NBER WORKING PAPER SERIES

WHY IS INTERMEDIATING HOUSES SO DIFFICULT? EVIDENCE FROM IBUYERS

Greg Buchak
Gregor Matvos
Tomasz Piskorski
Amit Seru

Working Paper 28252
http://www.nber.org/papers/w28252

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2020

We thank Peter DeMarzo, Darrell Duffie, Tim McQuade, Adriano Rampini, Martin Schneider, Randall Wright, Jeff Zwiebel and participants at Kellogg, Stanford, Columbia Workshop in New Empirical Finance, Duke Fuqua, National University of Singapore, NBER Summer Institute, Search and Matching in Macro and Finance Virtual Seminar Series and Stanford Institute of Theoretical Economics for useful comments. Piskorski and Seru thank the National Science Foundation Award (1628895) for financial support. Buchak is at Stanford Graduate School of Business (GSB), Matvos is at Northwestern University and the National Bureau of Economic Research (NBER), Piskorski is at Columbia University and NBER, and Seru is at Stanford GSB, the Hoover Institution, the Stanford Institute for Economic Policy Research (SIEPR), and NBER. First Draft: November 2019 The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Why is Intermediating Houses so Difficult? Evidence from iBuyers
Greg Buchak, Gregor Matvos, Tomasz Piskorski, and Amit Seru
NBER Working Paper No. 28252
December 2020
JEL No. G0,G2,G5,L0,R20

ABSTRACT

We study the frictions in dealer-intermediation in residential real estate through the lens of "iBuyers," technology entrants, who purchase and sell residential real estate through online platforms. iBuyers supply liquidity to households by allowing them to avoid a lengthy sale process. They sell houses quickly and earn a 5% spread. Their prices are well explained by a simple hedonic model, consistent with their use of algorithmic pricing. iBuyers choose to intermediate in markets that are liquid and in which automated valuation models have low pricing error. These facts suggest that iBuyers' speedy offers come at the cost of information loss concerning house attributes that are difficult to capture in an algorithm, resulting in adverse selection. We calibrate a dynamic structural search model with adverse selection to understand the economic forces underlying the tradeoffs of dealer intermediation in this market. The model reveals the central tradeoff to intermediating in residential real estate. To provide valuable liquidity service, transactions must be closed quickly. Yet, the intermediary must also be able to price houses precisely to avoid adverse selection, which is difficult to accomplish quickly. Low underlying liquidity exacerbates adverse selection. Our analysis suggests that iBuyers' technology provides a middle ground: they can transact quickly limiting information loss. Even with this technology, intermediation is only profitable in the most liquid and easy to value houses. Therefore, iBuyers' technology allows them to supply liquidity, but only in pockets where it is least valuable. We also find limited scope for dealer intermediation even with improved pricing technology, suggesting that underlying liquidity will be an impediment for intermediation in the future.

Greg Buchak
Graduate School of Business
Stanford University
655 Knight Way
Stanford, CA 94305b
buchak@stanford.edu

Gregor Matvos
Kellogg School of Management
Northwestern University
2211 Campus Drive
Global Hub 4361
Evanston IL, 60208
and NBER
gregor.matvos@kellogg.northwestern.edu

Tomasz Piskorski
Columbia Business School
3022 Broadway
Uris Hall 810
New York, NY 10027
and NBER
tp2252@columbia.edu

Amit Seru
Stanford Graduate School of Business
Stanford University
655 Knight Way
and NBER
aseru@stanford.edu

I. Introduction

Residential real estate, valued at more than $30 trillion, is the main asset of US households, accounting for about 70% of median household net worth.[1] The substantial frictions in the buying and selling of homes make housing quite illiquid. These frictions in the housing market can affect households' matching with the appropriate houses and affect household mobility. Imagine a household, which wants to sell its house to pursue a new job. To purchase the house in the new location, they must first have to sell their current house. If the process takes a while, they may rent a suboptimal house in the new location during this period, which could take over a year. In fact, the difficulty in selling and purchasing a new home may force the household to abandon the new job entirely. These difficulties in homeowner-to-homeowner sales suggest a natural role for dealer intermediation: a homeowner could sell their house directly to an intermediary, which would resell it once it finds a buyer. The homeowner could then purchase a new house without delay. An immediacy discount on the sale to the intermediary would split the gains from trade. Yet, despite seemingly large demand for such intermediation, until recently, such transactions were rare, suggesting that dealer intermediation in this market is subject to substantial frictions.

This has changed with the entry of iBuyers, a recent technological disruption in the real estate market. iBuyers, such as Opendoor, RedfinNow, and Zillow Offers, are real estate companies that use an automated valuation model and other technology to make cash offers on homes quickly, within hours, through their on-line acquisition platforms. In other words, iBuyers offer exactly the kind of dealer intermediation that has been absent from the real estate market until now. In this paper, we use iBuyers as a window to study frictions in dealer intermediation in residential real estate, and the role that their technology has played in making dealer intermediation viable.

This paper proceeds in two main steps. We first use rich micro data to document where and how iBuyers' intermediate in real estate. These facts generate insights on the main economic frictions that limit intermediation in real estate. We then build a calibrated structural search model that explicitly incorporates the economic forces we document. The model reveals the central tradeoff to intermediating in residential real estate. Intermediation is only valuable if intermediaries can purchase houses quickly. However, with the current technology, speed comes at the cost of information loss concerning house attributes. Because this information is likely available to the property seller, intermediaries are vulnerable to adverse selection. The intermediation problem is exacerbated in homes with low underlying liquidity, which expose the intermediary to cost shocks, and reinforce adverse selection. A slower or less precise "low-tech" dealer would not be able to survive in this market. Even with perfect technology, the extent of intermediation is limited to 20%

[1] See US Census Bureau https://www.census.gov/data/tables/2016/demo/wealth/wealth-asset-ownership.html.

of transactions. Finally, we use the model to study the limits to liquidity provision by intermediaries in durable goods markets more broadly.

We begin our analysis by documenting a significant growth in the iBuyer market share since their entry in 2014. For example, in Phoenix, Arizona, iBuyers market share had grown from less than 1% in 2015 to about 6% of all real estate transactions by 2018. We then turn our attention to the iBuyer business model. We first document that iBuyers act as a dealer intermediary. They allow the seller to forgo listings and sell quickly. The average time for a listed house to sell in iBuyer markets is roughly 90 days. Sellers to iBuyers are almost 30pp more likely to forgo listings and sell to iBuyers directly, saving this time. Once they acquire a property, they hold them in inventory for only short-period of time: about a half of homes they buy are sold within three months and about three-quarter of homes within six months from acquiring. iBuyers use traditional selling channels relying on multiple listing services to dispose their inventory. They earn a positive spread (gross return) of about 5% on the houses they buy and sell.

A large portion of this spread is due to the 3.6pp discount of home value at which iBuyers purchase homes. This estimate compares houses purchased by iBuyers to those purchased by others in the same zip code, at the same point in time, and with the same characteristics. This estimate suggests that an average seller to iBuyers is willing to pay $9,000 to sell their house immediately. Such high liquidity demand suggests a large demand for dealer intermediation. Yet, until the entry of iBuyers, such transactions were rare, indicating large frictions in supplying liquidity. We learn about these frictions from observing which segments of the housing market iBuyers choose to intermediate.

We document that iBuyers choose to intermediate in markets, in which automated valuation models have low pricing error. These facts suggest that iBuyers are concerned that their choice of providing speedy offers comes at the cost of information loss, specifically, information that is difficult to capture in an algorithm. We first confirm iBuyers' claims that they use automated valuation model, which allows them to offer speedy transactions. We follow the strategy in Buchak et al. (2018) and show that observable property characteristics and zip times quarter fixed effects explain over 80% of the variation in prices for iBuyer transactions, versus 68% of the variation in non-iBuyer transactions. The lower R^2 of non-iBuyers suggests that they use information that is not captured by standard hedonics when pricing houses. For example, it is difficult for an algorithm to capture the views, the quality of the neighboring park, or if the neighbors' house is poorly maintained. These aspects affect the value of a property but are difficult to code and capture with an algorithm. Because such information is likely also available to the property seller, iBuyers are vulnerable to adverse selection.

If iBuyers' algorithmic pricing exposes them to adverse selection, then they should intermediate in segments, in which their informational disadvantage is smallest: those in which their algorithmic pricing of hard hedonic information works well, leaving little room for other information to affect prices. iBuyers' market share declines substantially in segments in which pricing errors using hedonics are largest. Even when they are present in a specific geographic market, they choose not to purchase any houses in the quartile of houses that are most difficult to price with hedonics. Consistent with adverse selection, we also find that iBuyers earn the lowest returns when they transact difficult to price houses. These facts suggest that dealer intermediation in real estate, which requires providing speedy offers comes at the cost of potential adverse selection.

We also find that iBuyers choose to intermediate in houses with the highest underlying liquidity. Even if they are present in a geographic market, iBuyers do not transact in houses whose probability of selling in less than 3 months is below 20%. This may be a bit surprising. One would expect more illiquid houses have higher demand for liquidity provision. These results suggest that despite higher demand for liquidity, it may be difficult to supply liquidity for these houses, and the latter effect dominates. Our evidence suggests that liquidity provision is efficient only when houses are already relatively easy to value and liquid—i.e., when additional liquidity is least valuable.

Next, we develop a search-based equilibrium model, similar in structure to Anenberg and Bayer 2020, of house trading and introduce iBuyers. The model has several goals. In the data we find evidence consistent with several frictions that may impede intermediation. We model these frictions to understand how they affect house choices, trading, and prices in equilibrium. The reduced form evidence we present suggest the presence of frictions, but without our model it does not allow us to understand which frictions are central in limiting intermediation, or how technology plays a role. We calibrate the model to the data to identify the main tradeoff faced by iBuyers when they intermediate in this market. We also quantify which aspects of technology were central for these types of intermediaries to succeed. Last, we use the model to better understand the overall limitations to intermediation in this market, even if technology improves beyond its current level.

We build on a standard continuous time search and matching equilibrium model of homeownership, into which we introduce a dealer intermediary: iBuyers. A homeowner is initially matched with a house from which she receives a flow utility benefit of housing services and pays a maintenance cost. With some probability, she becomes unmatched from her current house and begins the process of moving. The homeowner can only own one house at a time. In consequence, she must move sequentially: she first needs to find a buyer for her current house using the listings process, and then looks to buy a new house. Once she has bought her new house, she once again becomes a matched homeowner. Instead of listing her house and wait for it to sell, a homebuyer can sell the house to iBuyers who list them for resale. iBuyers are not constrained to hold only one house at a time, which allows them to intermediate. They possess a pricing technology that allows them to purchase almost immediately—the speed at which they can undertake a transaction is one of the features we study. This speed comes at the cost of information loss, which results in adverse selection. This technology may also allow them to find buyers faster—they may have a different matching function than other sellers. Last, iBuyers do not obtain utility flows from homeownership although they still must pay maintenance costs.

We calibrate the model to the post iBuyer entry period, using the model to match the features of the data such as iBuyer penetration, the discount iBuyers pay for houses, the time their houses stay in inventory relative to other households' time on the market, as well as the fact that iBuyer penetration is lower in less liquid market and markets in which houses are difficult to price. The model can replicate the patterns we document, suggesting that the frictions we built into the model are consistent with the data. To provide external validation of the model, we examine the predictions of the model with respect to iBuyer entry. Intuitively, we perform a difference in difference exercise in the model and in the data, where the entry of iBuyer is the "natural experiment". The model estimated on post-iBuyer entry data does a good job matching the reduced form difference in difference estimates of decreases in equilibrium prices and increases in transaction speeds. Thus, this validation exercise provides further comfort in the model estimates.

In the data we find evidence consistent with several frictions that may impede intermediation. The calibration reveals that the central tradeoff to intermediating in residential real estate markets comes down to three forces: speed, information quality, and liquidity. First, the speed of transaction is critical. Consider a slow, but precise "low-tech" intermediary, which does not do algorithmic pricing and therefore cannot close the transaction quickly. Even with perfect information, their ability to provide intermediation would essentially vanish, and their share of transactions fall to at most 1-2% of the current iBuyer markets. That is intuitive, because this additional liquidity is one of the main benefits of dealer intermediation. So, the ability to close transactions quickly is essential and quantitatively important.

This speed comes at the cost of information loss about homes, which results in adverse selection. Suppose iBuyers could maintain their current speed but suffer no information loss. They could use all the information of other participants in their pricing, such as whether the house has good views or the quality of the neighboring park. We find that under this scenario their market share would quadruple. In other words, adverse selection is severe, even in the markets iBuyers choose to enter. On the other hand, iBuyers algorithmic pricing offers them an information advantage over other intermediaries who could try to offer quick closings. Consider a quick but imprecise low-tech intermediary, which closes transactions quickly, but because it does not do algorithmic pricing, suffers more information loss than iBuyers. We find that such intermediaries would also essentially vanish. This intuition explains why iBuyers have been able to provide dealer intermediation where others have failed. They provide quick transactions but limit the information loss with sophisticated algorithmic pricing. Moreover, they limit themselves to segments, in which their potential information loss is the smallest – i.e., those where algorithms have small pricing errors.

The model also explains why iBuyers only provide liquidity in already liquid markets. Our model does predict that households' wiliness to pay for liquidity is highest in those markets. A key limitation in the intermediation of housing assets is that in contrast to a homeowner, the intermediary keeps the house vacant while listing and therefore does not derive the consumption benefit that the owner-occupant would. Quantitatively, we estimate a small disadvantage on this dimension. However, longer time on the market exposes iBuyers to maintenance shocks. Because the house is unoccupied, these shocks loom large for iBuyers—for example, being arm's length, they may notice a leaking roof only after substantial damage. This already lowers the profits from dealer intermediation, and thus its viability. Lower profits from intermediating in low liquidity houses also force iBuyers to lower purchase prices. Through this secondary channel, low underlying liquidity also exacerbates adverse selection. This intuition explains why it is difficult for iBuyers to intermediate in markets with low underlying liquidity. We also find that conditional on choosing to enter a low liquidity segment, the liquidity benefits are low. Days on the market decline least in segments, which are illiquid. In other words, iBuyers are most able to provide liquidity in already liquid segments.

We also find two forces in the model that are quantitatively small. iBuyers do not obtain a house service flow but unmatched households do. This could potentially result in a large disadvantage of iBuyers. We find that the owners who are looking to move do not receive large utility flows from a house either, so this wedge is small. In addition, we also find that iBuyers are no better at selling houses than other households. Formally, their current matching technology is almost identical to other sellers. This is intuitive since they have to sell their house through a listing process. On the other hand, they have their own and related party websites (Zillow, RedFin), which are heavily trafficked. They do not seem to derive any advantage from those, at present.

Our analysis points to why dealer intermediation in real estate has been so limited up to this point. To provide valuable liquidity service, transactions must be closed quickly. At the same time, the intermediary must be able to price houses precisely, which is difficult to accomplish quickly. Low underlying liquidity exacerbates this problem. Our analysis suggests that iBuyers technology has found a middle ground, which allows them to transact quickly with limited information loss. Even with this technology, they have been limited to the most liquid and easy to value houses, where they can provide most liquidity. In other words, iBuyers comparative advantage allows them to add liquidity to the market, but in pockets where liquidity is the least valuable. We also find limited scope for dealer intermediation even with improved pricing technology, suggesting that underlying liquidity will be an impediment for intermediation in the future. The model suggests that one large avenue for technology to improve intermediate would be to improve matching. Matching frequency could increase in the market overall, because of technology improvements in listings. iBuyers could also find better matches though related party websites. Either of these improvements could increase the scope for dealer intermediation in this market, and improve liquidity in one of the most important asset markets for households.

Our paper is related to the recent work focusing on the technological disruptions in the real estate marketplace. Most of this emerging literature has focused on the role of online fintech lenders (Buchak et al. 2018; Fuster et al. 2019) and the impact of sharing economy on the housing market (e.g., Calder-Wang 2019). We contribute to this literature by studying the emergence of iBuyers and their role in improving liquidity in the housing market. In doing so we also expand recent work analyzing the role of non-bank intermediaries in the housing market (e.g., Buchak et al. 2020; Jiang et al. 2020). Our work is also related to the literature that studies how search-based frictions and other factors affect the housing trading market (e.g., Wheaton 1990; Genesove and Mayer 1997; Levitt and Syverson 2008; Piazessi and Schneider 2009, Genesove and Han 2012; Guren 2018; Guren and McQuade 2020; Anenberg 2016; Chinco and Mayer 2016; Anenberg and Bayer 2020; Piazessi, Schneider, and Stroebel 2020; Fu et al. 2015; Agarwal et al. 2020; Andersen et al. 2020; Arevefa 2017; Gilbukh and Goldsmith-Pinkam 2019; Barwick and Pathak 2015; Barwick, Pathak, and Wong 2017; Head et al. 2014; Hendel et al. 2009; Kurlat and Stroebel 2015; Stroebel 2016; DeFusco, Nathanson, and Zwick 2017; Nathanson and Zwick 2018; Mian and Sufi 2019; Gorback and Keys 2020). We contribute to this literature by assessing how iBuyer technology may help alleviate some of these frictions by making housing markets more liquid. More broadly, our analysis of the intermediation in the housing market is also related to a large body of work focusing on intermediation and trading frictions in decentralized asset markets (e.g., Grossman and Miller 1988; Duffie, Garleanu, and Pedersen 2005; Gavazza 2016).

II. Data and Institutional Background

II.A. Data Sources

Transactions Data: We use Corelogic deeds records data on housing transactions from five markets with large iBuyer presence as of 2018: Phoenix, Las Vegas, Dallas, Orlando, and Gwinnet County, a suburb of Atlanta. We use data between 2013 and 2018 and restrict the sample to arms-length, non-foreclosure transactions in single family homes or condominiums with transaction prices below $10 million and land footage below 50,000 sq. feet. The data reports each transaction tagged to a specific property, with seller name, owner name, transaction date, sale amount, and mortgage amount. Transactions without a recorded sale date are excluded. Merging these transaction records with tax assessment files enables us to observe property-specific attributes, including the census tract, land square footage, building square footage, the number of stories, the year of construction, the type of air conditioning, garage, heating, sewer, water, and electricity. The assessment file also includes evaluations of the construction quality and location desirability. Table 1 Panel A provides summary statistics for this data.

Listings data: We use listings data from the Multiple Listings Service (MLS) provided by ATTOM Data. The data spans 2010 through 2018, and our main sample period is 2013 and 2018. Individuals, brokers, and companies selling their properties post listings on a set of common platforms, and we observe the combined data. The data is at the individual listing level. That is, for a given attempt to sell a house, the lister will make an initial listing with an asking price. As time passes, the seller may find an interested buyer at that price, or she may amend her listing with the different (typically lower) price, in order to attract other buyers. The listings data contain similar house-level information as well as the identifying information of the homeowner as the transaction-level data, listing agent, and buying agent. We aggregate the data to a "listing-spell," which captures a single period over which a homeowner, whether an individual or an iBuyer, attempts to sell her house. Each listing spell may contain multiple amendments and price changes, which we summarize for each transaction. Table 1 Panel B provides these summary statistics.

Redfin and Zillow: We use publicly available data from Redfin, which includes at the zip code level, the fraction of listings that sell within two weeks of listing, the average sale-price-to-list-price, and the average sale price. Additionally, we use house price indices from Zillow in robustness checks, which provide quality-adjusted transaction prices at a zip-quarter level.

Other data: We use the American Community Survey (ACS) data from the U.S. Census Bureau to measure several zip-level demographic characteristics including median income, median age, fraction of adults with a bachelor's degree or higher, population, fraction of the population that is white, and fraction of the population that pays over 50% of their disposable income on rent.

II.B. Classification of Buyers and Sellers

II.B.1 Identifying iBuyers

We classify parties to the transaction---buyers and sellers---as iBuyers or not. In our analysis, a party is an iBuyer if it is one of Opendoor, Offerpad, Knock, Zillow, and Redfin. These parties are not always recorded in the data as "Opendoor" or "Offerpad," but rather as a specific business entity such as "OD ARIZONA D LLC." "OD ARIZONA D LLC" is, in fact, a private company registered to the same address as Opendoor. To ensure our classification covers these separate corporate entities, we use a set of regular expression search terms to make sure that the most common parties are included. Appendix A.2 details this classification procedure. The Corelogic transaction data captures more than 6,000 iBuyer purchases and sales.

II.B.2 Tracking Individuals over Time

From the Corelogic transaction records, we create a panel at the individual-year level, of household ownership and geographical location. From the baseline dataset of transactions between 2000 and 2018, we begin by extracting a list of unique names at the market level. To construct these names, we first remove all names with corporate or business markers[2] and absentee owners, and impose a series of cleaning and filtering steps.[3]

We next take the baseline transaction records and extract the last purchase transaction for each property for each year. We then define a person to be owning a house if at year t, he or she was the buyer in the most recent transaction in all years prior to t and he or she is not recorded as selling the house prior to year t. If by this methodology we identify a particular person as living in more than one house in a given year, we break ties in favor of the house with the latest sale date. Finally, if there are still duplicates, we choose the property that appears first in the dataset.[4] For each name in each market, this methodology yields at most a single owned home per year. However, there are years for which an individual will not own a house. We retain these years in order to keep the panel balanced; these missing years can be interpreted either as the individual living in a different market, or as the individual renting or living with another homeowner.

Putting this together, the panel provides key details of homeowner's behavior: We observe sales directly from deeds records. Then, conditional on selling her house, the homeowner either buys a new house in the same market or leaves the market entirely. Conditional on buying a new house, we measure changes in house size and leverage. Leaving the market means that the homeowner either owns a house in a new geographical area, or becomes a renter (in any geographical area). Thus, we observe not only sales, but also the homeowner's subsequent actions in terms of mobility and house consumption.

II.C. The Rise of iBuyers

iBuyers began significant growth in 2015 in Phoenix and between 2016 and 2018 in Las Vegas, Orlando, Gwinnet County, Georgia, and Dallas (Figure 1 Panel (a)). iBuyers had roughly 1% market share in Phoenix in 2015; by 2018 this had grown to roughly 6%. Similar striking growth has occurred in Gwinnet (4%), Las Vegas (3%), Orlando (~2%), and Dallas (~2%).

---

[2] For example, "Corp," "INC," "LLC," and so on.

[3] We remove white space, names where the first or last name has fewer than one character, and names that appear on more than ten unique purchase transactions in the data set.

[4] Under this methodology, before this final step, 0.8% of homeowners appear to be living in more than one house in a given year.

iBuyers focus on a relatively narrow band of homes. As Figure 2 shows, they typically buy houses that are in the \$100k - \$250k price range, relatively new, of modest property (lot) size, and multistory. With respect to demographics, Figure 3 shows that they have the greatest market share in zip codes with younger, middle-class individuals: Those with median incomes between \$70,000 and \$90,000 (Panel (a)); those with average ages 30 and below (Panel (b)); those where residents possess bachelor's degrees (Panel (c)).

As their activity expanded, iBuyers inventory of houses expanded as well, both in terms of numbers of houses and dollar value (based on purchase price) of their houses (Figure 1, Panels (b) and (c)). By the end of 2018, iBuyers had roughly 1,500 houses in inventory, with a combined purchase price of roughly \$350 million. iBuyers in 2018 purchased between 400 and 500 houses per quarter (Panel (d)). Their inventory turnover, defined as the number of sales in a quarter divided by their total inventory, is typically between 0.3 and 0.6 per quarter (Panel (e)). iBuyers typically hold inventory for a short period of time, holding a house for a median period of roughly 100 days.

Based on completed transactions, iBuyers typically earn roughly a 5% spread between purchase and sale -- defined as the difference between the price at which they sell and price at which they buy, as a percentage of the acquisition price. The spread has been consistently positive over time, and the 25-75th percentile of realized spread on a per-house basis has been also positive for all but two quarters in 2015 (Figure 1 Panel (f)).

III. iBuyers' Business Model and Liquidity Provision

In a standard housing transaction, the seller is a homeowner who currently occupies the house, and the buyer plans to occupy the house upon purchase. Houses are advertised though listings and brokers connect buyers and sellers. This transaction requires matching a seller, who is ready to leave, with a buyer who is ready to move in at roughly the same time.[5] A natural alternative is a dealer-intermediary, which purchases the house immediately when the seller wants to move. The dealer holds the house in inventory and sells when the appropriate occupant-buyer appears. As we show, iBuyers follow such a model: they purchase houses, hold them in inventory, and sell them, earning a spread. Here, we delve deeper into iBuyers' business model, and generate a set of facts.

III.A. iBuyers' Transaction Speed and Listing Dynamics

A homeowner who wants to sell her house traditionally works with a broker to list her house on a traditional listing platform. She then waits for an appropriate buyer and sells the house. This process can be slow: As Table 1 Panel (b) shows, the average time between a listing and a

[5] While an individual homeowner may be willing to temporarily own two houses to facilitate moving into a new home, such an activity requires a substantial amount of wealth on their part. This is not typical of most individual transactions.

successful sale is 91 days. We begin by comparing this traditional process to a transaction intermediated through an iBuyer.

III.A.1. Selling to iBuyers avoids listing the house

We begin by examining the extensive margin of listing: to what extent do homeowners avoid the slow listing process by selling to an iBuyer? With the merged transaction-listing dataset, we estimate whether houses sold to or by iBuyers were more or less likely to be listed on MLS prior to purchase. To do so we estimate the following specification:

$$Listing_{izt} = \beta Buyer\_is\_iBuyer_{izt} + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \quad (1)$$

An observation is at the deeds-records transaction level where i indexes a house in zipcode z at quarter t, and each deeds records transaction record may or may not have an associated listing in MLS. $Buyer\_is\_iBuyer_{izt}$ is an indictor for whether an iBuyer buys the house, and is a zero-one indicator for whether there is an MLS listing on the same property with a sale date within one week of the sale date in Corelogic. This indicator captures whether the sale is listed on MLS prior to the transaction. H_i is a vector of house controls, such as price, age, lot size, air conditioning type, garage type, heating type, location influence, and build quality. μ_{zt} is the zip times quarter (interacted) fixed effect. In other words, the variation we present is not simply variation across zip codes, but reflects house characteristics within a given zip code and a quarter.

The results in Table 2 Panel A show that selling to iBuyers provides a substantially faster sale with a certain outcome. Sellers are roughly 27 percentage points (pp) less likely to list a property, if they sell it to iBuyer. If they list the house instead of selling directly to iBuyer, the time to sale can be substantial. When selling through a listing, slightly less than 50% of listings result in a sale within three months, and only 70% result in a sale within one year (Figure 4 Panel (b)). Even conditional on a sale, these findings imply that selling directly to an iBuyer may allow the seller to speed up the time of sale by on average 91 days.

III.A.2. iBuyers Sell Houses using Listings, set higher list prices which they adjust more often

iBuyers Sell Houses using Listings: We first show that iBuyers utilize the traditional listing process. We then show that they list houses at higher prices than homeowners, but lower prices more aggressively if houses are not sold. We first estimate the probability that iBuyers sell houses using the listing process, equivalent to equation (1) above:

$$Listing_{izt} = \beta Seller\_is\_iBuyer_{izt} + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \quad (2)$$

An observation is at the deeds-records transaction level where i indexes a house in zipcode z at quarter t, and each deeds records transaction record may or may not have an associated listing in MLS. $Seller\_is\_iBuyer_{izt}$ is an indicator that captures whether the sale is listed on MLS prior to the transaction. As before H_i is a vector of hedonics and. μ_{zt} is the zip times quarter fixed effect. iBuyers are roughly 12% *more* likely to go through the traditional listing process than other sellers (Table 2 Panel A). iBuyers do not appear to a differentiated technology for selling houses: they rely on the standard listing process instead of targeting buyers through a website, for example.

iBuyers Set Higher List Prices and take longer to sell the house: We next examine differences in listing behavior between iBuyers and other sellers. Central in the listing decision is the tradeoff between the aggressiveness of the listing price and the speed of the sale. Levitt and Syverson (2008) shows that brokers list their own houses at higher prices than those of their clients.[6] We first examine whether iBuyers also follow the higher listing price strategy, and then examine whether they engage in any other strategies when selling houses. We compare iBuyers to two types of sellers: typical homeowners, who form the base category in the subsequent analysis, and *Flippers*, whom we define, as before, as absentee owners who re-list the house within one year of purchase. Flippers are a useful comparison group because they share some similarities with iBuyers: They are absentee owners, who likely purchase houses as an investment.[7] With this in mind, we estimate whether iBuyers listing prices differ from other listers using the following:

$$\log(List\ price_{izt}) = \beta Lister_{izt} + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \qquad (3)$$

Here i indexes a house in zipcode z at quarter t. The dependent variable is a listing price, not a sale price. $Lister_{izt}$ is an indicator for whether the lister is an ordinary homeowner, an iBuyer, or a Flipper. As before, we control for house characteristics in H_i and quarter x zip fixed effects μ_{zt}. We compare listing prices set by iBuyers to those of observably similar homes listed within a given zip code at the same point in time by individuals and home flippers. iBuyer listing prices are 2.1% higher than ordinary sellers' listings on comparable properties (Table 2 Panel B). Flippers also list more aggressively than ordinary buyers, with a markup of 2.0%. In other words, both flippers and iBuyers appear to follow the strategy of listing at a high price.

The classic tradeoff of a higher listing price is that it results in a higher transaction price, but at a reduced probability of transaction and longer time on the market. On average, iBuyer houses spend approximately 6 days longer on the market (Table 1, Panel B). One issue that clouds simple

[6] Guren (2018) further shows that sellers do not set a unilaterally high or low list price because they face a concave demand curve: that increasing the price of an above-average-priced house rapidly reduces its sale probability, but cutting the price of a below-average-priced house only slightly improves its sale probability

[7] iBuyer's business model is not simply that of a large-scale house flipper. iBuyers are roughly 5% less likely than ordinary sellers to mention renovations, while Flippers are 15% more likely to do so. Thus, while Flippers appear to add value by renovating, iBuyers do not.

comparison are “failed” sales (Figure 4, Panel b). Once iBuyers list the house, they are very likely to sell it. This is not surprising, since they are an intermediary who does not utilize the house. Homeowners, on the other hand, sometimes choose to pull the house from the market, and decide not to sell it at all. In fact, homeowners are 18pp more likely to have a “failed” sale once the house is listed (Table 2, Panel B). When examining *houses that eventually sold,* iBuyers’ houses take longer to sell relative to other homeowners. Within that sample, iBuyers sell their homes more slowly especially in early months: they are 10% less likely to sell a home within 3 months than other sellers.

The second issue that arises is censoring. Since iBuyers are relatively new players in the market, perhaps their time on the market is a result of sales that did not yet have time to close. To account for “failed” sales and censoring we estimate a Cox proportional hazard model on sales propensity:

$$\lambda(t|X_i) = \lambda_0(t)\exp\left(\beta Buyer_i + H_i' \mathrm{B}\right) \tag{4}$$

Here, *i* refers to the individual listing spell, and *t* is the time between the initial listing and the sale. The dependent variable is the days to sale (which may be censored if a listing is withdrawn or does not lead to a sale). $Buyer_i$ is an indicator for whether the seller is an ordinary seller (the base category), a Flipper, or an iBuyer. H_i' is the vector of house hedonics (for example, square footage).

The hazard rate of an iBuyer sale from a listing is greater when we consider the fact that iBuyer sales are more likely to succeed. The magnitudes suggest that before conditioning on whether a sale occurs, iBuyer sales occur at roughly a 16% greater rate than non-iBuyer sales. In contrast, Column (9) shows that conditional on the sale occurring, the iBuyer hazard rate is significantly lower: conditional on a sale occurring, iBuyer sales occur at roughly a 14% lower rate. Columns (8) and (10) initial listing price to control for listing aggressiveness, and the addition of these controls do not meaningfully alter the results.

Finally, using the text of iBuyer listings, we rule out that iBuyers are making significant renovations. Table 2 Panel B Column (2) shows that iBuyers are no more likely to advertise making renovations, while Flippers are significantly more likely to do so. Additionally, Appendix Section A.5, we examine seasonality, which has been documented (e.g., Ngai and Tenreyo (2014)) to play an important role in residential real estate transactions. We find that iBuyers tend to post listings specifically in off-season times, consistent with the above ideas that they can hold inventory cheaply and list strategically.

III.B. Returns for Liquidity Provision

We showed that iBuyers purchase houses quickly from homeowners and resell them. This section shows that in exchange for this service, iBuyers earn a positive gross return (spread) on average. This section decomposes the sources of return and shows that the return comes primarily through buying at a discount and selling at a premium, rather than through market appreciation.

III.B.1. iBuyer Earn a positive Bid / Ask Spread that is not Market Timing

We now document that iBuyers earn a positive spread on their housing transactions even accounting for overall price changes in the market. The spread is one way to assess how much market participants seem to be willing to pay for the liquidity provision in the real estate market. Because of different holding periods of iBuyers and homeowners, we annualize the spreads, and define the annualized gross return (spread) on a given transaction,[8] as

$$Gross\ Return_{iztt'}^{Ann} = \left(\frac{Price_{izt'}}{Price_{izt}}\right)^{\left[\frac{1}{t'-t}\right]} - 1 \tag{5}$$

The subscript *i* denotes a house, *z* the zipcode of the house, and *t* the time of the purchase, and t' the time of the sale. iBuyers earn an annualized spread of 17.78% relative to homeowners' spread of 9.28% (Table 3). While iBuyer spreads are positive on average and exhibit significantly less volatility, they are also negative a significant fraction of the time, suggesting that iBuyers are sometimes willing to sell houses for a loss, even if they hold them for a short time (Figure 5).

To confirm that these differences are not driven by differences in market conditions or in the types of houses that iBuyers purchase, we regress annualized gross realized return on house hedonics and zip-quarter fixed effects at the transaction level:

$$Gross\ Return_{iztt'}^{Ann} = H_i'\mathrm{B} + \mu_{zt} + \epsilon_{iztt'} \tag{6}$$

$Gross\ Return_{iztt'}^{Ann}$ is the gross return of property *i* in zip *z* between its purchase time *t* and its sale time *t'*. All controls on the right-hand side are as of time *t*, the purchase date. H_i is a vector of house hedonics, and μ_{zt} is a vector of zip-quarter-of-purchase fixed effects. The regression therefore compares realized returns for purchases by iBuyers and non-iBuyers of similar houses as of the same date. Even controlling for differences in house types and local market conditions, iBuyers' annualized gross return is roughly 6.6% percentage points higher than those of typical

[8] The gross return does not capture other fees that iBuyers charge consumers as well as other operating costs including labor costs, financing costs, housing renovation costs, and property taxes.

individuals (Table 3). We separate the gross return into a component that is attributable purely to overall house price appreciation and the bid/ask spread—the decomposition is described in detail in Appendix A.6. iBuyers earned roughly 1.5pp from overall market movements relative to the average household. The vast majority of iBuyers returns, 5pp, on the other hand comes from the bid / ask spread even accounting for their successful market timing (Table 3 Panel B).[9]

III.B.2. Decomposition of Bid / Ask Spreads: iBuyer Purchase Discounts and Sale Premia

iBuyers can earn the bid ask spread by either purchasing houses cheaper, or selling them for more than an average household. We investigate the purchase discount and the selling premium using the following hedonic specification:

$$\begin{aligned} \log(Sale\ Price_{izt}) &= \beta(Buyer\ is\ iBuyer_{izt}) + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \\ \log(Sale\ Price_{izt}) &= \beta(Seller\ is\ iBuyer_{izt}) + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \end{aligned} \tag{7}$$

An observation is a house transaction, where i indexes a house in zipcode z at quarter t. $Sale\ Price_{itz}$ is the transaction price. $Buyer\ is\ iBuyer_{izt}$ and $Seller\ is\ iBuyer_{izt}$ are zero-one indicators for whether the buyer or seller is an iBuyer, respectively. H_i is a vector of house characteristics, and μ_{zt} is the zip code times quarter (interacted) fixed effect. We compare the price of properties acquired by iBuyers compared to observationally similar properties that transacted within a given zip code at the same point in time acquired by other market participants.

iBuyers earn both a purchase discount as well as a selling premium. The purchase discount represents most of the spread. Over the 2013-2018 sample, iBuyers' purchase prices were roughly 3.6% lower than other purchasers in the market (Table 4 Panel A). Hence, selling to iBuyers instead of another purchaser is costly: for the average house, the discount amounts to $9,000. Our results are consistent with the notion that liquidity that sellers receive from iBuyers is valuable since sellers are willing to pay for it. iBuyers' purchased homes at a discount but sold them at prices that were roughly 1.6% higher than other sellers. For the average iBuyer house with a price of approximately $250,000, this premium amounts to approximately $4,000. This result is consistent with the fact that iBuyers list houses at a higher price, resulting in higher transaction prices but a longer time to sale. While smaller than the purchase discount, the selling premium significantly contributes to the iBuyer average realized gross returns that we established earlier to be around 4.9% per transaction.

[9] Because they hold multiple properties, iBuyers are also substantially more diversified than homeowners, and earn substantially higher risk adjusted returns. The mean annualized gross return on iBuyers portfolio is 24% with a standard deviation of 8.67% and is 11% with a standard deviation of 15.66% for homeowners (Figure 4 Panel (d))

A natural alternative explanation for iBuyer's purchase discount is that they simply purchase houses that have worse characteristics on unobservable dimensions. For example, the house could be poorly kept up, have low curb appeal, or noisy neighbors. The positive sale premium suggests this is not the case. If a house has bad hedonics when purchased, then it would have similar hedonics when sold. This is especially true given the short time between iBuyer buy and sale, and the earlier listing results that iBuyers are unlikely to renovate homes. iBuyer price discount do not seem to reflect different fees charged by iBuyers. For example, according to Opendoor, the largest iBuyer in our sample, the company charged the home sellers an average service fee of about 7.5% of home value per transaction, which is substantially larger than the typical real estate agent fees of 6% or less.[10]

These results taken together are consistent with the idea that iBuyers, in exchange for providing liquidity to homeowners looking for an instant sale, purchase the house at a significant discount. They go on to sell the house at a small premium by listing it at a higher price. The gross spread they earn is compensation for their liquidity provision. These results indicate that like fintech lenders in the mortgage market (see Buchak et al, 2018), iBuyers provide consumers with non-price attributes like convenience rather than simple cost savings.

III.C iBuyers Intermediate in Easy-to-price and Liquid Homes

We have documented that iBuyers act as liquidity providers, buying earning a bid ask spread and carrying properties on their inventories for a relatively short period of time. The large purchase discount indicates that sellers are willing to pay a significant amount for liquidity provision in this market. A high liquidity demand suggests a natural role for dealer intermediation. Yet, until the entry of iBuyers, such transactions were rare. To better understand why liquidity provision in real estate markets is difficult, we examine which market segments iBuyers chose to enter. We use the characteristics of these segments as an indicator that in these markets, intermediation is easiest. We focus on the role of information and underlying market liquidity. These two forces play a central role in intermediation. Moreover, iBuyers tout their algorithmic pricing as an advantage. Several iBuyers are offshoots of firms, which specialize in collecting house price data, as well as pricing houses. Appendix A.1 shows screenshots from Opendoor's website."

III.C.1. iBuyers' use algorithmic pricing

Intermediaries who purchase and sell assets must be concerned about adverse selection. This is especially the case in the housing market, where houses have diverse characteristics, some of which are difficult to measure, and homeowners have an advantage in the knowledge of these

[10] See https://www.opendoor.com/w/pricing (accessed on January, 2020).

characteristics. We examine how iBuyers price houses that they purchase, and find that a simple algorithm of hedonics, which account for local market conditions can explain a large part of their pricing strategy. We estimate the following hedonic regression:

$$\log(Sale\ Price_{izt}) = H_i'\mathbf{B} + \mu_k + \epsilon_{izt} \tag{8}$$

An observation is a house transaction, where i indexes a house in zipcode z at quarter t. $Sale\ Price_{izt}$ is the transaction price. H_i is the vector of house characteristics. We include a sequence of fixed effects, μ_k with k indexing the level of saturation. We include zip, quarter, zip and quarter, and zip times quarter fixed effects.

Across specifications, observable characteristics explain a substantially higher share of variation in iBuyer transaction prices – both for purchases and sales – relative to transaction prices of other market participants (Table 4 Panel B). House characteristics explain roughly 50% of the variation in price for transactions involving iBuyers relative to 40% for transactions by other participants. With zip times quarter fixed effects capturing local time-varying market trends, observable characteristics explain over 80% of the variation in prices for iBuyer transactions, versus 68% of the variation in transactions by other market participants. These results suggest that a simple algorithm of hedonics, which account for local market conditions can explain a large part of iBuyers' pricing strategy. Moreover, non-iBuyer real estate buyers use other inputs to determine prices that does not seem to be captured in the iBuyer algorithm. Such information can either arise from other participants using difficult to encode information that is available or information acquired through a thorough and lengthy inspection, which iBuyers do not conduct because they offer a speedy closure. If iBuyers' pricing is not contingent on this additional information, which is likely also known to property sellers they may be vulnerable to adverse selection.

The reliance on easy to assemble hard information also differentiates iBuyers from several other fintech participants. For example, fintech lenders in the mortgage market rely less on standard hard information than other market participants, when pricing mortgages (Buchak et al, 2018).

III.C.2. iBuyers' intermediate in easy-to-value and liquid segments of the market

As we discuss in Section II.C, iBuyers entry is very selective, both geographically, and, conditional on geography, which types of homes they purchase. In this section, we use iBuyers' revealed preferences to study why intermediation in real estate markets is so limited. As we suggest above, because iBuyers rely on algorithmic pricing, they are potentially vulnerable to adverse selection. If that is the case, they should intermediate in segments, in which their informational disadvantage is smallest: those in which their algorithmic pricing of hard hedonic information works well. The underlying liquidity of the house should also play a first order role in both the demand and supply of liquidity. More illiquid houses have higher demand for liquidity provision. On the other hand, it may be also more difficult to the supply liquidity for these houses. We look at iBuyer entry to better understand which force dominates.

We first estimate which houses can be easily priced with an algorithm using of hard information, i.e. which types of houses have a small pricing error when priced with hedonics. To ensure that iBuyers' pricing decisions do not mechanically affect our classification, we estimate a hedonic pricing model using 2008-2012 data, which precedes iBuyers. We then study which markets iBuyer chose to enter from 2013 through 2018. To estimate which houses are easy to price, we estimate a model of the form of Equation (8), which regresses log sale prices on house hedonics at the level of house *i*, in zip code *z*, at quarter *t*, on the training sample defined above. Houses with higher standardized residuals $e_{izt}^2 = \frac{\hat{\epsilon}_{it}^2}{\sigma_{\epsilon^2}}$ from this specification are those that are not priced well by hedonics.[11] We then predict which house characteristics make them difficult to price:

$$e_{izt}^2 = H_i' \mathbf{\Delta} + \zeta_{\mathrm{izt}} \tag{9}$$

As before, H_i' is a vector of house hedonics. A positive coefficient on a particular house characteristic, for example, means that on average, houses with that characteristic will have greater pricing errors when priced with a hedonic model. The results are intuitive: newer houses, larger houses, and multistory houses command higher prices (Table 5). Houses with large property sizes, on the other hand, are more difficult to price with a simple hedonic model.[12] Intuitively differences in land characteristics can results in different opportunities to develop the land. The larger the land, the larger the valuation differences.

We follow a similar process when trying to estimate how the ex-ante liquidity of a market relates to iBuyer entry. We use the listing data to estimate a hedonic model to predict whether a given listing sells within 90 days form the listing date, our measure of a liquid market from 2008-2012:

$$Sells\ Within\ 90\ Days_{izt} = H_i' \mathbf{B} + \epsilon_{izt} \tag{10}$$

$Sells\ Within\ 90\ Days_{izt}$ is a zero-one indicator for whether house i in zip *z* listed at time *t* sells within ninety days of its listing. Similar to the results on pricing errors, we find that cheaper (as measured by the *previous* sale price), smaller, and single-story houses are more likely to sell quickly. Having said this, there is enough independent variation in these predictions that including

[11] The normalization allows us to assess changes residuals in units of standard deviations of prediction pricing errors.
[12] As a robustness check, we estimate the same analysis for a larger training sample spanning 2006-2012. The remarkable stability in the coefficient estimates provide confidence that iBuyers using different sets of data would come to largely similar conclusions.

them both as right-hand side variables in subsequent regressions does not alter coefficient estimates. Using the estimates from these two equations, we construct for every house its predicted standardized pricing error $\hat{e}^2_{izt}$ and underlying liquidity $Sells\ Within\ 90\ Days_{izt}$.

Figure 6 graphically shows that iBuyer market shares are highest in segments of easy to price and liquid houses. We formally test whether iBuyer choice of which houses to purchase from 2013-2018 is related to the measures of house valuation accuracy and liquidity using the following:

$$iBuyer_{izt} = \beta\hat{e}^2_{izt} + \gamma \widehat{Sells\ Within\ 90}\ Days_{izt} + \mu_{zt} + \epsilon_{izt} \tag{11}$$

As with the earlier specification, an observation is a house transaction, where *i* indexes a house in zipcode *z* at quarter *t*. $iBuyer_{itz}$ is a zero-one indicator for whether the buyer is an iBuyer. $\hat{e}^2_{izt}$ is the predicted pricing error normalized to the standard deviation of the pricing errors, and $\widehat{Sells\ Within\ 90}\ Days_{izt}$ is the predicted probability of a listing selling within 90 days. As before, we control for quarter x zip fixed effects μ_{zt}. This means we study which houses iBuyers choose to intermediate, conditional on having entered a geographic market.

A house with a one standard deviation greater predicted pricing error is 3.7% less likely to be purchased by an iBuyer (Table 6). This is a large effect relative to the base rate of iBuyer purchases over this sample period of roughly 0.60% and demonstrates the importance of price predictability in iBuyer participation. The predicted liquidity of a house is also strongly associated with iBuyer intermediation. An increase in the probability of selling within 90 days of 10pp corresponds with an increase in iBuyer market share of 0.2%. These results suggest that iBuyers indeed intermediate in more liquid houses and those which are easiest to price. We argue that iBuyers are reluctant to transact in houses with a high pricing error, because these types of houses expose them to adverse selection. Then, if iBuyers *do* buy such houses, they earn smaller profits. In Appendix Section A.7, we confirm this is indeed the case.

These results suggest that two forces limit the provision of dealer intermediation in the real estate market despite its high potential benefits. To provide liquidity, intermediaries need to transact in homes quickly and are therefore subject to adverse selection. Even firms, which specialize in algorithmic pricing such as iBuyers are at an information disadvantage relative to other buyers, who can take the time to conduct a thorough investigation. Second, while low liquidity of a house increases the demand of homeowners for liquidity, it also decreases the intermediaries' ability to supply liquidity. On net, our results suggest that the second effect dominates. As we illustrate in the next section, the results are natural when applied to real estate intermediation. Illiquid homes make it relatively more efficient for the seller to live in the house during the sale process rather than keep the house vacant exposing it to adverse maintenance shocks. Critically, liquidity provision is therefore efficient only when houses are already relatively easy to value and liquid—when additional liquidity is least valuable.

IV. Equilibrium Housing Trading Framework with iBuyers

In this section we develop an equilibrium model of house search and matching, in which we introduce an intermediary, which purchases houses from households, holds them, and resells them to other households—iBuyers. We study the equilibrium effect of the pricing technology available to the intermediary, and the associated adverse selection problem, as well as the speed at which it can close transactions, and thus provide liquidity to sellers. We calibrate the model to the data, to explore the qualitative and quantitative forces, which constrain the provision of liquidity in the market, even when demand for liquidity is high.

IV.A Model Setting

The model is in continuous time in which all agents discount the future at rate ρ. Figure 7 shows the timeline of the model within a period, tracing out the role of homeowners and iBuyers through the transaction. A homeowner is initially matched with a house from which she receives a flow benefit (consumption value less costs). With some probability, she becomes unmatched from her current house and begins the process of moving. We assume that the homeowner's balance sheet is constrained and can only own one house at a time. Therefore, to buy a new house she must sell her old house. Once she finds a new house she likes, and purchases it, has bought her new house, she again becomes a matched homeowner. The transactions among homeowners occur in standard search market, in which sellers list houses and are randomly matched with buyers.[13]

We depart from the standard setting by introducing an intermediary which can provide liquidity in the market: iBuyers. Instead of listing houses and waiting for a buyer, sellers can sell them directly to iBuyers who then list houses for resale, using the standard listing process. iBuyers are a balance sheet intermediary: they are not constrained to hold only one house at a time. On the other hand, iBuyers do not live in the house when trying to sell it—the house remains vacant. This means that they do not obtain utility flows from homeownership although they must pay maintenance costs.

We endow iBuyers with three different characteristics, which can affect their ability to intermediate in this market. The first is speed; in other words, the reason why intermediaries are valuable to sellers in the first place is because they can execute the transaction without waiting for a buyer. The second is information. As we document above, even if iBuyers have great algorithmic pricing, they are still at an information disadvantage relative to homeowners, and other potential

[13] Analogous to, e.g., job seekers and job postings in Diamond (1982).

sellers, who can take time to thoroughly screen a purchase. The third is matching technology. While we see little evidence of differences in matching homeowners with houses study the effect of these characteristics on the effectiveness of intermediation in this market, this is a popular explanation of iBuyers advantage, and we explore its consequences in the model. We study the model by varying how changes in these characteristics affect the equilibrium outcomes in the market, and the profits from intermediation, to see if intermediation is viable.

IV.A.1. Market and information structure

Homeowners: At any instant, a homeowner is one of three states, between which she transitions over time (e.g., Anenberg and Bayer (2020)). These states are denoted $\{h, s, b\}$. h denotes a matched homeowner, who is happy with the house in which she currently resides. s denotes a selling homeowner: a homeowner who is unhappy with her current house and is in the process of selling it. b denotes a buying homeowner: a homeowner who currently does to own a house and is looking for one. The total homeowner population has an exogenous mass $M = 1$, with $\{m_h, m_s, m_b\}$ denoting respectively the endogenous mass of h-types, s-types, and b-types. Homeowners become unmatched at rate μ.

Matched h-type homeowners own a house producing flow utility $\bar{u}_i = \bar{u} + \tilde{\epsilon}_i$. $\bar{u}_i$ captures the benefits of living in the house such as housing services, proximity to work, and so on, net of holding costs. $\bar{u}$ capturing the flow component common across homeowners; $\tilde{\epsilon}_i$ allows for idiosyncratic differences in homeowners utility flows from their current property. When homeowners become unmatched, they receive utility flow $\underline{u} < \bar{u}$. This represents the idea that while they still obtain some utility benefits from occupying the house, the house is no longer ideal. For example, their place of work may have changed, increasing their current commute, or they have had children and desire to switch to a different school district. Or, if they sold their current house, they occupy a non-ideal rental residence.

Listings: Selling households can list their house and wait to be randomly matched with potential buyers. Buyers and s-type households meet at an aggregate rate $F^{hh}(m_s, m_b) = \lambda m_s m_b$. λ measures the underlying liquidity of the market. A high λ implies a market in which matching is faster, all else equal, because buyers and sellers can, for example, meet on the internet. Of course, the final matching rate $F^{hh}(m_s, m_b)$ is endogenous. The probability of a given seller matching with a buyer declines with the overall number of sellers. Let subscripts s and b, denote the rate for an individual buyer or seller to match; then $F_s^{hh}(m_s, m_b) \equiv F^{hh}(m_s, m_b)/m_s$. Given a listing price p, a matched buyer accepts the offer with endogenous probability $\pi(p)$.

iBuyers: iBuyers are intermediaries which purchase houses directly from households, hold them until sale, and sell the houses using a listing. Instead of listing their house, households can sell it to iBuyers. The iBuyer transaction closes in τ days, for example. Closing delays arise because of documentation, but also because of inspections of the property. This parameter allows us to study the importance of immediacy in the business model of an intermediary in this market and highlights the tradeoff between speed and precision of information, which we introduce below. We also allow households to differ in their preferences over transacting with iBuyers. For example, some households have to move urgently, or they are technologically savvier. We capture these preferences with an idiosyncratic utility shock, ϵ_{ib}^i. ϵ_{ib} is distributed type-1 extreme value distribution with scale parameter σ_{ib}.

Upon purchasing the house, iBuyers sell the house using listings. iBuyers can be more or less effective at finding buyers for their properties than households, $F^{ib}(m_s, m_b) = \lambda_{ib} F^{hh}(m_s, m_b)$. $\lambda_{ib} > 1$ would imply that iBuyers are better able to find buyers than other sellers in the market, potentially by using their own websites for listings. While the house is on the market, iBuyers pay maintenance costs m^L, which we normalize to 0. Because the house is unoccupied, iBuyers cost may increase over time, for example, if the roof leaks, and no one notices because the house is vacant. With probability η, the costs become high, m^H. The increase in costs is important to rationalize the fact that iBuyers are more active in liquid homes and markets.

House quality and information: iBuyers close housing transactions without a lengthy inspection, and instead use algorithms to set prices. We model the potential information disadvantage that Buyers face as a "repair cost" r. If the house can be sold as is, $r = 0$ with probability $1 - \phi_R$. Alternatively, with probability ϕ_R the house may need some repairs, that are not visible at first blush, e.g., noise in the neighborhood, the quality of light at different times of day, or the effectiveness of the insulation, then $r = R$. These repair costs are known to the seller, who has lived in the house. Moreover, these costs can be uncovered by a thorough inspection by a potential buyer. For tractability, we assume that inspections by b-types uncover this information completely, and that the repair cost is paid by the seller.[14] Because they perform more cursory inspections, iBuyers receive a noisy signal v of repair costs. They observe whether a house is "Good" and "Bad," where

$$\phi(G|r = R) \equiv \phi_{G|R} = \xi \tag{M.1}$$

[14] This assumption is without loss of generality, but allows for listed houses to be homogenous in quality, increasing model tractability

$$\phi(G|r=0) \equiv \phi_{G|\sim R} = 1-\xi$$

A low ξ implies a better technology, which has a low probability of classifying a high repair cost house as good. In essence, one can think of iBuyer technological problem as trading off speed of closing τ with accuracy ξ. iBuyers then condition houses prices on the signal, $p_b^{ib}(v)$. Upon purchasing the house, iBuyers find out whether the house will actually require repairs before listing, and pay the required cost.

IV.A.2. Homeowners' problem

Homeowners choose their actions to maximize their expected utility. Let $\{v_h, v_s, v_b\}$ denote the value functions of *h*-, *s*-, and *b*- type homeowners, respectively.

Matched homeowners do not need to take any actions. At any point, their consumption flow is that of their current house $\bar{u}+\tilde{\epsilon}_i$, and the continuation value of living in the current house. The latter depends both on how likely they are to become unmatched, and, conditional on being unmatched, how likely their house is to require repairs, and their utility of selling to an iBuyer. Formally, a matched homeowner *i* has the following value function:

$$(\rho+\mu)v_h^i = \bar{u}+\tilde{\epsilon}_i+\mu\int_{r,v,\epsilon_{ib}^i} \max\{v_s-r, \delta(\tau)\left(p_{ib}^b(v)+v_b\right)+\epsilon_{ib}^i\}\,dG\left(\epsilon_{ib}^i, v, r\right) \qquad \text{(M.2)}$$

The integration is over the repair cost, the probability of being unmatched (a seller), and idiosyncratic value of selling to an iBuyer. These random variables are jointly distributed as $dG\left(\epsilon_{ib}^i, v, r\right) = d\mathrm{E}^{\mathrm{ib}}\left(\epsilon_{ib}^i\right)dG(v,r)$. Given the above decision problem, $\pi_{ib}(p,r) = 1-\mathrm{E}^{\mathrm{ib}}[v_s - r - \delta(\tau)(p+v_b)]$.

v_h^i can be expressed as a sum of a common component v_h, which is how the average homeowner values their house, and the idiosyncratic home valuation $\tilde{\epsilon}_i$, how homeowner *i* values her house relative to the average homeowner . Hence, for the remainder of the paper we focus on v_h and $\epsilon_i \sim \mathrm{E}(\epsilon_i)$, with $v_h^i = v_h + \frac{\tilde{\epsilon}_i}{\rho+\mu} \equiv v_h + \epsilon_i$. We interpret ϵ_i as the capitalized idiosyncratic flow utility from the house. ϵ_i is distributed type-1 extreme value distribution with scale parameter σ_m.

Selling homeowners have two choices. They either sell the house to the iBuyer or choose to list it. If the homeowner chooses to list the house, she pays the repair cost, if any, and becomes a seller. She sets the listing price to maximize her expected utility and faces a standard tradeoff: the higher the house price p, the higher the profit once the house is sold. On the other hand, the endogenous probability that a buyer accepting the offer $\pi(p)$ declines, and she cannot start buying a new house until she sells the old one. Formally, her value function is:

$$\rho v_s = \underline{u} + F_s^{hh}(m_s, m_b) \max_p \pi(p)(p + v_b - v_s) \qquad \text{(M.3)}$$

If she accepts the iBuyer's offer, she gets the price and becomes a buyer after the closing period, τ the value of which she discounts by $\delta(\tau)$.

Buyers: b-type homeowners have sold their houses and are trying to purchase a new house. They decide whether to purchase a house for the lister price. Upon encountering the seller and seeing the house, the buyer's idiosyncratic valuation, ϵ_i, realizes, she pays a viewing cost κ, and she chooses whether to accept or to continue looking. Her value function is given by:

$$\rho v_b = \underline{u} + \sum_j F_b^j(m_j, m_b) E\left[\max\{v_h + \epsilon_i - p_j, v_b\} - v_b - \kappa\right] \qquad \text{(M.4)}$$

Where j indexes the seller type. The buyer accepts the offer if $v_h + \epsilon_i - p_j > v_b$. Thus, $\pi(p) = 1 - E[v_b + p - v_h]$.

IV.A.3. iBuyers' problem

When a homeowner becomes unmatched, iBuyers inspect the house for repair costs. iBuyers then offer a price $p_{ib}^b(v)$ that depends on their quality signal. A homeowner, who knows the actual repair cost r accepts the price with probability $\pi_{ib}(p, r)$. Because repair costs are asymmetric information, this is the source of adverse selection in the model. Upon acceptance, the iBuyer pays the repair cost, if any, and takes possession of the home. Let v_{ib}^L and v_{ib}^H denote the value functions for a low- and high-maintenance iBuyer, respectively. The iBuyer's expected profit when making an offer to an unmatched homeowner given signal v is as follows:

$$v_{ib}^{offer}(v) = \max_p \int_r \pi_{ib}(p, r)(v_{ib}^L - p - r) dF(r|v) \qquad \text{(M.5)}$$

After buying the house, the iBuyer's decision is like a listing seller. In the beginning, her maintenance costs are low, m^L. When setting the price, she trades off the probability of a sale, and the profits she realizes conditional on a sale. Moreover, she sets the price accounting for the fact that her costs might increase in the future:

$$\rho v_{ib}^L = m^L + \eta(v_{ib}^H - v_{ib}^L) + F_s^{ib}(m_s, m_b) \max_p \pi(p)(p - v_{ib}^L) \qquad \text{(M.6)}$$

If iBuyer's maintenance costs increase to m^H, she sets the price to maximize expected profits given her match rate:

$$\rho v_{ib}^{H} = m^{H} + F_{s}^{ib}(m_s, m_b) \max_{p} \pi(p)(p - v_{ib}^{H}) \tag{M.7}$$

IV.A.4. Population dynamics

Having described the decision problems of individual participants in the market, we can turn to population dynamics. There are five prices in the market at any point in time: the price at which households list their houses, p_{hh}, the prices at which iBuyers buy high and low quality houses, $p_{ib}^{b}(v)$, and the listing price that iBuyers start with when their maintenance costs are low, p_{ib}^{L}, and the listing price of iBuyers once the maintenance costs increase p_{ib}^{H}. For a vector of prices $\boldsymbol{P} \equiv \{p_{ib}^{b}(v), p_{hh}, p_{ib}^{L}, p_{ib}^{H}\}$, we define $\pi_{ib}(\boldsymbol{P})$ as the unconditional probability that a seller sells to an iBuyer, given by integrating jointly over repair costs and signals:

$$\pi_{ib}(\boldsymbol{P}) \equiv \int_{v,r} \pi_{ib}\left(p_{ib}^{b}(v), r\right) dG(v,r) \tag{M.8}$$

Then, first three equations describe how the population of different types of households change over time. The population of matched households' changes as a function of the exogenous unmatching rate, and the endogenous rate at which buyers rematch with new houses:

$$\frac{dm_h}{dt} = -\mu m_h + \sum_{j \in \{hh, ib^L, ib^H\}} F^{j}(m_j, m_b)\pi(p_j) \tag{M.9}$$

The population of individual sellers is a function of the exogenous unmatching rate, the share of the unmatched population choosing iBuyers $\pi_{ib}(\boldsymbol{P})$, and the speed at which households can sell their houses to become buyers:

$$\frac{dm_s}{dt} = \mu m_h\left(1 - \pi_{ib}(\boldsymbol{P})\right) - F^{hh}(m_s, m_b)\pi(p_{hh}) \tag{M.10}$$

The share of iBuyer owners' houses evolves as a function of how many households choose iBuyer houses, the speed at which iBuyers sell their houses,

$$\begin{aligned} \frac{dm_b}{dt} &= \mu m_h \pi_{ib}(\boldsymbol{P}) + F^{hh}(m_s, m_b)\pi(p_{hh}) \\ &\quad - \sum_{j \in \{hh, ib^L, ib^H\}} F^{j}(m_j, m_b)\pi(p_j) \end{aligned} \tag{M.11}$$

Further, the population of iBuyer houses can be split by their maintenance costs:

$$\frac{dm_{ib}^L}{dt} = \mu m_h \pi_{ib}(\boldsymbol{P}) - \eta m_{ib}^L - F^{ib}(m_{ib}^L, m_b)\pi(p_{ib}^L) \tag{M.12}$$

$$\frac{dm_{ib}^H}{dt} = \eta m_{ib}^L - F^{ib}(m_{ib}^H, m_b)\pi(p_{ib}^H) \tag{M.13}$$

To close the model, since the housing stock is fixed, for every house on the market, there is exactly one potential buyer:

$$m_s + m_{ib}^L + m_{ib}^H = m_b \tag{M.14}$$

IV.A.5. Equilibrium

We look for a stationary equilibrium. The equilibrium is a set of prices $\boldsymbol{P}$ such that

1) iBuyers first-order conditions determining prices are satisfied (M.3, M.6, M.7)
2) Value function equations are satisfied and iBuyers earn positive profits in expectation, (M.2—M.7)
3) Stationarity: State variables $\{m_h, m_s, m_b, m_{ib}^L, m_{ib}^H\}$ are constant as determined by their laws of motions, $\frac{dm_h}{dt} = \frac{dm_s}{dt} = \frac{dm_b}{dt} = \frac{dm_{ib}^L}{dt} = \frac{dm_{ib}^H}{dt} = 0$ (M.9—M.14)
4) Beliefs: iBuyers beliefs about housing repairs are consistent as described above. (M.2)

IV.B Model Calibration

We first calibrate the model. We calibrate several parameters externally in relation to existing literature, parameters that map directly to observable quantities. We then calibrate the remaining parameters by matching model-implied moments to moments we observe in the data. Table 7 Panel A describes these moments and our model's fit.

IV.B.1 Externally calibrated parameters

We follow Anenberg and Bayer (2020) and set the discount rate ρ to 0.05. The census[15] estimates that individuals move roughly 9.1 times after they turn 18, or at a rate of roughly 0.152 (9.1 / 60 years) per year. Agents in our model move after becoming unmatched, and consequently this number corresponds to the unmatching rate μ in our model. We set the probability that a house needs serious repairs, p_f, to the fraction of listings mentioning renovation, which is 0.109 in the

[15] https://www.census.gov/topics/population/migration/guidance/calculating-migration-expectancy.html

MLS data. Finally, we assume for the baseline analysis that iBuyers' time to close, τ, is one day—we explore how changing this parameter affects iBuyers' ability to intermediate in Section VI.

IV.B.2 Parameters calibrated to the data: Identification

We calibrate the remaining 10 parameters by matching moments in the equilibrium model with the empirical target in 2018, the most recent year in our data. We summarize the parameters and the moments in Table 7. As the estimates highlight, the model can match the data quite well even quantitatively. Discussing the identification of the remaining parameters also presents an opportunity to provide exposition on the economics underlying the model.

IV.B.2.1 Household preferences and shocks

Match utilities: The gap between mean utilities of housing between matched and unmatched households, $\bar{u}$ and $\underline{u}$, are reflected in listing prices and iBuyer discounts. A buyer is willing to pay more for a house rematching is more beneficial—when this gap is larger. In response, sellers will list at a higher price. By selling directly to an iBuyer, sellers become rematched sooner and obtain a utility increase faster. When rematching is more valuable, the iBuyer purchase discount grows.

Variance of preference: Consumers differ in their preferences with respect to houses (σ_m) and selling to iBuyers (σ_i). If differences are small, then the average utility difference across choices should predict actions well. Because iBuyers offer to purchase houses at discounts, a higher σ_i makes potential sellers more likely to sell to iBuyers, and conversely, a lower σ_i makes potential sellers less likely to sell to iBuyers. Thus, iBuyer market share, conditional on the offer price, is informative about σ_i.

σ_m imply that buyers view houses as differentiated, thereby increasing sellers' market power and in turn increase markups. Importantly, however, this logic applies asymmetrically between ordinary sellers and iBuyers. Ordinary sellers are impatient to sell in part because they want to move from a bad match to a good match. iBuyers, on the other hand, are less impatient, and thus more able to take advantage of their market power to wait for a high-quality match. Thus, σ_m impacts both house prices overall, but in particular iBuyer markups.

Finally, we set the meeting cost κ to 0.5772. Given our distributional assumptions on the buyer's taste shock ϵ_i, this normalization implies that the ex-ante value of choosing between a house offer offering zero expected utility and a continued search offering zero expected utility is zero. In other words, the meeting cost offsets the potential buyer's option value in refusing the offer.

IV.B.2.2 Matching and Intermediation

Match rates: The match intensity, λ, is related to how long a house stays on the market. When λ is high, matches occur more frequently. Likewise, iBuyer's relative match advantage / disadvantage, λ_{ib}, maps to time on market for iBuyer listings. A higher λ does not mechanically map into shorter duration on the market. With a higher λ buyers can reject sellers and see more offers per unit time, which reduces seller markups. This force tends to reduce time on market. On the other hand, sellers see more buyers per unit time, and therefore may want to raise prices, which, other things equal, tends to increase time on market. The model can replicate the average 90-day time on the market. iBuyer homes spend approximately 6 days longer on the market but do so at higher list prices. Interestingly, while a popular explanation of iBuyers' advantage is through their matching technology, our calibration suggests that iBuyers do not possess a better matching technology than other sellers, with a $\lambda_{ib} = 0.97$.

iBuyer holding costs: We can use iBuyers selling behavior to compare their cost of holding the house to the cost of an unmatched household. If living in an unmatched house has lower utility for a homeowner than the maintenance costs faced by iBuyers, then they would face more urgency in selling the house. They would list it at a lower price than iBuyer. This is consistent the iBuyers selling at a premium, which we find in the data. It is about $3,000 more expensive to remain in the house for a poorly matched homeowner than an iBuyer keeping it empty.

Because iBuyers houses are vacant, they face the probability η that maintenance costs increase by c, if issues are undetected for a while. When iBuyers experience a cost increase, their urgency to sell the house grows, and they lower their listing price. We match the probability that an iBuyer reduces prices before successfully finding a seller to match η. The cost increase c to a first order governs the size of the price reduction. Additionally, these parameters broadly impact iBuyer market share, through the fact that a higher c or η increase expected iBuyer costs and therefore their market share.

These parameters also influence the relationship between iBuyer market share and the liquidity of the house. Fixing c and η, the adverse cost shock is more likely to realize the longer the iBuyer possesses the house. Thus, when selling a particular house is expected to take longer for any seller, iBuyers are at a comparative disadvantage relative to homeowners, who do not receive the cost shock. Thus, the model generates a negative relationship between iBuyer market share and market liquidity, as measured in the data by the probability that homes sell within 90 days. Recall that our reduced form results also found a negative relationship. Our model generates a predicted derivative, d(iBuyer share)/d(P(sells in 90 days), which is another moment we match in the data to discipline the calibration.

Information Structure and iBuyers Information Disadvantage: Houses may need repairs costing R, and iBuyers receive signals regarding whether they need repairs with false positive and true negative probabilities ξ. The repair costs are the source of unexplained house price variation. Because homeowners can observe whether the house needs repairs but iBuyers cannot, there is adverse selection. iBuyers offer a single pooling price conditional on a noisy signal. Homeowners with houses needing repairs attempt to pool with homeowners with houses not needing repairs. Thus, homeowners not needing repairs will therefore list themselves, while homeowners needing repairs will attempt to sell through iBuyers, in a classic lemons problem.

In Section III we show that iBuyers' pricing technology can be well approximated with a hedonic regression. A larger R relative to the price generates greater unexplained variation. We take this to the data by mapping it to the residual mean square error of the regression of house prices on house hedonics, with the interpretation that unexplained variation captures unobserved repair costs (or the costs of improving the house quality to what is required to sell it).

The noisier the iBuyer's signal is, the more severe the adverse selection becomes, and fewer and fewer homeowners will benefit from selling through iBuyers. Thus, more noise, ξ, leads to a lower iBuyer market share in the model. We thus calculate the market share derivative with respect to pricing error, d(iBuyer share)/d(Mean pricing error). We map this moment to its empirical analog, which we obtain from regressing whether an iBuyer is involved in a transaction with the hedonic pricing error on the house, which in the data, provides a negative coefficient.

IV.C External Validation

IV.C.1. iBuyer Entry

We calibrate the model to the data after the entry of iBuyers. Here, we examine how the model performs when evaluated

In each case, the model produces equilibrium house prices and times on market. As shown in Figure 8 Panels (a), our model predicts that without iBuyers, median house prices (in the calibrated market) is roughly \$275,000, and roughly \$262,000 thousand with iBuyers. This represents a reduction of roughly 4.7%. Recall that in our calibration, iBuyer market share is 4.9%, giving an elasticity between prices and iBuyer market share of close to -1. Panel (b) shows that the average time on market decreases from 115 days to 90 days once iBuyers enter. Assuming an exponential distribution, this corresponds to an increase of roughly 11.5% of listings selling within two weeks to roughly 14.5% of listings selling within two weeks,[16] or an elasticity between share of houses sold within two weeks and iBuyer market share of roughly 0.65.

We next look for reduced form validation of these quantities. To do so we use regional variation and exploit Redfin data at the zip code level. The data reports listing prices, and the fraction of listed homes in a zip code that sell within two weeks of listing. We investigate how these variables change with iBuyer market hare using the following specification:

$$\Delta Liquidity_z = \beta iBuyerShare_z + X_z'\mathbf{\Gamma} + \epsilon_z \tag{12}$$

$$\Delta Price_z = \beta iBuyerShare_z + X_z'\mathbf{\Gamma} + \epsilon_z \tag{13}$$

$\Delta Liqidity_z$ and $\Delta Price_z$ are the 2013-2018 changes in the percentage of houses selling within two weeks of listing and percent change in house prices. X_z' is the vector of zip-level controls, and $iBuyerShare_z$ is the growth in iBuyer Market share from entry in 2015 to 2018.[17] The coefficients on iBuyer market share map directly to the elasticities reported above. Because iBuyer entry may be endogenously correlated with liquidity (indeed, our model suggests that it is), we instrument for iBuyer market share using the physical characteristics of the housing stock transacting before iBuyer entry. Specifically, we use the following to predict which homes iBuyers purchase in Phoenix in 2018:

$$iBuyer_{izt} = H_i'\mathbf{B} + \epsilon_{izt} \tag{14}$$

Then, at the zip code level, we calculate the predicted iBuyer market share among houses that transacted between 2011 and 2014 in the zip code, defining:

$$\%\,\widehat{iBuyer}_z = \frac{1}{N_z} \sum_{i\in z;t\in(2011-2014)} \widehat{iBuyer}_{izt} \tag{15}$$

As before, $\widehat{iBuyer}_{izt}$ is the house-level prediction for whether iBuyer would buy the house, *i* indexes over all houses in zip code *z*, and time *t* spans 2011 to 2014. We use this measure to instrument for $iBuyer\,Share_z$. Thus, our instrument for iBuyer market share in 2018 (equivalently, iBuyer market share growth from 2015 to 2018), is the predicted iBuyer share based on the physical homes transacted between 2011 and 2014. Appendix A.8 shows the empirical first stage relationship.

[16] This is calculated as $1 - \exp\left(-\frac{1}{115} \times 14\right)$ and $1 - \exp\left(-\frac{1}{90} \times 14\right)$.

[17] iBuyer market share began at 0%, so changes and levels are the same.

Table 8 Column (1) shows that the first stage effect is very strong: A 1% increase in predicted share based on the physical characteristics of houses transacting in 2011-2014 is associated with a 0.65% increase in actual iBuyer market share in 2018. Columns (2) through (7) show the OLS, reduced form, and IV results for the liquidity and price outcomes. Consistent with the model's predictions, we find elasticity of price to iBuyer market share roughly around -1, depending on the specification, and between 0.15 and 2 for fraction of houses selling within two weeks of listing, again, depending on the specification. Broadly, our model makes predictions that are qualitatively and quantitatively consistent with this reduced form exercise.

IV.C.2. Individuals

Appendix Section A.9 performs a more qualitative model validation exercise. To summarize, our model predicts that iBuyers specifically target those individuals with an idiosyncratically high valuation of transacting early. To take this prediction to the data, we show that individuals living in iBuyer-type houses are significantly more likely to leave the market (e.g., move to another city) once iBuyers enter. We interpret these households as those placing the greatest value on moving early, consistent with our model's predictions.

V. The Economics, Technology, and Limits of iBuyer Liquidity Provision

As our model illustrates, there are three characteristics of financial intermediaries which affect their ability to intermediate in this market. The first force is speed: A listing homeowner has to go through the lengthy listing process, whereas selling to the dealer-iBuyer takes place almost instantaneously. In other words, the reason why intermediaries are valuable to sellers in the first place is because they can execute the transaction without waiting for a buyer. Our model reflects this through the fact that iBuyers buy directly, but that closing potentially takes some time, τ. The second force is occupancy: A listing homeowner (typically) remains in her house during the listing process, allowing her to derive utility flows and perform routine maintenance. In contrast, a dealer-iBuyer leaves the house unoccupied, foregoing the utility flows and potentially failing to perform routine maintenance. Our model reflects this through differences in flow utilities, $\underline{u}$, and the chance that an iBuyer's house might become more expensive to maintain, η. The third force is information: Homeowners are better equipped to observe hard-to-measure differences in value than dealer-iBuyers, who value the home remotely. Our model reflects this through the precision of the signal, specialized in our calibration as ξ.

In this section, we quantify the importance of each of these channels by altering these parameters away from their calibrated values and assessing the impacts on predicted iBuyer market share. We study the model by varying how changes in these characteristics affect the equilibrium outcomes in the market, and the profits from intermediation, to see if intermediation is viable.

V.A. The Economics of Intermediation

V.A.1. Speed

We investigate the quantitative importance of iBuyers' transaction speeds by varying the parameter governing time to close, τ. The baseline value is $\tau = 1$ days, and we calculate counterfactual iBuyer market shares by setting $\tau = 90$ days, roughly the time an average homeowner takes to sell her house through a listing. We leave all other parameters equal to their calibrated values, and compare the baseline iBuyer market share to this counterfactual "slow" iBuyer's market share.

Figure 9 Panel (a) shows the results. The first column shows the market share for the baseline case, roughly 5%. The second column shows the market share for the slow iBuyer case, roughly 0%. This result shows the perhaps unsurprising importance of speed in the viability of an iBuyer transaction. Without their speed advantage, iBuyers offer essentially nothing of benefit to households that they could not effect better themselves.

V.A.2. Occupancy

We next investigate the quantitative importance of the fact that selling homeowners occupy their houses, while iBuyers do not. This fact brings two potential disadvantages to iBuyers. First, while homeowners are not situated in their ideal home, they still live in a house and derive some consumption benefit from it. Second, the fact that they are in the home means that they engage in routine maintenance, which protects from potential adverse events like a roof caving in. iBuyers potentially face both of these drawbacks when intermediating. To examine these impacts, we consider a counterfactual where iBuyers rent the house to a homeowner (e.g., the original selling homeowner) in order to produce the utility flow of an unmatched homeowner, $\underline{u}$, and set the rate of maintenance cost increases η to zero.

Figure 9 Panel (a) shows the results. The third column shows the market share for the iBuyer offering second-best occupancy. We find essentially no difference in iBuyer market share, suggesting that this margin is not quantitatively important. The intuition can be seen from our calibrated parameters: The unmatched flow utility is actually negative, suggesting that it is better to leave the house unoccupied than to have the unmatched homeowner living in it. The interpretation is that the unmatched homeowners utilizing iBuyer services are better served by living somewhere else than remaining in their old house. This is broadly consistent with our earlier reduced from evidence showing that owners of iBuyer houses tend to leave the market entirely when selling.

V.A.3. Information

Finally, we investigate the role of information asymmetry in limiting residential real estate intermediation. The intuition is that ordinary homeowners, both buyers and sellers, are better able to detect minor issues with the house than iBuyers running a remote valuation. We call these issues "repair costs" but the interpretation can be broadened to include hard-to-detect items like loud neighbors, good midday light, and pleasant ambiance. In our model, the parameter ξ controls the noise in the iBuyer's signal. To investigate the importance of adverse selection, we set $\xi = 0$ and recompute the equilibrium iBuyer market share.

Figure 9 Panel (a) again shows the results. The fourth column shows that with a perfect valuation technology, iBuyer market share jumps from 5% (Column (1)) to 20% (Column (4)). Intuitively, given repair costs, iBuyers are forced to offer lower prices. These lower prices are unappealing to homeowners whose houses are in good condition and do not require repairs. As homeowners with high quality houses leave the market, the discount that iBuyers have to offer increases further, driving both high- and low-quality home homeowners out of the market. Giving iBuyers a perfect valuation technology eliminates this death spiral. The large quantitative impact here suggests that this is an important economic force in residential real estate intermediation.

V.B. iBuyer Technology and Balance Sheets

We now use the model to attempt to understand the source of iBuyers' advantage. We note that iBuyers differ from homeowners, because they derive no intrinsic value when holding on to the house. iBuyers therefore face a disadvantage relative to homeowners when it comes to holding real estate. They therefore need some other advantage to be willing to engage in intermediation. In particular, are iBuyers merely an intermediary with a balance sheet, or does their technology provide an important distinct benefits? We examine three aspects of iBuyer potential technological advantage over a potential intermediary with a balance sheet capacity: their valuation speed, their valuation accuracy, and their matching technology when selling.

To shed light on it, Panel (b) of Figure 9 shows the comparison of market shares of intermediaries having the baseline iBuyer technology, a fast and inaccurate technology, and a slow and accurate technology. In particular, for speed, we compare the iBuyer baseline closing speed of 1 day to a more typical 25 day closing time. For accuracy of valuation technology, we compare a valuation technology with iBuyers' precision to an uninformative valuation technology (uninformative signal regarding the true value of the house).

Intuitively, our counterfactual considers the case of an intermediary with a balance sheet but unsophisticated valuation technology. This intermediary can either undertake the accurate valuation at the expense of slow purchase speed, or they can purchase quickly at the cost of performing the valuation inaccurately. iBuyers, in contrast, can do these tasks both quickly and relatively accurately. We examine the counterfactual market shares of these intermediaries. The results highlight the fact that merely having balance sheet capacity with no technological advantage is not sufficient. The low-tech valuation intermediary would counterfactually achieve between 1 and 2% market share, in contrast to the iBuyer, which has two to five times that market share. These findings indicate that transaction speed and valuation accuracy are the key elements of technological advantage of iBuyers over other intermediaries. They also help explain why intermediation in real estate market has been fairly rare prior to the iBuyer entry.

This analysis helps us understand why iBuyers are predominately active among homes that can be fairly accurately priced using (algorithmic) automatic valuation models as we established in Section III.F. Among these homes their technological advantage is the highest, which is a key factor behind their significant market share. Among homes that are difficult to price our model predicts a low market penetration, which is exactly what we find in the data.

V.C. The Limits of iBuyer Liquidity Provision

Finally, we examine the extent to which, and in what contexts, iBuyers are able to provide liquidity. Intuitively, a naïve prediction might be that iBuyers provide the greatest liquidity benefit in markets that are illiquid before iBuyers enter. However, the data show that iBuyers focus on the most liquid markets. To understand the economic mechanism behind this finding we consider iBuyer market shares and percent changes in transaction speeds as a function of pre-iBuyer transactions speeds as captured by the parameter governing the matching rate, λ. Pre-iBuyer transaction speeds serve as a measure of ex-ante liquidity.

Figure 10, Panel (a) show that the association between pre-iBuyer entry market liquidity and the iBuyer market share implied by our model. The results show that greater ex-ante liquidity is associated with greater iBuyer market share. The model provides two mechanisms leading to this result. First, iBuyers maintain empty houses, and when maintaining an empty house, there is the possibility that an unobserved negative shock (e.g., a collapsed or leaking roof) occurs which significantly increases maintenance costs. Thus, the longer that an iBuyer has to hold the house, the more likely it is that this shock occurs. In a thinner markets where sales are slow, iBuyers must either face this risk, or alternatively reduce their sale prices to sell the house faster. In both cases, low liquidity markets put iBuyers at a disadvantage.

As iBuyers face more adverse holding costs and lower profits, they eventually have to compensate by offering lower prices to potential sellers. This, due to the adverse selection that iBuyers face, has the effect of collapsing the market for good houses that do not need repairs: Given these low prices, good types would rather list houses themselves, and thus only bad types sell their houses to iBuyers. As this part of the market disappears, iBuyers' market share collapses dramatically. Similarly, for liquidity provision, while iBuyer entry reduces the time it takes to become rematched regardless of ex-ante liquidity, the effect is stronger when markets are more liquid. This is because in the more liquid markets, more iBuyers enter, and thus have both a greater direct and indirect effect, though competitive pressures, on time to rematch.

To summarize, iBuyer benefits are largest in the markets that you might think need them the least. This is illustrated in Panel (b) of Figure 10 showing that iBuyers have much more pronounced relative effect on the housing turnover (time-to-rematch) of already liquid homes.

Taken together our findings highlight why liquidity provision in real estate markets has been limited, despite the high potential benefits to market participants. Difficult to price and illiquid homes make it relatively more efficient for the seller to live in the house during the sale process rather than keep the house vacant. Liquidity providers, such as iBuyers, are subject to adverse selection, and have to keep houses vacant while holding them for resale exposing themselves to potential maintenance shocks. Liquidity provision is therefore efficient only when houses are already easy to price and relatively liquid. This ensures that such homes can be acquired and resold quickly while limiting the scope for adverse selection and adverse maintenance shocks. This argument suggests that iBuyers, with their current use of technology are not likely to impact a large part of the market – i.e., they will make already liquid and easy to price houses more liquid, rather than unlocking the sale of illiquid and harder to price homes.

VI. Discussion and Conclusion

In this paper, we studied the growth of "iBuyers," online real estate companies that buy and sell residential real estate, which have gained significant market share since 2015, to provide novel evidence on the effects and challenges of making housing markets more liquid. We show that these firms act as liquidity providers, buying low and selling high, and carrying properties on their inventories for only a short period of time. Like in the case of online fintech lenders in mortgage origination, consumers appear to greatly value the convenience that iBuyers offer, and sell their properties to them at a considerable discount.

We also document considerable limitations to the liquidity provision by iBuyers. Their pricing relies more on hard information and hence they do not enter market segments with difficult-to-value homes to also limit the scope of adverse selection. Moreover, since homes are empty during the intermediation phase and subject to adverse upkeep shocks, iBuyers tend to focus on properties that can be resold relatively quickly.

We rationalize these findings within a search-based housing trading model with iBuyers. Our model highlights why liquidity provision in real estate markets has been limited, despite its high potential benefits. While the intermediary keeps the house vacant while listing, forgoing these consumption benefits are not quantitatively important. Rather, intermediaries are subject to significant adverse selection which significantly limits their expansion in harder-to-value homes. However, despite the difficulties in fast, remote valuation, we show that the transaction speed and valuation accuracy that iBuyers possess are nevertheless an important innovation over other potential dealer intermediaries. In contrast to iBuyers, the low-tech valuation intermediary with just balance-sheet capacity would counterfactually achieve a negligible market share, which explains why prior to the iBuyer entry intermediation in the housing market has been rare.

We conclude by making a few observations regarding our findings. First, it is possible that development of better pricing algorithms and collection of new data could considerably expand the range of properties that iBuyer could accurately price in the future. Our analysis suggests, however, that for this to meaningfully affect their market penetration and hence the liquidity provision, the iBuyers would need to be able to resell such properties relatively quickly. In other words, a substantial increase in the market penetration of iBuyers -- and hence in the liquidity provision in the market -- will require not only technological improvements in algorithmic pricing but also in the ability to match homes quickly with subsequent buyers. Our analysis suggests that iBuyers at present do not possess such technological advantages when selling their inventory.

Second, the growth of iBuyer market share we focus on occurred during relatively good times in the housing market (2013-2018), when on average most of the properties were holding or appreciating in value. It is unclear how viable the iBuyer business model would be during an economic downturn accompanied by a decline in house prices. On the one hand, an increase in expected time to resell the property and challenges in accurately pricing homes during rapidly changing economic environment may considerably limit if not shut-down altogether the liquidity provision by iBuyers.[18] This indeed occurred during the early stages of COVID-19 pandemic when most of iBuyers temporarily suspended their operations.[19] On the other hand, the economic downturn could increase the share of homeowners that value convenience of a quick sale, making liquidity provision by iBuyers more valuable. We leave the analysis of viability of iBuyer business model across various economic environments for future research.

Finally, our findings have broader implications for balance sheet intermediation of consumption goods. Assets such as homes that are relatively illiquid, harder to price, and have high utilization value have seen little intermediation in the past. Only recent technological advances in valuation

[18] In addition, iBuyers could face considerable financial stress due to their need to finance a large inventory of homes that may be declining in value.

[19] https://finance.yahoo.com/news/zillow-redfin-realogy-opendoor-suspend-045712124.html

accuracy and speed of transacting facilitated by on-line acquisition platforms have allowed some inroads into provision of intermediation services in such markets. On the other hand consumption goods such as cars are relatively more liquid, easier to price, and have relatively lower carry cost, which explains why intermediation in such markets have been historically at much higher levels.

References

Anenberg, E., 2016, Information frictions and housing market dynamics, *International Economic Review* 57, 1449-1479.

Anenberg, E., and P. Bayer, 2020, Endogenous Sources of Volatility in Housing Markets: The Joint Buyer-Seller Problem, forthcoming in the *International Economic Review*.

Andersen, S., C. Badarinza, L. Liu, J. Marx, T. Ramadorai, 2020, Reference Dependence in the Housing Market, working paper.

Agarwal, S. and S.H. Ang, Y. Deng, Y. Wang, 2020, Mortgage Brokers and the Effectiveness of Regulatory Oversights, *Management Science*, forthcoming.

Arevefa, A., 2017, How Auctions Amplify House Price Fluctuations, working paper.

Barwick, P. J. and P. A. Pathak, 2015, The Costs of Free Entry: An Empirical Study of Real Estate Agents in Greater Boston, *RAND Journal of Economics* 46, 103–145.

Barwick, P. J., P. A. Pathak, and M. Wong, 2017, Conflicts of Interest and Steering in Residential Brokerage, *American Economic Journal: Applied Economics* 9, 191–222.

Buchak, G., G. Matvos. T. Piskorski, and A. Seru, 2018, Fintech, Regulatory Arbitrage and the Rise of Shadow Banks, *Journal of Financial Economics* 130, 453-483.

Buchak, G., G. Matvos. T. Piskorski, and A. Seru, 2018, Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy, Working Paper.

Calder-Wang, S., 2019, The Distributional Impact of the Sharing Economy on the Housing Market, Working Paper.

Chinco, A., and C. Mayer, 2016. Misinformed Speculators and Mispricing in the Housing Market. *Review of Financial Studies*, 29, 486-522.

DeFusco, A. C. Nathanson, and E. Zwick, 2017, Speculative Dynamics of Prices and Volume, working paper.

Diamond, P, 1982, Wage Determination and Efficiency in Search Equilibrium, *The Review of Economic Studies* 49, no. 2 (1982): 217-227.

Duffie, D., N. Garleanu, and L. H. Pedersen, 2005, Over-the-Counter Markets, *Econometrica* 73, 1815–1847.

Fu Y., W. Qian, B. Yeung, 2015, Speculative investors and transaction tax: Evidence from the housing market, *Management Science*, 62, 3254-327.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery, 2019, The Role of Technology in Mortgage Lending, *Review of Financial Studies* 32, 1854–1899.

Gavazza, 2016, An Empirical Equilibrium Model of a Decentralized Asset Market, *Econometrica* 85, 1755-1798.

Genesove, D., and C. Mayer, 1997, Equity and Time to Sale in the Real Estate Market, *American Economic Review* 87, 255–269.

Genesove, D., and L. Han, 2012, Search and Matching in the Housing Market, *Journal of Urban Economics* 72, 31-45.

Gilbukh., S, and P. Goldsmith-Pinkam 2019, Heterogeneous Real Estate Agents and the Housing Market, working paper.

Gorback, C.S., and B. J. Keys, 2020, Global Capital and Local Assets: House Prices, Quantities, and Elasticities, working paper.

Grossman, S. J., and M. H. Miller, 1988, Liquidity and Market Structure, *Journal of Finance* 43, 617–633.

Guren, A., 2018, House Price Momentum and Strategic Complementarity, *Journal of Political Economy* 126, 1172-1218.

Guren, A., and T. J. McQuade, 2020, How Foreclosures Exacerbate Housing Downturns, *Review of Economic Studies* 87, 1331-1364.

Head, A., H. Lloyd-Ellis, and H. Sun, 2014, Search, Liquidity, and the Dynamics of House Prices and Construction, *American Economic Review* 104, 1172–1210.

Hendel, I., A. Nevo, and F. Ortalo-Magné, 2009, The Relative Performance of Real Estate Marketing Platforms: MLS versus FSBOMadison.com, *American Economic Review* 99, 1878–1898.

Jiang, E., G. Matvos, T. Piskorski, A. Seru, 2020, Banking without Deposits: Evidence from Shadow Bank Call Reports, Working Paper.

Kurlat, P., and J. Stroebel, 2015, Testing for information asymmetries in real estate markets, *Review of Financial Studies*, 28, 2429-2461.

Levitt, S.D., and C. Syverson, 2008, Market Distortions when Agents are Better Informed: The Value of Information in Real Estate Transactions, *Review of Economics and Statistics* 80, 599-611.

Mian, A., Sufi, A., 2019. Credit Supply and Housing Speculation. Working paper.

Nathanson, C, and E. Zwick, 2018, Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market, *Journal of Finance* 73, 2587-2633.

Ngai, L. R., and S. Tenreyro, 2014, Hot and Cold Seasons in the Housing Market, *American Economic Review* 104, 3991-4026.

Piazzesi, M., and M. Schneider 2009, Momentum Traders in the Housing Market: Survey Evidence and a Search Model, *American Economic Review* 99, 406–411.

Piazzesi, M, M. Schneider, and J. Stroebel, 2020, Segmented Housing Search, *American Economic Review* 110*,* 720-59.

Stroebel, J., 2016, Asymmetric Information about Collateral Values, *Journal of Finance*, 71, 1071-1112.

Wheaton, W. C., 1990, Vacancy, Search, and Prices in a Housing Market Matching Model, *Journal of Political Economy* 98, 1270–1292.

Table 1: Summary Statistics

This table shows summary statistics for the main datasets used in the paper: the Corelogic transaction deeds records between 2013 and 2018 (Panel A), and the MLS listings data between 2013 and 2018 from ATTOM Data (Panel B). Data are from Phoenix, Orlando, Dallas, Gwinnet County, and Las Vegas. For a given variable we show number of observations, mean, standard deviation (S.D.), and 5 through 95 percentiles of the data. For the Corelogic data (Panel A), *Sale price* is the sale price, *Land sq ft* is the assessed land square footage, *House age* is the age of the house at the time of transaction. *iBuyer is buyer* indicates when an iBuyer is buying the property. *iBuyer is seller* indicates when an iBuyer is selling the property. *All other* is all transactions not involving an iBuyer as either buyer or seller. For the MLS data (Panel B), *first list price* is the first listed price of the property on MLS. *Mentions renovation* is an indicator for whether the listing mentions "renovation," "refurbish," or "remodel." *Total listings* is the number of listings in the listing spell. *Has sold* is an indicator for whether the property ultimately sells. *Days on market* is the number of days between initial listing and sale (only among sold listings), and *Discount to list* is the ratio of the sale price to the initial listing price minus one (only among sold listings). *iBuyer* is when an iBuyer is listing the property. *Flipper* is when an absentee owner who has owned the house for less than one year before listing is listing the property. *Other* is when a non-iBuyer, non-lister seller is listing the property.

Panel A: Transaction Data (Corelogic)

Variable	N	Mean	S.D.	5%	25%	50%	75%	95%
Sale price								
iBuyer is buyer	5,887	251,982	194,389	146,653	191,000	230,400	281,350	390,000
iBuyer is seller	7,384	269,795	206,276	164,664	208,000	245,000	295,000	398,000
All others	885,451	280,251	372,086	82,500	156,000	218,175	305,000	582,500
Land sq ft								
iBuyer is buyer	6,003	7,094	3,880	2,800	5,227	6,580	8,073	12,324
iBuyer is seller	7,460	7,208	3,900	2,614	5,227	6,664	8,273	12,946
All others	966,261	9,074	6,948	2,614	5,720	7,405	9,798	21,622
House age								
iBuyer is buyer	5,978	20	12	4	12	17	28	45
iBuyer is seller	7,431	21	12	5	12	17	29	46
All others	954,313	27	19	6	13	22	40	63

Table 1: Summary Statistics, Continued

Panel B: Listing Data (ATTOM Data)

Variable	N	Mean	S.D.	5%	25%	50%	75%	95%
First list price								
Other	924,490	325,627	213,028	124,500	193,000	265,000	380,000	750,000
iBuyer	1,353	241,471	75,131	160,000	193,000	226,000	269,900	383,000
Flipper	63,328	319,038	209,176	119,900	185,900	260,000	379,000	740,000
Mentions renovations								
Other	924,490	0.097	0.296	0	0	0	0	1
iBuyer	1,353	0.033	0.179	0	0	0	0	0
Flipper	63,328	0.282	0.450	0	0	0	1	1
Total listings								
Other	924,490	3.686	2.335	1	2	3	5	8
iBuyer	1,353	6.997	4.073	3	4	6	9	15
Flipper	63,328	3.837	2.835	1	2	3	5	9
Has sale								
Other	924,490	0.705	0.456	0	0	1	1	1
iBuyer	1,353	0.960	0.196	1	1	1	1	1
Flipper	63,328	0.668	0.471	0	0	1	1	1
Days on market								
Other	652,039	91.124	85.670	26	42	63	106	249
iBuyer	1,299	96.810	70.013	29	45	74	127	242
Flipper	42,332	89.835	79.029	26	44	66	106	229
Discount to list								
Other	651,153	-0.033	0.061	-0.133	-0.057	-0.024	0	0.032
iBuyer	1,299	-0.028	0.043	-0.101	-0.052	-0.021	0	0.026
Flipper	42,270	-0.036	0.059	-0.132	-0.060	-0.027	0	0.023

Table 2: iBuyer Transaction Behavior

This table examines iBuyer transaction behavior on the intensive and extensive margin of listing. Panel A shows the propensity to list a property on multiple listing service (MLS) using merged transaction-listing data with sale dates between 2013 and 2017. The table presents the OLS estimates from a regression of the dummy variable that takes value of one if the seller lists the property on MLS and is zero otherwise on the dummy variable taking the value of one if the property buyer was an iBuyer and is zero otherwise (Columns 1-3), and the dummy variable taking the value of one if the property seller was an iBuyer and zero otherwise (Columns 4-6). Columns (1) and (4) have no controls or fixed effects. Columns (2) and (5) have zip-quarter fixed effects. Columns (3) and (6) additionally include square footage, house age, and whether the house is multistory. Panel B compares the pricing dynamics of listings where an iBuyer is the seller to listings of home flippers and regular homeowners (excluded category). *Log first price* is the log of the first listing price. *Mentions renovations* is an indicator for whether the listing description describes the house as being renovated, i.e., includes "renovation," "refurbish," or "remodel." *Total listings* is the number of price adjustments in a given listing spell. *Leads to sale* is an indicator for whether the listing leads to a sale. *Days on market* is the number of days between the first listing and the sale. *Sale-to-list* is the sale price divided by the initial listing price. Columns (1)-(6) and (11) are linear specifications; (7—10) are Cox Proportional Hazard Rate models. Columns (1)-(4) and (7—8) consider all listings. Columns (5), (6), (10), and (11) consider only listings leading to sales. Columns (6), (8), and (10) include the log of the initial listing price. A *Flipper* is an absentee owner who lists the house within one year of purchasing it. The *iBuyer* and *Flipper* categories are measured relative to the base category of other lister. All columns include house controls including square footage, whether the house is multistory, and house age. The linear models include zip times quarter fixed effects. Data are from Corelogic and MLS provided by ATTOM Data between 2013 and 2018 at the combined listing level. Standard errors are in parentheses.

Panel A: Propensity to List on MLS

	Dependent variable: Lists on MLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer is iBuyer	-0.314	-0.272	-0.275	-	-	-
	(0.006)	(0.006)	(0.006)	-	-	-
Seller is iBuyer	-	-	-	0.121	0.135	0.128
	-	-	-	(0.006)	(0.005)	(0.005)
Hedonics	N	N	Y	N	N	Y
Zip-Quarter FE	N	Y	Y	N	Y	Y
Observations	822,081	822,081	807,102	822,081	822,081	807,102
R^2	0.003	0.134	0.171	0.001	0.133	0.169

Panel B: iBuyer Listing Behavior

Specification	Linear	Linear	Linear	Linear	Linear	Linear	Hazard	Hazard	Hazard	Hazard	Linear
Dependent variable	Log list price	Mentions renovations	Total listings	Leads to sale	Days on market	Days on market	Days on market	Days on market	Days on market	Days on market	Sale-to-list price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
iBuyer	0.023	-0.057	1.338	0.136	27.115	26.191	0.309	0.309	-0.019	-0.020	-0.005
	(0.007)	(0.007)	(0.037)	(0.009)	(1.700)	(1.639)	(0.024)	(0.024)	(0.024)	(0.024)	(0.001)
Flipper	0.008	0.142	0.172	-0.012	2.180	1.394	-0.080	-0.079	-0.069	-0.070	-0.002
	(0.001)	(0.001)	(0.006)	(0.001)	(0.317)	(0.307)	(0.005)	(0.005)	(0.005)	(0.005)	(0.0002)
Hedonics	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Initial list price	N	N	N	N	N	Y	N	Y	N	Y	Y
Zip-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sample		All			Sales only		All		Sales only		
Observations	1,348,518	1,348,518	1,348,518	1,348,518	800,182	789,168	1,348,518	1,348,518	800,182	800,182	789,168
R^2	0.748	0.176	0.489	0.357	0.392	0.413	0.042	0.043	0.049	0.050	0.176

Table 3: Gross Returns: iBuyers versus Individuals

Panel A shows holding periods and the realized gross housing investment return for iBuyers and non-corporate individuals. Observations are all purchases in Corelogic data between 2013 and 2018 where the buyer sells the house during this sample period. Column (1) shows the average holding period in years, defined as the number of years between purchase and sale. Column (2) shows *Gross Return*, calculated as the percentage change in house price from purchase to sale. Column (3) shows annualized gross returns calculated by annualizing gross returns by the holding period. Column (4) shows the number of houses a purchaser purchases in a given quarter conditional on purchase. Column (5) shows the annualized portfolio returns, calculated by averaging the annualized returns of all houses purchased by a single buyer in a single quarter. The top number in each row is the mean; the bottom number in parentheses is the standard deviation. Panel B shows the regression of holding period returns on house controls and zip-quarter fixed effects and the iBuyer dummy taking the value of one if the property is purchased by an iBuyer and zero otherwise. Columns (1) and (2) show annualized gross return in decimals. Columns (3) and (4) show the *Index Return*, defined as the percentage change in median house prices in the three-digit zip code from the quarter of purchase to the quarter of sale, in decimals. *Non Index Return* is the residual: *Gross Return* minus *Index Return*. Columns (1), (3), and (5) include no controls or fixed effects. Columns (2), (4), and (6) include house hedonic controls including square footage, house age, and whether the house is multistory (and excluding price). Standard errors are in parentheses. The table excludes extreme observations where the total or annualized return is greater than 50% in absolute value.

Panel A: Raw returns

	Holding period given sale (years)	Gross Return (Raw %)	Gross Return (Ann %)	Quarterly portfolio size	Portfolio return (Ann %)
	(1)	(2)	(3)	(4)	(5)
Individuals	2.65	24.66	9.28	1.02	11.21
	(1.28)	(19.83)	(9.09)	(0.69)	(15.66)
iBuyer	0.39	4.91	17.78	113	24.15
	(0.38)	(6.39)	(19.72)	(117)	(8.67)

Panel B: Spread regressions

	Dependent variable:					
	Gross Return (ann)		IndexSpread (ann)		NonIndexSpread (ann)	
	(1)	(2)	(3)	(4)	(5)	(6)
iBuyer	0.074	0.066	0.004	0.015	0.068	0.050
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
House Controls	N	Y	N	Y	N	Y
Zip x Quarter FE	N	Y	N	Y	N	Y
Observations	102,140	94,499	102,140	94,499	102,140	94,499
R^2	0.014	0.225	0.0004	0.581	0.011	0.231

Table 4: iBuyer Discounts, Premia, and Pricing Strategies

Panel A examines the extent to which iBuyers buy and sell properties at a premium or discount relative to similar properties that did not involve iBuyers, i.e., individual or corporate owners. The table presents the OLS estimates of the logarithm of the acquisition price on the dummy variable taking the value of one if the property buyer was an iBuyer and is zero otherwise (Column 1 and 2), and the dummy variable taking the value of one if the property seller was an iBuyer and is zero otherwise (Column 3 and 4). The house controls are those as in previous tables, except for price: *House age* is the difference between the transaction date and the year of construction. *Land square footage* is the tax-assessed property square footage. *Multistory* is an indicator for whether the house has greater than 1 stories (including partly-multilevel houses that have "1.5" stories.) Other house characteristics are air conditioning type, garage type, heating type, location influence, and build quality. Columns (1) and (3) user zip times quarter fixed effects. Columns (2) and (4) include zip-year fixed effects, to explore the effect that seasonality has on iBuyer pricing. Data are from Corelogic between 2013 and 2018. Standard errors are shown in parentheses. Panel B examines the extent to which the physical house characteristics and local economic conditions can explain the variation in pricing of properties that iBuyers intermediate in. The table shows the R^2 from regressions of log house price on house characteristics and fixed effects for transactions where iBuyers are buyers, where iBuyers are sellers, and other transactions that do not involve iBuyer, using Corelogic transaction data between 2013 and 2018. Each row differs in the fixed effects it includes. In the first, there are no fixed effects. In the second row, there are zip fixed effects. In the third row, there are quarter fixed effects. In the fourth row, there are zip and quarter fixed effects. In the fifth row, there are zip times quarter fixed effects. A *High iBuyer market* is a zip code in above the 75th percentile for iBuyer market share over the sample period, 2013-2018. (1) represents how much hedonics (and fixed effects) explain price variation when iBuyers purchase. (2) measures this for when iBuyers sell. (3) measures this for transactions in which no iBuyer is involved. (4) and (5) split the no-iBuyer transactions into those taking place in markets where iBuyers are common (4), and markets where iBuyers are uncommon (5).

Panel A: iBuyer Purchase Discount and Sale Premium

	Dependent variable: Log(sale amount)			
	(1)	(2)	(3)	(4)
Buyer_is_iBuyer	-0.036	-0.031	-	-
	(0.005)	(0.005)	-	-
Seller_is_iBuyer	-	-	0.016	0.019
	-	-	(0.004)	(0.004)
House Controls	Y	Y	Y	Y
Zip-Quarter FE	Y	N	Y	N
Zip-year FE	N	Y	N	Y
Observations	822,166	822,166	822,166	822,166
R^2	0.705	0.693	0.705	0.693

Panel B: Determinants of iBuyer Transaction Prices

				All markets	*High iBuyer Market*	*Other Markets*
Hedonic controls	Fixed effects	iBuyer buyer	iBuyer seller	No iBuyer involved	No iBuyer involved	No iBuyer involved
		(1)	(2)	(3)	(4)	(5)
Y	None	0.483	0.471	0.401	0.520	0.417
Y	Zip	0.675	0.671	0.625	0.593	0.637
Y	Qtr	0.552	0.508	0.443	0.592	0.449
Y	Zip + Qtr	0.740	0.712	0.676	0.669	0.673
Y	Zip x Qtr	0.833	0.803	0.684	0.674	0.683

Table 5: House Characteristics and Algorithmic Pricing Errors

This table shows the estimated relationship between property characteristics, house prices, and pricing errors. We use Corelogic transaction data between 2008 and ends at the end of 2012., which corresponds to the data that an entering iBuyer would have available when making a pricing decision once they enter the market. Column (1) shows the regression of log of house price on house characteristics and Column (2) shows the regression of squared pricing errors (normalized by mean price) on house characteristics. This residual is obtained directly from Column (1), squared, and divided by the standard deviation of the residuals. Omitted house characteristics include garage type, heating type, air conditioning type, and house quality. Columns (3) and (4) show a robustness checking using data between 2006 and 2012, with Column (3) corresponding to the pricing model and (4) corresponding to the errors model. Standard errors are shown in parentheses.

	2008-2012 (Main specification)		2006-2012 (Robustness)	
	Dependent variable:			
	Log(house price)	Squared deviation from predicted price	Log(house price)	Squared deviation from predicted price
	(1)	(2)	(3)	(4)
House age (omitted category: > 50 years)				
Age < 5 years	0.364^{***}	-0.060^{***}	0.363^{***}	-0.065^{***}
	(0.003)	(0.002)	(0.003)	(0.002)
Age 5-15 years	0.320^{***}	-0.060^{***}	0.313^{***}	-0.062^{***}
	(0.003)	(0.002)	(0.002)	(0.001)
Age 15-50 years	0.111^{***}	-0.048^{***}	0.111^{***}	-0.050^{***}
	(0.003)	(0.001)	(0.002)	(0.001)
Land square footage (omitted category: > 25k)				
Square footage < 5k	-0.808^{***}	-0.016^{***}	-0.796^{***}	-0.019^{***}
	(0.004)	(0.002)	(0.003)	(0.002)
Square footage 5-10k	-0.532^{***}	-0.023^{***}	-0.531^{***}	-0.027^{***}
	(0.003)	(0.002)	(0.003)	(0.002)
Square footage 10-25k	-0.271^{***}	-0.014^{***}	-0.279^{***}	-0.016^{***}
	(0.003)	(0.002)	-0.796^{***}	-0.019^{***}
Multistory	0.172^{***}	-0.002^{**}	0.176	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Other house characteristics	Y	Y	Y	Y
Observations	680,640	680,640	889,661	889,661
R^2	0.665	0.029	0.696	0.024

Table 6: Limits to iBuyer Technology: Easy-to-Price and Liquid Homes

This table shows the regression of whether an iBuyer purchases the house on predicted pricing errors, $\hat{e}^2_{izt}$ based on house hedonics and the predicted probability that a house sells within 90 days of listing. $\widehat{SellsWithin90Days}_{izt}$ based on house hedonics and MLS data. All columns include zip times quarter fixed effects. Standard errors, clustered at the property level, are shown in parentheses. $\widehat{SellsWithin90Days}_{izt}$ relies on knowing the last sale price, which is not available for all properties, which explains the drop in observations from Column (1) to (2) and (3). Standard errors, clustered at the property level, are shown in parentheses.

	Dependent variable:		
	iBuyer buyer (%)		
	(1)	(2)	(3)
$\hat{e}^2$	-3.686	-	-3.796
	(0.272)	-	(0.469)
$\widehat{SellsWithin90Days}$	-	1.919	1.716
	-	(0.192)	(0.197)
Zip x Quarter FE	Y	Y	Y
Observations	557,164	259,771	259,771
R^2	0.026	0.030	0.031

Table 7: Equilibrium Housing Trading Model with iBuyers: Calibration and Fit

This table provides details of the model calibration. Panel A shows targeted moments in the data and calibrated model. Panel B shows parameters calibrated externally or as normalizations, together with their values and sources. Panel C shows parameters calibrated through the method of moments, where parameters are chosen to match the model-predicted moments to the empirical moments in the data as shown in Panel A.

Panel A: Moments Targeted in Calibration and Fit

Moment	Data (2018)	Model
Median house price ($k)	262.000	262.424
iBuyer market share (%)	4.881	4.918
iBuyer purchase discount (%)	2.673	2.862
iBuyer selling premium (%)	0.050	0.009
Time on market (days)	91.000	90.895
ΔiBuyer Time on market (days)	6.000	6.205
P(iBuyer reduces listing price)	0.562	0.576
iBuyer price reduction (%)	3.266	1.545
Mean pricing error	0.143	0.148
d(iBuyer share)/d(P(sells in 90 days)	0.017	0.011
d(iBuyer share)/d(Mean pricing error)	-0.017	-0.016

Panel B: Parameters Calibrated Externally / Normalizations

Parameter	Description	Value	Source
ρ	Discount rate	0.050	Anenberg and Bayer (2020)
μ	Unmatching rate	0.152	Census
p_f	Probability needs renovation	0.109	Fraction of listings mentioning renovation
τ	iBuyer closing time (days)	1.000	Industry reports

Panel C: Parameters Calibrated by Method of Moments

Parameter	Description	Value
$\bar{u}$	Matched flow utility ($k/dt)	15.1
$\underline{u}$	Unmatched flow utility ($k/dt)	-3.1
λ	Matching rate (/dt)	148
λ_{ib}	Relative iBuyer matching rate (/dt)	0.97
c	Cost increase from iBuyer possession ($k)	2.61
η	Likelihood of additional cost from iBuyer possession (/dt)	5.10
ξ	Noise in iBuyer signal	0.18
R	Repair cost ($k)	5.24
σ_m	Variance on T1EV selling shock ($k^2)	0.21
σ_i	Variance on T1EV iBuyer transaction shock ($k^2)	0.56

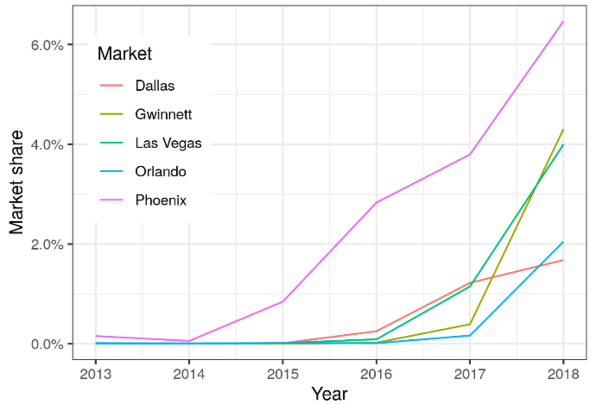
Table 8: Model Validation: iBuyer Entry and Regional Outcome Variables

This table shows the regional effects of iBuyer entry using the zip-code level data from Redfin. iBuyer Share is the change in iBuyer share between pre (2013) and post (2018), omitting Phoenix, which is used to fit the hedonic model. *% Sold in 2 weeks* is the change in houses sold within two weeks of listing. *Sale Price* is the percentage change in sale prices. $\% \widehat{iBuyer}$ is the predicted market share of iBuyer based on the physical characteristics of houses sold in the zip code from 2011 to 2014 using a model based on 2018 Phoenix transactions. iBuyer share is the actual iBuyer share. $\widehat{iBuyer\ Share}$ is the instrumented iBuyer share, using the $\% \widehat{iBuyer}_z$ based on physical characteristics as an instrument. All columns include the zip level regional controls utilized earlier. 1st Stage is the first stage regression of iBuyer share on iBuyer propensity based on house characteristics. OLS is the regression of outcomes on actual iBuyer share. RF is the reduced form regression of outcomes on iBuyer propensity. IV is the instrumental variables regression using propensity to instrument for iBuyer share. Standard errors are shown in parentheses.

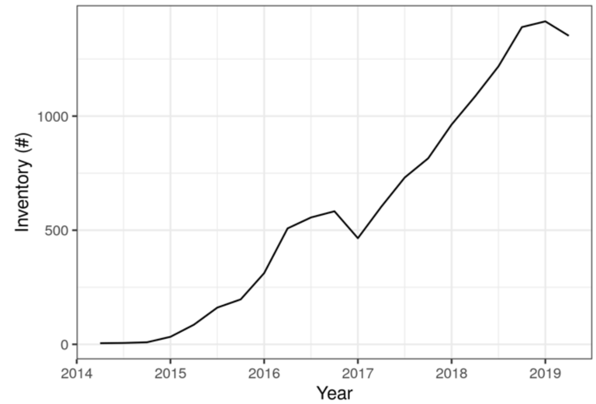
	iBuyer Share	ΔLiquidity: % Sold in 2 weeks			Sale Price		
	(1st Stage)	(OLS)	(RF)	(IV)	(OLS)	(RF)	(IV)
$\% \widehat{iBuyer}_z$	0.653	-	1.424	-	-	-1.491	-
	(0.079)	-	(0.243)	-	-	(0.312)	-
$iBuyer$	-	0.140	-	-	-0.887	-	-
$share$	-	(0.163)	-	-	(0.201)	-	-
$\widehat{iBuyer}$	-	-	-	2.180	-	-	-2.282
$share$	-	-	-	(0.498)	-	-	(0.515)
Zip controls	Y	Y	Y	Y	Y	Y	Y
Observations	330	330	330	330	330	330	330
R^2	0.455	0.182	0.259	0.330	0.657	0.661	0.606

Figure 1: iBuyer Market Shares, Inventory, and Realized Gross Return (Spread)

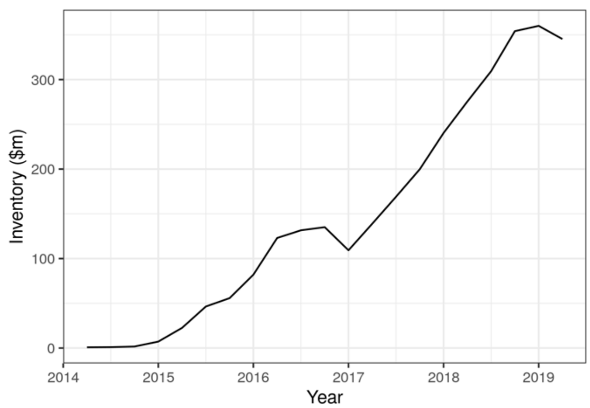
Panel (a) shows iBuyer market share in buying or selling transactions across five large markets: Dallas, Texas, Gwinnett County, Georgia, Las Vegas, Nevada, Orlando, Florida, and Phoenix, Arizona using Corelogic data. Panel (b) shows the stock of houses owned by iBuyers at the end of every quarter. Panel (c) shows the dollar value of this inventory (based on purchase price, in millions of dollars). Panel (d) shows the number of purchases by quarter. Panel (e) shows the inventory turnover, defined as sales per inventory, for iBuyers, individuals, and other corporate owners, which are tagged in the Corelogic data and shown here to contrast with iBuyer corporate owners. Panel (f) shows the median realized spread, that iBuyers earn on purchased and sold homes with 25% and 75% bands shown.



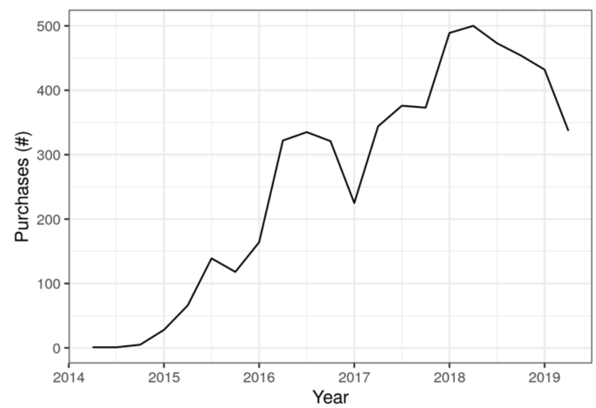
(a) Market shares of transactions



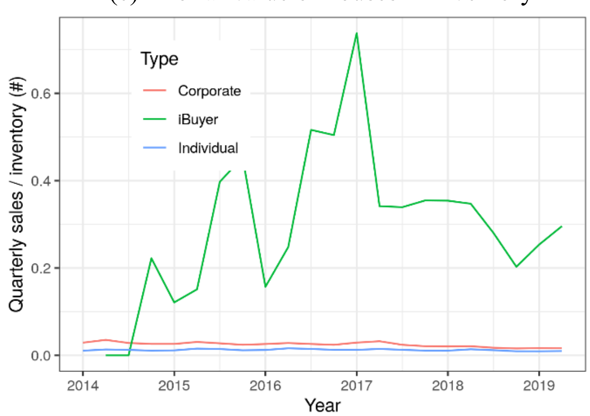
(b) Houses in inventory



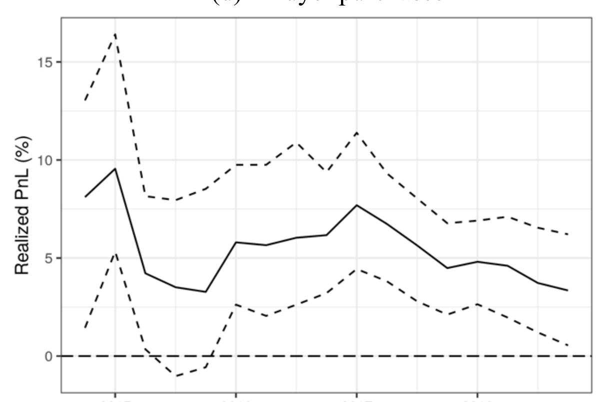
(c) Dollar value of houses in inventory



(d) iBuyer purchases



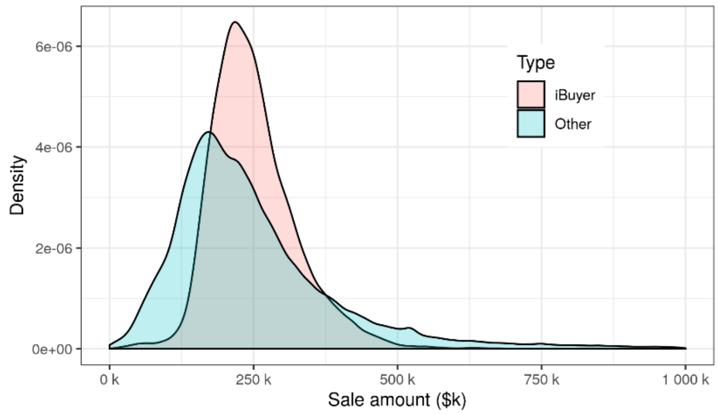
(e) iBuyer inventory turnover



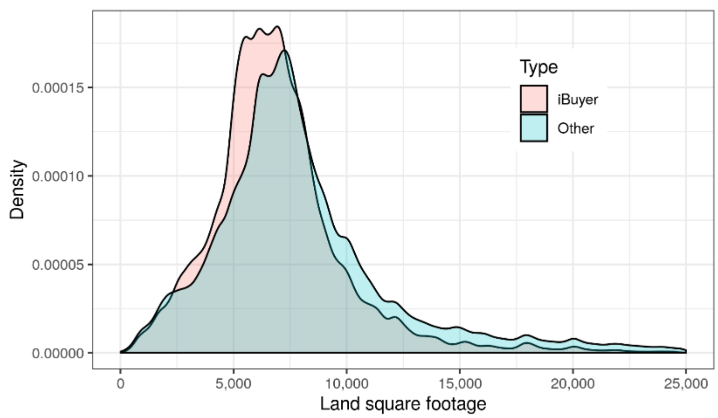
(f) iBuyer realized gross return

Figure 2: Characteristics of iBuyer Houses

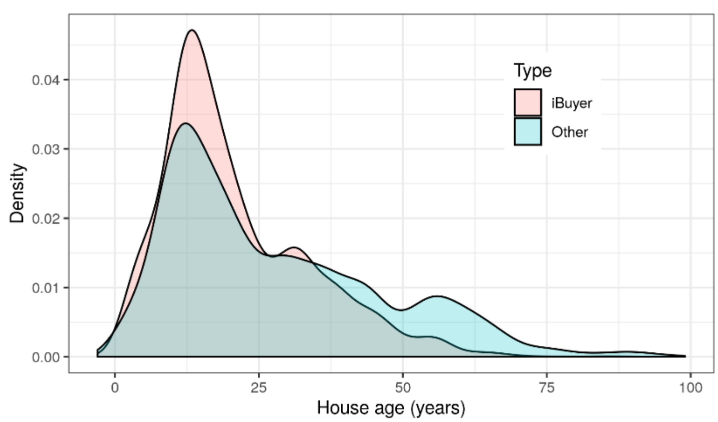
This figure shows the distribution of house prices (panel a), land square footage (panel b), and house age (panel c) for iBuyer (red) versus non-iBuyer (blue) house purchases. The figure uses transaction-level data from Corelogic between 2013 and 2018.



(a) House sale price



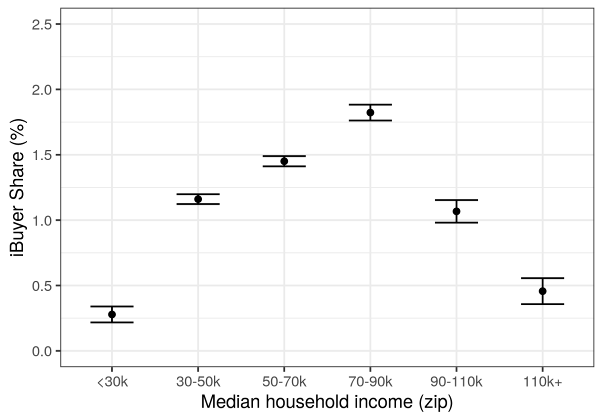
(b) Land square footage



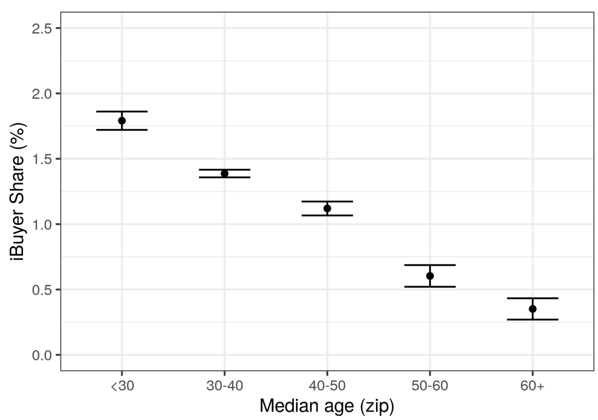
(c) House age

Figure 3: Demographics of iBuyer Markets

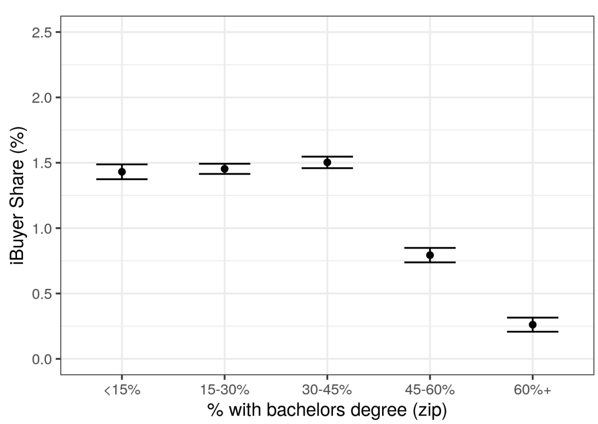
This figure shows average iBuyer market share in a zip code using Corelogic transaction data in 2013-2018 versus binned demographics at the zip code level. iBuyer market share is defined as the fraction of houses that are sold to iBuyers. Panel (a) shows iBuyer share for median household income; (b) for median age, and (c) for college education. Bars represent 95% confidence intervals.



(a) iBuyer share versus household income



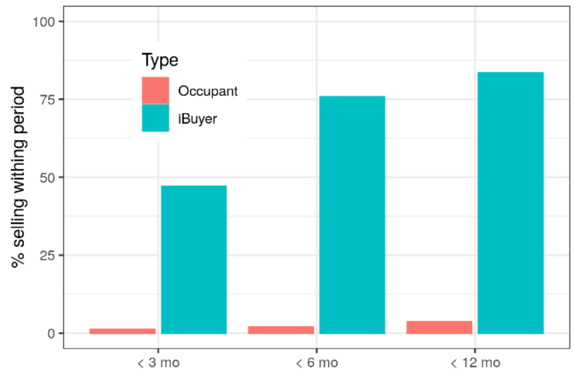
(b) iBuyer share versus age



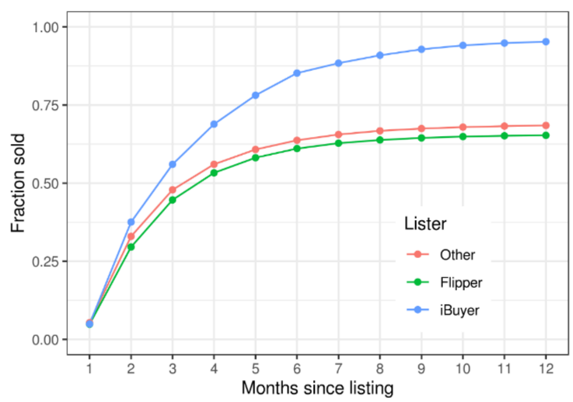
(c) iBuyer share versus % with college education

Figure 4: Inventory Holding Times and Hazard Rates of Sales of iBuyers

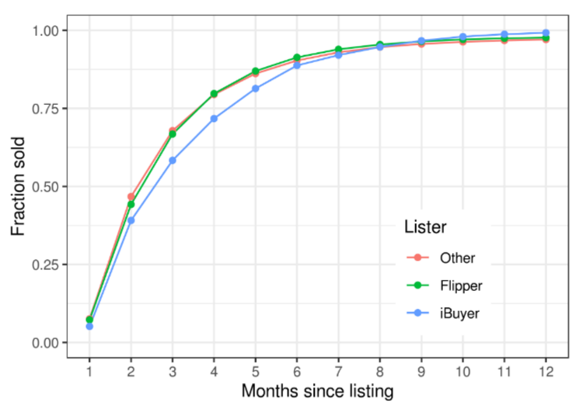
Panel (a) shows the fraction of houses purchased and sold within one year using housing transaction data between 2013 and 2017, omitting 2018 to have a full year of data for the most recent transactions. Panel (b) shows the cumulative fraction of houses sold by month after listing for all listings in MLS data between 2013 and 2017. Panel (c) shows the fraction of houses sold by month for all listings in MLS between 2013 and 2017 that eventually lead to a sale. In Panel (a), an "Occupant" is a non-iBuyer owner-occupier of the house. In Panels (b) and (c), a "flipper" is a "non-occupant" owner who lists the house within one year of purchasing it, and "other" is other (non-iBuyer, non-flipper) listers.



(a) Fraction sold by owner type



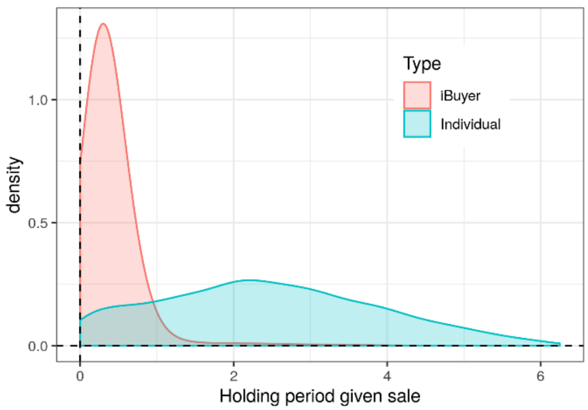
(b) Fraction sold by month among all listings



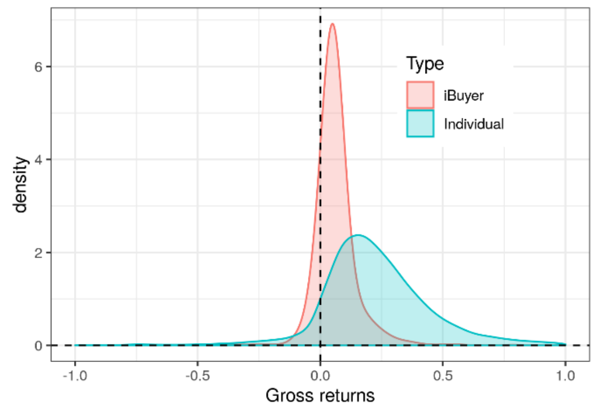
(c) Fraction sold by month among sold listings

Figure 5: Gross Returns: iBuyers versus Individuals

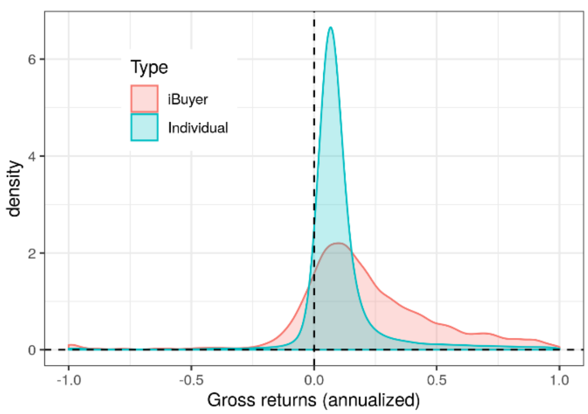
This figure shows holding periods and realized gross returns for iBuyers (red) versus non-corporate individuals (blue) from Corelogic transaction data. Observations are all purchases in Corelogic between 2013 and 2018 where the buyer sells the house during the sample period. Panel (a) shows the distribution of holding periods in years. Panel (b) shows raw gross returns, calculated as the change in price (in percentage terms) between purchase and sale. Panel (c) shows annualized returns, calculated by annualizing the gross returns. Panel (d) shows annualized portfolio returns, calculated by examining the average annualized return for all houses purchased in a given quarter by a single purchaser.



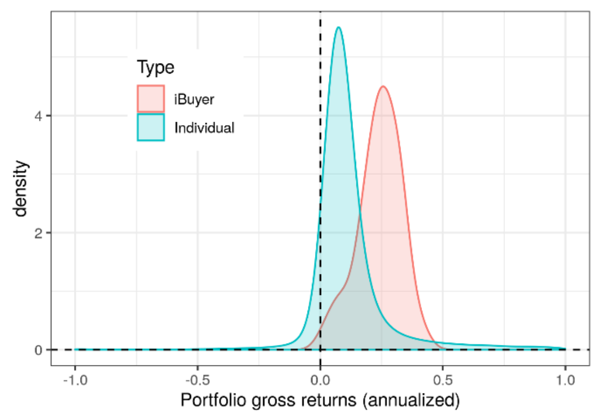
(a) Holding period given sale



(b) Gross returns



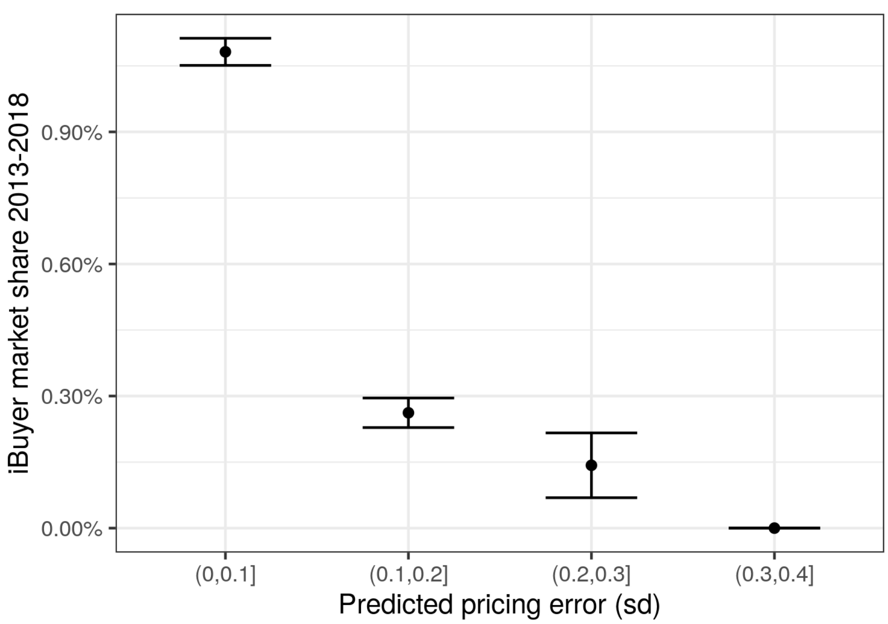
(c) Gross returns (annualized)



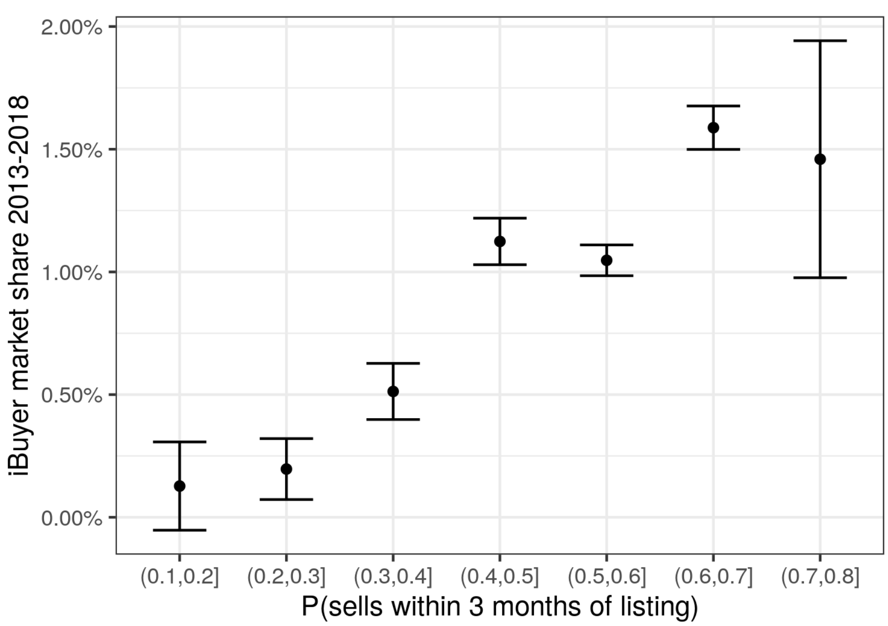
(d) Portfolio gross returns (annualized)

Figure 6: iBuyer Market Share and Pricing Errors and Liquidity

This figure shows iBuyer market share (Y axis) and various proxies for pricing errors and liquidity. We use Corelogic transaction data between 2013 and 2018. iBuyer market share is the fraction of homes purchased by iBuyer. In Panel (a), predicted pricing error is the predicted squared residual based on house hedonics, normalized by the standard deviation of the residuals. In Panel (b), predicted liquidity is the predicted probability that a house sells within 90 days of listing based on house hedonics and MLS data. Bars indicate 95% confidence intervals of standard errors of the estimates.



(a) Pricing error and iBuyer market share



(b) House liquidity and iBuyer market share

Figure 7: Equilibrium Housing Trading Model with iBuyers: Transition Paths

This figure illustrates graphically the transition paths in our equilibrium housing trading model with iBuyers. Once the homeowner becomes unmatched she wants to sell a house. She needs to decide whether to sell to an iBuyer or to list a house using a traditional selling channel. This decision will depend on her mismatch shock, the cost of accessing iBuyer, and the house repair shock. If she decides to list she needs to repair the house if it needs repairs and decide the listing price p_{hh}. She will be matched with potential buyers at the rate $\lambda F(m_s, m_b)$. Once she sells she will transition into a buyer while the buyer will transition into a matched homeowner. Alternatively she can sell to an iBuyer that offers a (quick) closing time, τ, and an acquisition price p_{ib}^b that also depends on the noisy signal the iBuyer receives regarding the house quality. If iBuyer buys a home then it subsequently lists it and decides the listing price strategy p_{ib}^s. The iBuyer will be matched with potential buyers will be matched with potential buyers at the rate $\lambda_{ib} F(m_s, m_{ib})$.

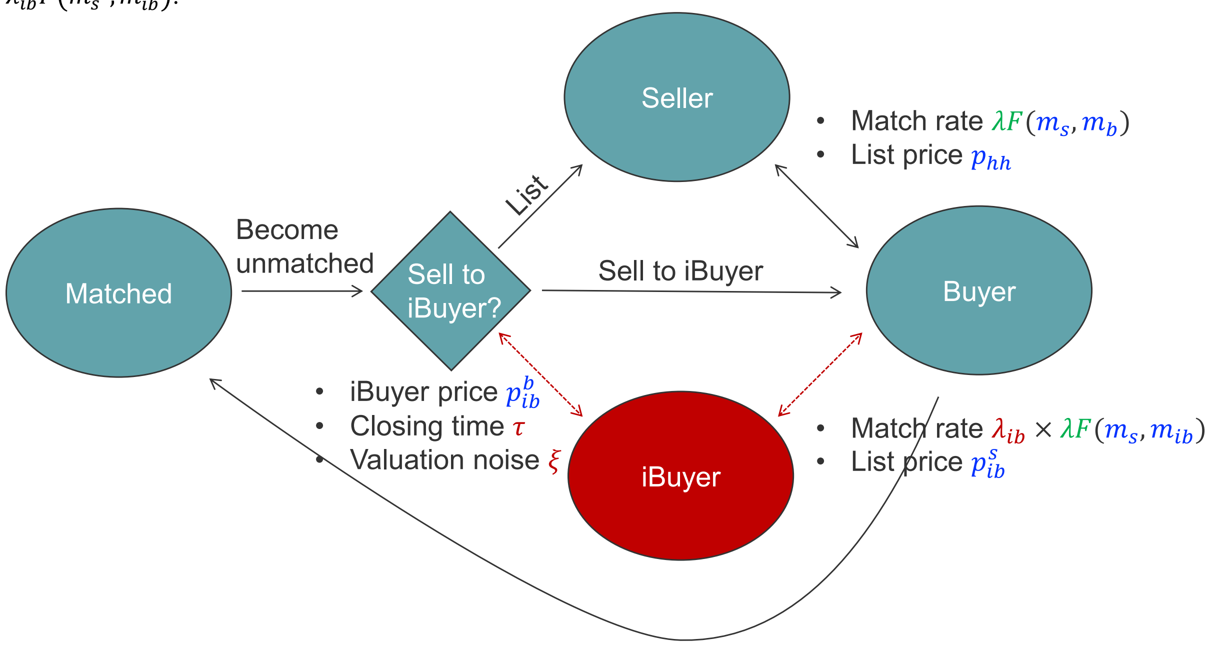
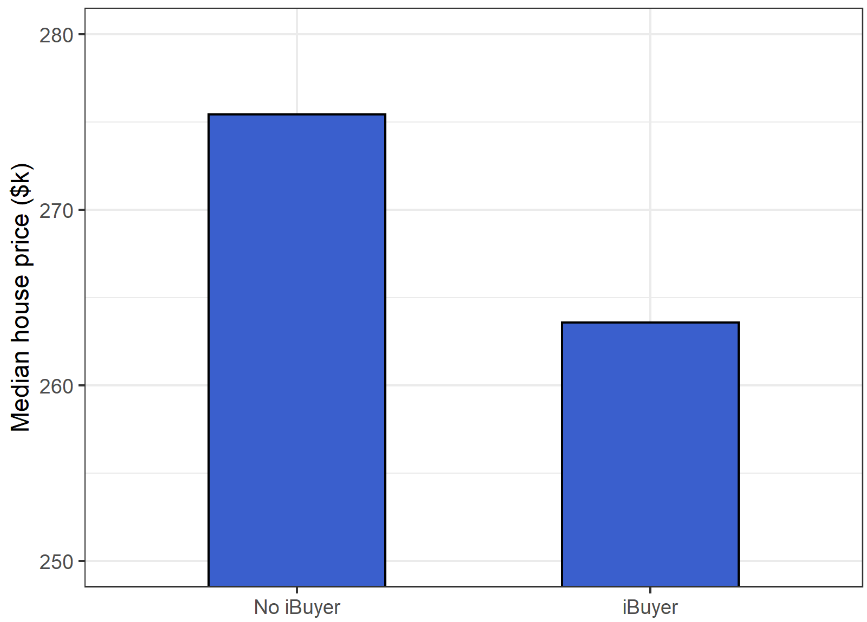
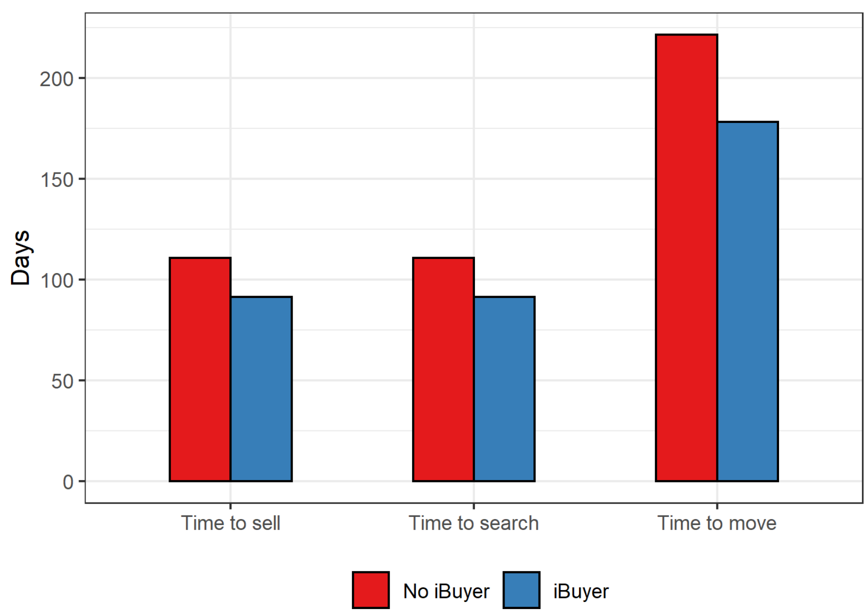


Figure 8: Equilibrium Housing Trading Model with iBuyers: Transition Paths

This figure shows counterfactual simulations from the model with and without iBuyers. Panel (a) shows median house prices in a word without iBuyers (left) and in a world without iBuyers (right). Panel (b) shows relocation times in a world without iBuyers (red bars) and a world without iBuyers (blue bars). Time to sell is the average time for a property to sell (including both iBuyer and household listers). Time to search is the average time a buyer spends looking for a new house. Time to move is the sum.



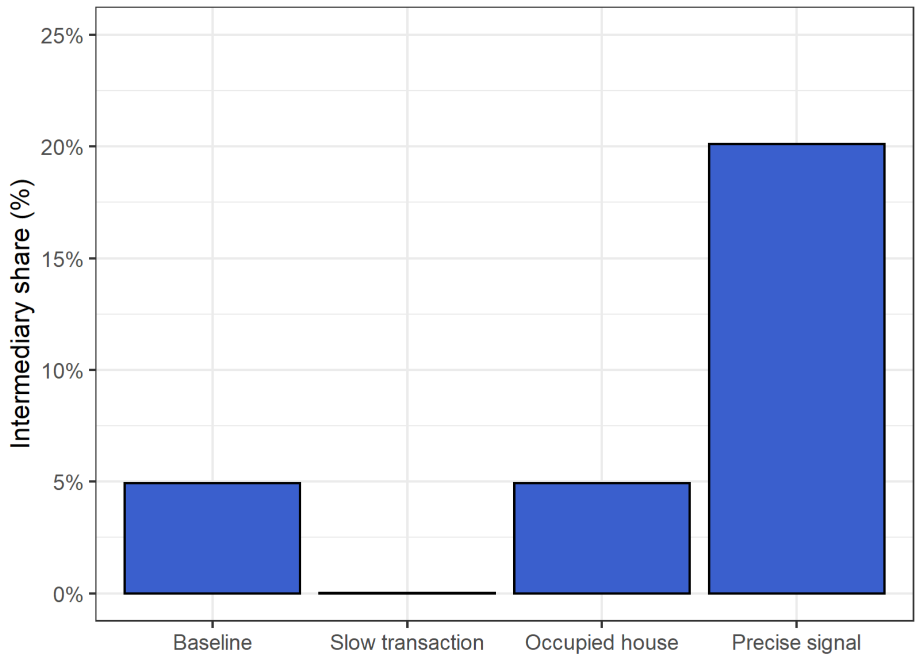
(a) iBuyer presence and median house prices



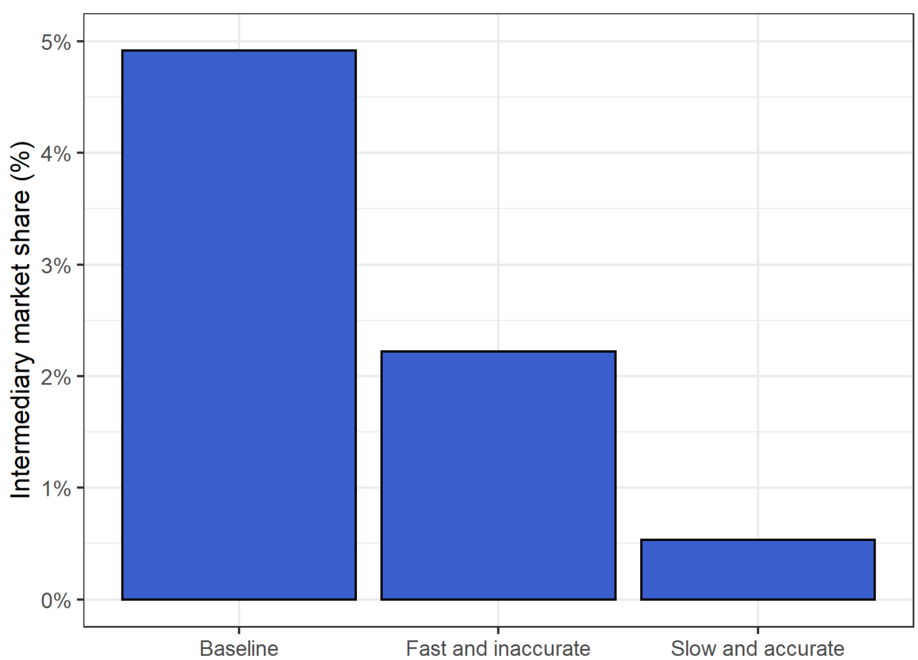
(b) iBuyer presence and relocation times

Figure 9: Intermediation Economics and the role of Technology

This figure shows counterfactual simulations from the model with and without iBuyers. Panel (a) shows median house prices in a word without iBuyers (left) and in a world without iBuyers (right). Panel (b) shows relocation times in a world without iBuyers (red bars) and a world without iBuyers (blue bars). Time to sell is the average time for a property to sell (including both iBuyer and household listers). Time to search is the average time a buyer spends looking for a new house. Time to move is the sum.



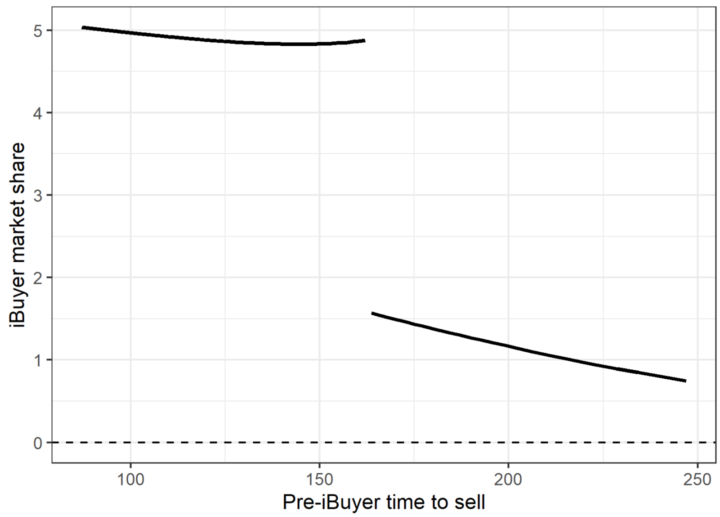
(a) Importance of intermediary characteristics



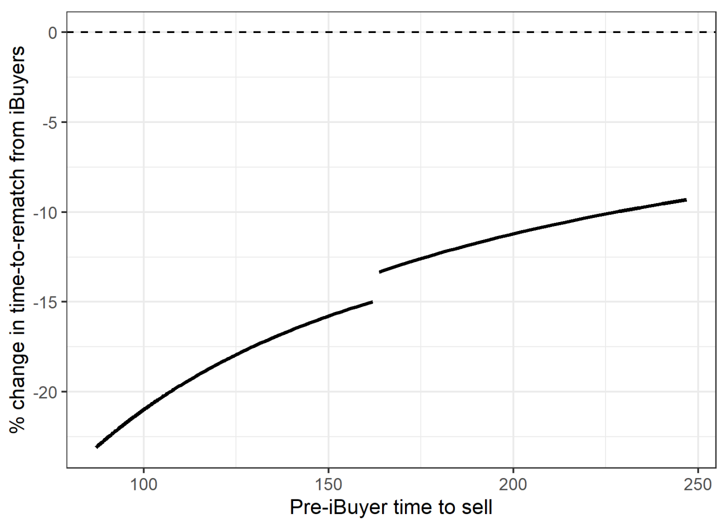
(b) Technological alternatives

Figure 10: Limits of iBuyer Market Penetration and Liquidity Provision

Panel (a) shows the association of pre-iBuyer entry housing liquidity (time to sell) and iBuyer market share implied by our calibrated model. Panel (b) shows the relative change in time to move (re-matching time) in percentage terms as a function of pre-iBuyer entry housing liquidity implied by our model.



(a) iBuyer market share

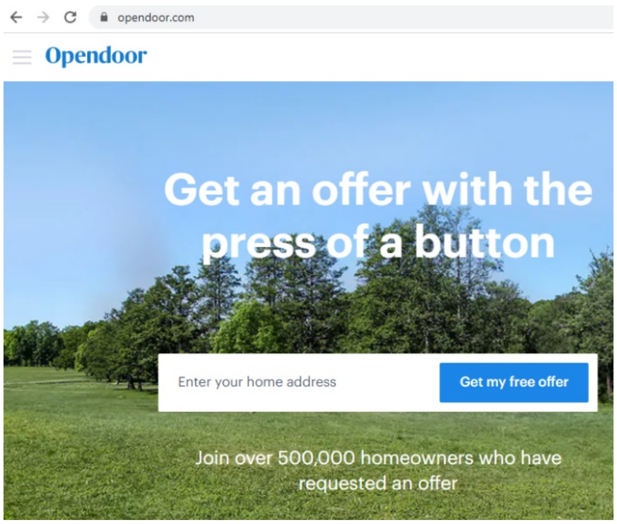


(b) Rematching time

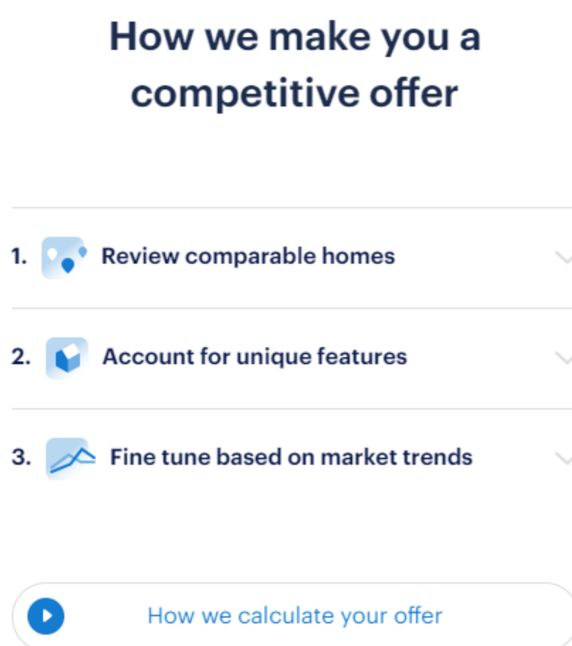
Online Appendix

Appendix A.1: Opendoor.com

This figure shows screenshots from Opendoor's website. The website was visited on January 21, 2020.



(a) Opendoor's main page



(b) Opendoor's process

(c) Opendoor's value proposition

Appendix A.2: iBuyer Classification

This section documents the classification procedure for iBuyers in the Corelogic and MLS data. The companies we consider are Opendoor,[20] Offerpad,[21] Knock,[22] Zillow Offers,[23] and RedfinNow.[24] We identify buyers and sellers in Corelogic and MLS as follows.

Corelogic: Corelogic identifies the owner name (which corresponds to the buyer in a recorded sale transaction) and the seller name. In the case of corporate owners, these are often the names of one-off legal entities with ties to the "main" iBuyer, e.g., "OFFERPAD SPVBORROWER5 LLC." In both cases, we identify a buyer or a seller as an iBuyer if the match one of the following regular expressions:

Company	Regular Expression
Opendoor	opendoor
	open door
	\\<od [a-z].*
Offerpad	offerpad
	offer pad
Redfin	redfin
	red fin
Zillow	zillow
Knock	knock

The match counts buyer or seller names that contain the string. For example, "offerpad" matches with the corporate entity "OFFERPAD SPVBORROWER5 LLC." The expression "\\<od [a-z].*" captures cases such as "OD ARIZONA BORROWER 2 LLC," which can be traced as a corporation registered at Opendoor's San Francisco headquarters. Manual inspection shows that our search strings do not leave out any common buyers or sellers, but there is the possibility of being underinclusive of transactions with unusual corporate entity names. A transaction has an iBuyer seller if we find a match in the seller's name. A transaction has an iBuyer buyer if we find a match in the owner's name.

MLS: We use the same set of regular expressions as above. A listing has an iBuyer seller if we find a match in the listing agent's name or the owner's name. A listing has an iBuyer buyer if we find a match in the buyer office name or the buyer agent name. As above, manual inspection shows

[20] https://www.opendoor.com/
[21] https://www.offerpad.com/
[22] https://www.knock.com/
[23] https://www.zillow.com/offers/
[24] https://www.redfin.com/now

that our search strings do not leave out common buyers or listers, but there is the possibility that our search is underinclusive of iBuyer transactions with unusual corporate entity names.

Appendix A.3: Corelogic and MLS Matching and Tie-out

This table shows the matching rate and consistency between Corelogic transactions and MLS listings. Panel A presents the fraction of single family, arms-length transactions in Corelogic with a match in MLS. *Day match* is the fraction of Corelogic transactions with a sale in MLS where the property ID and sale date matches exactly. *Week*, *month*, and *quarter match* is the fraction of Corelogic transactions with a sale in MLS where the property ID matches exactly and the sale date is within seven days, in the same calendar month, or in the same quarter, respectively. Panel B shows the consistency of reported MLS and Corelogic sale prices by various match windows and buyer/seller types: *Cor(log(MLS),log(Corelogic))* is the correlation between the log MLS sale price and the log Corelogic sale price. *Exact price match* is the fraction of matches where the sale price matches exactly; *|Deviation| < 1%* is the fraction of matches where the absolute deviation is within 1%. *|Deviation| < 5%* is the fraction of matches where the absolute deviation is within 5%. *Mean(|Deviation|)* is the mean of the absolute value of the deviation, e.g., 0.120 means that the mean of the absolute value of Corelogic price divided by MLS price minus one is 0.120.

Panel A: Corelogic transactions with an MLS listing

Year	N	# iBuyer Buys	# iBuyer Sales	Day match	Week match	Month match	Quarter match
All	182,486	6,555	9,922	0.145	0.343	0.411	0.537
2010	95,146	2	0	0.069	0.139	0.166	0.218
2011	101,780	1	1	0.090	0.189	0.227	0.292
2012	109,205	0	2	0.125	0.266	0.315	0.408
2013	106,800	3	0	0.158	0.345	0.417	0.548
2014	132,406	9	1	0.145	0.370	0.448	0.587
2015	148,971	447	333	0.149	0.342	0.411	0.538
2016	159,916	1,407	1,185	0.160	0.399	0.479	0.634
2017	145,648	1,583	2,050	0.170	0.427	0.509	0.667
2018	128,340	2,241	3,964	0.186	0.447	0.531	0.685
2019	54,274	862	2,386	0.176	0.445	0.536	0.681

Panel B: Corelogic and MLS sale price consistency

Match Window	Cor(log(MLS),log(Corelogic)	Exact price match	|Deviation| < 1%	|Deviation| < 5%	Mean(|Deviation|)
All Transactions					
Day	0.956	0.651	0.760	0.808	0.120
Week	0.967	0.780	0.851	0.891	0.068
Month	0.967	0.807	0.870	0.907	0.065
Quarter	0.966	0.830	0.885	0.921	0.061
iBuyer Buys					
Day	0.948	0.881	0.952	0.976	0.021
Week	0.988	0.916	0.980	0.992	0.004
Month	0.989	0.907	0.978	0.992	0.004
Quarter	0.859	0.355	0.417	0.624	0.076
iBuyer Sells					
Day	0.773	0.708	0.776	0.808	0.057
Week	0.797	0.856	0.891	0.913	0.048
Month	0.819	0.868	0.902	0.923	0.043
Quarter	0.837	0.892	0.919	0.939	0.040

Appendix A.4: Listing Dynamics Robustness

This table shows a robustness check on the pricing dynamics of listings where an iBuyer is the seller. In particular, allows for the possibility that listers withdrawal unsuccessful listings and relist shortly thereafter. Therefore, in contrast to the main Table in the body of the paper, the outcome variables (total listings, whether a sale occurs, days between first listing and sale, and sale-to-first listing price) are augmented with outcomes from subsequent relistings that occur within 30 days of the time that the first listing is withdrawn. Data are from MLS provided by ATTOM Data between 2013 and 2018 at the combined listing level. *Log first price* is the log of the first listing price. *Mentions renovations* is an indicator for whether the listing description describes the house as being renovated, i.e., includes "renovation," "refurbish," or "remodel." *Total listings* is the number of price adjustments in a given listing spell. *Leads to sale* is an indicator for whether the listing leads to a sale. *Days on market* is the number of days between the first listing and the sale. *Sale-to-list* is the sale price divided by the initial listing price. In Panel (a), Columns (1)-(5) and (8) are linear models; (6) and (7) are Cox Proportional Hazard Rate models. Columns (1)-(4) and (6) consider all listings. Columns (5), (7), and (8) consider only listings leading to sales. A *Flipper* is an absentee owner who lists the house within one year of purchasing it. The *iBuyer* and *Flipper* categories are measured relative to the base category of other lister. All columns include house controls including square footage, whether the house is multistory, and house age. The linear models include zip times quarter fixed effects. Standard errors are shown in parentheses.

	Dependent variable:						
Model	Linear	Linear	Linear	Linear	Hazard	Hazard	Linear
Outcome	Relists within 30 days	Total listings	Leads to sale	Days-on-market	Days-on-market	Days-on-market	Sale-to-list
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Flipper	0.065	0.387	-0.009	4.862	-0.101	-0.099	-0.002
	(0.003)	(0.010)	(0.002)	(0.391)	(0.005)	(0.005)	(0.0003)
iBuyer	-0.021	1.444	0.149	29.733	0.240	-0.095	-0.007
	(0.066)	(0.064)	(0.011)	(2.141)	(0.028)	(0.028)	(0.001)
Hedonic controls	Y	Y	Y	Y	Y	Y	Y
Zip-Quarter FE	Y	Y	Y	Y	N	N	Y
Sample	Failed first list	All		Sales only	All	Sales only	
Observations	265,805	887,208	887,208	653,385	791,798	653,385	615,834
R^2	0.157	0.341	0.251	0.385	0.070	0.057	0.142

Appendix A.5: iBuyer Seasonality

Seasonality plays an important role in residential real estate transactions. For example, Ngai and Tenreyo (2014) document that every year housing markets in the U.K. and U.S. experience systematic above-trend increases in prices and transactions during the spring and summer ("hot season") and below-trend falls during the autumn and winter ("cold season"). Motivated by this observation we now investigate how iBuyers listings vary across seasons and if they are able to navigate seasonality (off season versus on season) better than other sellers. To study these seasonality patterns formally, we estimate the following sets of regressions:

$$Qtr_{izt}^{q} = \beta Lister_{izt} + H_i'\mathrm{B} + \mu_{zt} + \epsilon_{izt}$$

Here *i* indexes a house in zipcode *z* at quarter *t*. Qtr^q is an indicator for whether the listing occurs in a quarter q. $Lister_{izt}$is an indicator for whether the lister is an ordinary seller, a flipper, or an iBuyer. As before, we control for house characteristics in H_i such as square footage, and quarter x zip fixed effects μ_{zt}.

Panel A of the Table below show the results. Each column corresponds to a quarter of listing. Relative to ordinary sellers, iBuyer listings are concentrated in quarters three and four: they are 8% and 16% less likely to occur in quarters one and two, respectively, and 4% and 20% more likely to occur in quarters three and four, respectively. Flippers, in contrast, have much smaller differences relative to ordinary sellers and do not exhibit the same strong patterns of seasonality.

We next explore whether indeed iBuyers list more aggressively and spend more time on the market during off season by estimating the following specification:

$$\log\,(List\ Price_{izt}) = Qtr_t + \beta Lister_{izt} \times Qtr_t + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt}$$

$$Days\ on\ Market_{izt} = Qtr_t + \beta Lister_{izt} \times Qtr_t + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt}$$

This mirrors the earlier regression on listing outcomes with the addition of a *Lister* times *Qtr* interaction. Panel B of the Table below show the results. Column (1) shows that iBuyer listing prices are relatively higher than other market participants in quarters three and four, and not different in quarters one and two, with initial listing prices being roughly 3% higher in the third quarter and 2.6% higher in the fourth quarter, while there are no significant differences in quarters one or two. Column (2) shows that iBuyer houses listed in the third quarter are the ones who spend longest on the market relative to other listings at the same time, spending roughly 47 days longer relative to ordinary sellers. Finally, Column (3) shows that these are also houses iBuyers discount most upon the ultimate sale in terms of how much the eventual sale price has been discounted relative to the aggressive initial listing price.

Listing Seasonality: iBuyers versus Other Sellers

This table examines listing seasonality of iBuyers, home flippers, and other sellers using MLS data between 2013 and 2018 at the combined listing level. Panel (a) shows which quarters iBuyers list houses. Q1-4 are indicator variables for the quarter of listing. *Flipper* and *iBuyer* are indicators for whether the listers are flippers (absentee owners who list within one year of purchase) or iBuyers, with other listers being the base category Panel (b) examines the seasonality of listing characteristics. Columns (1) examines the log initial listing price and include all listings; (2) the days on market and (3) the sale-to-list discount, and include listings that lead to sales only. A *Flipper* is an absentee owner who lists the house within one year of purchasing it. The *iBuyer* and *Flipper* categories are measured relative to the base category of other lister. All columns include house controls including square footage, whether the house is multistory, and house age. Additionally, all columns include zip-year fixed effects. Standard errors are shown in parentheses.

Panel A: Listing seasonality

	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Flipper	0.746	-1.413	-0.687	1.354
	(0.191)	(0.194)	(0.190)	(0.181)
iBuyer	-8.379	-16.369	4.015	20.733
	(1.211)	(1.228)	(1.202)	(1.149)
Hedonic controls	Y	Y	Y	Y
Zip-year FE	Y	Y	Y	Y
Observations	887,208	887,208	887,208	887,208
R^2	0.037	0.017	0.013	0.074

Panel B: Seasonality of listing characteristics

	Log first list price	Days on market	Sale to list price
	(1)	(2)	(3)
iBuyer x Q1	-0.003	19.790	-0.007
	(0.021)	(4.997)	(0.004)
iBuyer x Q1	0.007	33.567	-0.010
	(0.022)	(5.032)	(0.004)
iBuyer x Q3	0.031	47.228	-0.011
	(0.015)	(3.478)	(0.002)
iBuyer x Q4	0.026	25.909	-0.003
	(0.014)	(3.142)	(0.002)
Hedonic controls	Y	Y	Y
Zip-Quarter FE	Y	Y	Y
Observations	887,208	621,403	615,825
R^2	0.755	0.429	0.142

Appendix A.6: PnL Decomposition

We augment our analysis of iBuyer PnL with a simple decomposition. The objective is to separate the gross return into a component that is attributable purely to overall house price appreciation and the remainder where iBuyers buy below prevailing (median) market prices and sell above prevailing (median) prices – i.e., the bid/ask spread. In particular, at the three-digit zip code-quarter level, we calculate the median transaction price of all transactions (including iBuyers):[25]

$$Local\ Price_{zt} = median_{i\in(z,t)}(SalePrice_i)$$

We then define the house price index appreciation in market *z* between time *t* and *t'* as:

$$Index\ Appreciation_{ztt\prime} = \frac{LocalPrice_{zt\prime}}{LocalPrice_{zt}} - 1$$

Then, for a house purchased at time *t* for price $Price_{izt}$ and sold at time *t'* for price $Price_{izt\prime}$, we define the *Index Return*, and the *Non Index Return*, as:

$$Index\ Return_{iztt\prime} = Index\ Appreciation_{ztt\prime}$$
$$Non\ Index\ Return_{iztt'} = GrossReturn_{iztt\prime} - Index\ Retrun_{iztt\prime}$$

Table 3 Panel B shows the results of this decomposition.

[25] In an unreported robustness check, we use Zillow house single family house price indices at the quarter-zip code level rather than median transaction price. This index takes into account compositional changes of the types of houses trading at a given point in time. The results are qualitatively unchanged.

Appendix A.7: Evidence of Adverse Selection

We augment our analysis on iBuyers' preference for liquid and easy to price homes by investigating how iBuyer realized annual gross returns on their transactions relate to our ease-of-pricing and liquidity measures. In the body of the paper, we show that iBuyers concentrate in houses which are easy to price with simple hedonics. Here we show that the realized gross spread for iBuyers on such houses is also the highest, consistent with the notion that iBuyers may face adverse selection in harder to price homes.

To investigate this formally, we regress the realized annualized gross return of sellers on the expected pricing errors and liquidity as follows:

$$Gross\ Return_{iztt'}^{Ann} = \beta_0 iBuyer_{izt} + \beta_1 \hat{e}_{izt}^2 + \gamma_1 \widehat{Sells\ Within\ 90}\ Days_{izt} +$$
$$iBuyer_{izt} \times \left(\beta_2 \hat{e}_{izt}^2 + \gamma_2 \widehat{Sells\ Within\ 90}\ Days_{izt}\right) + \mu_{zt} + \epsilon_{iztt'}$$

An observation is a house sale, where *i* indexes a house in zip code *z* at quarter *t* of purchase, and *t'* is the quarter of sale. $Gross\ Return_{iztt'}^{Ann}$ is the annualized return on the given transaction, as defined in Equation (9). $\hat{e}_{izt}^2$ is the predicted pricing error normalized by the standard deviation of the pricing errors, and $\widehat{Sells\ Within\ 90}\ Days_{izt}$ is the predicted probability of a house selling within 90 days of listing. As before, we control for quarter x zip fixed effects μ_{zt} for month of purchase. Our specification therefore compares how the return realized by iBuyers varies with our measures of house's ease of pricing and liquidity as compared to non-iBuyer transactions for similar houses purchased within the same zip code and a point of time.

We include all transactions when estimating the above specification, including non-iBuyer transactions. We then compare how iBuyer returns differ from non-iBuyer systematically with house pricing error and liquidity. It is important to not consider only iBuyer transactions in isolation, because there could be persistent differences in realized returns *on average* across houses with high pricing errors or low liquidity. In particular, the coefficients on pricing error and liquidity absorb these differences, and the interactions of these characteristics with $iBuyer_{izt}$ show how iBuyers and non-iBuyers' returns vary with these characteristics. For example, a negative coefficient on iBuyer interacted with pricing error, β_2, indicates that when transacting in a hard to price home, iBuyer returns are lower than an individual's return would be when transacting in a similarly hard to price home. The differences here therefore highlight how iBuyer and non-iBuyer transaction strategies relate to gross returns.

The results below show that even among the houses that iBuyers chose to buy, their realized gross returns were greater for easier to price homes. The interaction term in Columns (1) and (3) show that compared to non-iBuyers, iBuyers' realized spread is relatively lower on houses with a high expected squared pricing error. Additionally, iBuyers' realized spread is relatively higher on houses with a higher probability of selling within 90 days, as shown in Columns (2) and (3). These results are consistent with the idea that iBuyers face more adverse selection in houses, which are more difficult to price. Moreover, their lower returns on homes -- that would otherwise take more time to sell -- can reflect their willingness to sell such homes quickly at a reduced price to avoid costs of carrying empty homes for a longer period of time.

Next, we investigate how time to sell relates to our ease-of-pricing and house liquidity measures. Similar to above, we regress:

$$Holding\ Period_{iztt'} = \beta_0 iBuyer_{izt} + \beta_1 \hat{e}^2_{izt} + \gamma_1 \widehat{Sells\ Within\ 90\ Days}_{izt} +$$

$$iBuyer_{izt} \times \left(\beta_2 \hat{e}^2_{izt} + \gamma_2 \widehat{Sells\ Within\ 90\ Days}_{izt}\right) + \mu_{zt} + \epsilon_{izt}$$

An observation is a house sale, where *i* indexes a house in zipcode *z* at quarter *t* of purchase, and *t'* is the quarter of sale. *Holding Period* is the time the house remains in inventory, expressed in years. As before, β_1 and γ_1 capture how holding periods differ systematically between easy- and hard-to-price homes and liquid and illiquid homes, respectively. The coefficients of interest are β_2 and γ_2, which capture how iBuyers outcomes are different from typical sellers along these dimensions. μ_{zt} is a vector of zip-quarter fixed effects.

In the Table below, Column (4), shows that harder-to-price homes remain in iBuyer inventory for relatively longer, and these results are robust to the inclusion of controlling for the liquidity of the house in Column (6). The interaction term on house liquidity is negative, as expected, but not statistically significant either by itself in Column (5) or including the interaction term with pricing error in Column (6). To summarize, when iBuyers purchase houses, which are difficult to price with simple hedonics, they earn lower spreads, and realize higher cost of carrying the house.

iBuyer PnL in Easy-to-Price and Liquid Homes

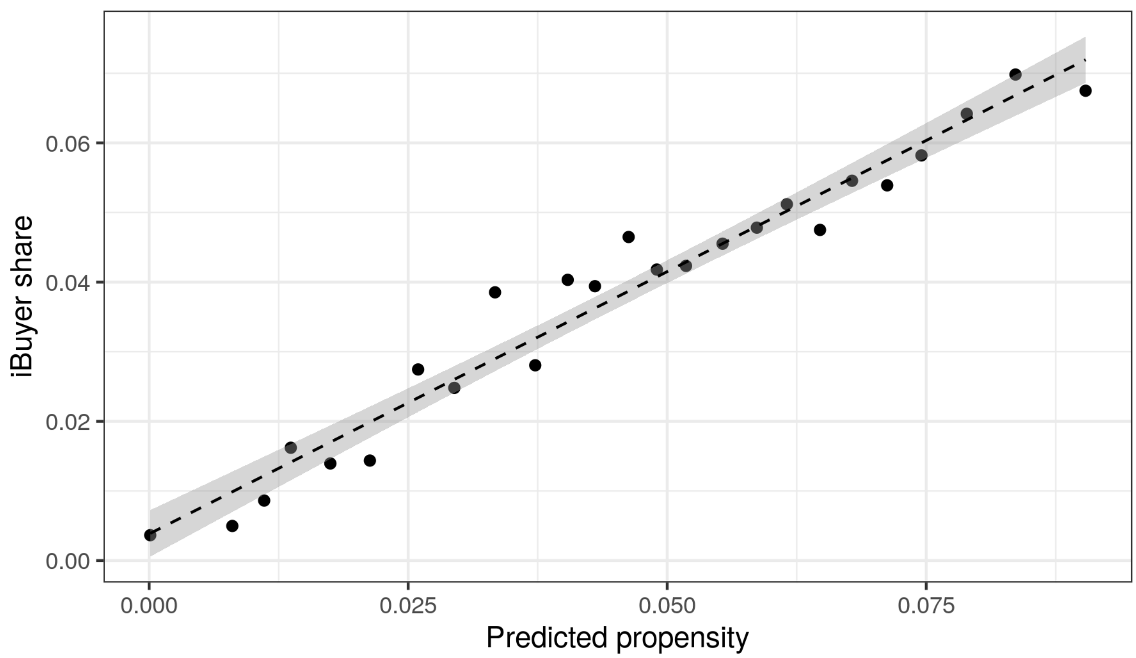
This table shows how iBuyer market penetration and gross returns relate to ease-of-pricing and liquidity measures using Corelogic transaction data from 2013-2018. Panel B shows how the realized gross return and holding period varies by ex-ante pricing error and liquidity among iBuyers and other sellers. The regression includes all transactions where the property is bought and sold within two years. Columns (1)-(3) use realized gross return (annualized, in percentage terms) as the left-hand side variable. Columns (4)-(6) use holding period (in years) as the left-hand side variable. All columns include zip-quarter fixed effects. Standard errors, clustered at the property level, are shown in parentheses.

iBuyer Realized Annualized Gross Return and Ease-of-Pricing and Liquidity Measures

	Dependent variable:					
	$Gross\ Return^{Ann}$			Holding period (years)		
	(1)	(2)	(3)	(4)	(5)	(6)
iBuyer	0.281	0.083	0.213	-0.422	-0.382	-0.466
	(0.022)	(0.066)	(0.070)	(0.017)	(0.055)	(0.059)
$\hat{e}^2$	0.799	-	0.856	-0.384	-	-0.353
	(0.071)	-	(0.121)	(0.056)	-	(0.094)
$\widehat{SellsWithin90Days}$	-	0.145	0.211	-	-0.109	-0.136
	-	(0.047)	(0.047)	-	(0.047)	(0.048)
iBuyer x $\hat{e}^2$	-1.105	-	-1.573	1.033	-	1.211
	(0.310)	-	(0.504)	(0.246)	-	(0.415)
iBuyer x $\widehat{SellsWithin90Days}$	-	0.314	0.278	-	-0.051	-0.047
	-	(0.115)	(0.115)	-	(0.096)	(0.096)
Zip x Quarter FE	Y	Y	Y	Y	Y	Y
Observations	46,746	19,675	19,675	46,746	19,675	19,675
R^2	0.213	0.263	0.267	0.240	0.301	0.302

Appendix A.8: Instrument Regional Analysis

This figure shows the first stage relationship between predicted iBuyer market share and actual market share at the zip code level used as an instrument in the regional analysis. Predicted propensity, the x-variable, is 25 equally-sized bins of predicted iBuyer market share at the zip-code level. The y-axis is the average realized iBuyer market share in each zip code falling within the predicted market share bin. The dashed line is a best-fit linear regression, with the shaded region showing the 95% confidence interval.



Appendix A.9: Model Validation: Individual Mobility and iBuyer Entry

We explore why consumers transacting with iBuyers may value selling their home quickly. One potential reason could be they want to move to a new location, either because they found a new job, or they want to move closer to family. Alternatively, they might live in a house that is too large, and may want to downsize. We now investigate if this is the case in the data.

We follow a panel of individuals' homeownership records through time, and test whether their behavior in terms of sales, moving, house size, and leverage varies following the entry of iBuyers. One approach would be to document changes in these outcomes for households selling to iBuyers relative to other households. A potential concern with that approach is that iBuyer may not facilitate moving to a different location or downsizing. Instead the same characteristics that drive the household preference for speed are correlated with their preference to move or downsize.

Instead, to alleviate such concerns, we employ a difference in difference style analysis to address this concern. The event is the entry of iBuyer. We define treatment and control in terms of whether the individual's home is the "type" that an iBuyer would target for purchase. As discussed in Section IV and illustrated again below, iBuyers focus on a predictable subset of homes based on their physical characteristics. This allows us to create control and treatment groups. The treatment group is individuals living in homes that are similar to those typically targeted by iBuyers – the notion is that following iBuyer entry it should be easier for them to sell their homes. Similarly, the control group is individuals living in homes that are not similar to those typically targeted by iBuyers – the notion is that they are unlikely to be directly affected by iBuyer entry. We then evaluate how outcome variables of interest evolve in the two groups following iBuyer entry, using data between 2013 and 2017:[26]

$$Outcome_{izt} = \beta \widehat{\imath Buyer}_{izt} \times Post_t + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt}$$

Here i indexes an individual in zipcode z at quarter t. $Outcome_{izt}$ is an outcome variable of interest. We study three outcomes: whether the individual sells their house, whether the individual moves to a different location, defined as moving to a new MSA relative to the prior house, or downsizes, defined as moving to a house with a lower effective price. $\widehat{\imath Buyer}_{izt}$ is an indicator for whether the home is likely to be one that an iBuyer transacts in, which we construct as described below. $Post_t$ is an indicator variable that takes a value of 1 after the entry of iBuyer, which we define as 2015. H_i is a vector of house characteristics such as square footage, and μ_{zt} is the zip times quarter (interacted) fixed effect. The identifying variation being used here comparing individuals in iBuyer-targeted homes relative to other individuals in the same zip code and point in time differentially around iBuyer entry.

[26] We end the data at 2017 rather than 2018 so that movers have one year to relocate before the end of our dataset.

We construct $\widehat{\iota Buyer}_{\iota zt}$ as an indicator that effectively sorts individuals into treatment and control groups based on whether they reside in a home that is likely to targeted by iBuyers. We do this in three steps. First, we estimate the likelihood that a home would be targeted for purchase by an iBuyer using the same method in Section III. As noted there, we do this by estimating specification (3) using 2018 data from Phoenix. This data is then not used in our subsequent analysis. Second, we apply the estimated model to homes in our main regions of analysis, Phoenix, Gwinnet County, Las Vegas, Orlando, and Dallas over the period 2013-2017 to construct a probability that a given home would be targeted by iBuyers for purchase. Finally, we convert (continuous) iBuyer likelihood into a discrete zero-one indicator variable, defining $\widehat{\iota Buyer}_{\iota zt}$ to be one if house i is predicted to be above median based on the probability that the home would be targeted by iBuyers.

The Table below presents our main results. We first show that propensity of sale in treatment group relative to control group increases with the entry of iBuyer. The result is not mechanical, because we estimate what homes iBuyer prefer outside of the window of our diff-diff specification. Column (1) shows that the probability of sale of a home that is typically targeted by iBuyers relative to control group increases by roughly 0.5 pp per annum. This is large relative to a mean of 8.3pp. In other words, to the extent our control group is a reasonable comparison group, we can conclude that iBuyers are not simply replacing sales that would have occurred otherwise—they are increasing the rate of sales. We find a strong effect among low LTV individuals -- those with LTVs below the 75$^{\text{th}}$ percentile (Column 2). There is no impact among those with high LTVs (Column 3). A possible explanation is that if the need to deleverage compels a household to sell their house – a more likely scenario with high LTV households -- they will do so whether or not iBuyers enter.

One potential reason why a consumer sells to an iBuyer may be that they want to move to a new location, for example, because they found a new job or they want to move closer to family. If entry of iBuyer makes it easier to move, it could increase overall mobility. We track individuals in states in which iBuyers enter, and assess whether their propensity of moving out of their market (defined as an MSA) changes. We do this by following individual names and testing whether we observe a subsequent name match within the same MSA after moving. We find that iBuyers entry increases the mobility of individuals in the treatment group relative to the control group – Column (4) shows that the probability that they leave their market increase by 0.81pp relative to the baseline rate of 21pp. These results are consistent with the idea that entry of iBuyers makes it easier for some individuals to sell their house and relocate.

Finally, unlike individuals who moved to different markets, we now investigate whether iBuyer entry allows some individuals to downsize in the same market. Individuals with houses that are too large or expensive who want to move into a smaller house need to sell their house first. We test whether the presence of iBuyer accelerates this transition. To do this analysis we restrict the sample to individuals who sold their house each year and purchased another house in the same market within the sample period ending in 2018. In doing this we consider the house purchased nearest in time to the sold house. We compare the purchase price of the new home with the original purchase price, adjusted for local market price appreciation since the original purchase. That is, the change in house price is equal to:

$$Price\ Imputed_{it}^{Old} = Purchase\ Price_{it_0}^{Old} \times \frac{PriceIdx_{it}^{New}}{PriceIdx_{it_0}^{Old}}$$

$Price\ Imputed_{it}^{Old}$ represents the estimated value of the sold house *i* at time *t* based on local price appreciation in the market between the time of purchase and the time of sale. In particular, $Purchase\ Price_{it_0}^{Old}$ is the original purchase price of property *i* at original purchase time t_0. $PriceIdx_{it}^{New}$ is the median sale price in the same county as *i* at the time of sale *t* and $PriceIdx_{it_0}^{Old}$ is the median sale price in the same county as *i* at the original time of purchase t_0.

The Table below Column (5) shows that, relative to individuals in the control group, those in the treatment group are more likely to move into smaller houses following iBuyer entry. The change in home price is roughly 1.8% lower relative to control group, following iBuyer entry. We also explore whether iBuyers help over-levered individuals to delever. We find essentially no effect: Column (6) shows that relative to control group, individuals in treatment group do not tend to increase or decrease their leverage as they transition from their old house to a new one.

The Figure below shows the timing of these effects. It presents annual differential change in individuals' selling, moving, and downsizing of individuals in treatment group relative to control group, following iBuyer entry in 2015, where Panel (a) corresponds to the probability of selling a home among all owners, (b) among high LTV owners, and (c) among low LTV owners. Panel (d) shows the propensity to remain in the market, (e) shows the change in house prices, and (f) shows the change in LTV. Broadly, these figures show that the timing of these changes is consistent with the timing of iBuyer entry.

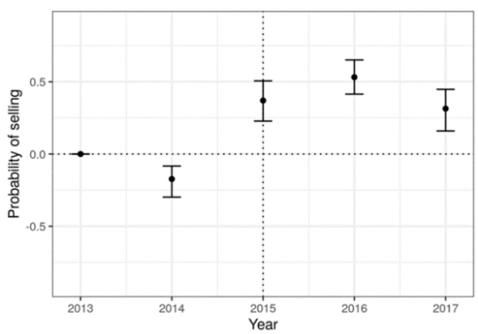
Model Validation: iBuyer Entry and Homeowner Mobility

This table shows the impact of iBuyer entry on geographical mobility, home downsizing, and deleveraging of existing homeowners. Data are from Corelogic between 2013 and 2017, two years around iBuyer entry in 2015, at the individual-year level. The outcome variables are as follows. *Sells* is an indicator for whether the individual sells his house in the given year (Columns 1-3). *Remains in market* is an indicator for whether the selling individual remains a homeowner in the same market (Column 4). *ΔBuy Price (imputed)* is the change (in %) of the current imputed house rice to the new house's price (Column 5). *ΔLTV (imputed)* is the change (in %) of the imputed old LTV to the new house's LTV (Column 6). $\widehat{\iota Buyer}$ is an indicator for whether the individual's property is in the top 50% of predicted iBuyer shares based on its physical characteristics. *Post* is an indicator for 2015 or later. House controls are those used in Table 2: *Price*, the transaction price in the deeds records, *house age,* the difference between the transaction date and the year of construction, *land square footage,* the tax-assessed property square footage, and *multistory* is an indicator for whether the house has greater than 1 stories (including partly-multilevel houses that have "1.5" stories.) Other house characteristics are air conditioning type, garage type, heating type, location influence, and build quality.

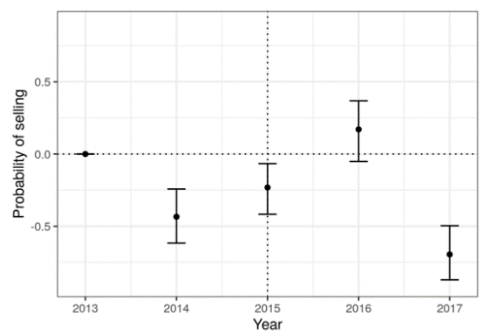
	Dependent variable:					
	Sells			Remains in Market	ΔBuy Price (imputed)	ΔLTV (imputed)
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\iota Buyer}$	1.677	1.720	1.556	-2.212	-0.543	-0.404
	(0.046)	(0.055)	(0.081)	(0.243)	(0.753)	(0.296)
$\widehat{\iota Buyer} \times Post$	0.490	0.622	-0.032	-0.809	-1.854	-0.572
	(0.058)	(0.069)	(0.109)	(0.303)	(0.919)	(0.358)
Sample	All	Low LTV	High LTV	All	All	All
House Controls	Y	Y	Y	Y	Y	Y
Market x Year x Tenure FE	Y	Y	Y	Y	Y	Y
Observations	4,161,751	3,121,313	1,040,438	346,136	73,264	66,563
R^2	0.012	0.010	0.019	0.050	0.028	0.424

Model Validation: iBuyer Entry and Homeowner Mobility

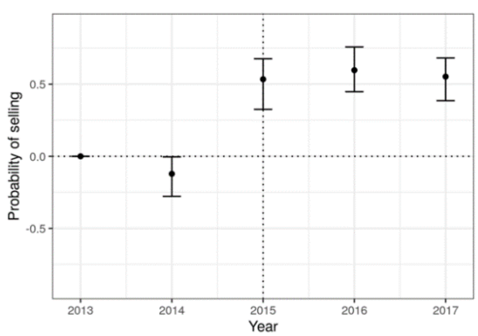
This figure shows the estimated differential change in individuals' selling, moving, and downsizing propensities around the iBuyer entry time of more exposed homeowners to iBuyer entry (treatment) relative to less exposed ones (control). We define treatment and control based on whether the individual's home is the type that an iBuyer would purchase based on the out-of-sample predictive model. The model is based on binned house characteristics, including square footage, age, and price. An iBuyer-type home is then defined as being in the top 50% of predicted iBuyer likelihood. The figures show the estimated coefficient on year times iBuyer-type dummy. The regressions are on the individual-year level. We use Corelogic data from 2013 to 2017, so that sellers in 2017 have one year in the data to find a new house. We plot the estimated differential change along with 95% confidence bounds. Panel (a) considers all individuals; panel (b) considers those with high LTVs (above the 75th percentile relative to other homeowners at origination); panel (c) considers those with low LTVs (below the 75th percentile relative to other homeowners at origination). Panel (d) considers the differential change in the probability of staying within the market, defined as whether the individual purchases another house in the same market; panel (e) considers change in imputed home value from the old house to the new house; panel (f) considers the change in LTV from the old house to the new house.



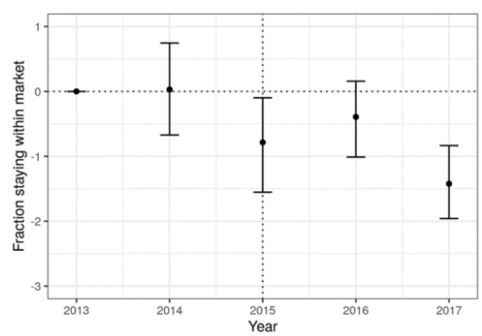
(a) Selling, all iBuyer homes



(b) Selling, high-LTV iBuyer homes



(c) Selling, low-LTV iBuyer homes



(d) Staying in market, all iBuyer homes