a$  represents the period's expenditure spent on a good of vintage  $a \in \{0, 1\}$ <sup>13</sup>. We set  $\kappa_2 = 0$  for a "non-owner" (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  $\epsilon_\theta$  is drawn from a type 1 extreme value distribution.  $\epsilon_{\theta,\rho,\gamma,a}$  is assumed to be i.i.d. across  $(\theta, \rho, \gamma, a)$ <sup>14</sup>.

## C Markets

Trade takes place every period. New goods are supplied at a constant and exogenous price  $p_0$ <sup>15</sup>. There is a rental market (the peer-to-peer 'sharing economy' marketplace) where good  $a$  can be rented at price  $r_a$  that is endogenously determined at the level that matches rental supply and demand after accounting for matching frictions. An owner (non-owner renter) of type  $\gamma$  will match a fraction  $\gamma_s$  ( $\gamma_d$ ) of the flow she supplies (demands) in the rental market.<sup>16</sup> There is also a resale market

---

choice set for now is for analytical tractability, and makes our subsequent empirical estimates more conservative than they otherwise would be.

<sup>13</sup>Vehicle expenditures include maintenance, insurance and repairs. Expenditure on fuel is included in  $x_a$ .

<sup>14</sup>The preference shocks  $\epsilon$  are introduced to incorporate more interesting behavior on the demand side of the peer-to-peer rental market, and to capture the reality that often, one's need for an asset has a time-varying component. Having an exogenous utilization rate  $\rho$  already generates interesting dynamics on the supply side of the peer-to-peer rental market. We hope to make  $\rho$  endogenous in future model iterations.

<sup>15</sup>We will run the analysis with different types of supply curves for the new good.

<sup>16</sup>We assume that  $(\gamma_s, \gamma_d) = (0, 0)$  for people who do not have access to or are not yet aware of the existence of peer-to-peer rental markets.

(the traditional secondary market) where good  $a$  can be purchased at price  $p_a$ , also endogenously determined. 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  $(\theta, \rho, \gamma)$  "arrives" with a good of vintage  $a$ , having observed the rental prices  $r$ , the resale prices  $p$  and her own preference shocks  $\epsilon_{\theta, \rho, \gamma}$ . 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 unutilized service flow  $(1 - \rho)$  in the rental market – since only a fraction  $\gamma_s$  will be matched, she will receive a service flow of  $\gamma_s(1 - \rho)\theta r_a$  from supplying rental – or (b) leave her unutilized capacity idle. Her decision rule is given by <sup>17</sup>:

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

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

$$u_{\theta, \rho, \gamma, \epsilon}^o[a = 2] = \max_{\hat{b} \in \{0, 1, 2\}} \left\{ \gamma_d (\rho x_{\hat{b}} - \theta \rho r_{\hat{b}}) + \epsilon_{\hat{b}} \right\} \quad (1)$$

Using the properties of type 1 extreme value distributions, the fraction of renters of type  $(\theta, \rho, \gamma)$  who demand vintage  $\hat{b} \in \{0, 1, 2\}$  in the rental market can be rewritten as:

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

---

<sup>17</sup>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.

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 out the full amount of non-utilized capacity she owns.<sup>18</sup> Each renter pays a cost  $\rho r_b$  which is proportional to the usage she will have of her preferred vintage, instead of paying the fixed cost of ownership  $\kappa_b$ .

Following this "consumption" phase, rental markets 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  $(\theta, \rho, \gamma)$  is given by:

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

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

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

These choices made by consumers when faced with the options created by these markets is examined in the next section.<sup>19</sup>

## E The Consumer's Problem

Let  $V_{\theta, \rho, \gamma, \epsilon}$  be the value function for a consumer of type  $(\theta, \rho, \gamma)$  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:

---

<sup>18</sup>In practice owners would choose their desired level of rental supply somewhere on the interval  $[0, 1 - \rho]$  rather than making the binary choice we model; we do not believe this alters our results significantly.

<sup>19</sup>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 or scrappage rates as a function of usage to estimate equation (3). We are exploring an extension with more than 2 vintages.

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

The expectation of her value function is given by:

$$EV_{\theta,\rho,\gamma}[a \in \{0, 1\}] = \rho x_a - \theta k_a + \max_{b \in \{0,1\}} \left\{ \mathbb{1}\{b = 1\} \gamma_s (1 - \rho) \theta r_a + \left( 1 - \delta_{\rho,\gamma}[a; b] \right) V_{\theta,\rho,\gamma}^c[a; b] + \delta_{\rho,\gamma}[a; b] V_{\theta,\rho,\gamma}^c[a + 1; b] \right\}. \quad (5)$$

her continuation value is given by:

$$V_{\theta,\rho,\gamma}^c[a \in \{0, 1, 2\}; b] = \max_{a' \in \{0,1,2\}} \left\{ \beta EV_{\theta,\rho,\gamma}[a'] + \mathbb{1}\{a' \neq a\} \theta \left( p_a - \tau_{\rho,\gamma}[a; b] - p_{a'} \right) \right\}. \quad (6)$$

In a stationary equilibrium the owner of a good which has not depreciated has no incentive to replace it. Due to transaction costs in the resale market, owners may choose to wait until their good has depreciated sufficiently to make it worth replacing it with their preferred vintage. However a consumer who chooses to own would never 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:

$$V_{\theta,\rho,\gamma,\epsilon}[a = 2] = u_{\theta,\rho,\gamma,\epsilon}^o[a = 2] + V_{\theta,\rho,\gamma}^c[a = 2; b = 0]. \quad (7)$$

where the net service flow  $u_{\theta,\rho,\gamma,\epsilon}^o[a = 2]$  is given by equation (1). In the continuation value of equation (7), we have set  $b = 0$  since a non-owner cannot supply service flow to the rental market. In a stationary equilibrium a consumer who chooses to hold the outside option (or to not own a good) at the beginning of a period will always find it optimal to continue to not hold.

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

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

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 non-utilized capacity; however if her utilization rate is too low she will be better off holding the outside option.

## F Stationary Distribution

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

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

The first term on the right hand side of equation (9) corresponds to the fraction of consumers of type  $(\theta, \rho, \gamma)$  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 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

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.

## G.I Rental Market

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

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

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

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

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

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

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:

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

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

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

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

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

In a stationary equilibrium the supply of used goods is generated by owners of a new good which has just depreciated and who optimally choose to replace it with a new good. The demand for used goods is created by owners of a used good which has just depreciated to being of no value and who optimally choose to replace it with a used good. For now, 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  $\lambda[a\{0, 1, 2\}|\theta, \rho, \gamma]$ , replacement rules  $a_{\theta, \rho, \gamma}^*[a\{1, 2\}]$ , rental rules for owners  $b_{\theta, \rho, \gamma}^*[a \in \{0, 1\}]$  and rental rules for renters  $\pi_{\theta, \rho, \gamma}[\hat{b}^* \in \{0, 1, 2\}]$  such that:

1. Each consumer of type  $(\theta, \rho, \gamma)$  chooses decision rules which satisfy the Bellman equations (5), (6) and (8).
2. The stationary distribution  $\lambda[a|\theta, \rho, \gamma]$  verifies equation (9) which defines it recursively.
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 automobile marketplace. 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. Potential economic impacts are also quite significant: spending on new vehicle purchases are about \$500 billion annually in the US alone, and annual spending on used vehicle purchases in the US is also close to \$500 billion.

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. cities that include San Francisco, Portland, Chicago, Austin and San Diego, and has raised over \$43 million in venture financing. RelayRides, 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, SocialCar in Spain, and SnappCar in the Netherlands.

#### A.I Peer-to-Peer Automobile Rental Marketplace

We use data about each peer-to-peer automobile rental transaction conducted in San Francisco through Getaround during the period July 2012 through July 2014.<sup>20</sup> 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'**.<sup>21</sup>

Figure (2) illustrates a cross-section of car availability on the Getaround peer-to-peer rental marketplace:

---

<sup>20</sup>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 is about the state of California.

<sup>21</sup>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.

[Figure 2 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 from time-to-time.

Table (1) presents a comparison between moment conditions estimated using rental marketplace data, 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 the average revenue generated by suppliers. On the demand side, we have computed the average payments renters make.

The moment conditions presented in table (1) are used to calibrate the distribution of matching frictions in the rental markets  $\gamma_s$  and  $\gamma_d$ .

## **A.II Estimate of Vehicle's Utilization Rate**

Rental supply is driven by variations in utilization rates across consumers. We proxy utilization rate with the fraction of time a consumer would drive a vehicle for personal use each year if she was to own one. Our sample of utilization rates for vehicle owners in California is drawn from the NHTS 2009 Survey. The distribution of utilization rates in our sample is described in figure (3) <sup>22</sup>:

[Figure 3 about here.]

---

<sup>22</sup>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.

For each household in this sample, we extract the number of miles driven per year using their most recently acquired vehicle.<sup>23</sup> We convert miles into usage time using each vehicle's average driving speed.<sup>24</sup>

Figure (3) illustrates the low level at which vehicle owners use their vehicle: the average vehicle is used 4.6% of the time with a standard deviation of usage time equal to 3.5%.

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

Table (2) summarizes all the parameters estimates we describe in this section <sup>25</sup>:

[Table 2 about here.]

The largest cost of ownership comes from depreciation which is directly impacted by vehicle 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 (4):

[Figure 4 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 10 most popular vehicles in California,<sup>26</sup> we compute the percentage difference between the retail price and the trade-in price, for different used car mileage levels and different vehicle ages. We convert yearly mileage into usage time by using an average driving speed in California of 25.8 mph reported in the NHTS 2009

---

<sup>23</sup>According to the NHTS 2009 Survey, households hold 1.9 vehicles on average. In our current 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.

<sup>24</sup>In our sample, the average driving speed is 25.8 mph.

<sup>25</sup>Our estimates are calculated for 2009, the latest year for which the NHTS Survey is available.

<sup>26</sup>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.

Survey. We take the transaction costs function for the vehicle of average age,<sup>27</sup> and we then fit a polynomial to the data. We use the fitted polynomial for our counterfactual exercise.

As shown in figure (4), the transaction costs function increases with age for a given usage level.<sup>28</sup> 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 are reported in table (2). They are equal to 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. 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 used cars simplifies to:

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

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

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

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 (5):

[Figure 5 about here.]

Data from the NHTS 2009 Survey allows us to 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

<sup>27</sup>The average vehicle age in our sample is 7 years.

<sup>28</sup>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.

which they have purchased when it was already used.<sup>29</sup> By computing this ratio for different utilization rates observed in the data, we obtain an empirical estimate of  $\delta[\rho]$ . We then fit a polynomial to the data, which we use for our calibration exercise.<sup>30</sup>

As shown in figure (5), 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%. This value for the depreciation rate implies an approximate vehicle age of 7.1 years, which is equal to the average vehicle age of 7 years observed in our sample<sup>31</sup>.

Finally we estimate average vehicle expenditures using the 2009 Consumer Expenditure Survey from the Bureau of Labor Statistics (BLS).<sup>32</sup> 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 \$1,100, which we report in table (2).

## B Calibrated Parameters

### B.1 Car Ownership Parameters

Our remaining model parameters cannot be directly estimated from the data. We assume that  $\theta$  follows a log normal distribution with parameters  $(\mu_\theta, \sigma_\theta)$  and that  $\rho$  follows a Beta distribution with parameters  $(\alpha_\rho, \beta_\rho)$ . We first calibrate the parameters which determine the distribution of car ownership  $(x_0, x_1, \mu_\theta, \sigma_\theta, \alpha_\rho, \beta_\rho)$ . We set  $\gamma = (0, 0)$  for the calibration of these parameters, which corresponds to closing rental markets<sup>33</sup>.

---

<sup>29</sup>Again, we select the most recent vehicle for households who possess more than one vehicle.

<sup>30</sup>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.

<sup>31</sup>In order to match the model's assumptions, we assume that households only derive utility from their most recent car

<sup>32</sup>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.

<sup>33</sup>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  $\theta$  and utilization rate  $\rho$ .

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.<sup>34</sup> Table (4) presents the values for the calibrated parameters.

[Table 4 about here.]

## B.II Supply and Demand Matching Parameters

As a first approximation, we calibrate the average value of  $\gamma_s$  as the ratio of the average supply of rental time and the average supply which gets rented. In table (1), we have reported that the average supply of rental time is equal to 76.6% and the average fraction of time cars actually get rented is equal to 7.6%, yielding  $\langle \gamma_s \rangle \approx 10\%$ . We use a beta distribution for  $\gamma_s$ .

Next, we calibrate  $\gamma_d$  by matching the average revenue of suppliers and the average payment of renters on the peer-to-peer platform, which yields  $\langle \gamma_d \rangle \approx 60\%$ . We assume that  $\gamma_d$  follows a beta distribution.<sup>35</sup>

## V Counterfactual Analyses

We use the calibrated model as a stripped-down "laboratory" to examine how peer-to-peer rental markets will affect future economic activity. Our primary focus will be on understanding consumption

---

<sup>34</sup>We believe that the calibration can be further improved by incorporating some of the refinements discussed in section (III), in particular allowing consumers to hold multiple vintages.

<sup>35</sup>As part of a survey of platform users in 2014, we asked them: "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.

changes and surplus redistribution as peer-to-peer rental marketplace access increases across the population, and how sensitive these projections are to varying the liquidity of the peer-to-peer rental marketplace.

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

1. Fix a set of  $\gamma_s$  and  $\gamma_d$  values, and a level of access.
2. Start with an initial vector of prices  $p$  and  $r$ .
3. Draw  $N = 5000$  consumers of type  $(\theta_i, \rho_i)$ .
4. For each consumer, compute the set of decision rules  $b_i^*[a \in \{0, 1\}]$ ,  $\pi[\hat{b}_i^* \in \{0, 1, 2\}]$ ,  $a_i^*[a \in \{1, 2\}, b \in \{0, 1\}]$  which satisfy (5),(6) and (8).
5. Find the corresponding stationary distribution of goods  $\lambda_i[a \in \{0, 1, 2\}]$  which satisfies (9).
6. 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.
7. Stop when the maximum relative excess supply is smaller than  $\frac{1}{N}$ .

Currently, only a fraction of the potential population is aware of the existence of peer-to-peer car rental markets,<sup>36</sup> and perhaps an even smaller fraction have actual access. Towards a forward-looking analysis, apart from our base case of no access, we compute outcomes for levels of peer-to-peer marketplace access that are at 25%, 50%, 75% and 100%. Note that these are not levels of participation we are exogenously imposing: rather, these are the fractions of consumers who are potential renters and suppliers. As our results will show, the realized values of participation are lower.

Additionally, beyond our baseline liquidity levels of  $\gamma_s = 10\%$  and  $\gamma_d = 60\%$  we have computed outcomes across a wide variety of candidate levels of access and liquidity. In what follows, apart from the baseline, we focus on two other cases: of high liquidity ( $\gamma_s = 15\%$ ,  $\gamma_d = 75\%$ ) and of low liquidity

---

<sup>36</sup>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.

( $\gamma_s = 5\%$ ,  $\gamma_d = 50\%$ ). The results obtained from other cases have the same directional flavor as those discussed below. We assume that all agents have access to the resale (secondary) market.

## A Ownership and consumption patterns

Table (5) summarizes variation 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.

[Table 5 about here.]

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.

At one extreme (100% access, high liquidity), vehicle ownership in the population falls by over 50%, the population of non-owners grows six-fold, and more than half the population fulfils their consumption needs through peer-to-peer rental. 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 vehicles on the road, and a shift towards non-ownership based-consumption for millions of people.<sup>37</sup>

Tables (6) and (7) unpack these consumption shifts in a little more detail by mapping out the switching behaviors of consumers, measured at a 50% level of access.

[Table 6 about here.]

[Table 7 about here.]

Consider the first set of results, corresponding to our baseline levels of access. As one would anticipate, the shift away from ownership is more pronounced for below-media 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 and older owners above the media 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%), while comparable fractions of used-car owners shift to peer-to-peer rental across income brackets. Finally, the eventual total fraction of non-owners, users who fulfil 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. The same patterns persist with lower or higher liquidity, so we do not discuss those results in detail.

## **B Asset usage efficiency and marketplace supply**

Table (5) 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

---

<sup>37</sup>We used data from the 2010 US Census to arrive at the estimate of 153 million. An extension to our analysis, which is in progress, will create a separate calibration for each major metropolitan area, using city-specific data about ownership rates and maintenance costs.

intensity of vehicles, and especially of older vehicles, grows significantly. The projected efficiency gains increase with access levels and marketplace liquidity. Total per-person usage levels remain relatively stable, driven in part by our model's focus on person-to-person car rentals rather than ridesharing.

What population serves as the source of supply in the peer-to-peer rental market? Figure (6) 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 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.

[Figure 6 about here.]

## **C Gains in consumer surplus**

As summarized in Table 5, 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. Given the dynamics of the model, 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. 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.

How are these gains distributed across the population? Figure (7) illustrates that the changes in consumer surplus (relative to having no access to rental market) vary significant across households below and above media income, as we increase the level of access to peer-to-peer rental markets and the marketplace liquidity.

[Figure 7 about here.]

Below-median income households consistently see significantly higher percentage increases in surplus, roughly three-fold or so higher percentage increases. In light of results we have discussed already, this finding should be anticipated: 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.

## **VI 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 varying marketplace matching frictions. We use data on two years of peer-to-peer marketplace transactions, we calibrate the model to match aggregate data from the US automobile industry and obtain a good fit. Using the calibrated version of the model, we conduct counterfactual analyses that vary the level of rental marketplace access and the level of supply and demand liquidity. Our counterfactual 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 grows.

Our ongoing work is along a number of different lines that will enhance both the theoretical and empirical contributions of this study. Theoretical extensions that we are working on include linking vehicle maintenance, repair and insurance expenditures to utilization rates; admitting ownership of multiple assets; endogenizing the utilization rate  $\rho$ ; allowing non-binary rental supply decisions; and developing a more sophisticated model of the outside option that could proxy for services like Zipcar, or alternatives like Lyft and Uber. The extension we are working most actively on is a model that admits multiple vintages, as well as a more nuanced integration of marketplace matching parameters,

one that allow them to vary across consumers in the eventual calibration.

Empirically, we continue to work on improving our existing calibration. We are calibrating 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. We are also working on acquiring marketplace data sets from France and the Netherlands that will allow us to understand international impacts and cross-country variations.

Perhaps the most important takeaway from our current findings, one we fully expect to 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 a 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. Our hope is that our economic findings will inform policy makers as they formulate appropriate regulatory policy for this increasingly important part of the economy.

## 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 Inertial 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.
- Botsman, Rachel and Roo Rogers**, *What’s Mine Is Yours: The Rise of Collaborative Consumption*, Harper Business, 2010.
- 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.
- Cullen, Zoe and Chiara Farronato**, “Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms,” 2014. Mimeo, Stanford University.
- 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.
- Fradkin, Andrey**, “Search Frictions and the Design of Online Marketplaces,” 2014. NBER Working Paper.
- Gansky, Lisa**, *The Mesh: Why The Future of Business Is Sharing*, Portfolio Trade, 2010.

**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," *American Economic Review*, 2014, 104 (11), 3668–3700.

**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.

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

**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), 1097–1115.

— 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.

**Horton, John**, "The Effects of Subsidizing Employer Search," 2013. Available at [http://john-joseph-horton.com/papers/employer\\_search.pdf](http://john-joseph-horton.com/papers/employer_search.pdf).

**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," 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**, "Why The Government Doesn't Need to Regulate the Sharing Economy," *Wired*, 2012. Available at <http://www.wired.com/2012/10/from-airbnb-to-coursera-why-the-government-shouldnt-regulate-the-sharing-economy/>.
- , "From Zipcar to the Sharing Economy," *Harvard Business Review*, 2013. Available at <https://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 Effects of Durability in the U.S. Automobile Market," 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. Mimeo, National Research University.
- Zervas, Georgios, Davide Proserpio, and John Byers**, "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," 2015. Available at <http://ssrn.com/abstract=2366898>.

Table 1: Peer-to-Peer Rental Marketplace Estimates

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

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: Parameter Estimates

	Estimates	Model Quantities
Average price of new cars (in \$10,000)	2.9	$p_0$
Average transactions cost	29.4%	$\tau[ < \rho > ]$
Average depreciation rate	17.6%	$\delta[ < \rho > ]$
Average car expenditures (in \$10,000 per year)	0.1	$\kappa$

Notes: This table presents directly estimated parameters. 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 10 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 ( $< \rho > = 4.6\%$ ). 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

	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%
Stdev. utilization rate	3.5%	3.9%

Notes: 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 the data estimates obtained using the NHTS 2009 Survey. The right column presents their counterparts in the model.

Table 4: Calibrated Parameters

Quantity	Calibration Value
$x_0$	187.9
$x_1$	162.8
$\mu_\theta$	0.9
$\sigma_\theta$	0.6
$\alpha_\rho$	1.1
$\beta_\rho$	23.8
$\rho_1$	0.7

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

Table 5: 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 : $\langle \gamma_s \rangle = 10\%$ , $\langle \gamma_d \rangle = 60\%$				
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 : $\langle \gamma_s \rangle = 5\%$ , $\langle \gamma_d \rangle = 50\%$				
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 : $\langle \gamma_s \rangle = 15\%$ , $\langle \gamma_d \rangle = 75\%$				
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%

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

Table 6: Changes in Ownership by Income Level

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

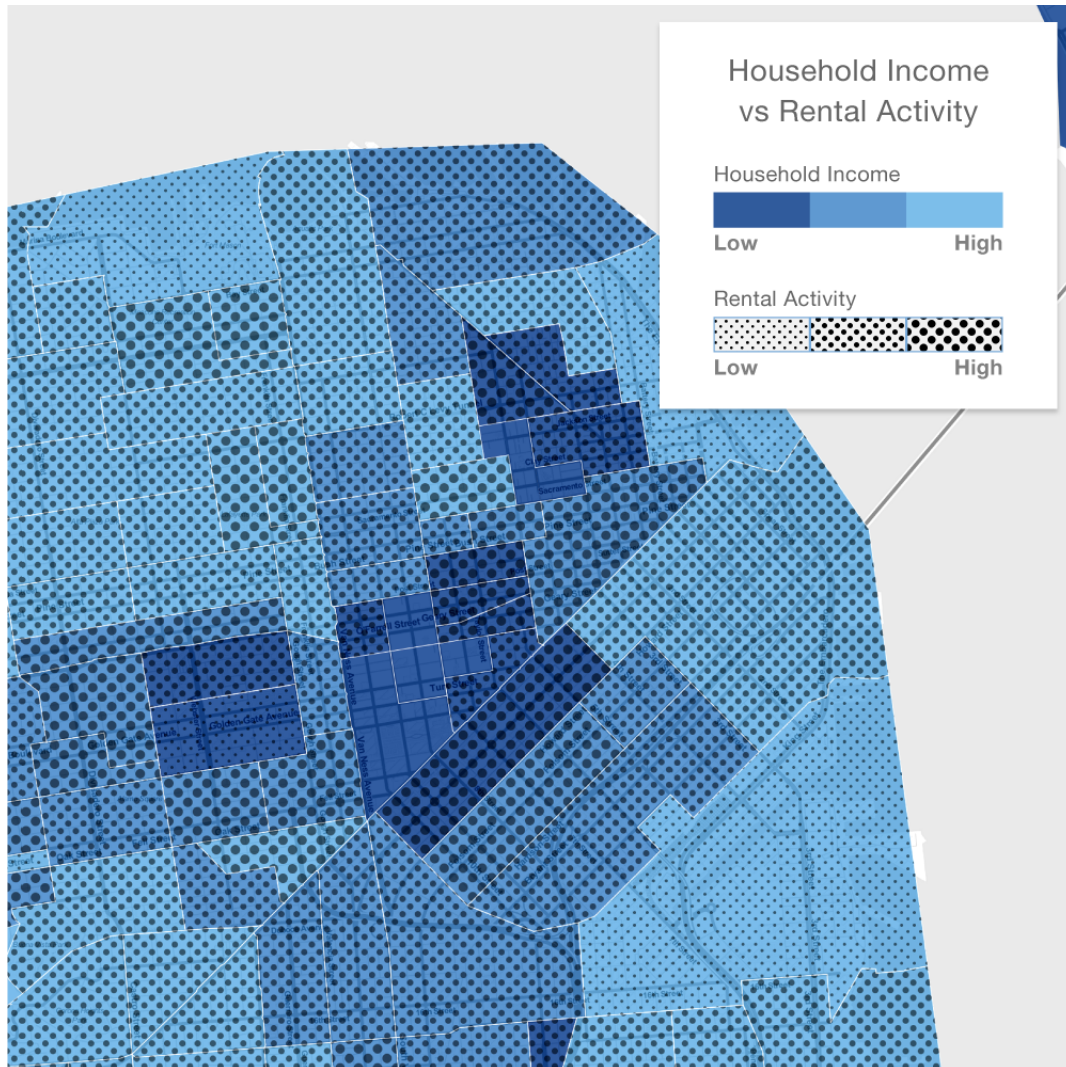
Notes: This table shows changes in ownership by income level (relative to having no access to peer-to-peer rental markets) when 50% of households have access to peer-to-peer rental markets. Column 1 shows ownership allocation when there is no access to rental markets. Column 2,3 and 4 shows how these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

Table 7: Changes in Ownership by Usage Level

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

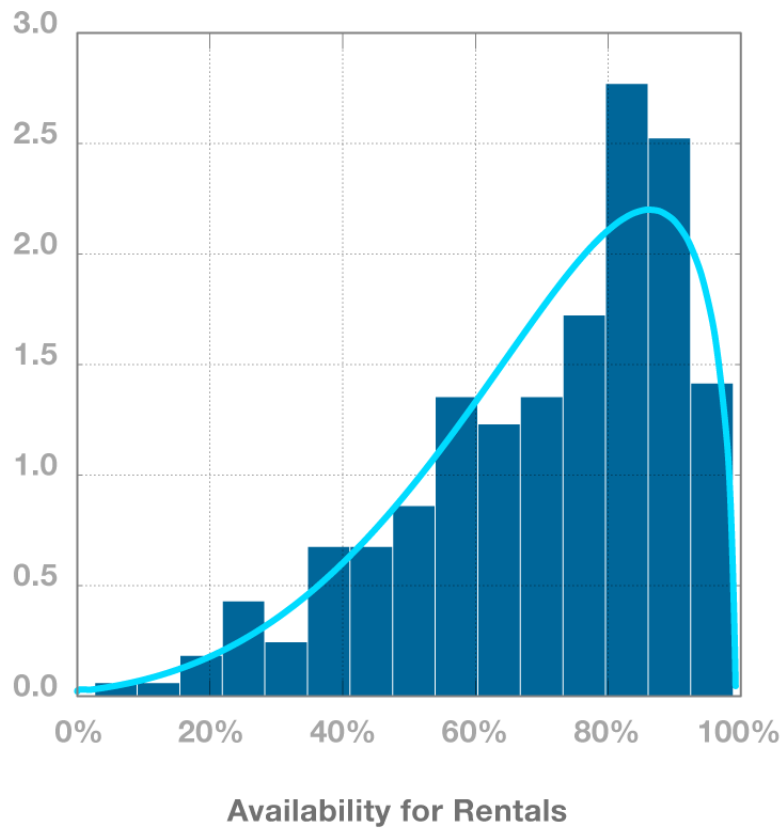
Notes: This table shows changes in ownership by usage level (relative to having no access to peer-to-peer rental markets) when 50% of households have access to peer-to-peer rental markets. Column 1 shows ownership allocation when there is no access to rental markets. Column 2,3 and 4 shows how these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

Figure 1: How Current Usage of Getaround in SF Varies With Income



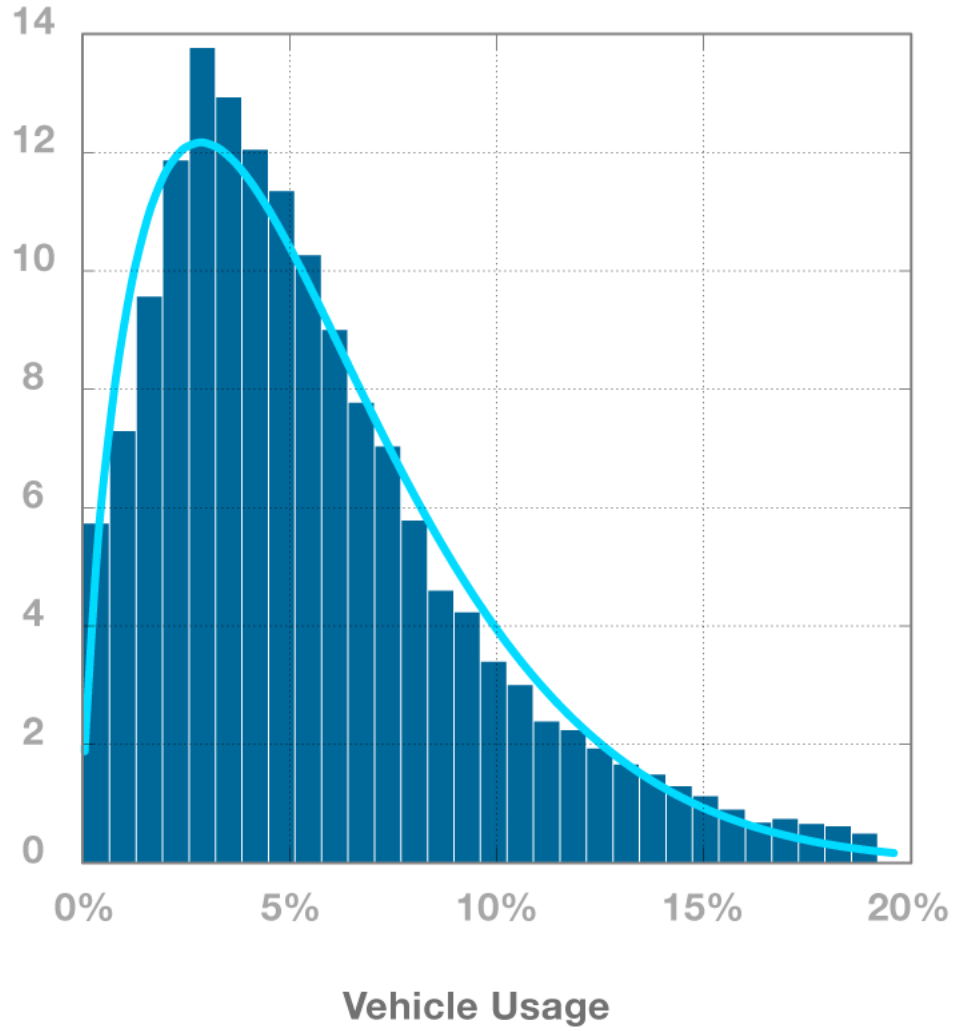
Notes: This figure illustrates the peer-to-peer vehicle rental activity on the Getaround platform in San Francisco between 2012 and 2014, plotted by census tract, and how it varies with average household income in that census tract. Neighborhoods with a higher level of activity are those with, on average, a lower level of household income.

Figure 2: Distribution of Vehicle Availability for Rental



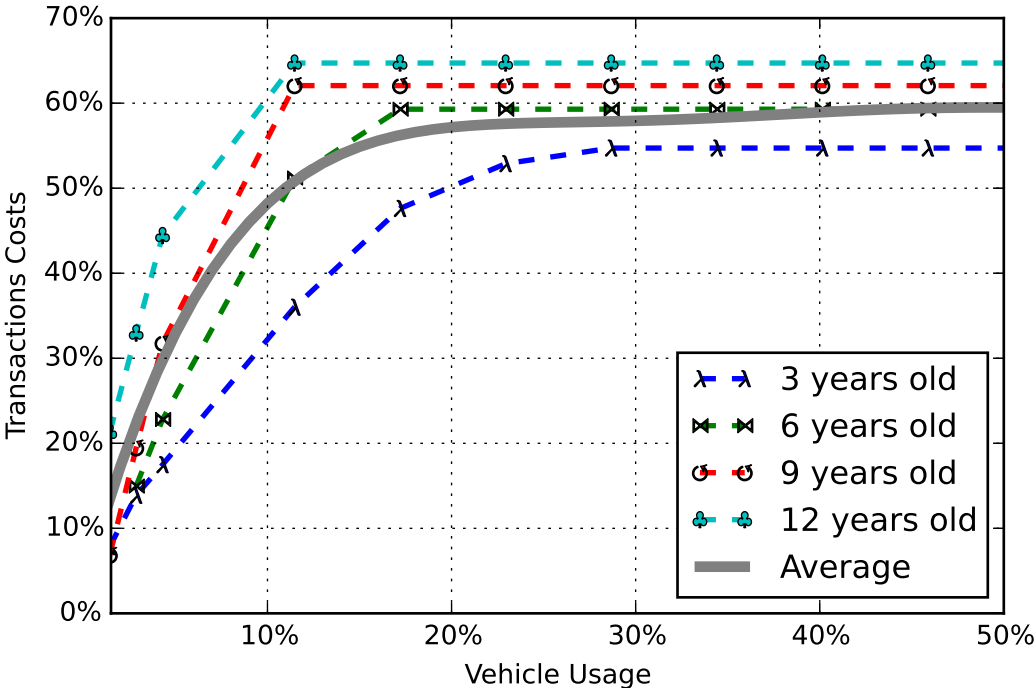
Notes: This figure shows the distribution of the fraction of time a representative sample of the vehicles listed on the peer-to-peer marketplace were available for rental. The horizontal axis measures the fractional availability of the vehicle, and the vertical axis measures the fraction of vehicles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

Figure 3: 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.

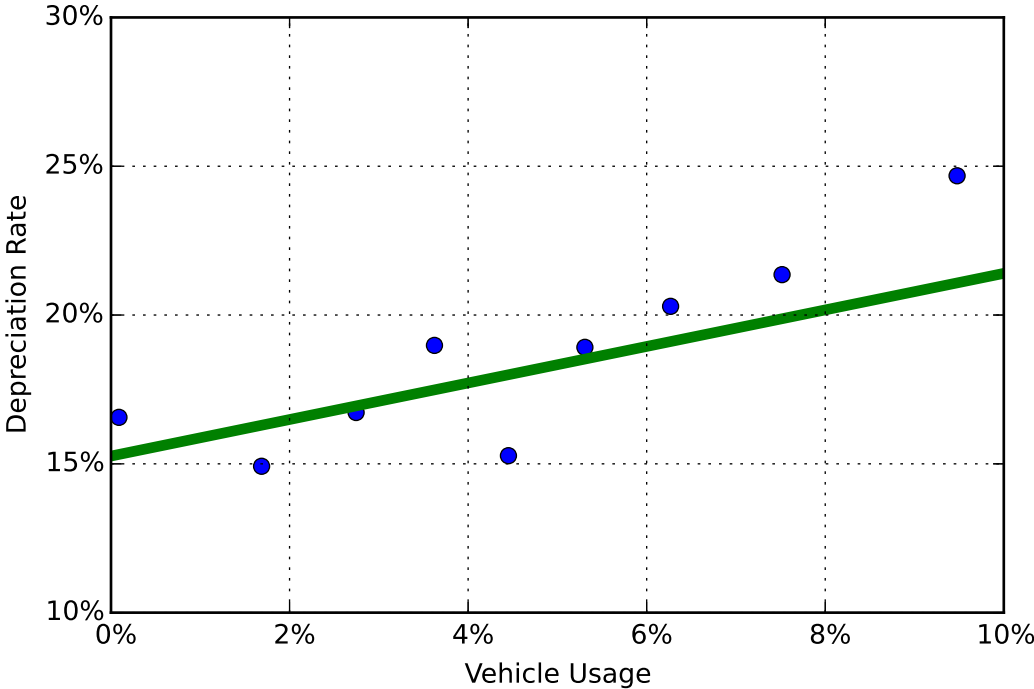
Figure 4: Transaction Costs Function



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 10 most popular vehicles in California, for different mileage. We convert miles driven into usage time using an average speed of 25.8 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).

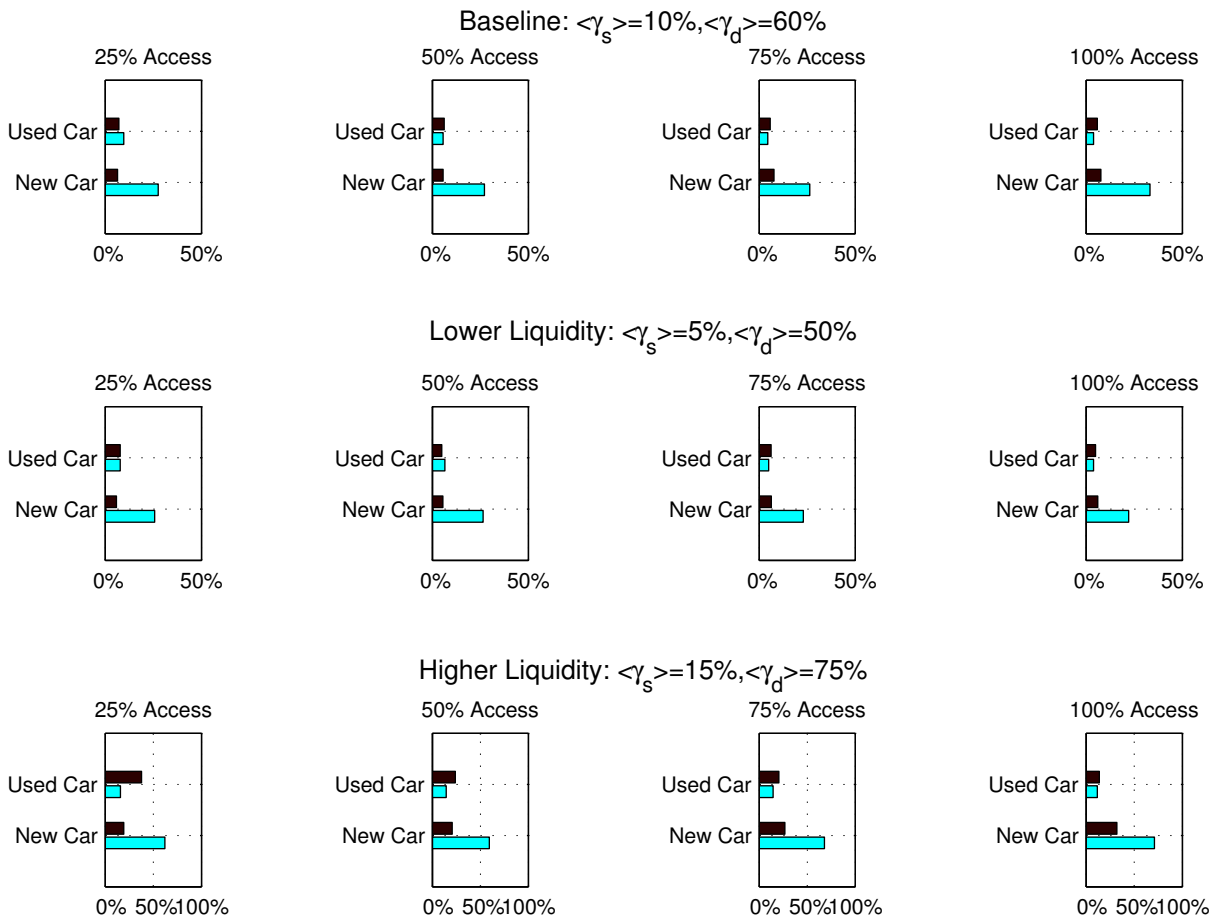


Figure 5: Depreciation Rate Function



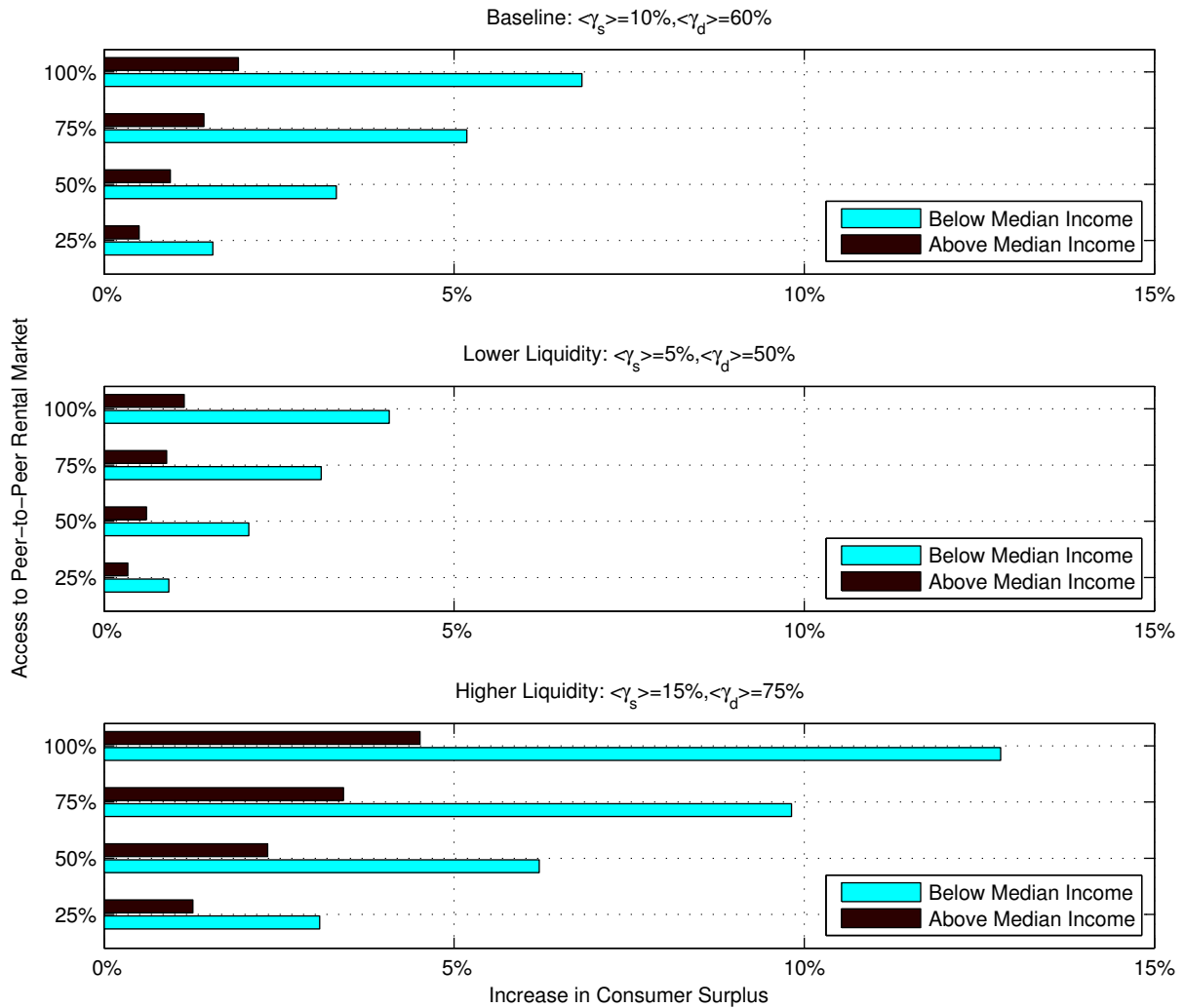
Notes: This figure shows estimates of the depreciation rate as a function of utilization rate (blue dots). The depreciation rate function is computed using equation (12). We convert miles driven into usage time using an average speed of 25.8 mph. We then fit a linear function to the data (green line). (Source: NHTS 2009 Survey).

Figure 6: How the Supply of Peer-to-Peer Rental Vehicles Varies With Income



Notes: 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 7: Distribution of Changes in Consumer Surplus



Notes: 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.