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WHY IS INTERMEDIATING HOUSES SO DIFFICULT? EVIDENCE FROM IBUYERS

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ABSTRACT

We examine frictions in dealer intermediation in durable consumer goods markets through the lens of "iBuyers," technology-driven entrants that facilitate transactions via online platforms and algorithmic pricing. iBuyers provide liquidity to households by bypassing the lengthy household-to-household sale process and earn a positive gross spread. However, their intermediation is limited to relatively liquid and easierto- value homes. We build and calibrate a dynamic search model with intermediaries facing adverse selection to quantify the economic frictions in this market. The central trade-off is that while providing liquidity requires fast transactions, this leads to less accurate valuations and exposes intermediaries to adverse selection. iBuyer technology offers a limited middle ground, enabling fast transactions with limited information loss, but it works best for liquid, easy-to-value homes. We then use our model to explore intermediation in durable goods markets, adjusting key asset and market properties based on (i) informational asymmetry, (ii) market liquidity, and (iii) the benefits of search driven by subjective value dispersion. Illiquid and hard-to-price assets, like homes, experience less intermediation, especially if underutilized during the process. In contrast, the greater homogeneity and easier pricing of goods like cars, along with their higher liquidity due to mobility, may help explain why intermediation in these markets has historically been higher.

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I. Introduction

We examine frictions in dealer intermediation in durable consumer goods markets through the lens of "iBuyers," technology-driven entrants which purchase assets via online platforms. Our analysis focuses on the largest durable asset class—the U.S. housing market—valued at $50 trillion and representing about 70% of the median household's net worth as their primary asset.[1] We explore how factors such as asymmetric information between intermediaries and asset holders (influenced by intermediation technology), transaction speed and asset use, and match quality in non-intermediated markets affect the scope and effectiveness of intermediation. We then apply these insights to consider how intermediation might operate in other durable goods markets, depending on their unique characteristics.

We begin by noting that several frictions in buying and selling homes contribute to housing's illiquidity, often limiting households' ability to match with suitable homes and constraining mobility.[2] For instance, households looking to relocate for a job or change house type typically need to list their current home hoping to find a buyer before purchasing another. This slow, homeowner-to-homeowner process may force households to make suboptimal choices, such as temporarily renting, living in a sub-optimally sized house or even passing up new job opportunities. The delays inherent in homeowner-to-homeowner sales suggest a natural role for dealer intermediation: A homeowner could immediately sell to an intermediary, who would later find a buyer. This enables the homeowner to buy a new home without delay, with a potential discount on the sale to intermediary reflecting intermediation costs and any gains from trade appropriated by the intermediary. Yet, despite this potential, dealer intermediation in housing transactions has historically been rare—until recent technological advancements made it more feasible.

This dynamic has shifted with the emergence of iBuyers, a recent technological disruption in the real estate market. Companies like Opendoor and Offerpad[3] leverage automated valuation models and other technologies to make rapid cash offers on homes—often within hours—through their online platforms.[4] In effect, iBuyers provide precisely the type of dealer intermediation that has been largely absent until now. In this paper, we use iBuyers as a lens

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

[2] Liquidity refers to the discount at which an asset can be quickly bought or sold in the market, for example, because buyers arrive slowly. One symptom of illiquidity is that it takes a long time to sell a house without experiencing a large discount.

[3] Zillow, a large online marketplace for homes, and Redfin, a tech-enabled brokerage, both offered iBuying services but chose to exit the market in November 2021 and November 2022, respectively (see Section V for more discussion).

[4] Appendix A.1 shows screenshots from Opendoor's website as of 2020.

to examine frictions in dealer intermediation within residential real estate and durable assets more broadly, focusing on how their technology has made this model viable.

This paper proceeds in three main steps. First, we use detailed microdata to document where and how iBuyers intermediate within the real estate market, shedding light on the key economic frictions that limit dealer intermediation. Next, we develop a calibrated structural search model that incorporates these frictions. The model highlights a central trade-off in real estate intermediation: intermediaries can only create value if they purchase homes quickly, but current technology requires sacrificing some information precision in property valuation to achieve this speed. This information gap, typically known by property sellers, exposes intermediaries to adverse selection. As we show, this problem is compounded by the inherent illiquidity of real estate. Finally, we use the calibrated model to examine the broader limits of liquidity provision by intermediaries across durable goods markets. By adjusting key asset characteristics, we simulate various market settings. Immobile and less homogeneous goods like homes tend to be more illiquid and harder to price than more movable, homogeneous assets like cars. This difference helps explain the much lower prevalence of dealer intermediation in the housing market compared to consumer goods markets like automobiles.

We begin by documenting the significant growth in iBuyer market share in areas like Phoenix, Arizona, where their transaction share increased from about 1% at their 2014 entry to around 6% by 2018. We show that iBuyers act as dealer intermediaries, enabling households to bypass the lengthy—often 90 days or more—listing process by selling nearly instantly to an iBuyer. They purchase properties at a 3.1 percentage point (pp) discount compared to similar listed homes. As market makers, iBuyers hold properties for a short duration, with roughly half sold within three months, achieving an average gross return of about 5% on these transactions. This substantial iBuyer price discount reflects a strong household demand for dealer intermediation, a service that was rarely available before iBuyers entered the market, indicating significant frictions in liquidity provision. We learn about these frictions by observing which segments of the housing market iBuyers choose to intermediate.

We show that dealer intermediation in real estate relies on providing rapid offers, but this speed comes with the cost of adverse selection. Anecdotal evidence suggests that iBuyers suffer from adverse selection: Zillow, which incurred large losses in its iBuying business, reported that sellers accepted only 10% of its offers. [5] We formalize this idea in two ways. First, following Buchak et al. (2018), we first demonstrate that—consistent with iBuyers using algorithmic pricing—observable property characteristics and ZIP-quarter fixed effects explain over 80% of the price variation in iBuyer transactions, compared to only 68% in other

[5] https://www.curbed.com/2021/11/zillows-i-buying-algorithm-house-flipping.html

transactions. The lower R^2 for non-iBuyers suggests they rely on information that a standard buyer would notice but which is difficult to algorithmicize. For example, a bad house odor or a poorly maintained neighbor's property are either difficult to formalize or not likely captured in data. If sellers have access to this information and normal buyers (non iBuyers) can find the information by spending time evaluating the property, iBuyers may face adverse selection relative to other potential buyers. We find that iBuyers actively mitigate adverse selection by focusing on market segments where their informational disadvantage is smaller. We measure algorithmic pricing errors across properties and find that iBuyers presence is lowest in areas where algorithmic models perform poorly i.e., where pricing errors are highest). Consistent with adverse selection, we also find that as iBuyers expand into segments with higher pricing errors, they experience lower profits.

Second, we find that iBuyers choose to intermediate houses with the highest underlying liquidity. Even within a geographic market, iBuyers avoid transacting in houses with less than a 50% probability of selling within three months. This suggests that, despite high demand for liquidity, providing it may be challenging for less liquid houses, with this difficulty outweighing demand. Overall, our findings indicate that liquidity provision is efficient only when homes are already relatively liquid and easier to value—precisely when additional liquidity is least needed.

Next, we develop and calibrate a search-based equilibrium model of house trading with iBuyers, with several objectives. First, while we identify multiple frictions in the data that hinder dealer intermediation, the model enables us to quantify their impact on house choice, trading, and prices in equilibrium, going beyond reduced-form evidence. Second, we use the model to quantify which technological aspects are essential for intermediary success and to explore the limitations of intermediation, even with improved technology. Finally, the calibrated model allows us to explore how intermediation of durable goods might function in other markets, depending on their specific characteristics.

We extend a standard continuous-time search and matching equilibrium model of durable goods (houses) by introducing a dealer intermediary subject to adverse selection. A homeowner is initially matched with a house of a certain quality (utility flow), which persists over time but may change with ownership. With some probability, the homeowner becomes unmatched and begins the moving process, experiencing varying degrees of impatience. Crucially, the homeowner can only own one house at a time, requiring a sequential move: She must sell her current house before purchasing a new one. Her key decision is whether to opt for a slower listing or a quicker sale to an intermediary.

The intermediary is unconstrained by single-ownership limits and has a pricing technology that enables almost immediate purchases of the asset from the impatient household. Then the intermediary looks to match with a home buyer on its own. This type of intermediation allows the seller to immediately start their house search and realize the gains of a more suitable home sooner. As the model formalizes, this type of intermediation has two drawbacks. The instantaneous pricing technology has its limits in differentiating between higher- from lower-quality houses resulting in adverse selection. Additionally, the traditional selling model keeps the house occupied during the sale process while a dealer intermediary leaves the house empty, resulting in lost housing services despite the same or higher maintenance cost.

We calibrate the model to the post-iBuyer entry period using empirical moments from the first part of the paper, such as iBuyer market shares, discount and premia, time on market, and sensitivity to liquidity and adverse selection. The model accurately replicates these observed patterns. For external validation, we examine the effect of iBuyer entry across markets. We compare the model's predictions of iBuyers' equilibrium impact on house prices and transaction speeds to actual changes observed in a difference-in-differences analysis. The model successfully matches these empirical outcomes, reinforcing confidence in its estimates.

Our model calibration reveals that the primary trade-off in residential real estate intermediation centers on three factors: speed, information quality, and occupancy. First, transaction speed is critical. A counterfactual slow intermediary would capture much smaller market share. The model shows that most of iBuyer transactions involve impatient sellers motivated to move quickly. The data supports this mechanism: sellers to iBuyers are more likely to exit the market post-sale, aligning with the interpretation that they are impatient and driven by relocation-related reasons, such as a new job. This extreme sensitivity of iBuyer market share to transaction speed underscores that quick execution is the key value proposition of liquidity provision through dealer intermediation.

Second, pricing homes quickly to achieve a speedy transaction results in information loss, leading to adverse selection. Our model suggests that over half of the homes acquired by iBuyers are of lower quality. If iBuyers would further lose this imperfect ability to distinguish between lower- and higher-quality homes (beyond contractable features), their market share would drop from around 5% to just above 1%. Third, a significant drawback of the iBuyer model is the loss of valuable housing service flows due to unoccupied homes. Enabling rental of these homes during the sales process—regardless of tenant compatibility—could substantially increase iBuyer market share. This would allow iBuyers to offer higher purchase prices and offset the cost through rental income, potentially boosting their market share in transactions above 7.5 percentage points.

These forces help explain why iBuyers provide liquidity primarily in already liquid markets: illiquidity amplifies adverse selection. Low liquidity extends the time homes are unoccupied resulting in the loss of housing services. Unoccupied homes also expose iBuyers to higher maintenance risks; for example, being arm's length, they may only detect a leaking roof after significant damage has occurred, reducing profitability from intermediation. Lower profits from handling less liquid properties result in iBuyers offering reduced purchase prices. This secondary effect means that low underlying liquidity exacerbates adverse selection due to the need for quick purchases, as only owners of (unobservably) lower-quality houses are likely to sell at these reduced prices. As a result, the proportion of homes where iBuyers face adverse selection rises.

Our calibrated model explains why dealer intermediation in real estate remains limited. Even with technological advantages, iBuyers focus primarily on the most liquid and easy-to-value properties. In other words, while iBuyers add liquidity to the market, they can do so mainly in segments where liquidity is already fairly high. We also find that, even with enhanced pricing technology, the scope for dealer intermediation remains narrow, with strong incentives for iBuyers to avoid markets where algorithmic valuation will be difficult, such as those with older and less homogenous homes. Finally, iBuyers do not seem to hold a technological edge when selling properties. Our findings suggest that advancements in customer matching or buyer targeting could expand the potential for dealer intermediation and enhance liquidity in one of the most significant asset markets for households.

We also use our model to interpret two recent large-scale (out of sample) events. First, our analysis may explain why most iBuyers temporarily suspended operations during the early stages of the COVID-19 pandemic. At first glance, the need for social distancing should have benefited iBuyers, as their process requires no physical contact with sellers. However, our model suggests that social distancing reduced overall market liquidity, severely limiting iBuyers' ability to intermediate. As transaction speeds recovered later in the pandemic, iBuyers resumed operations.

Our analysis also *predates* Zillow's decision to exit the iBuying market in November 2021 due to transaction losses. This was seemingly surprising given rising house prices and highly liquid market at the time. Our model illustrates that in very liquid markets iBuyers lose their speed advantage leading to increased adverse selection as homeowners exploit valuation errors. Intuitively, an owner who can sell their house very fast in the traditional market only sells their home to an iBuyer when algorithmic error overvalues their home. By late 2021, concerns over the housing market's future and difficulties in pricing homes during economic uncertainty may have reduced the accuracy of algorithms, further increasing adverse selection.

While Zillow struggled the most, other iBuyers have faced similar challenges, in line with the factors discussed in our paper.[6]

Finally, we use our model to derive implications for balance sheet intermediation across durable goods markets more broadly. To do this, we adjust key asset characteristics to simulate various market settings. Our analysis suggests that assets that are relatively illiquid and difficult to price experience much less balance sheet intermediation, especially if assets remain underutilized during the intermediation process. On the other hand, while subjective value dispersion plays a significant role in influencing search market equilibrium, its effect on the overall level of intermediation is comparatively less pronounced.

This may explain why markets like housing have only recently seen limited intermediation, facilitated by recent technological advances in valuation accuracy and transaction speed through online platforms. In contrast, goods like cars and airplanes are more homogeneous and easier to price. Because they are mobile, they can be moved across markets, which reduces geographic segmentation and enhance asset liquidity. Their opportunity cost of occupancy also differs from houses. While a house depreciates at least as quickly when vacant as when occupied, many durable goods—like cars, planes, or machinery—depreciate more rapidly with use. In other words, when depreciation is primarily driven by usage rather than time, holding these goods on dealer balance sheets results in lower value loss, making dealer intermediation more feasible. These factors help explain why intermediation in these markets has reached significantly higher levels—around 50% market share—compared to housing.

Overall, our analysis suggests that intermediation in the housing market presents larger challenges compared to other consumer durable markets. These challenges stem primarily from significant informational asymmetries that current technology struggles to fully overcome, as well as the immobility of housing, which reduces overall market liquidity, and much larger opportunity cost of the asset not being used. Given the housing market's size and its central role for households and the broader economy, our findings highlight these frictions as key obstacles to effective intermediation of durable goods.

Our paper is related to a large body of work focusing on dealer intermediation and trading frictions in decentralized asset markets (see Weill 2020 for a survey). Relative to the canonical models such as Rubinstein and Wolinsky (1987), Duffie, Garleanu, and Pedersen (2005), or Atkeson, Eisfeldt, and Weill (2015) our central focus is on the intermediary in the durable

[6] More specifically, RedfinNow also shut down its iBuyer business in late 2022, and Opendoor continues to operate albeit without significant market share gain. See https://www.geekwire.com/2022/redfin-to-cut-13-of-workforce-and-shut-down-home-flipping-business-redfinnow/ and https://techcrunch.com/2022/11/02/opendoor-lays-off-about-550-employees-or-18-of-its-workforce/

goods market (homes) exposed to asymmetric information relative to other market participants. In this way, we contribute to the literature analyzing the impact of asymmetric information in asset markets, similar to Hendel and Lizzeri (1999); Guerrieri, Shimer, and Wright (2010); Guerrieri and Shimer (2014, 2018); Eisfeldt (2014); Chang (2018); and Lester et al. (2019), who study the interaction between asymmetric information and other frictions. We differ from these papers with our focus on intermediaries who are subject to asymmetric information, which we assume is not present in the rest of the market, and study how this information wedge and other forces limit the scope of intermediation. Our tractable model, matched to the data, allows us to provide quantitative answers to these questions.

In this regard, perhaps the closest to our work are the structural and quantitative models of Gavazza, Lizzeri, and Roketskiy (2014) and especially Gavazza (2016). Similar to Gavazza (2016), in our setting intermediaries provide the benefits of faster trade, and direct trade can occur between consumers in addition to trading with intermediaries. Whereas Gavazza (2016) focuses on the role of bargaining and the entry/exit decisions of intermediaries, we instead focus on the role of asymmetric information faced by the intermediary. In Gavazza (2016), frictions can lead to excess intermediation, while in our setting, frictions limit the extent of valuable intermediation.

Given our focus on the housing market, we also contribute to the literature on frictions in matching households to houses. We build on a large literature of quantitative search and matching models (Wheaton 1990; Genesove and Mayer 1997; Landvoigt, Piazzesi, and Schneider 2015; Guren 2018; Piazzesi, Schneider, and Stroebel 2020; Guren and McQuade 2020; Andersen et al. 2020; Rekkas, Wright, and Zhu 2020). The presence of search frictions and household balance sheet constraints provides a natural demand for intermediation. The existing literature has focused on the matchmaking role of intermediaries—i.e., real estate brokers (Levitt and Syverson 2008; Hendel, Nevo, and Ortalo-Magné 2009; Barwick and Pathak 2015; Barwick, Pathak, and Wong 2017;) and speculators (Chinco and Mayer 2016; DeFusco, Nathanson, and Zwick 2017; Mian and Sufi 2022). In contrast, our focus is on trying to understand the lack of balance sheet (dealer) intermediation, which should naturally occur in a market in which consumers demand immediacy. We contribute by introducing balance sheet intermediaries into the existing models and analyze the frictions that limit intermediation in real estate markets.

Our work is also related to the work on the housing market, including recent work that studies the role of asymmetric information in real estate markets (e.g., Kurlat and Stroebel 2015; Stroebel 2016; Indarte 2021; Gupta and Hansman 2022); what differs is that we focus on the impact of asymmetric information in limiting intermediation. Our paper is also broadly related to recent quantitative studies of housing and mortgage markets (e.g., Corbae and Quintin 2015; Berger et al. 2017; Favilukis, Ludvingson, and Van Nieuwerburgh 2017; Beraja et al. 2019; Greenwald 2018; Ganong and Noel 2020; Kaplan, Mitman, and Violante 2020; Buchak et al. 2020; Gorback and Keys 2020; Benetton 2021; Calder-Wang 2021; Wong 2021; Demers and Eisfeldt 2022), which are interested in the setting of house prices, as we show that the presence of dealer intermediaries could affect the overall house price level. Lastly, our discussion of iBuyers' responses to the COVID-19 pandemic and Zillow's exit also relates our work to models of dealer intermediation, which study how intermediaries respond to market-level shocks. For example, the model of Weill (2007) shows that intermediaries may respond to temporary shocks by providing liquidity (i.e., they absorb shocks). In contrast, our model suggests that intermediaries in durable goods markets subject to asymmetric information may provide less liquidity once exposed to such shocks, consistent with the data.[7]

II. Data and Institutional Background

II.A. Data Sources

Transaction Data: We use CoreLogic deed record data on housing transactions from five markets with a 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 arm's-length, non-foreclosure transactions in single-family homes or condominiums with transaction prices below \$10 million and land below 50,000 ft^2. The data report 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 transaction records with tax assessment files enables us to observe property-specific attributes, including the census tract, land square footage, building square footage, number of stories, year of construction, type of air conditioning, garage, heating, sewer, water, and electricity. The assessment file also includes evaluations of the construction quality and location desirability. Summary statistics for these data are in Table 1 Panel A.

Listing Data: We use listing data from the multiple listing service (MLS) provided by ATTOM Data. The data span 2010 through 2018, and our main sample period is 2013–2018. Individuals, brokers, and companies selling their properties post listings on a set of common

[7] Lagos, Rocheteau, and Weill (2011) show that when trading frictions are large, well-capitalized dealers may be unwilling to provide liquidity during crises, even under circumstances when it would be socially efficient for them to do so. This echoes the behavior of iBuyers in very illiquid markets, though the economic mechanism is different from the one we consider.

platforms, and we observe the combined data. The data are at the individual listing level. The listing 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 individual listings 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 2 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 data from the U.S. Census Bureau to measure several ZIP-level demographics 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.

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 Opendoor, Offerpad, Knock, Zillow, or Redfin. Purchases are often effected through a structure of corporate entities, and Appendix A.2 details this procedure. Appendix A.3 performs a tie-out of CoreLogic and MLS data.

II.B. The Rise of iBuyers

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

iBuyers earn a 5% gross 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 also been positive for all but two quarters in 2015 (Figure 1(b)). Additionally, iBuyers charge home sellers a service fee in line with the typical real estate agent fees associated with a traditional house sale.[8] They typically purchase homes

[8] These fees are approximately 6.5%; see https://www.opendoor.com/w/pricing (accessed January 2020).

within a narrow band of characteristics: houses that are in the $100,000–$250,000 price range (Figure 1(c)), relatively new (Figure 1(d)), of modest lot size (Table 1 Panel A), and, as we argue in Section III.C, houses that are easy to price with hedonics.

III. iBuyers' Business Model and Liquidity Provision

In a standard 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.[9] This process can be slow; the average time between a listing and a successful sale is 91 days (Table 1 Panel B).

A dealer intermediary, who purchases the house immediately and holds it on balance sheet while reselling, presents a natural alternative. Holding data suggest that iBuyers are balance sheet intermediaries; they hold inventory for a short period of time, with a median of 105 days (Table 1, Panel A). This section documents other aspects of iBuyers' business model: By allowing households to quickly transact, they earn a spread on housing transactions. They focus on market segments that minimize the associated frictions in doing so.

In a typical human-to-human transaction, a buyer's broker and seller's broker each receive a 3% fee, although the seller pays both. When an iBuyer purchases a house, it typically charges the seller a 6% fee. When an iBuyer ultimately sells the house, (as we show) it typically lists the house as if it were a human seller, utilizes a broker, and thus incurs a 6% fee. Thus, while in our analysis we report prices gross of fees, from the perspective of a human transactor, there is a 6% fee to sell, and from the perspective of the iBuyer, the 6% fee the iBuyer receives on purchasing the home is ultimately paid out to the broker when it sells the home. Therefore, we are making an apples-to-apples comparison.

III.A. iBuyers' Transaction Dynamics

Selling to iBuyers Avoids Listing the House: We begin by showing that by transacting with iBuyers, homeowners avoid a slow listing process. With the merged transaction listing dataset,

[9] An individual homeowner could temporarily own two houses to facilitate moving into a new home, but such an activity requires a substantial amount of wealth. This is not typical of most individual transactions.

we examine whether houses sold to or by iBuyers were more or less likely to be listed on MLS prior to purchase by estimating the following specification:[10]

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

An observation is at the deeds records transaction level, where *i* indexes a house in ZIP code *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 $Listing_{izt}$ is a zero-one indicator for whether there is an MLS listing on the same property with a sale date within 1 week of the sale date in CoreLogic. Our empirical approach exploits buyer variation for similar homes at the same time in the same market by controlling for a vector of house controls, H_i,[11] and ZIP-quarter fixed effects, μ_{zt}.

Sellers are roughly 27 pp less likely to list a property if they sell it to an iBuyer (Table 2 Panel A Column 1), suggesting that selling to iBuyers provides a substantially faster sale with a certain outcome. Since the typical listing period conditional on selling a house is 91 days (Table 1 Panel B), these findings imply that selling directly to an iBuyer allows the seller to substantially speed up the sale.[12]

iBuyers Sell Houses Using Listings: In contrast to iBuyer purchases, we find that iBuyers sell using the traditional listing process. We first estimate the probability that iBuyers sell houses using the listing process, equivalent to Equation (1):

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

The results in Table 2 Panel A Column (2) show that iBuyers are roughly 12% *more* likely to go through the traditional listing process than other sellers. Thus, iBuyers do not appear to have a different technology for selling houses, relying on the standard listing process instead of targeting buyers through their on-line platforms.

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[10] CoreLogic and MLS transactions "match" if they share a property ID and transaction within 1 week of each other. In Appendix A.4 Panel A, we examine stricter or more permissive match windows with similar results.

[11] These are price, log living square footage, binned overall square footage, binned house age, indicators for whether the house is multistory, the type of air conditioning, the type of heating, the type of garage, an assessed measure of build quality, and an assessed measure of location quality, and zip-times-quarter fixed effects. The number of bedrooms and bathrooms is not well reported in our data, although presumably well proxied for with measures of size.

[12] In Appendix A.4 Panel B, we examine whether iBuyers are more likely to purchase houses that correspond to previously "failed" listings. The results suggest that this is not the case.

iBuyers' Listings: Having established that iBuyers utilize the standard listing process, we next examine differences in listing behavior between iBuyers and other sellers. We document three facts: iBuyers list at slightly higher prices, take slightly longer to sell, and do not engage in major renovations. 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 absentee owners who relist the house within 1 year of purchase.[13] *Flippers* are a useful comparison group to iBuyers, because they purchase houses as an investment and leave the house unoccupied. Our main specification is as follows:

$$Outcome_{izt} = \beta Lister_{izt} + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \tag{3}$$

$Lister_{izt}$ is an indicator for the lister type. As before, we include house characteristics, H_i, and quarter × ZIP fixed effects, μ_{zt}. Table 2 Panel A Column (3) examines *log list price* and shows that iBuyer listing prices are 2.3% higher than ordinary sellers' listings on comparable properties. Flippers also list more aggressively than ordinary buyers, with a markup of 0.8%. Column (4) examines whether the listing indicates renovations and shows that whereas iBuyers are roughly 5% *less* likely than ordinary sellers to mention renovations, flippers are 15% more likely to do so. Unlike flippers, iBuyers' business model does not rely on adding value though renovating houses.

iBuyer listings are 13.6% more likely to result in a successful sale as compared to homeowners, but conditional on a sale, iBuyer listings spend 27 more days on market (Table 2 Panel A, Columns 5 and 6).[14] Therefore, iBuyers do not seem to have any special technology in effecting sales more quickly, conditional on the sale price.[15] Broadly, this analysis reveals that iBuyers face the same central trade-off in listing that other sellers face: aggressiveness in pricing versus the speed of the sale (Levitt and Syverson 2008; Guren 2018).

III.B. Returns to Liquidity Provision

This section shows that in exchange for purchasing homes quickly, iBuyers earn a positive bid-ask spread both by purchasing homes cheaper and selling them at a small premium relative

[13] We can only identify flippers using this definition in the MLS dataset (and not in the CoreLogic dataset). Thus, MLS results will differentiate flippers and other individuals; results from CoreLogic will not.

[14] The unconditional difference is 5 days. To account for "failed" listings and censoring, we estimate a Cox proportional hazard model on sales propensity. Before conditioning on a sale, iBuyer sales occur faster than non-iBuyers (Column 7), but conditional on the sale, iBuyers' hazard rate is significantly lower (Column 8).

[15] Appendix A.4 Panel C allows for pulled-and-relisted listings and does not find significant differences.

to the average transacting household. We investigate these pricing effects with the following hedonic specification at the house transaction level:

$$\begin{aligned} \log(Sale\ Price_{izt}) &= \beta(iBuyer\ is\ Buyer_{izt}) + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \\ \log(Sale\ Price_{izt}) &= \beta(iBuyer\ is\ Seller_{izt}) + H_i'\mathbf{B} + \mu_{zt} + \epsilon_{izt} \end{aligned} \tag{4}$$

$iBuyer\ is\ Buyer_{izt}$ and $iBuyer\ is\ Seller_{izt}$ are zero-one indicators for whether the buyer or seller is an iBuyer, respectively. We use the same set of house hedonic controls and fixed effects as in previous specifications, comparing observationally similar properties that transacted within a given ZIP code at the same time. Our results in Table 2 Panel B show that iBuyers earn both a purchase discount and a selling premium, with the purchase discount representing most of the spread. Over the 2013–2018 sample, iBuyers' purchase prices were roughly 3.1%, or $9,000, lower than other purchasers of similar houses in the same market at the same time (Column 1). Conversely, iBuyers sell at roughly a 1.5%, or $4,000, premium above comparable houses. Together, this discount and premium amounts to the nearly 5% unconditional average spread throughout our sample as shown in Figure 1, panel (b). Columns (3) and (6), which examine iBuyer buyers and sellers, respectively, in 2018 only, show that price differences fell over time to roughly a 2.6% buy premium and a 0.8% sale premium, for a gross spread of roughly 3.4%. We also observe that as the iBuyers' market share grew over time, this spread gradually contracted, reaching 4.78% across the combined markets in 2018. The simultaneous buy discount and sell premium helps rule out the alternative explanation that iBuyers' purchase discount simply reflects houses with worse unobservable characteristics.

These returns are consistent with the idea that iBuyers provide liquidity to homeowners looking for an instant sale in exchange for purchasing the house at a significant discount. They 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—in this case speed—rather than simple cost savings.[16]

[16] On the surface iBuyers might resemble cash buyers, who can also offer greater speed than ordinary mortgage-financed buyers. One of the key differences between iBuyers relative to cash buyers is that finding a cash buyer involves costly search, matching and other frictions typical to a traditional selling channel. Unlike iBuyers, traditional cash buyer intermediaries often target distressed properties, such as foreclosures, short sales, or homes in need of renovations. Additionally, in our data, iBuyer transactions are typically non-cash sales, indicating that cash sales are a distinct form of expedited sale.

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

Our findings that sellers are willing to accept lower offers in exchange for faster transactions suggests a demand for liquidity, and therefore a natural role for dealer intermediation. Yet, until the entry of iBuyers, such transactions were rare. To understand why liquidity provision in real estate markets is difficult, we utilize the fact that housing markets are segmented (Piazzesi, Schneider, and Stroebel 2020) and examine which market segments iBuyers chose to enter. We use the characteristics of these segments to understand which segment has the smallest frictions to intermediation. We focus on the role of information and underlying market liquidity.

III.C.1. iBuyers' Use of Algorithmic Pricing

We first provide evidence that iBuyers utilize algorithmic pricing in their purchasing decisions.[17] We estimate the following hedonic regression at the transaction level:

$$\log(Sale\ Price_{izt}) = H_i'\mathbf{B} + \mu_k + \epsilon_{izt} \tag{5}$$

The specification is as before, with k indexing fixed-effect saturation. We estimate the specification separately by buyer/seller type. The statistic of interest is how the R^2 varies across type. Table 3, Panel A shows the results. Across specifications, observable characteristics explain a substantially higher share of variation in iBuyer transaction prices relative to transaction prices of other market participants. Including ZIP-quarter fixed effects, observable characteristics explain over 80% of the variation in prices for iBuyer transactions, versus 68% of the variation in other transactions. These results suggest that households use other "soft" inputs to determine prices that are not captured in the iBuyer algorithm. Such information can arise from other participants using information that is difficult to encode in an algorithm or only available after a lengthy inspection, which iBuyers forgo in order to offer speedy closure. For example, iBuyer algorithms would not notice that the house smells, but a buyer visiting the house should.

III.C.2. The Consequences of Algorithmic Pricing and Limited Liquidity

If iBuyers' pricing is algorithmic, and does not condition on information known to sellers but which is left out by the algorithm, iBuyers may face adverse selection. Consistent with adverse selection, Zillow reported that sellers accepted only 10% of its iBuying offers. It would be

[17] Indeed, iBuyers tout their algorithmic pricing as an advantage. Several iBuyers are offshoots of firms that specialize in collecting house price data as well as pricing houses.

very surprising if the selection of houses, which were sold, were unrelated to the information of homeowners. If adverse selection is indeed a problem faced by iBuyers, they should respond to it by focusing on houses where this informational disadvantage is minimized: those in which their algorithmic pricing of hard hedonic information works well. We test whether this is indeed the case. Moreover, if the hard to price segments are subject to adverse selection and more difficult to intermediate, they should be less profitable conditional on entry. We also confirm this hypothesis in the data. Additionally, because the market-making business model relies on selling homes quickly, we test whether iBuyers are more active in more liquid segments, and whether these segments are more profitable conditional on entry.

We first model which houses have small pricing errors when priced with hedonics. To avoid mechanical contamination from iBuyers' own transactions, we estimate a hedonic pricing model using 2006–2012 pre-iBuyer data. We estimate a model of the form of Equation (5), 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 residuals in absolute value, $|\hat{e}_{izt}|$, from this specification are those that are not priced well by hedonics. We then predict which house characteristics make them difficult to price:[18]

$$|\hat{e}_{izt}| = H_i'\mathbf{\Delta} + \zeta_{\mathrm{izt}} \tag{6}$$

As before, H_i' is a vector of house hedonics.

Next, we estimate how the ex-ante liquidity of a market relates to iBuyer entry. We formally define liquidity in the model in Section IV, where it refers to the matching rate between buyers and sellers. Here, we proxy the degree of liquidity of a home by creating a measure that reflects an expected time to sell a home with given attributes (based on pre-iBuyer entry data). We estimate a hedonic model to predict whether a given listing sells within 90 days from the listing date:[19]

$$Sells\ Within\ 90\ Days_{izt} = H_i'\mathbf{B} + \epsilon_{izt} \tag{7}$$

Finally, using the estimates from Equations (6) and (7), we construct for every house its predicted standardized pricing error, $|\hat{e}_{izt}|$, and underlying liquidity,

[18] Appendix A.5 shows the results. Younger, middle-sized, and multistory houses have smaller pricing errors in expectation. We redo the analysis for a narrower training sample of 2008–2012. The remarkable stability of estimates provides confidence that iBuyers using different sets of data would come to similar conclusions.

[19] Similar to the results on pricing errors, we find that cheaper (measured by *previous* sale price), smaller, and single-story houses are more likely to sell quickly.

$Sells\ Within\ 90\ Days_{izt}$, and then study which houses iBuyers chose to intermediate from 2013 through 2018 with the following regression:

$$iBuyer_{izt} = \beta\widehat{|e|}_{izt} + \gamma \widehat{Sells\ Within\ 90}\ Days_{izt} + \mu_{zt} + \epsilon_{izt} \tag{8}$$

As with the earlier specification, an observation is a house transaction, where *i* indexes a house in ZIP code *z* at quarter *t*. $iBuyer_{itz}$ is a zero-one indicator for whether the buyer is an iBuyer. $\widehat{|e|}_{izt}$ is the predicted pricing error, and $\widehat{Sells\ Within\ 90}\ Days_{izt}$ is the predicted probability of a listing selling within 90 days. As before, we control for quarter × ZIP fixed effects, μ_{zt}. In other words, we study which houses iBuyers choose to intermediate, conditional on having entered a geographic market.

Table 3 Panel B Column (3) confirms that adverse selection and low liquidity discourage iBuyer intermediation: Relative to the 0.60-pp base rate of iBuyer purchases over the period, iBuyers are 0.52 pp less likely to purchase a house with a 10-pp greater predicted pricing error. Similarly, iBuyers are 0.15 pp less likely to purchase a house with a 10-pp lower probability of selling within 90 days. Panels (e) and (f) of Figure 1 show graphically these results. As we observe, iBuyer market shares are highest in segments of easier to price and liquid houses.

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 should earn smaller profits. We test this by investigating how iBuyer realized annual gross returns on their transactions relate to our ease-of-pricing and liquidity measures. To investigate this formally, we regress the realized annualized gross return of sellers on the expected pricing errors and liquidity as follows:

$$\begin{aligned} Gross\ Return^{Ann}_{iztt'} &\\ &= \beta_0 iBuyer_{izt} + \beta_1\widehat{|e|}_{izt} + \gamma_1 \widehat{Sells\ Within\ 90}\ Days_{izt} + \\ iBuyer_{izt} \times \big(\beta_2\widehat{|e|}_{izt} &+ \gamma_2 \widehat{Sells\ Within\ 90}\ Days_{izt}\big) + \mu_{zt} + \epsilon_{iztt'} \end{aligned} \tag{9}$$

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. $Gross\ Return^{Ann}_{iztt'}$ is the annualized return on the given transaction defined as

$$Gross\ Return^{Ann}_{iztt'} = \left(\frac{Price_{izt'}}{Price_{izt}}\right)^{\left[\frac{1}{t'-t}\right]} - 1.$$

Here, the subscript *i* denotes a house, *z* the zip code of the house, and *t* the time of the purchase, and t' the time of the sale.[20] $\widehat{[e]}_{izt}$ is the predicted pricing error, 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 in Table 4 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:

$$\begin{aligned} & Holding\ Period_{iztt'} \\ & \quad = \beta_0 iBuyer_{izt} + \beta_1 \widehat{[e]}_{izt} + \gamma_1 \widehat{Sells\ Within\ 90}\ Days_{izt} + \end{aligned} \tag{10}$$

[20] Notably, we discuss how iBuyer Gross returns compare with other investors as well as decompose them in Appendix A.6.

$$iBuyer_{izt} \times \left(\beta_2 \widehat{|e|}_{izt} + \gamma_2 Sells\ \widehat{Within\ 90}\ Days_{izt}\right) + \mu_{zt} + \epsilon_{izt}$$

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.

Columns (4)-(6) of Table 4 show that harder-to-price homes remain in iBuyer inventory for relatively longer. These results are robust to controlling for the liquidity of the house, where, as expected, homes that are more liquid based on our measure have lower holding periods. 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.

These results suggest that two forces limit the provision of dealer intermediation in the real estate market despite its high potential benefits. First, to provide liquidity, intermediaries need to transact in homes quickly and are therefore subject to adverse selection. Second, low liquidity of a house decreases the intermediaries' ability to supply liquidity. Critically, therefore, liquidity provision through dealer intermediation works best for houses that are already liquid and relatively easy to value—when additional liquidity is least valuable. The model in the next section explains why balance sheet intermediation is difficult in markets with low underlying liquidity, even though households in these markets have the highest willingness to pay for such intermediation.

IV. Equilibrium Housing Trading Framework with Dealer Intermediation

We now develop an equilibrium model of search and matching in decentralized asset markets for durable goods into which we introduce a balance sheet intermediary subject to adverse selection. We apply the model to housing search. The intermediary purchases houses from households quickly but at an information disadvantage, holds them, and resells them to other households. 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 U.S. housing market post-iBuyer entry using facts we documented above. We then use the model to explore the role of technology and the qualitative and quantitative forces that constrain the provision of liquidity in the market.

IV.A Model Setting

The model is in continuous time. A homeowner is initially matched with a house from which she receives a flow benefit (consumption value less costs). The house is either “higher quality” or “lower quality,” with higher quality houses providing a greater flow benefit than lower quality houses. With some probability, the homeowner becomes unmatched from her current house and begins the moving process, at which point house quality, which is fixed over the ownership spell can also switch. Homeowners differ in their flow cost of being unmatched: Some have an urgent motivation to move (e.g., relocating for a job), whereas others have less urgent motives (e.g., downsizing).

Critically, we assume that the homeowner’s balance sheet is constrained, so owning two homes at the same time is prohibitively costly. This can arise, for example, if households have limited wealth and borrowing against a house comes with loan-to-value (LTV) constraints imposed by the lender. Therefore, to buy a new house, she must first sell her old house. Once she finds a new house she likes and purchases it, she again becomes a matched homeowner. The transactions among homeowners occur in a standard search market in which sellers list houses and are randomly matched with buyers.[21] For reasons discussed earlier, we do not explicitly model the non-iBuyer brokers, as the fees paid to brokers are equivalent in an iBuyer or non-iBuyer transaction.[22]

We introduce a deep pocket intermediary that can provide liquidity in the market. Instead of listing houses and waiting for a buyer, sellers can sell them directly to a balance sheet intermediary, who then lists houses for resale using the standard listing process. The intermediary has no balance sheet constraints. On the other hand, intermediaries 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 and must pay maintenance costs. The intermediary is endowed with three key technologies. The first is the speed at which they can purchase a home. The reason why intermediaries are valuable to sellers in the first place is because they

[21] Analogous to, for example, job seekers and job postings as in Diamond (1982). We believe that our main qualitative insights would be robust to alternative modeling assumptions regarding the search process (e.g., directed search). See Piazzesi, Schneider, and Stroebel (2020) for a recent analysis of implications of various modeling assumptions regarding the search behavior for the housing market equilibrium.

[22] In a typical human-to-human transaction, a buyer’s broker and seller’s broker each receive a 3% fee, although the seller pays both. When an iBuyer purchases a house, it typically charges the seller a 6% fee. When an iBuyer ultimately sells the house, (as we show) it typically lists the house as if it were a human seller, utilizes a broker, and thus incurs a 6% fee. Thus, while in our analysis we report prices gross of fees, from the perspective of a human transactor, there is a 6% fee to sell, and from the perspective of the iBuyer, the 6% fee the iBuyer receives on purchasing the home is ultimately paid out to the broker when it sells the home. Therefore, we are making an apples-to-apples comparison.

can execute the transaction without waiting for a buyer, but such transactions may not be instantaneous. Time to transact can depend on the speed at which the intermediary can process the paperwork, potentially inspect the property and other sources of delay. It also could mean cutting out the need for staging before the property can be sold. The second is the precision with which they can differentiate a higher quality house from a lower quality house when buying it from the selling homeowner. As we document above, the speed at which iBuyers can close transactions puts them at an information disadvantage relative to homeowners and other potential sellers, who can take time to thoroughly screen a purchase, even if iBuyers can use algorithmic pricing. The third is their matching technology when reselling the house. While we see little evidence of differences in matching homeowners with houses, we want to study the potential for intermediation if iBuyers improved matching technology in the future. Appendix A.7 shows the model structure graphically.

IV.A.1. Market and Information Structure

Homeowners: A homeowner is either matched in a house, is an unmatched seller trying to sell her current house, or is an unmatched buyer who has solder her house trying to buy her next house. She transitions between these states over time. As a matched homeowner, she may either be in a higher quality house ("good") or a lower quality house ("bad"), with these states denoted as $\{h^g, h^b\}$. This aspect of house quality is common across homeowners, is persistent (but occasionally changes over time), and reflects, for example, difficult to measure differences in build quality, location, neighbors, noise, and so on. We will often use $q \in \{g, b\}$ to index house quality. As an unmatched seller (s), can either be either patient (P) or impatient (I), where $T \in \{P, I\}$ indexes patience type. Therefore, unmatched seller (s) states are denoted as $\{s_P^g, s_P^b, s_I^g, s_I^b\}$ capturing house quality and patience. For tractability, we assume that buyers are neither patient nor impatient and their previous house quality does not impact their flow utility. Thus, there are seven homeowner states: $\{h^g, h^b, s_P^g, s_P^b, s_I^g, s_I^b, b\}$. The total homeowner population has an exogenous mass $M = 1$, with $\{m_{h^g}, m_{h^b}, m_{s_P^g}, m_{s_P^b}, m_{s_I^g}, m_{s_I^b}, m_b\}$ respectively denoting the endogenous mass of each type. For notational convenience, we denote the total mass of sellers as $m_s = \sum_{q,T} m_{s_T^q}$ obtained by summing over all seller types.

Homeowners become unmatched at rate μ, and conditional on becoming unmatched, become patient or impatient with probability distribution denoted by $dT(T)$. When the homeowner becomes unmatched, the house has a chance to switch types from higher- to lower-quality or vice versa. Denoting the subsequent house quality as q', the subsequent house quality is distributed as $dQ(q'|q)$, allowing quality to be persistent.

All agents discount the future at rate ρ. Matched h^q-type homeowners, own a house producing flow utility $u_i^q = \bar{u}^q + \tilde{\epsilon}_i$. $\bar{u}^q$ captures the common component across homeowners such as housing services and amenities net of holding costs, conditional on the house type, with $\bar{u}^g > \bar{u}^b$. $\tilde{\epsilon}_i$ allows for idiosyncratic differences in homeowners utility flows from their current property representing household-specific preferences over build or location. In effect, this allows for the possibility that sellers may have some market power since houses are also horizontally differentiated. When homeowners become unmatched, sellers receive utility flow u^T with patient sellers receiving a greater utility flow than impatient sellers, $u^I < u^P < \bar{u}^g$. This represents the idea that while unmatched homeowners still obtain some utility benefits from occupying the house, the house is no longer a good match. This discount captures, for example, an increased commute, an inferior school district, loss of income associated with better labor income prospects in different location or a nonideal rental residence. Buyers receive utility flow u^P. Observe that the current house quality does not enter the utility flow of buyers or sellers until they become matched.

Listings: Selling households can list their house and randomly encounter potential buyers. Buyers and sellers meet at an endogenous aggregate rate $F^{hh}(m_s, m_b) = \lambda m_s m_b$. λ parametrizes the underlying liquidity of the market. Let subscripts *s* and *b* denote the rate for an individual seller or buyer, respectively, 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 $\pi(p)$.

Intermediary: The intermediary purchases houses directly from households, holds them until sale, and sells the houses using a listing. Households can choose to sell the house to the intermediary instead of listing it, which closes the transaction in $\tau \geq 0$ days. Closing delays can arise because of the time it takes to gather and process the documentation, but also because of some 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. Households differ in their preferences over transacting with the intermediary. For example, some households may prefer the convenience of transacting online, while others may experience disutility costs related to accessing new technology, all other things constant. We capture these preferences with an idiosyncratic utility shock, ϵ_{ib}^i. $\epsilon_{ib}^i \sim dE^{ib}(\epsilon_{ib}^i)$ is distributed type-1 extreme value distribution with scale parameter σ_{ib}.

Upon purchasing the house, the intermediary sells the house through the listing process. It possesses its own matching technology, $F^{ib}(m_s, m_b) \equiv \lambda_{ib} F^{hh}(m_s, m_b)$. $\lambda_{ib} > 1$ implies that the intermediary is better able to find buyers than other sellers in the market—for example, by using their websites for listings—and $\lambda_{ib} < 1$ implies that they are worse. While the house is on the market, the intermediary pays flow maintenance costs. At first, the maintenance cost is low, m^L. Because the house is unoccupied, intermediary cost may increase over time—for example, if the roof leaks and no one notices because the house is vacant. At rate η, the flow costs become high, with m^H, $m^H > m^L$. We often use c$\in \{L, H\}$ to index maintenance costs.

House Quality and Information: The intermediary closes housing transactions without a lengthy inspection, and instead uses algorithms to set prices. We model the potential information disadvantage that the intermediary faces as asymmetric information over whether the house is of higher or of lower quality. Recall that higher-quality houses provide higher flow utilities to their (human) occupants and thus in equilibrium will command higher prices. In particular, when a homeowner becomes unmatched, the house quality evolves from q to q' according to the distribution $dQ(q'|q)$. We assume that the homeowner and potential future human buyers observe the subsequent quality q', but that the iBuyer does not. Rather, the iBuyer receives a positive or negative noisy signal $\nu \in \{P, N\}$ about the house quality ν and only discovers the house quality after purchasing it. The signal distribution is given by:

$$\begin{aligned} \phi(P|q' = G) &\equiv \phi_{P|G} = 1 - \xi \\ \phi(P|q' = B) &\equiv \phi_{P|B} = \xi \end{aligned} \tag{M.1}$$

That is, the ξ parameterizes the signal noise, where a smaller ξ implies a more precise algorithmic pricing technology, which has a lower probability of misclassification. In essence, one can think of intermediary's technological problem as trading off speed of closing τ with accuracy ξ.

Additionally, because *past* prices are publicly observable and purchases by *homeowners* occur between fully informed parties, the iBuyer can perfectly infer the *previous* house quality q. Thus, the iBuyer conditions the house prices it offers on the signal ν and the previous house quality q, offering $p_b^{ib}(\nu, q)$. Additionally, the intermediary does not directly observe whether the seller is patient or impatient, although it will rationally consider which types of sellers are most likely to accept its offer. Upon purchasing the house, the iBuyer discovers the actual next house quality q' and sets its selling price $p_s^{ib}(m^c, q')$, that is, it conditions the price on whether the house has experienced the repair cost shock and on the house's realized quality q'.

IV.A.2. Homeowner's Problem

Homeowners maximize expected utility. Let $\left\{v_{h^q}, v_{s_T^q}, v_b\right\}_{q,T}$ denote the value functions of matched households, patient sellers, and buyers, respectively.

Matched homeowners take no actions. Their consumption flow is that of their current house, $\bar{u}^q + \tilde{\epsilon}_i$, and the continuation value of living in the current house. The latter depends both on how likely they are to become unmatched and realizations of random variables after becoming unmatched, as well as their future choice of selling through listings or to the intermediary. A matched homeowner *i* has the following value function:

$$(\rho + \mu) v_{h^q i} = \bar{u}^q + \tilde{\epsilon}_i + \mu \int_{s_*, q', v, \epsilon_{ib}^i} \max\left\{ v_{s_T^{q'}}, \delta(\tau)\left(p_{ib}^b(v, q) + v_b\right) + \epsilon_{ib}^i \right\} dG\left(\epsilon_{ib}^i, v, q', T | q\right) \quad \text{(M.2)}$$

Recall that ρ is the subjective discount rate and μ is the unmatching rate. $v_{s_T^{q'}}$ is the value function for a seller of patience type $T \in \{P, I\}$ with house type $q' \in \{g, b\}$. $\delta(\tau)\left(p_{ib}^b(v, q) + v_b\right) + \epsilon_{ib}^i$ is the discounted value of selling immediately to an intermediary and becoming a buyer, where $\delta(\tau)$ is the time discount factor from the intermediary's closing time τ; $p_{ib}^b(v, q)$ is the intermediary offer price conditional on the signal and previous house type, and ϵ_{ib}^i is the consumer's idiosyncratic preference over an intermediary transaction. This idiosyncratic preference captures, for example, familiarity with the platform or comfort with transacting online. The random variables are jointly distributed as $dG\left(\epsilon_{ib}^i, v, q', T | q\right)$. Note that ϵ_{ib}^i and T are independent of all other random variables and state variables, q' is conditional on q, amd the distribution of the signal v depends on q'. Denote the (optimized) probability of selling to an intermediary given the price offered, subsequent house type, and patience type, as $\pi_{ib}(p, q', T)$. Observe that the offered price impounds information contained in the signal realization and the previous house type, but that the household's acceptance probability also depends on the actual house type and whether they are patient or impatient.

The value that a matched homeowner obtains from the house, $v_{h^q i}$, can be expressed as a sum of a common component, v_{h^q}, which is how the average homeowner values their house of type q, and the idiosyncratic home valuation, $\tilde{\epsilon}_i$. For the remainder of the paper, we focus on v_{h^q} and $\epsilon_i \sim \mathrm{E}(\epsilon_i)$, with $v_{h^q i} = v_{h^q} + \frac{\tilde{\epsilon}_i}{\rho + \mu} \equiv v_h^q + \epsilon_i$. We interpret $\epsilon_i \equiv \frac{\tilde{\epsilon}_i}{\rho + \mu}$ as the capitalized idiosyncratic flow utility from the house, in line with the earlier separation of flow utility into a common component, $\bar{u}^q$, and idiosyncratic component, $\tilde{\epsilon}_i$. We assume that ϵ_i is distributed type-1 extreme value distribution with scale parameter σ_m.

Selling homeowners either sell the house to the intermediary or choose to list it. If the homeowner chooses to list the house, its type becomes known to the (human) buyers by assumption. She becomes a seller with value function $v_{s_T^q}$, where q denotes the house's quality and T denotes whether the seller is patient or impatient. She sets the listing price to maximize her expected utility, trading off a higher price conditional on sale versus a lower probability that a matched buyer accepts the offer. After selling, utility changes by $v_b - s_T^q$. Recall that sellers can be patient or impatient with flow utility u^T. Due to different preferences over the speed of sale, they list their homes at different prices. Intuitively, impatient sellers are willing to set lower listing prices to speed up the sale. The value function for a seller of type (q, T) is:

$$\rho v_{s_T^q} = u^T + F_s^{hh}(m_s, m_b) \max_{p_T^q} \pi^q(p_T^q)(p_T^q + v_b - v_{s_T^q}) \quad \text{(M.3)}$$

where $\pi^q(p_T^q)$ is the probability that a buyer buys the house of quality q at price p_T^q.

Buyers have sold their houses and are trying to purchase a new house. Upon matching, they decide whether to purchase a house for the list price. Let j index the seller type (including house quality). Upon encountering the seller and seeing the house and its list price, the buyer's idiosyncratic valuation, ϵ_i, realizes, she pays a viewing cost κ, and she chooses whether to accept or to continue looking. The buyer accepts the offer if her utility from homeownership exceeds that of remaining a buyer by the sale price. Her value function is given by:

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

Where j indexes over the eight types of sellers she may encounter and q is the seller's house type.

IV.A.3. Intermediary's Problem

When a homeowner becomes unmatched, the intermediary observes the previous house quality q and receives a signal v about the actual house quality and offers price $p_{ib}^b(v, q)$. A homeowner, who knows the actual house quality q', accepts the price with probability $\pi_{ib}(p, q', T)$. Upon acceptance, the intermediary observes the true quality. Let $v_{ib}^{cq'}$ denote its value when owning a house with maintenance cost state $c \in \{L, H\}$ and quality $q' \in \{g, b\}$. The intermediary's expected profit from an offer to an unmatched homeowner given signal v and previous quality q is:

$$v_{ib}^{offer}(v, q) = \max_{p_{ib}} \int_{T,q'} \pi_{ib}(p_{ib}, q', T)(v_{ib}^{Lq'} - p_{ib}) dF(q'|v, q) dS(T) \quad \text{(M.5)}$$

Because a seller's acceptance probability π_{ib} depends on the true house quality, the intermediary faces adverse selection: If it offers lower purchase prices, sellers with high-quality houses are less likely to sell to them. The market does not break down for two reasons: First, sellers derive idiosyncratic values of selling to an intermediary such as preferences for transacting online, so at least some homeowners with high-quality houses are willing to sell to the intermediary, even at lower prices. Second, impatient sellers have a higher incentive to sell to the intermediary, and so impatient sellers with high quality houses may be willing to sell to the iBuyer even at a discount to what they could receive if they list their house.

The intermediary sale process and corresponding pricing decisions closely resemble those of a selling homeowner but must account for changes in maintenance costs. These start off low, as $m = m^L$. As time passes, the maintenance cost increases to $m = m^H$ with an arrival rate η.[23] The intermediary value functions at low and high maintenance costs, v_{ib}^{Lq} and v_{ib}^{Hq}, for house quality q is:

$$\rho v_{ib}^{Lq} = m^L + \eta\left(v_{ib}^{Hq} - v_{ib}^{Lq}\right) + F_s^{ib}(m_s, m_b) \max_{p_{ib}^{Lq}} \pi(p_{ib}^{Lq})(p_{ib}^{Lq} - v_{ib}^{Lq}) \tag{M.6}$$

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

IV.A.4. Population Dynamics

Having described the decision problems of individual participants in the market, we turn to population dynamics. There are twelve prices: patient and impatient households' listing prices for high- and low-quality houses, $\{p_{hh}{}_T^q\}$ (four); intermediary's offer prices for each signal realization and previous house quality, $p_{ib}^b(v, q)$ (four); and iBuyer listing prices for each maintenance cost and house quality, $\{p_{ib}^{cq}\}$ (four). For a vector of prices $\boldsymbol{P}$, we define $\pi_{ib}^q(\boldsymbol{P})$ as the probability that a seller sells to an intermediary, conditional on its previous quality q:

$$\pi_{ib}^q(\boldsymbol{P}) \equiv \int_{v,q',T} \pi_{ib}\left(p_{ib}^b(v, q), q', T\right) dG(v, q', T|q) \tag{M.8}$$

[23] We interpret this possible increase in maintenance costs over time as arising out of the house being unoccupied. For example, the roof may develop a leak. While this is equally likely in an occupied and unoccupied home, if the house is occupied, the occupant will notice the leak and address it before it causes more damage. In contrast, if the house is unoccupied, the unaddressed leaky roof will lead to more damage.

Define further $\pi_{ib}{}_{P}^{q}(\boldsymbol{P})$ and $\pi_{ib}{}_{p}^{q}(\boldsymbol{P})$ as acceptance probabilities conditional on being patient or impatient. The population size of matched households decreases by the exogenous unmatching rate and increases at the endogenous rate of new matches:

$$\frac{dm_h^q}{dt} = -\mu m_h^q + \sum_j F^j(m_j, m_b)\pi(p_j) \tag{M.9}$$

where j indexes over the eight seller types: patient and impatient sellers with high- and low-quality houses, and high- and low-maintenance cost iBuyers with high- and low-quality houses.

Household seller populations increase with the unmatching less the fraction of unmatched selling to the intermediary, and decrease as listings sell and they become buyers:

$$\begin{aligned}\frac{dm_{s_T}^{q'}}{dt} = &\sum_q \mu m_h^q \int_v \left(1 - \pi_{ib}\left(p_{ib}^b(v,q), q', T\right)\right) \, dG(v, q', T|q) \\ &-F^{hh}\left(m_{sT}^{q'}, m_b\right)\pi\left(p_{hh}{}_T^{q'}\right)\end{aligned} \tag{M.10}$$

Here, the first term captures the inflow. The inflow into sellers of type (q', T) is given as follows. For each matched homeowner with previous house quality q, a mass μm_h^q become unmatched. The probability that they become sellers with quality q' and patience level T is equal to the integral over realizations that they transition to that type conditional on their previous type, $dG(v, q', T|q)$, times the probability that they *do not* sell to an iBuyer given the signal realization and their new type. Summing over all previous types q gives the total inflow. The outflow is given by the match rate of sellers of that type with buyers times the probability that given a match, the buyer accepts the offer at the equilibrium price.

The share of household buyers' houses evolves as a function of sale speeds and purchase speeds from both households and the intermediary:

$$\begin{aligned}\frac{dm_b}{dt} = &\sum_q \mu m_h^q \int_{Tvq'} \pi_{ib}(p_{ib}^b(v,q), q', T) \, dG(v, q', T|q) \\ &+ \sum_{q,T} F^{hh}\left(m_{s_T^q}, m_b\right)\pi\left(p_{hh}{}_T^q\right) - \sum_j F^j(m_j, m_b)\pi\left(p_j\right)\end{aligned} \tag{M.11}$$

The first term captures just-unmatched households transitioning directly to being iBuyers by summing over past and current house types times the probability that the selling household sells to the iBuyer. The second term captures sellers transitioning into buyers by summing over all the types of sellers. The last term captures buyers transitioning into matched households by summing over all the ways they can buy a house.

The population of intermediary houses can be split by their maintenance costs:

$$\frac{dm_{ib}^{Lq'}}{dt} = \sum_q \mu m_h^q \int_{T,v} \pi_{ib}\left(p_{ib}^b(v,q), q', T\right) dG(v, q', T|q) - \eta m_{ib}^{Lq'} - F^{ib}\left(m_{ib}^{Lq'}, m_b\right)\pi\left(p_{ib}^{Lq'}\right) \tag{M.12}$$

$$\frac{dm_{ib}^{Hq'}}{dt} = \eta m_{ib}^{Lq'} - F^{ib}\left(m_{ib}^{Hq'}, m_b\right)\pi\left(p_{ib}^{Hq'}\right) \tag{M.13}$$

The first term in the first equation sums the probability that a just-unmatched homeowner of previous quality q transitions to quality q' and sells to the iBuyer. The second term in the first equation is the flow rate from low- to high-maintenance cost houses. The last term in the first equation is the rate at which low-maintenance cost houses are sold to buyers. The first term in the second equation calculates the flow rate from low- to high-maintenance cost houses, and the last term is the rate at which high-maintenance cost houses are sold to buyers.

Finally, with a fixed housing stock, for each seller there is one potential buyer:

$$m_s + m_{ib}^{Lg} + m_{ib}^{Hg} + m_{ib}^{Lb} + m_{ib}^{Hb} = m_b \tag{M.14}$$

IV.A.5. Equilibrium

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

1) The intermediary maximizes profits when setting listing prices (M.5, M.6, and M.7)
2) Households maximize utility when purchasing, listing, and selling houses to the intermediary (M.2, M.3, and M.4)
3) State variables $\{m_j\}$ are constant (M.9–M.14)
4) The intermediary beliefs on repairs are consistent as described above (M.1).

IV.B Model Calibration

We apply the model to the U.S. housing market calibrated over our sample period. We calibrate several parameters externally in relation to existing literature. We then calibrate the remaining parameters by matching model-implied moments to moments we observe in the data. Table 5 Panels A and C describe these moments and our model's fit. We provide external validation of the calibration using a difference-in-differences-style exercise to evaluate whether our model can capture the equilibrium impact of iBuyer entry in a market. Broadly, the model predicts that house prices increase and average time to sale decreases in equilibrium following iBuyer entry. Our reduced form analysis shows the same result.

IV.B.1 Externally Calibrated Parameters

Table 5 Panel B describes externally calibrated parameters. We follow Guren (2018) and set the discount rate ρ to 0.05. The U.S. Census 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,[24] which corresponds to the unmatching rate μ in our model. We set the probability that a house needs repairs, ϕ_R, to the fraction of listings mentioning renovation, which is 0.109 in the MLS data. We define half of the households as impatient and half as patient.[25] Finally, following industry reports, we set iBuyers' time to close, τ, as 15 days—we explore how changing this parameter affects iBuyers' ability to intermediate in Section V.A.1. We normalize the meeting cost κ to 0.577.[26]

IV.B.2 Parameters Calibrated to the Data: Identification

We calibrate the remaining 13 parameters by matching moments in the equilibrium model with the empirical targets. Where possible, we use empirical targets from 2018 (e.g., house prices, iBuyer market shares), the most recent year in our data, although some moments require more data to precisely estimate. We summarize the parameters and the moments in Table 5 Panel C. As the estimates highlight, the model can match the data quantitatively.

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

[25] In Appendix A.8, we examine whether our counterfactual conclusions are sensitive to this assumption by estimating the model with an assumption of 33% impatient sellers. In this exercise, we reestimate the model (rather than simply setting the number of impatient sellers 33%, keeping the rest of the parameters unchanged). In the reestimated model, the fewer number of impatient sellers are *more impatient*—in essence, to explain the data, the estimation finds that the overall amount of impatience must be fairly constant. The results are quantitatively and qualitatively similar. The main difference is that with fewer impatient sellers, the equilibrium in which iBuyers are able to intermediate both good- and bad-type houses is more fragile as there are fewer impatient sellers of good houses to pool with patient sellers of bad houses.

[26] This is the mean of a type-one extreme value distribution and prevents indefinite searching.

Discussing the identification of the remaining parameters also presents an opportunity to provide exposition on the economics underlying the model.

Match Utilities: The level of utility is a normalization, and we normalize $\bar{u}$, the utility flow for a matched homeowner as a baseline.[27] The utilities for patient and impatient unmatched households, u^P and u^I, are reflected in listing prices, differences in listing prices between patient and impatient sellers, and iBuyer discounts. A larger gap between matched and unmatched utility flows makes rematching more valuable, and so sellers will list at a higher price. Similarly, when rematching is more valuable, households will pay more to rematch sooner, and so the iBuyer purchase discount grows. To identify the different flow utilities for patient and impatient sellers, we exploit the fact that impatience changes the preference between price and selling speed. Having imposed that the bottom 50% of list prices, controlling for observables, are made by impatient sellers, differences in median list prices for patient and impatient sellers identifies u^I, with a lower u^I generating a larger gap in list prices as impatient sellers try to sell faster. Listing in the presence of iBuyers is an equilibrium outcome: to make sure the model and data are consistent, we match listing prices from the data (households which have endogenously not sold to iBuyers) to the non-iBuyer listing prices in the model (also households which have endogenously not sold to iBuyers). Finally, our calibration indicates that an average seller in the housing market experiences a hedonic disutility to selling to iBuyers. This can reflect psychological, cognitive, or informational barriers associated with adopting new technology compared to traditional selling channel, which may result in a perceived loss of personalized support or expertise.

Variance of Preference: σ_m and σ_i capture the size of households' idiosyncratic preferences over houses and selling to iBuyers, respectively. If differences are small, average utility difference across choices should predict actions well. Broadly, iBuyers purchase houses at discounts, so they are a "bad deal" for the average seller, and the average seller dislikes the iBuying experience. Therefore, dispersion in preferences increases sellers' likelihood of selling to iBuyers, and thus iBuyer market share, conditional on the offer price, is informative about σ_i. Next, a large σ_m implies that buyers view houses as more differentiated, thereby increasing seller market power. Importantly, this force impacts households and iBuyers asymmetrically: Because sellers will become buyers, the market power effect of σ_m is tempered by an increased desire to become a buyer. In contrast, iBuyers do not become buyers. Thus, σ_m impacts house prices overall, but in particular iBuyer prices.

[27] This normalization of $\bar{u} = 24$ is for numerical convenience.

Match Rates: The match intensity, λ, is related to how long a house stays on the market. A higher λ, holding prices fixed, tends to reduce times on market, as market participants see more matches per unit time. λ_{ib} controls the extent to which iBuyer time on market, controlling for price, sell faster or slower than comparable household listings. Additionally, we assume there is a hedonic cost of transacting with an iBuyer, capturing, for example, a disutility of transacting online or unfamiliarity with iBuyers, given by the parameter δ_{ib}. A greater disutility directly reduces iBuyer market share. Thus this parameter is disciplined by, other things equal, iBuyer market share.

iBuyer Holding Costs: When iBuyer holding cost is low relative to sellers, they are able to offer higher prices and sell at lower prices, leading to a higher market share. Additionally, a lower iBuyer holding cost means iBuyers can be more patient in selling, leading to longer listing times. When iBuyer maintenance costs increase (which occurs at a rate η), they set a new listing price. Thus, the observed probability that an iBuyer adjusts its listing price from the MLS informs this parameter. The observed size of the price adjustment informs the underlying change in the maintenance cost $m^H - m^L$.

These parameters also influence the relationship between iBuyer market share and the liquidity of the house. 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, reducing their market share. The rate of this decline is increasing in the likelihood and severity of the maintenance cost shock. Quantitatively, we measure the predicted derivative, ∂(iBuyer share)/∂(P(sells in 90 days).

House quality: Lower quality-type houses have an incremental flow cost, $\bar{u}^b$, that reduces the utility flow to the occupant. As a result, these houses trade at lower equilibrium prices. The simultaneous presence of higher- and lower-quality houses in the market introduces cross-sectional variance in house prices. While these quality differences are observable to households, they remain hidden from iBuyers (or econometricians). The empirical counterpart of this price variation is the unexplained residual after performing a hedonic regression of log house prices on observable characteristics. This cross-sectional variance provides information about the incremental flow cost of bad-quality houses: a larger quality gap between good and bad houses results in greater unexplained variance. Note that this parameter is calibrated independently of iBuyer presence and is informed completely by household-to-household transactions. For model tractability, our calibration assumes that all unexplained house price heterogeneity is due to differences in vertical house quality, rather than other idiosyncratic differences such as buyer tastes or bargaining ability that could affect transaction prices. This likely explains why our calibration under-predicts this moment in the data.

The model also assumes that houses can switch between good and bad types with a certain probability, represented by the parameter p_{switch}. Such switching generates time-series variation in house prices for individual properties. A higher probability of switching leads to greater price variation over time. Therefore, the residual variation from a regression of log house prices on observables, controlling for house fixed effects, is informative about the likelihood of type-switching. As above, this parameter is calibrated independently of iBuyer presence and is informed completely by household-to-household transactions.

iBuyers Information Disadvantage and Adverse Selection: iBuyers are subject to asymmetric information, the severity of which is governed by the difference in (endogenous) prices of higher- and lower quality-type houses, and (the inverse of) iBuyers' signal precision, ξ. Most directly, the iBuyer's signal precision impacts the percentage of iBuyer purchases which are ultimately unprofitable: a more imprecise signal means that iBuyers, other things equal, mistakenly purchase low-quality houses thinking they are high quality houses and ultimately sell at a loss. Additionally, in Section III, we show that when iBuyers have a noisier pricing signal, their market share declines. Analogously in the model, 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, ∂(iBuyer share)/∂(Mean pricing error). We map this moment to its empirical analog obtained 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 Calibrated Values

We calibrate the model to the post-iBuyer entry period. Our holding cost estimates indicate that iBuyers have a cost advantage when intermediating for impatient sellers, but not for patient sellers. The annual net flow utility iBuyers receive from holding a house is comparable to that of a matched homeowner. However, their holding costs increase significantly—about 3.5 times higher than those of an impatient unmatched seller—if a maintenance shock occurs. We estimate the annualized flow utility difference between high- and low-quality houses to be approximately \$6,200, or 2.3% of the capitalized house value. This relatively small differential suggests that iBuyers can detect most significant issues with houses or address them contractually. Nevertheless, they remain vulnerable to smaller, harder-to-quantify valuation errors. Such mistakes are rare, with iBuyer valuation noise estimated at ξ=0.034.[28] However, even these relatively small errors and low misclassification rates have significant consequences for iBuyers, given their narrow profit margins and the strategic behavior of sellers when transacting with them.

IV.D Equilibrium Consequences of iBuyer Entry and External Validation

Because our data also contain the period prior to iBuyer entry, we can examine the predictions of the calibrated model with and without iBuyers using a difference-in-differences-style analysis. Because pre-entry quantities were not used in calibrating the model, we use this exercise to further validate our model's ability to fit data. The model predicts that the average time on market decreases from 91 to 86 days once iBuyers enter (Panel A Table 5). After iBuyer entry, majority of iBuyer customers are impatient types (73.1%). Patient households, in contrast, almost exclusively list their homes. The average time to sale declines significantly—by roughly 8% for impatient households. Equilibrium house prices rise by 4.0% after iBuyer entry. Intuitively, when households expect to spend less time in the low-utility transition state, the overall utility flow of homeownership increases. In consequence, buying households are willing to pay more to own houses.

To validate the model, we compare elasticities generated across markets after iBuyers enter using a difference-in-differences-style analysis to those from the model. We instrument for iBuyer entry using the physical characteristics of the housing stock transacting before iBuyer entry and compare pre- and post-iBuyer outcomes. We describe the details of the exercise in Appendix A.9. Consistent with the model's predictions, the results show positive elasticity of price to iBuyer market share, close to the model's prediction within standard error bounds, and a similarly positive relationship for fraction of houses selling within 2 weeks of listing.

The second part of Appendix A.9 performs a more qualitative model validation exercise. Our model predicts that impatient sellers are those that sell to iBuyers and who benefit most from iBuyer entry though swifter closing times. 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.

[28] Note that as we discussed in Section III, iBuyers focus on market segments with relatively easy-to-price homes. The valuation errors could be much higher in markets where iBuyers do not endogenously enter.

Finally, it is worth contrasting our findings with Gavazza (2016) who shows that in a search market with frictions dealers can reduce aggregate welfare because their operations are costly, and they impose a negative externality by decreasing the number of agents' direct transactions.

In our setting, these forces are unlikely to dominate due to two key distinctions. First, information frictions between iBuyers and households mean that households capture most of the rents from intermediation. This flows through to higher prices, which helps homeowners overall. Second, our model features a single iBuyer and so strong competitive pressures do not lead to an "overproduction" of intermediation. In addition, the functional form of our matching function mechanically does not feature iBuyer crowding out, which we justify with the observation that would-be homebuyers pursuing online listings can respond to more listings with more stringent filters, meaning that an additional listing does not reduce the probability of seeing existing listings.

V. Economics, Technology, and Limits of Intermediary Liquidity Provision

Our model highlights three key characteristics of financial intermediaries, beyond balance sheet capacity, that affect their ability to operate in this market. The first force is speed: a listing seller must endure the lengthy process of finding a buyer, while selling to an intermediary is much quicker, typically taking τ days. The second force is information: the need for speed compels intermediaries to rely on algorithmic, often remote pricing—at the expense of nuanced, hard-to-quantify aspects of a home's value that sellers and other local buyers can observe.

Our model captures this through the signal precision, ξ, and the magnitude of valuation errors, R, when such errors occur. The third force is the service flow from the asset: a listing seller continues to live in the house during the sale process, allowing them to derive some utility and perform routine maintenance. In contrast, intermediaries generally leave the house unoccupied, forgoing utility and potentially neglecting maintenance. This difference is reflected in our model by the variation in flow utilities, u^P and u^I, and the increased likelihood of maintenance costs, η, for intermediaries.

This section quantifies the impact of these forces and evaluates how changes in them affect the attractiveness of balance sheet intermediation in the housing market. Additionally, we explore how intermediation may function in other markets by adjusting key parameters, while also examining the role of fixed costs and their influence on iBuyer profitability.

V.A Quantifying the Economic Forces around the iBuyer Business Model: Accuracy, Speed, and Asset Utilization

We begin our analysis by quantifying the three key economic forces identified by our model: (1) the speed of closing, which tends to favor iBuyers, (2) asset utilization during the sale process, which favors traditional sales, and (3) model accuracy, which also favors traditional sales. To assess the quantitative significance of these forces, we simulate a counterfactual scenario where iBuyers' speed, asset utilization, or accuracy are altered, and evaluate the resulting outcomes around the counterfactual iBuyers' performance.

To set the stage, we first establish the baseline results. Figure 2 presents four key outcomes: iBuyer market share (the proportion of transactions involving iBuyers), iBuyer gross spread per transaction (the expected percentage difference between sale and purchase price), the share of iBuyer customers who are impatient sellers, and the share of houses purchased by iBuyers that are lower-quality properties. The baseline results, shown in the first column of each panel, indicate that iBuyers hold a market share of roughly 5% (panel a), with a gross spread of about 3.5% per transaction (panel b). Around 70% of iBuyer customers are impatient sellers (panel c), and approximately 70% of the houses iBuyers purchase are lower-quality properties (panel d). This suggests that while iBuyers attract impatient households due to their speed advantage, they also tend to acquire bad-type houses because of adverse selection. In facilitating transactions, they increase the equilibrium house price as the lifetime value of homeownership—including the eventual transaction—increases in expectation (see Table 5). As we adjust the iBuyer parameters, we analyze how these outcomes shift.

Model Accuracy: iBuyers use algorithmic pricing to determine offer prices, relying on observable property characteristics to set an optimal price. In our model, the iBuyer receives an imperfect signal about the house's quality and sets prices based on that signal. To evaluate the importance of pricing accuracy, we compare the baseline iBuyer with one operating under a significantly less precise signal "Inaccurate iBuyer". Specifically, we reduce the signal's precision, ξ, to 0.5 and recompute the equilibrium. The results are displayed in the second column of the Figure 2 subplots.

In the counterfactual analysis, the iBuyer's market share drops dramatically to approximately 1% (panel a). Interestingly, the expected gross transaction spread increases modestly from 3.5% to 4.5% (Figure 2, panel b). The share of sellers who are impatient also rises slightly, and the share of lower quality-type houses purchased by iBuyers increases to 100% (panel d).[29]

This outcome arises due to the classic "lemons market" unraveling. As the iBuyer's signal deteriorates, it can no longer reliably differentiate between higher and lower quality houses, making it unprofitable to intermediate higher quality homes. Enough lower-quality houses receive favorable signals that any offer attractive to sellers with higher quality homes also draws in too many low-quality sellers, resulting in losses. Since offering prices for higher quality-type houses becomes unprofitable, the iBuyer shifts to a pricing strategy that exclusively attracts lower-quality-type houses. As a result, the ability to intermediate good (higher-quality) houses collapses, leaving iBuyers only transacting with lower-quality houses, rendering the signal entirely uninformative. iBuyer market share declines because they now exclusively transact in lower-quality houses. As iBuyers focus solely on bad-type properties, they also cater more to impatient sellers, causing the impatient share to slightly rise (panel c).

In sum, with a poor signal, iBuyers are effectively limited to transacting with the lowest-quality homes. A more precise signal is crucial for enabling them to intermediate beyond this narrow segment.

Closing Speed: Next, we extend the time between transaction and closing from the baseline fast-paced iBuyer process (15 days) to a slower 30-day period ("Slow iBuyer"). The results, shown in the third column of the Figure 2 subplots, reveal a decline in iBuyer market share to roughly 3.75% (panel a). The profit margin decreases to just below 3%, while the share of impatient sellers falls, and the proportion of lower-quality-type houses purchased rises modestly.

iBuyers ability to profitably purchase houses declines, though the mechanism differs from having a less accurate pricing technology. In the baseline scenario, iBuyers can occasionally purchase higher-quality houses because impatient sellers with such properties are willing to accept a discount in exchange for a faster sale. However, when iBuyers can no longer offer a fast transaction, selling to them becomes less appealing for impatient sellers with good houses. Without the speed advantage, iBuyers attract fewer impatient sellers with higher quality houses and more patient sellers with lower quality houses. This causes the market for higher-quality iBuyer-intermediated houses to partially unravel. As a result, more iBuyer purchases become lower-quality houses. To be able to attract *any* higher-quality asset sellers, iBuyers are forced to earn smaller spreads.

[29] Although the per-transaction margin grows, the reduced market share leads to an overall decline in iBuyer profitability. As iBuyer market share falls overall, their impact on equilibrium house prices also becomes smaller.

Asset Occupancy During the Sale Process: iBuyers leave the house unoccupied while attempting to resell it, which presents two drawbacks. First, potentially valuable consumption flows from the house are forfeited. Second, an unoccupied house is more prone to degradation (e.g., an unnoticed roof leak could cause significant damage). To assess the quantitative impact of this, we simulate an iBuyer transaction where the house remains occupied during the sale process but the owner incurs some modest rental costs in renting out the property ("Renting iBuyer").[30] In this simulation, we (i) set the flow utility of the house to match that of an owner-occupied property reduced by rental costs and (ii) reduce the probability of degradation, η, to zero. The results of this counterfactual are displayed in the fourth column of the Figure 2 subplots.

As the figure shows, allowing for occupancy increases iBuyer market share to roughly 8%. Spreads rise modestly, although seller composition and house quality are largely unchanged versus the baseline scenario. In this counterfactual, iBuyers attract a larger share by modestly increasing their offering prices, and offset this change in profitability by modestly increasing their asking prices. Of course, by raising their asking prices, they increase their time-to-sale, from about 90 to 130 days. iBuyers are willing to make this tradeoff because in the interim sales period, they can earn rental income from the property. Thus, as iBuyers can earn money from renting out the property, they begin to act less as market makers and more as corporate landlords. In fact, in the limit, an iBuyer who earns the same income as a household renter endogenously chooses to hold the property on average for roughly 1,200 days—more than three years.

V.B Key Factors Influencing the Scope of Durable Goods Intermediation

Building on our insights from prior section, we next use our model to explore how intermediation of durable assets might function in other markets by counterfactually adjusting key properties of the asset to simulate different settings. We distinguish these markets based on: (i) the degree of informational asymmetry between intermediaries and end-users, (ii) the level of market liquidity, measured by the arrival rate of potential buyers, (iii) and the fundamental benefits of search, driven by the dispersion of subjective beliefs about asset values. We also explore the role of technology adoption and the potential fixed costs involved in operating the intermediation technology. As before, we compare these results to the

[30] In particular, we assume that the owner captures only 50% of the rental utility. Owner-occupier expenses, like utilities and maintenance, are implicitly accounted for in the net utility flow of housing. However, rental occupants typically exert great wear and tear on the property, and require a property manager to find tenants and manage the occupancy, which leads to the discount. See (https://www.zillow.com/learn/investing-101-estimating-rental-property-expenses/.

baseline iBuyer case, which we interpret as the intermediated market for houses, and analyze the effects of parameter changes around this baseline.

V.B.1 Asymmetric Information and Adverse Selection

We begin by varying the degree of adverse selection in the market by adjusting the noise in the intermediary's signal, ξ, and recomputing the equilibrium. This analysis is presented in Figure 3. In each subplot, the x-axis represents the value of ξ, with the vertical dashed line indicating the estimated baseline. Moving from left to right, the signal becomes less precise, representing increasing asymmetric information. One interpretation of this counterfactual is that it reflects changes in the technology available to the intermediary for assessing the quality of the asset as in our "Inaccurate iBuyer" counterfactual from Figure 2. Alternatively, it can be seen as representing different goods with varying levels of information asymmetry. For example, used cars may be relatively homogenous and easier to price than houses based on observable characteristics, at least relative to households who would otherwise purchase the car directly.

Figure 3, Panel (a), illustrates how the intermediary's market share changes with increasing signal noise. At the estimated signal precision, the intermediary can set prices for assets receiving favorable signals that still attract impatient sellers with higher-quality assets. As the signal becomes less precise, the equilibrium gradually unravels because more lower-quality -type assets receive favorable signals (panel d). Around the estimated value, the direct effect of a noisier signal is that the intermediary must offer lower prices for assets with good signals to remain profitable. This makes selling to the intermediary less appealing for sellers with good assets, leading to a decline in the total volume of intermediated sales. The seller composition shifts from impatient sellers with good assets to both patient and impatient sellers with low-quality assets who happen to receive a favorable signal (panel c). As the intermediary acquires an increasingly lower-quality pool of assets, they are forced to sell at a discount, reducing per-asset profitability (panel b).

Further from the calibrated signal precision, this equilibrium unravels due to adverse selection. Intermediating good-quality assets becomes impossible, as the intermediary is forced to offer prices so low that only buyers with lower-quality assets are attracted. The share of lower-quality assets in the intermediated pool jumps to 100% (panel d). Since only lower-quality-type assets are traded, there is no mispricing. As a result, the share of impatient sellers selling to iBuyers rises discontinuously (panel c). For the same reason, the profit margin widens (panel b) while market share declines (panel a): the intermediary extracts value from the impatient sellers' willingness to transact, boosting profit margins, but can only deal with impatient sellers holding lower-quality type assets, reducing its overall market share.

V.B.2 Market Liquidity

We next adjust the underlying liquidity in the non-intermediated market by varying the matching rate parameter, λ. This analysis is presented in Figure 4 where the x-axis represents the equilibrium time-on-market (in days) as λ is varied. A higher λ results in a shorter time-on-market. The counterfactual equilibria are displayed from left to right, with increasing time-on-market—meaning the markets on the far left are the most liquid, while those on the far right are the least liquid. This counterfactual can be interpreted as either comparing different housing submarkets with varying liquidity or as analyzing markets for different types of goods. For instance, used cars or planes can be generally considered more liquid than homes, as the ability to move these assets across various local submarkets can lead to higher overall market integration. For example, if there is low liquidity for convertibles in Minnesota, the dealer can purchase the convertible and ship it to Texas, where liquidity is higher.

Near our estimated value, indicated by the vertical dashed line, we observe an inverse U-shape for intermediary market share (panel a). As the market becomes highly liquid, impatient sellers place less value on the intermediary's service and are less willing to transact at disadvantageous prices. Consequently, the share of impatient sellers and the intermediary's market share decline in the most liquid markets. Since intermediaries earn spreads by purchasing at lower prices from impatient sellers, their profit margins shrink as these sellers leave the market (panel c). The share of lower-quality assets purchased by intermediaries modestly increases, as acquiring good houses from impatient sellers becomes more difficult (panel a).

As liquidity *decreases* around the estimated value, the intermediary's market share also declines (panel a). In this scenario, lower liquidity means the intermediary takes longer to sell the houses it purchases. Holding an empty house is highly costly for the intermediary, so to justify the extended holding period, it must charge a higher spread by offering lower purchase prices (panel b). As a result, the intermediary's market share decreases. This decline is somewhat mitigated by the fact that, as liquidity worsens, impatient sellers place a higher value on a quick sale. Consequently, the share of impatient sellers rises (panel c). Since some impatient sellers with good assets are willing to accept discounts, adverse selection is mitigated: the increase in the lower-quality asset share is only modest, despite the intermediary's lower offers (panel d).

As markets become highly illiquid, we observe a discrete shift where the equilibrium in which higher-quality transactions with intermediaries collapses (panel d). In this market, the lost occupancy and large carrying costs for intermediaries become so high that they require very large spreads to break even (panel b). To achieve these spreads, offer prices must drop significantly, causing sellers with higher-quality assets to stop transacting altogether. As a result, the intermediary's market share decreases sharply, spreads increase dramatically, the share of impatient sellers jumps (as they are the only ones benefiting from transacting with the intermediary), and only lower-quality assets are traded.

V.B.3 Subjective Value Dispersion

Next we examine the equilibrium impact on intermediation when increasing subjective value dispersion. Subjective value dispersion is the key factor underlying search models, as it drives agents to search more extensively and set higher prices in hopes of finding a buyer willing to pay more. The variation in perceived value hence importantly influences both search intensity and pricing strategies in the market. For instance, cars or planes can be considered more homogeneous by buyers than homes, reducing the incentives to search for better matches.

To investigate the role of this factor for intermediation we symmetrically increase the volatility of the idiosyncratic taste shock, σ_m in Figure 5. Panel (a) plots the intermediary market share against the shock volatility relative to the estimated value, indicated with the vertical dashed line. There are two partially offsetting forces through which subjective value dispersion impacts intermediation. On one hand, high value dispersion is good for sellers *in general*, especially the patient ones. They are more likely to meet buyers with idiosyncratically high valuations giving sellers increased market power. They take advantage of market power by charging higher prices and waiting longer to sell. Because intermediaries are somewhat impatient sellers due to lack of occupancy and maintenance cost, this benefit primarily accrues to patient sellers. Through this force, increased subjective valuation dispersion harms intermediaries who would transact with patient sellers. On the other hand, subjective value dispersion dampens the importance of adverse selection. iBuyer can make up for an objective valuation mistake by selling the house to a buyer with a high subjective valuation. Thus, this force means that greater subjective valuation helps iBuyers.

These forces play out in the inverse-u shape of intermediation market share shown in panel (a). To the left of the estimated value, intermediary market share decreases. A homeowner with a lower-quality assets but a good signal is more likely to sell to an iBuyer because the gain from taking advantage of the iBuyer's mispricing is greater than the now-small potential gain from finding a buyer with a high subjective valuation by patiently selling through a listing. In keeping with this logic, more patient sellers sell to intermediaries (panel c), again, because they would rather sell their lower-quality assets to intermediaries rather than wait to find a buyer with a high subjective valuation. iBuyers endogenously respond by pricing less aggressively to partially offset this increased adverse selection.

To the right of the estimated value, intermediary market share also declines (panel a). Here, the first force, where the benefit of high subjective value dispersion is mostly captured by patient sellers, dominates. When buyers have a large amount of subjective valuation volatility, sellers—especially patient sellers who can afford to wait to meet a buyer with a high subjective valuation—are at a large advantage. In consequence, patient sellers choose to list themselves while impatient sellers remain with iBuyers. Thus, the composition of households selling to iBuyers becomes more impatient on average (panel c). As the patient sellers exit the market, the overall intermediary market share declines (panel a). This has a less pronounced effect on iBuyer profitability and mispricing, however, because while iBuyers have a smaller market from which to purchase from, a major source of adverse selection—patient sellers with good signals but lower-quality assets—largely exit the market to sell on their own.

V.B.4 Technology Adoption and Fixed Operating Costs

We conclude the analysis in this section by shedding light on the potential scope of technology adoption and the role of fixed operating costs.

Technology Adoption Resistance and Trust

Our calibration suggests that, on average, sellers experience disutility from interacting with iBuyers—a somewhat surprising result, given that the home-selling process is typically viewed as unpleasant. This disutility may reflect psychological, cognitive, or informational barriers to adopting new technology, or the fact that human agents are particularly effective at establishing trust—something more difficult to achieve through an online interface. Our first counterfactual explores the possibility that, over time, intermediation through iBuyers becomes more familiar and trusted. Formally, we set the average disutility from interacting with iBuyers to zero. This counterfactual can be viewed as quantifying an upper bound on the adoption of intermediation technology, representing its total addressable market share.

As Appendix A.11 shows, the share of intermediated transactions rises significantly and steadily, reaching up to about 25% as the average hedonic disutility of using intermediary approaches zero (panel a). Panel (b) demonstrates that the gross spread per transaction also increases as the disutility decreases: sellers are willing to pay more for a service that becomes more "convenient." Panels (c) and (d) reveal that the composition of sellers (patient vs. impatient, or good vs. bad type) does not change significantly. Instead, as the service becomes more convenient, participation increases proportionally across all seller types relative to their baseline participation rates.

The 25% market share estimate applies to markets where the iBuyers chose to enter. These are markets with assets that are relatively easy to price, limiting asymmetric information and where asset liquidity is relatively high. Appendix A.12 studies the effect of removing technology adoption frictions as asymmetric information (signal noise), market illiquidity, and subjective value dispersion increase. Even when there are no adoption frictions, assets that are relatively difficult to price, asymmetric information and the associated adverse selection lead to a pronounced decline in the total addressable market share of intermediaries (from about 25% to less than 15%). Similarly, decreasing asset liquidity progressively reduces the intermediary share towards zero. On the other hand, and consistent with our prior insights, subjective value dispersion plays a relatively smaller role in affecting intermediary market share.

Overall, even if technology adoption frictions disappear, asymmetric information arising from instantaneous algorithmic pricing, and fundamental asset liquidity can severely limit the scope of dealer intermediation of housing and other durable assets.

Entry Cost: Technology and Operation

Up to this point, our analysis has assumed that iBuyers have entered a market and that any cost developing the pricing technology are sunk. Formally our analysis was focused on the intensive margin choices of iBuyers. Below, we conduct a simple assessment of the potential profitability of the iBuyer in the presence of fixed operating costs, for example, cost of building, maintaining and updating the hardware and software for algorithmic pricing, the user interface as well as corporate overhead, which can include factors such as management compensation, and marketing efforts.

Given that iBuyers were still a relatively new technology during our data period, we assume that adoption resistance diminishes over time. In this scenario, sellers no longer experience disutility from using iBuyers, allowing these intermediaries to capture up to 25% market share in segments characterized by relatively liquid and easily priced homes—the total addressable market in this space. Because fixed costs are not directly observable, we assume they amount to 2% of the home acquisition price when iBuyers operate at this scale, consistent with projections from iBuying firms.[31]

In Appendix A.13 we show that a market share of 6.6% is sufficient for iBuyers profits from housing sales to exceed the fixed cost of operation. Intuitively, at lower market shares, this fixed cost will be amortized over proportionally smaller share of homes.[32] Keeping other

[31] See for example "Zillow Investor Presentations, May 2020."
[32] With a 1% market share, the operating cost will be roughly 25% of the value of homes acquired in a given year, and with a 2% market share, it will be about 12.5%. Operating reports from iBuyers during their expansion phases generally align with this assumption. For instance, reported corporate operating expenses were 27% of

baseline parameters the same, the gross iBuyer spread covers the fixed operating cost at the market share of 6.6%. Achieving sufficient scale relatively quickly is therefore an important barrier to iBuyer profitability. This may also help explain why Opendoor, the largest iBuyer that achieved such market share has remained operational as of 2025.

V.B.5 Summary and Implications for Durable Goods Markets

Our analysis suggests that dealer intermediation in the housing market is difficult. On the other hand, such intermediation of other durable goods such as cars and airplanes is substantial —approximately 50% for cars (Cox Automotive/AutoTrader) and around 60% for business planes (Gavazza 2016). In housing, the key trade-off in facilitating effective liquidity provision lies in balancing the need for quick transactions with the potential loss of valuation accuracy, which can increase the risk of adverse selection for the intermediary. iBuyer "style" technology offers a partial solution by enabling fast transactions with limited information loss. However, this approach is most effective in markets where assets are relatively liquid and easy to value. While iBuyer technology does enhance liquidity, its impact is most notable in segments where liquidity is already abundant, thereby limiting its broader effectiveness in addressing trade frictions across all durable goods markets.

These insights also help explain variation in the extent of dealer intermediation across durable goods markets, particularly between housing and other sectors. Many durable goods—such as cars or airplanes—are more homogeneous than houses, making them easier to price. In these markets, the key informational asymmetry is the wedge between the intermediary and *other buyers* who transact in the brokered market. For example, Carvana, an online used car dealer analogous to iBuyers, likely has similar information about vehicle quality and value as the average car buyer.

Several additional factors make intermediation more feasible in non-housing durable goods markets. First, mobility: many of these goods can be physically moved across regions, allowing intermediaries to arbitrage geographic differences in liquidity. A dealer who purchases a car or aircraft in a low liquidity market can relocate it to a more liquid one if the expected gains outweigh transport costs. Second, the opportunity cost of holding inventory is lower. While an unoccupied home represents lost consumption value during resale, a car or plane sitting idle on a dealer lot or tarmac does not provide consumption flows either. However, because these assets depreciate primarily through use, not time, the cost of holding them is relatively lower.

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their house purchases in 2019 when their market share was below 1%, and decreased to about 11% when their market share increased to above 2% in 2021 (based on Zillow's quarterly reports).

Taken together, these features—greater homogeneity, reduced informational frictions, geographic mobility, and lower holding costs—make dealer intermediation more viable in markets for goods like cars and planes. Conversely, our framework would predict even lower intermediation levels in markets where assets are less liquid and harder to price than houses, such as fine art. Consistent with this, the art market features very limited dealer intermediation.[33]

V.C Out of Sample Events: COVID-19 Pandemic and the Exit of Zillow Offers

We conclude this section by discussing two recent out-of-sample events through the lens of our model. First is the COVID-19 pandemic, which occurred after our sample period. During the early stage of the COVID-19 pandemic, social distancing measures dramatically decreased transactions in the traditional listing market. Because iBuyers' business model limits physical contact with potential sellers who do not have to list their homes, one might have expected this to be a boon period for iBuying. In fact, most iBuyers temporarily suspended their operations. Our model explains why: Social distancing reduces overall market liquidity considerably, limiting iBuyers' ability to intermediate. As liquidity increased after the early part of the pandemic, iBuyers resumed their activity.

The second is the period of hot and very liquid housing markets post Covid-19 pandemic. Our analysis *predates*[34] a period when one of the main iBuyers, Zillow, decided to exit the iBuying market in November 2021 due to the losses incurred on house transactions during the hot market following the pandemic. Because house prices were trending upward in most markets during 2021, a balance sheet of owning homes should naturally generate a profit not a loss. We argue that an expansion of activity during the very hot housing market of 2021 was expected to be unprofitable for iBuyers from the perspective of our model, because the conditions were ripe for extensive adverse selection.

Due to increased demand for homes in 2021 and limited supply, the traditional selling channel became significantly faster in 2021, limiting the value of iBuyers services. According to Zillow data,[35] in June 2021 roughly 67% of U.S. metro areas saw the median days to pending fall below 30, in contrast to only 5% of metro areas in June 2020. Appendix A.14 shows these statistics between 2018 and 2022. As discussed in Section V.B, when houses trade sufficiently

[33] Auction houses like Christie's and Sotheby's primarily facilitate the sale of high-end art through auctions. While they do occasionally buy and sell art for their own accounts, this is less common. Their main business model involves charging commissions for organizing and conducting auctions rather than directly purchasing assets for resale.
[34] See, for example, the working paper draft from December 2020.
[35] https://www.zillow.com/research/data/

quickly in a traditional selling channel, iBuyers lose some of their comparative speed advantage resulting in decreased demand from impatient sellers with good houses, resulting in adverse selection. Moreover, the ability to accurately price homes may have deteriorated late 2021 according to many market observers due to the pandemic-era housing boom and growing uncertainty regarding the future state of the housing market. Again, our framework shows that challenges in accurately pricing homes during rapidly changing and uncertain economic environments lead to increased adverse selection. Both forces should lead intermediaries to reduce market shares. Consistent with this view, unlike Zillow, other iBuyers appeared to reduce their acquisitions during late 2021.[36] Through the lens of our model, the conditions in late 2021 were not favorable for iBuyers, so the continued expansion of Zillow's iBuying activity resulted in losses, and ultimately in its exit.

VI. Discussion and Conclusion

In this paper, we use the growth of iBuyers as a lens to better understand why there is so little balance sheet intermediation in the housing market, despite the seemingly large demand for such services. We show that iBuyers act as liquidity providers, buying low and selling high, and carry properties in their inventory for a short period of time. As in the case of online fintech mortgage originators, consumers appear to value the immediacy of sale to iBuyers and are willing to sell their properties to them at a considerable discount. We also document considerable limitations to liquidity provision by dealer intermediaries in such markets. They can only offer immediacy to sellers by algorithmic pricing based on hard information. Therefore, they do not enter market segments with difficult-to-value homes to limit the scope of adverse selection. Moreover, iBuyers tend to focus on fairly liquid properties that can be resold relatively quickly.

We rationalize these findings within a search-based housing trading model into which we introduce a balance sheet intermediary subject to adverse selection. Our model highlights why liquidity provision in real estate markets has been limited, despite its high potential benefits. First, unlike other sellers, intermediaries forgo valuable durable consumption flows while listing. Hence their technology only works in markets that already sufficiency liquid allowing a fairly quick resale. Second, intermediaries are subject to adverse selection, which significantly limits their expansion in difficult-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. A low-tech intermediary without these simultaneous abilities would

[36] https://www.latimes.com/business/story/2021-11-03/ibuyers-zillow-opendoor-home-sales-southern-california-housing-institutional-investors

achieve a negligible market share, which explains why prior to iBuyer entry, intermediation in the housing market was rare. More broadly, we provide a tractable quantitative model with an intermediary subject to adverse selection, which can be used to study balance sheet intermediation of consumption goods beyond housing.

Our analysis also has broader implications for balance sheet intermediation across durable goods markets. We show that assets that are illiquid and difficult to price experience much less intermediation, especially if underutilized during the process. This may explain why housing markets have only recently seen limited intermediation, facilitated by technological advances in valuation accuracy and transaction speed through online platforms. In contrast, goods like cars and airplanes are more homogeneous and easier to price, and their mobility reduces geographic segmentation, boosting liquidity. These factors help explain why intermediation in these markets has reached much higher levels—around 50% market share—compared to housing.

Overall, our analysis suggests that intermediation in the housing market presents unique challenges compared to other consumer durable markets. These challenges stem primarily from significant informational asymmetries that current technology struggles to fully overcome, as well as the immobility of housing, which reduces overall market liquidity. Given the housing market's size and its central role for households and the broader economy, our findings highlight these frictions as key obstacles to effective intermediation of durable goods.

We conclude by making a few observations. First, it is possible that developing better pricing algorithms and collecting new data could considerably expand the range of properties that can be intermediated. Moreover, iBuyers do not yet appear to have a technological advantage in reselling their houses, but developing this technology could dramatically expand their ability to intermediate. Second, we analyze the growth of iBuyer market shares during good times in the housing market (2013–2018). It is unclear how viable dealer intermediation would be during an economic downturn accompanied by a decline in house prices. Our model suggests that an increase in expected time to resell the property and challenges in accurately pricing homes during rapidly changing economic environments may considerably limit intermediary liquidity provision. On the other hand, an economic downturn could increase the share of homeowners that value the convenience of a quick sale, making liquidity provision more valuable. We leave this business cycle analysis for future research.

We also note that in our model, we focus on the case of a single iBuyer. The competition among iBuyers could intensify adverse selection, creating potential first-mover advantages in these markets and paving the way for a natural local monopoly. Interestingly, we observe that, following an initial period of competition among multiple iBuyers, local markets are increasingly becoming dominated by a single player, lending support to this argument.

Finally, other alternatives to balance sheet intermediation could serve a similar purpose. For example, households could use bridge financing during the period between selling their home and acquiring a new one. However, bridge financing does not address households' low net worth and financial constraints. In other words, the same frictions that prevent households from purchasing and financing two homes through traditional lenders likely limit the effectiveness of bridge financing. We leave the analysis of other liquidity provision methods in the housing market for future research.

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Table 1: Summary Statistics

This table shows summary statistics for the main datasets used in the paper: the transaction deeds records from CoreLogic (Panel A), and the MLS listings data from ATTOM (Panel B). Data are from Phoenix, Orlando, Dallas, Gwinnet County, and Las Vegas, 2013-2018. In Panel A, *Sale price* is the sale price in thousands, *Land sq ft* is the assessed land square footage, *House age* is the age of the house in years. *iBuyer buyer* and *iBuyer* seller indicates when an iBuyer is buying or selling the property, respectively. *iBuyer hold days* is the number of days the iBuyer holds the property before reselling among completed iBuyer transactions. In 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." *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). *iBuyer*, *flipper*, and *Other*, refer to the identity of the lister; a is an absentee owner who has owned the house for less than one year before listing.

Panel A: Transaction Data (CoreLogic)

Variable	N	Mean	S.D.	5%	25%	50%	75%	95%
Sale price (k)								
iBuyer buyer	5,887	251	194	146	191	230	281	390
iBuyer seller	7,384	269	206	164	208	245	295	398
All others	885,451	280	372	82	156	218	305	582
Land sq ft								
iBuyer buyer	6,003	7,094	3,880	2,800	5,227	6,580	8,073	12,324
iBuyer 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 buyer	5,978	20	12	4	12	17	28	45
iBuyer seller	7,431	21	12	5	12	17	29	46
All others	954,313	27	19	6	13	22	40	63
iBuyer hold days	3,958	130	133	38	70	105	148	273

Panel B: Listing Data (MLS/ATTOM)

Variable	N	Mean	S.D.	5%	25%	50%	75%	95%
First list price (k)								
Other	1,384,235	319	215	109	185	260	379	750
iBuyer	2,158	240	67	165	197	228	267	364
Flipper	106,714	296	206	94	164	244	359	699
Mentions renovations								
Other	1,384,235	0.104	0.305	0	0	0	0	1
iBuyer	2,158	0.023	0.149	0	0	0	0	0
Flipper	106,714	0.288	0.453	0	0	0	1	1
Has sale								
Other	1,384,235	0.602	0.490	0	0	1	1	1
iBuyer	2,158	0.823	0.381	0	1	1	1	1
Flipper	106,714	0.566	0.496	0	0	1	1	1
Days on market								
Other	833,190	91	84	25	43	63	107	247
iBuyer	1,777	86	64	28	42	66	111	221
Flipper	60,440	88	77	25	43	66	106	224

Table 2: iBuyer Transaction Behavior

This table examines iBuyer listing behavior (Panel A) and transaction behavior (Panel B). *Lists on MLS* is a zero-one indicator for whether an MLS listing exists within one-week of the CoreLogic transaction. *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. *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)--(2) use CoreLogic data merged with MLS. Columns (3)-(5) and (7) use all MLS listings; (6) and (8) use MLS listings that result in sales. All specifications cover 2013-2018. Columns (1)-(6) are linear; (7)-(8) are Cox Proportional Hazard Rate. *iBuyer buyer* and *iBuyer seller* are indicators for whether the purchaser or seller in the transaction is an iBuyer, respectively. *Flipper* is a non-iBuyer lister who purchased the house within one year of listing. All columns include house hedonic controls including square footage, whether the house is multistory, and house age. The linear models include zip times quarter fixed effects. *Flippers* are treated as non-iBuyer buyers/sellers in Columns (1)-(2). Panel B uses the CoreLogic data to examine log transaction prices. Columns (1-3) and (4-6) examine iBuyer buyers and sellers, respectively. House hedonic controls are as above. Columns (1), (3), (4), and (6) use zip times quarter fixed effects. Columns (2) and (5) include zip-year fixed effects. Columns (1), (2), (4), (5) cover 2013-2018. Columns (3) and (6) cover 2018 only. Standard errors are shown in parentheses.

Panel A: iBuyer Listing Behavior

Specification	Linear	Linear	Linear	Linear	Linear	Linear	Hazard	Hazard	Linear
Dependent variable	Lists on MLS	Lists on MLS	Log list price	Mentions renovations	Leads to sale	Days on market	Days on market	Days on market	Sale-to-list price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
iBuyer buyer	-0.274	-	-	-	-	-	-	-	-
	(0.006)	-	-	-	-	-	-	-	-
iBuyer seller	-	0.127	0.023	-0.057	0.136	27.115	0.309	-0.019	-0.005
	-	(0.005)	(0.007)	(0.007)	(0.009)	(1.700)	(0.024)	(0.024)	(0.001)
Flipper seller	-	-	0.008	0.142	-0.012	2.180	-0.080	-0.069	-0.002
	-	-	(0.001)	(0.001)	(0.001)	(0.317)	(0.005)	(0.005)	(0.0002)
Hedonics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip-qtr FE	Y	Y	Y	Y	Y	Y	N	N	Y
CoreLogic	Y	Y							
MLS (All)			Y	Y	Y		Y		
MLS (Sales)						Y		Y	Y
Observations	809,806	809,806	1,348,518	1,348,518	1,348,518	800,182	1,348,518	800,182	789,168
R^2	0.171	0.169	0.748	0.176	0.357	0.392	0.042	0.049	0.176

Panel B: iBuyer Purchase Discount and Sale Premium

	Dependent Variable: log(Sale price)					
	(1)	(2)	(3)	(4)	(5)	(6)
iBuyer buyer	-0.031	-0.026	-0.026	-	-	
	(0.004)	(0.004)	(0.005)	-	-	
iBuyer seller	-	-		0.015	0.019	0.008
	-	-		(0.003)	(0.003)	(0.004)
Sample	2013-2018	2013-2018	2018	2013-2018	2013-2018	2018
Hedonics	Y	Y	Y	Y	Y	Y
Zip-Quarter FE	Y	N	Y	Y	N	Y
Zip-year FE	N	Y	N	N	Y	N
Observations	773,709	773,709	113,297	773,709	773,709	113,297
R^2	0.745	0.738	0.723	0.745	0.738	0.723

Table 3: iBuyer Technology: Determinants of Pricing and Limits of Technology

Panel A 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. It 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. Rows contain, in order, no fixed effects, zip fixed effects, quarter fixed effects, zip and quarter fixed effects, and finally 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 B shows the regression of whether an iBuyer purchases the house on predicted pricing errors, $\widehat{|e|}_{izt}$ 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. Columns (1)-(3) use the full testing sample; columns (4)-(6) examine only 2018 transactions. 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) and (4) to (2), (3), (5), and (6). *Flippers*, as defined previously, are treated as non-iBuyer individuals because they are not observable in the CoreLogic data. Standard errors, clustered at the property level, are shown in parentheses.

Panel A: 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

Panel B: Limits to iBuyer Technology: Easy-to-Price and Liquid Homes

	Dependent variable:					
	iBuyer buyer (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\lvert e \rvert}_{izt}$	-4.713	-	-5.227	-9.360	-	-7.962
	(0.242)	-	(0.474)	(0.840)	-	(1.454)
$\widehat{SellsWithin90Days}$	-	1.919	1.582	-	4.235	3.713
	-	(0.192)	(0.199)	-	(0.549)	(0.577)
Sample		2014-2018			2018	
Zip x Quarter FE	Y	Y	Y	Y	Y	Y
Observations	557,172	259,772	259,772	96,273	50,725	50,725
R^2	0.027	0.030	0.031	0.025	0.028	0.028

Table 4: iBuyer Gross Returns and Ease-of-Pricing and Liquidity Measures

This table shows how iBuyer gross returns and holding period relate to ease-of-pricing and liquidity measures using Corelogic transaction data from 2013-2018. 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.

	Dependent variable:					
	$Gross\ Return^{Ann}$			Holding period (years)		
	(1)	(2)	(3)	(4)	(5)	(6)
iBuyer	0.779	0.070	0.605	-0.806	-0.375	-0.764
	(0.057)	(0.067)	(0.096)	(0.044)	(0.057)	(0.082)
$\hat{e}^2$	0.888	-	0.856	-0.546	-	-0.522
	(0.063)	-	(0.118)	(0.056)	-	(0.104)
$\widehat{SellsWithin90Days}$	-	0.088	0.112	-	-0.029	-0.042
	-	(0.051)	(0.051)	-	(0.051)	(0.051)
iBuyer x $\hat{e}^2$	-1.885	-	-2.076	1.489	-	1.534
	(0.190)	-	(0.297)	(0.143)	-	(0.252)
iBuyer x $\widehat{SellsWithin90Days}$	-	0.357	0.530	-	-0.091	-0.230
	-	(0.118)	(0.124)	-	(0.099)	(0.104)
Zip x Quarter FE	Y	Y	Y	Y	Y	Y
Observations	46,747	17,540	17,540	46,747	17,540	17,540
R^2	0.215	0.274	0.278	0.241	0.316	0.318

Table 5: Model Calibration and Fit

This table provides details of the model calibration. Panel A shows targeted moments in the data and calibrated model. Data values with "*" are calculated over the entire sample period, 2013-2018. Other values are calculated in 2018. 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	Model
Market characteristics		
List price ($k)	265	265
HH time on market (days)	91.0	90.9
XS price variation (%)*	18.1	9.43
TS price variation (%)*	9.89	8.13
Impatient price delta (%)*	5.65	2.89
Impatient time on market delta (days)*	56.5	56.4
iBuyer Characteristics		
iBuyer market share (%)	4.78	5.09
iBuyer time on market (days)	97.0	97.0
iBuyer gross spread (%)	3.44	3.27
iBuyer buy discount (%)	2.64	5.66
Share unprofitable (%)*	12.78	7.92
d(iB share)/d(P(sells in 90 days))	0.033	0.024
d(iB share)/d(Pricing error)	-0.045	-0.086
P(iBuyer cut prices) (%)	56.20	37.22

Panel B: Parameters Calibrated Externally / Normalizations

Parameter	Description	Value	Source
ρ	Discount rate	0.050	Guren (2018)
μ	Unmatching rate	0.152	Census
ϕ_R	Probability needs renovation	0.109	Fraction of listings mentioning renovation
p_I	Probability impatient	0.500	Definition
τ	iBuyer closing time (days)	15	Industry reports
$\bar{u}$	Matched flow utility	15	Normalization for numerical performance

Panel C: Parameters Calibrated by Method of Moments

Parameter	Description	Value
$\Delta\underline{u}$	Change in unmatched utility (patient, ($k/dt))	36.21
$\underline{\underline{\Delta u}}$	Change in unmatched utility (impatient vs. patient, ($k/dt))	40.15
δ_{ib}	Hedonic preference against selling to iBuyer	14.76
m_l	iBuyer baseline maintenance cost ($k/dt)	0.266
η	iBuyer house depreciation arrival rate (rate/dt)	1.66
$m_h - m_l$	iBuyer flow cost increase from depreciation ($k/dt)	146.77
λ	Matching technology (rate/dt)	724
λ_{ib}	iBuyer matching scalar (unitless)	0.98
ξ	iBuyer signal noise	0.034
u^b	Additional flow cost of bad house ($k)	6.21
σ_m	T1EV variance on house preference	9.77
σ_i	T1EV variance on iBuyer preference	6.35
p_{switch}	Probability that house type changes	0.24

Table 6: Impact of iBuyer Entry on Equilibrium Outcomes

This table shows the comparison between the iBuyer and non-iBuyer equilibria for selected outcomes. Panel A shows how prices and turnover changes after iBuyer entry. *All transactions* include household-to-household and iBuyer transactions (weighted by their respective shares). *Household-to-household* exclude transactions directly involving iBuyers. Panel B shows how consumer welfare (measured by household value functions) change after iBuyer entry. The *unconditional average* weights household value functions by the time spent in each state. All other rows are state-contingent value functions. Panel C shows equilibrium outcomes for patient versus impatient sellers.

Panel A: House prices and transaction times

	% change vs. No-iBuyer equilibrium
Price (all transactions)	4.0%
Price (Household-to-household)	4.4%
Time on market (all transactions)	-5.5%
Time on market (Household-to-household)	-0.4%

Panel B: Consumer welfare (value functions)

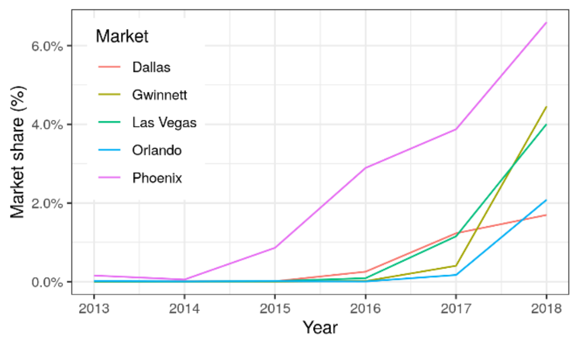
	% change vs. no-iBuyer equilibrium
Unconditional average	4.5%
Matched (good house)	4.1%
Matched (bad house)	4.9%
Patient seller (good house)	3.9%
Patient seller (bad house)	4.6%
Impatient seller (good house)	4.1%
Impatient seller (bad house)	4.6%
Buyer	0.0%

Panel C: Shares and Time on Market by Seller Type

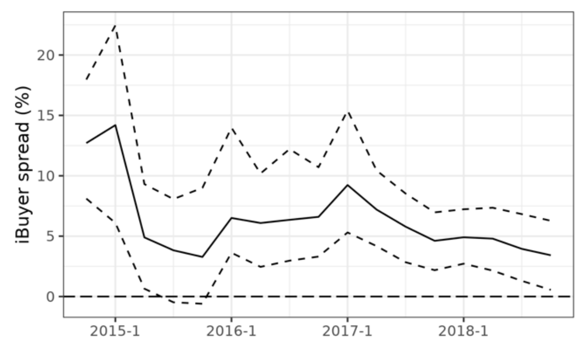
	No-iBuyer equilibrium	**iBuyer equilibrium**	**% change**
iBuyer share of patient sellers	-	2.7%	-
iBuyer share of impatient sellers	-	7.5%	-
Impatient share of iBuyer customers	-	73.2%	-
Time on market (patient sellers)	119.1	114.2	-4.1%
Time on market (impatient sellers)	62.7	57.7	-8.1%

Figure 1: iBuyer Market Shares, Gross Returns, and Asset/Market Characteristics

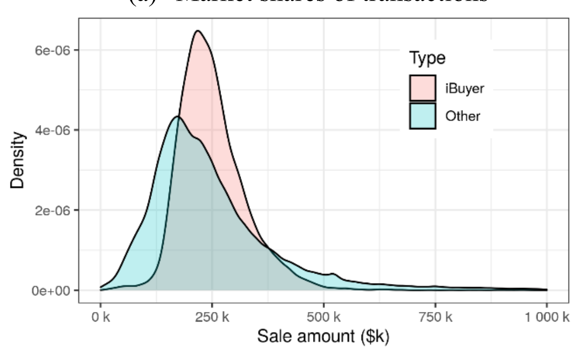
Panel (a) shows iBuyer market share in buying or selling transactions across five large markets: Dallas, Texas, Gwinnett County, Georgia, Las Vegas, Nevada, Orlando, Florida, and Phoenix, Arizona using CoreLogic data. Panel (b) shows the median realized gross return (spread), that iBuyers earn on purchased and sold homes with 25% and 75% bands shown. Panels (c) and (d) show the distribution of house prices and ages for iBuyers (red) and other owners (blue). Panels (e) and (f) show iBuyer market share across our two proxies for ease of algorithmic pricing and liquidity. iBuyer market share is the fraction of homes purchased by iBuyer. In Panel (e), predicted pricing error is the absolute predicted residual based on house hedonics. In Panel (f), 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. We use CoreLogic transaction data and MLS data from ATTOM Data covering period between 2013 and 2018.



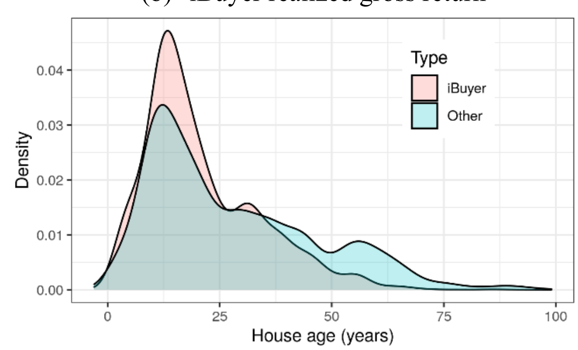
(a) Market shares of transactions



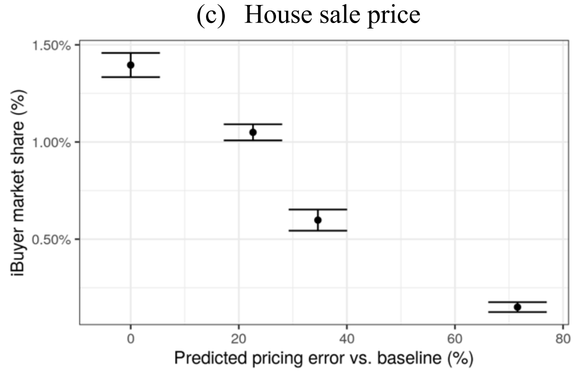
(b) iBuyer realized gross return



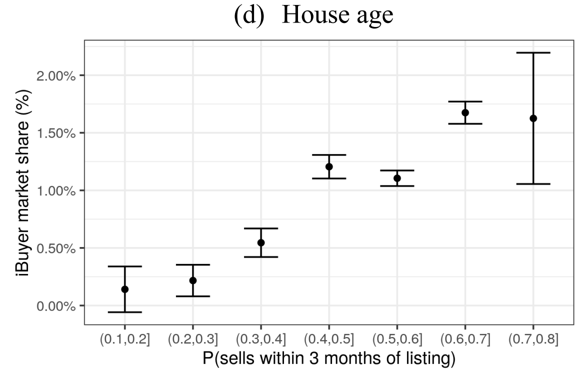
(c) House sale price



(d) House age



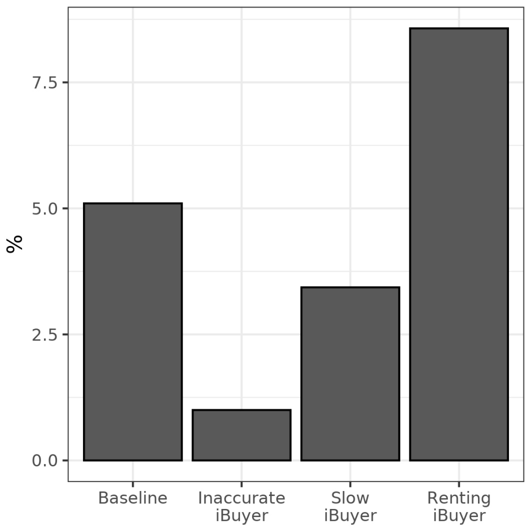
(e) Pricing error and iBuyer market share



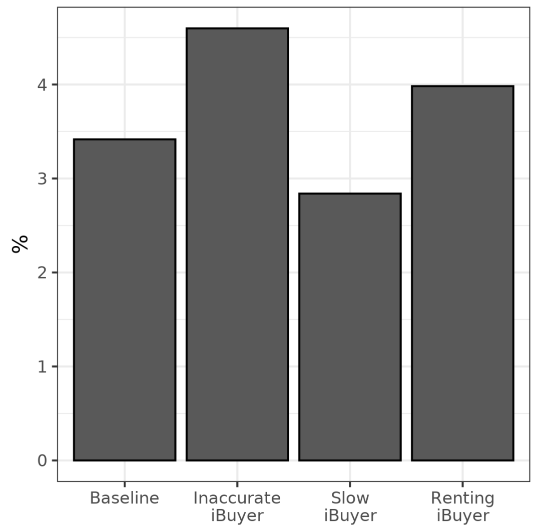
(f) Liquidity and iBuyer market share

Figure 2: Inaccurate, Slow, and Short-Term Rental iBuyers

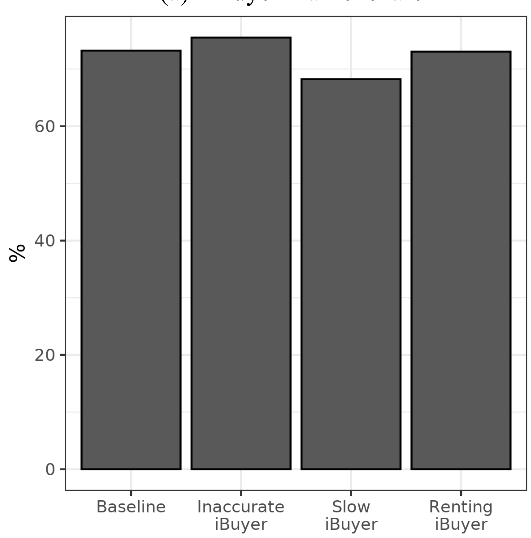
This figure shows iBuyer outcomes when varying key economic forces. *Baseline* is from the estimation. *Inaccurate* is an iBuyer with worse valuation technology ($\xi = 0.50$). *Slow* is an iBuyer with a slower closing speed (30 days rather than 15 days). *Renting* is an iBuyer that is able to rent the house to a (patient-equivalent) occupant. Panel A shows the iBuyer share of transactions. Panel B shows the iBuyer per-transaction gross spread. Panel C shows the share of sellers to iBuyers who are impatient sellers. Panel D shows the low-quality share of iBuyer purchases.



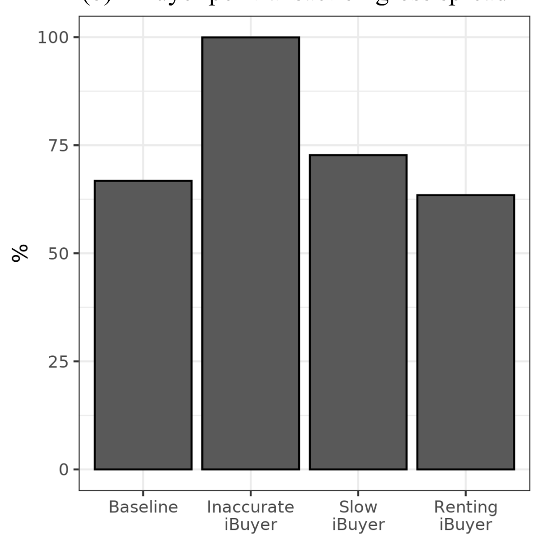
(a) iBuyer market share



(b) iBuyer per-transaction gross spread



(c) Impatient share of iBuyer customers



(d) Lower quality share of iBuyer purchases

Figure 3: Key Factors in Durable Good Intermediation: Algorithmic Pricing Precision and Adverse Selection

This figure shows how iBuyer outcomes vary as the noise in the iBuyer's valuation technology, ξ, increases. The vertical dashed line shows the baseline estimated signal precision. 0 indicates a perfect signal, with noise increasing from left to right. Panel A shows the iBuyer share of transactions. Panel B shows the iBuyer per-transaction gross spread (average sale price minus purchase price). Panel C shows the share of sellers to iBuyers who are impatient sellers. Panel D shows the share of houses that iBuyers buy that are of lower-quality types.

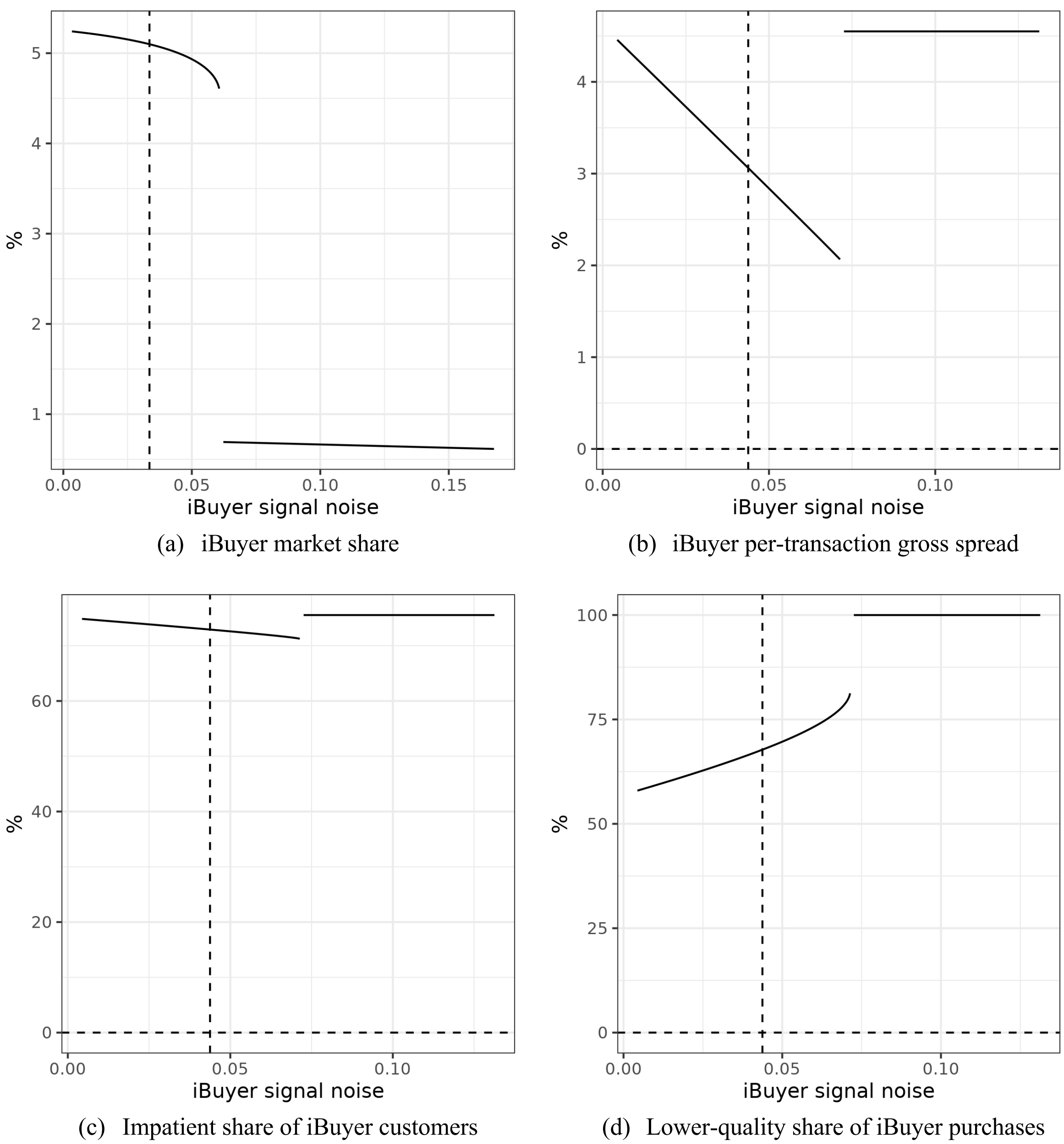
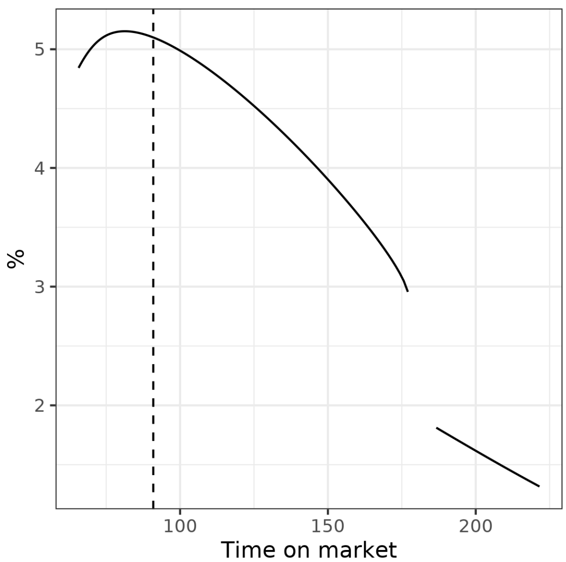
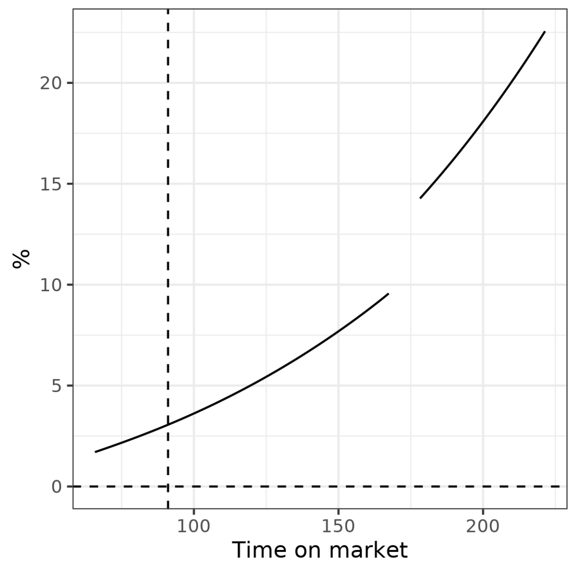


Figure 4: Key Factors in Durable Good Intermediation: Market Liquidity

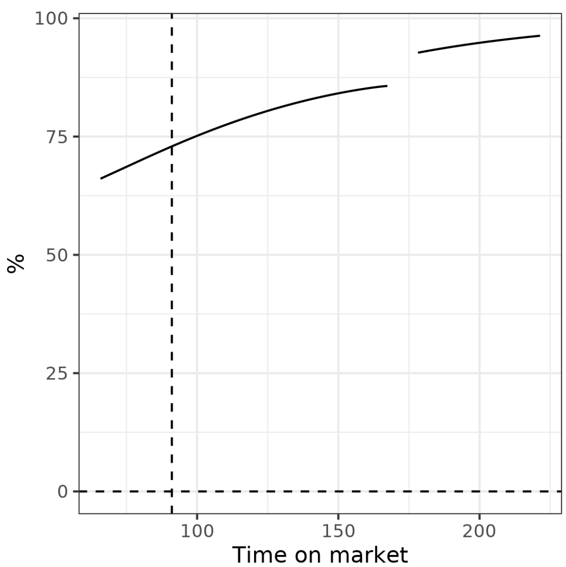
This figure shows how iBuyer outcomes vary as the average time-on-market (in days, for all transactions) varies by changing the matching rate λ. The vertical dashed line shows the baseline time on market. Market liquidity decreases (time on market increases) from left to right. Panel A shows the iBuyer share of transactions. Panel B shows the iBuyer per-transaction gross spread (average sale price minus purchase price). Panel C shows the share of sellers to iBuyers who are impatient sellers. Panel D shows the share of houses that iBuyers buy that are of lower-quality types.



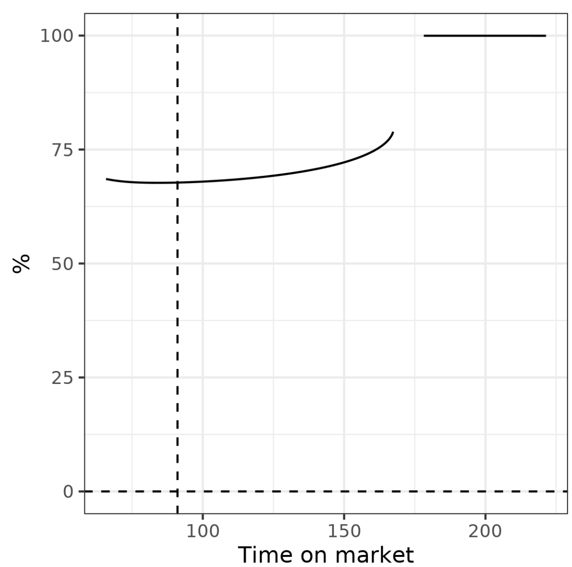
(a) iBuyer market share



(b) iBuyer per-transaction gross spread



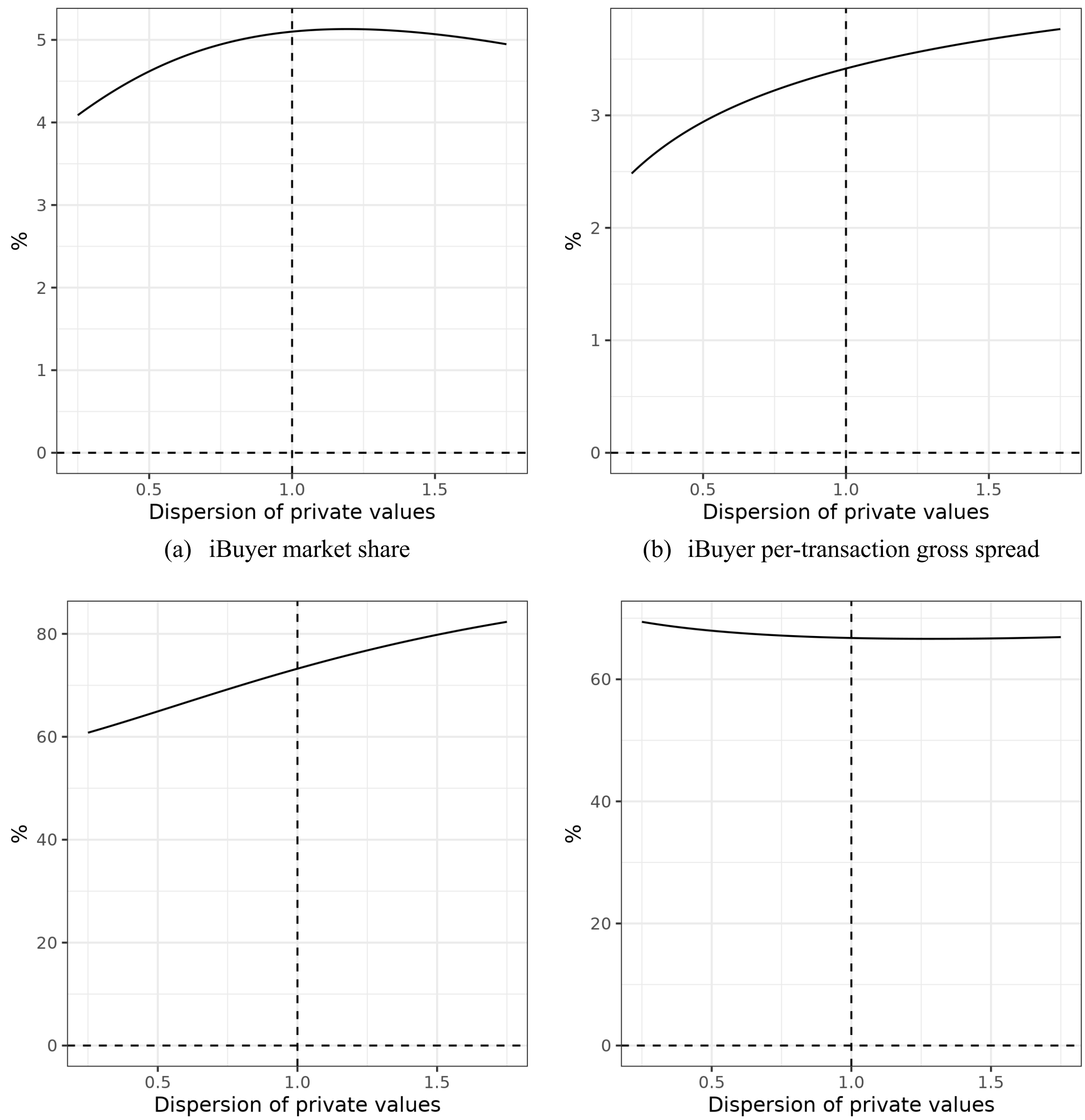
(c) Impatient share of iBuyer customers



(d) Lower-quality share of iBuyer purchases

Figure 5: Key Factors in Durable Good Intermediation: Dispersion of Private Values

This figure shows how iBuyer outcomes vary as the dispersion in private valuation of goods changes across individuals. The vertical dashed line shows the baseline dispersion of private values. Dispersion of private values increases from left to right. Panel A shows the iBuyer share of transactions. Panel B shows the iBuyer per-transaction gross spread (average sale price minus purchase price). Panel C shows the share of sellers to iBuyers who are impatient sellers. Panel D shows the share of houses that iBuyers buy that are of lower-quality types.



(a) iBuyer market share

(b) iBuyer per-transaction gross spread

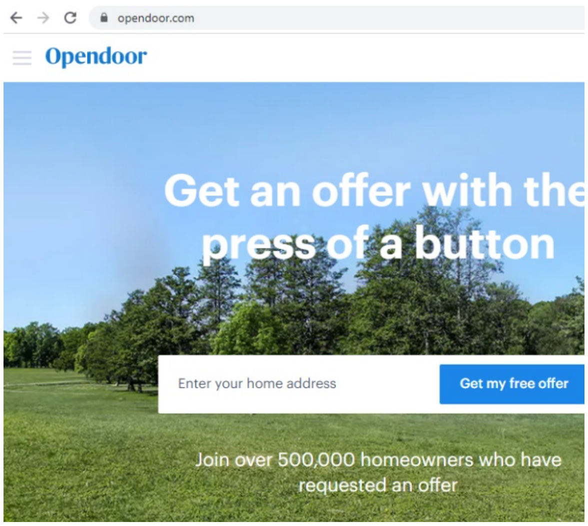
(c) Impatient share of iBuyer customers

(d) Lower-quality share of iBuyer purchases

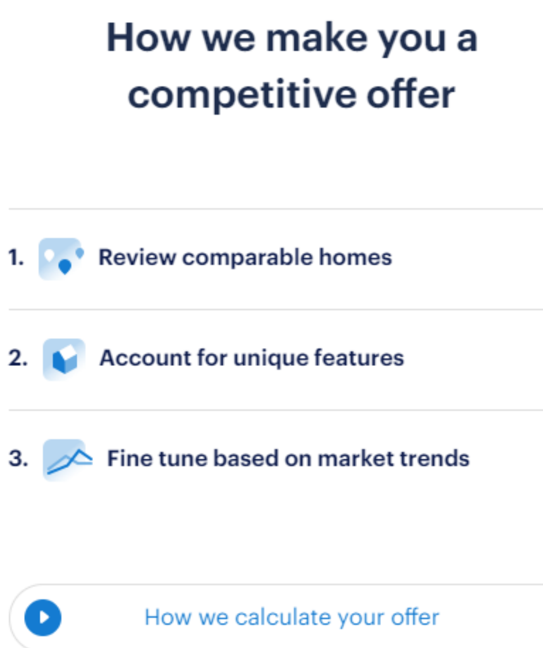
Internet Appendix

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, Offerpad, Knock, Zillow Offers, and RedfinNow.[37] 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. 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 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.

[37] As of July 2022: https://www.opendoor.com/; https://www.offerpad.com/; https://www.knock.com/; https://www.zillow.com/offers/; https://www.redfin.com/now

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: iBuyer Listing Robustness

This table shows robustness around iBuyer listing results. Panel A shows summary statistics for matching between MLS and deeds records. Match window is the allowed time between CoreLogic sale date and MLS sale date to be considered a match. Panel B statistics around failed listings. A failed listing is one with a listing date 90, 182, or 365 days prior to the iBuyer purchase that *does not* result in a sale. Panel C shows main listing results allowing for relistings. 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.

Panel A: iBuyer purchases-to-MLS-listings match rate by match window

Match window	# iBuyer buys with listings	% iBuyer buys with listings	# other buys with listings	% other buys with listings
Day	84	1.3	176,827	14.7
Week	491	7.5	418,414	34.8
Month	505	7.7	501,735	41.7
Quarter	1,464	22.2	654,702	54.4

Panel B: iBuyer purchases from failed listings

Window	# iBuyer buys with failed listings	% iBuyer buys with failed listings	# other buys with failed listings	% other buys with failed listings
90 days	12	0.2%	6,627	0.8%
182 days	18	0.3%	10,711	1.3%
365 days	27	0.4%	15,931	2.0%

Panel C: Relistings

	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: House Characteristics and Algorithmic Pricing Errors

This table shows the estimated relationship between property characteristics, house prices, and pricing errors. We use pre-iBuyer entry CoreLogic transaction data between 2006 and ends at the end of 2012. 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 2008 and 2012, with Column (3) corresponding to the pricing model and (4) corresponding to the errors model. Standard errors are shown in parentheses.

	2006-2012 (Main specification)		2008-2012 (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: > 50 years)				
Age < 5 years	0.662	-0.163	0.705	-0.171
	(0.003)	(0.001)	(0.003)	(0.001)
Age 5-15 years	0.563	-0.161	0.602	-0.175
	(0.002)	(0.001)	(0.003)	(0.001)
Age 15-50 years	0.269	-0.111	0.292	-0.113
	(0.002)	(0.001)	(0.003)	(0.001)
Land square footage (omitted: > 25k)				
Square footage < 5k	-0.913	-0.045	-0.936	-0.034
	(0.003)	(0.002)	(0.004)	(0.002)
Square footage 5-10k	-0.601	-0.062	-0.612	-0.048
	(0.003)	(0.002)	(0.003)	(0.002)
Square footage 10-25k	-0.281	-0.030	-0.274	-0.024
	(0.003)	(0.002)	(0.003)	(0.002)
Multistory	0.197	-0.009	0.195	-0.022
	(0.001)	(0.001)	(0.001)	(0.001)
Other house characteristics	Y	Y	Y	Y
Observations	889,661	889,242	680,640	680,360
R^2	0.661	0.037	0.623	0.044

Appendix A.6: Sources of iBuyer Gross Return

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,[38] as

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

The subscript i denotes a house, z the zip code 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% (Appendix Table A.7.1, Panel A). 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.

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:

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

$Gross\ Return_{iztt'}^{Ann}$ 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% pp higher than those of typical individuals (Appendix Table A.7.1, Panel B Column 2). We separate the gross return into a component that is attributable purely to overall house price appreciation and the bid/ask spread. The objective of the decomposition 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):[39]

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

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

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

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

$$Index\ Return_{iztt'} = Index\ Appreciation_{ztt'}$$

[38] 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.

[39] 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.

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

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.[40] 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 the overall house price appreciation 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). *Flippers*, as defined previously, are treated as non-iBuyer individuals because they cannot be identified directly in the Corelogic data. 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)

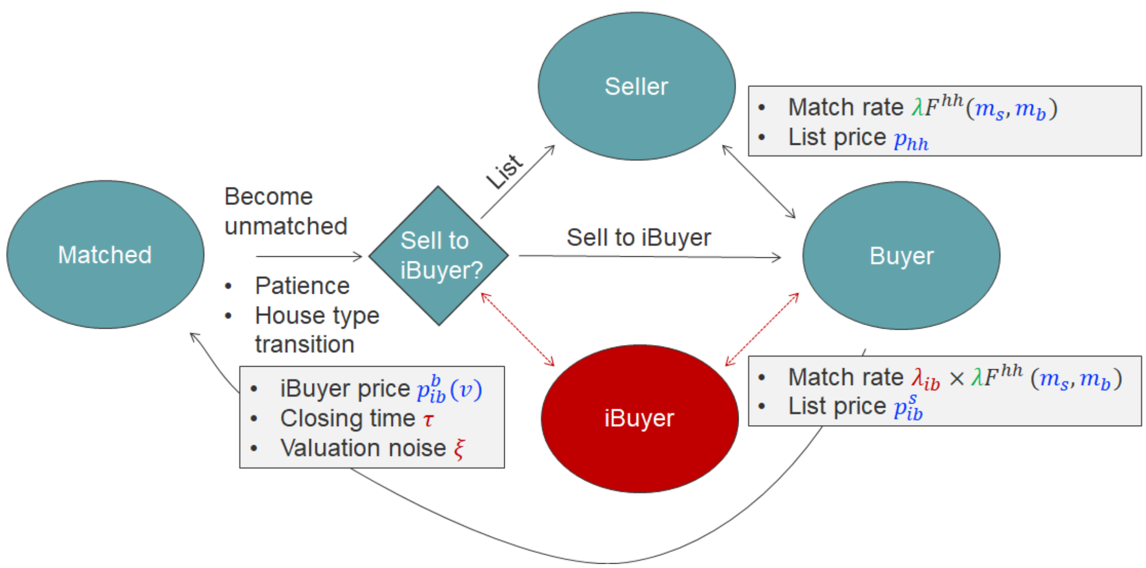
Panel B: Gross return (spread) regressions

	Dependent variable:					
	Gross Return (ann)		Index Return (ann)		Non Index Return (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

[40] 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))

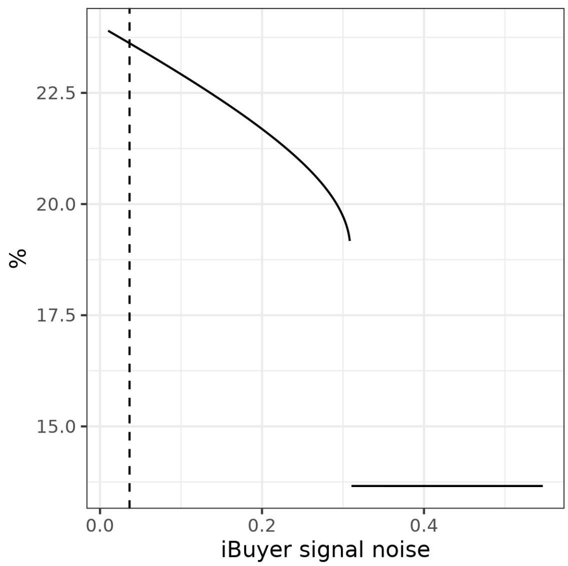
Appendix A.7: Equilibrium Housing Trading Model with iBuyers: Transition Paths

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. The seller becomes patient or impatient, and the house transitions to the next house type. 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 $\lambda_{ib} F(m_s, m_{ib})$.

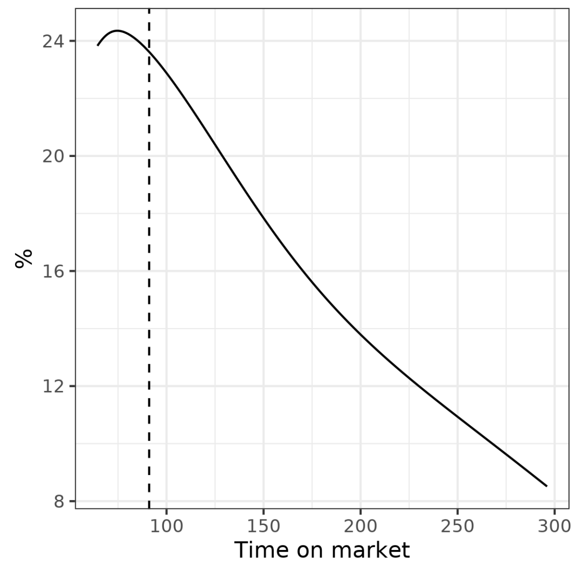


Appendix A.8: Robustness for: Key Frictions and iBuyer Market Share

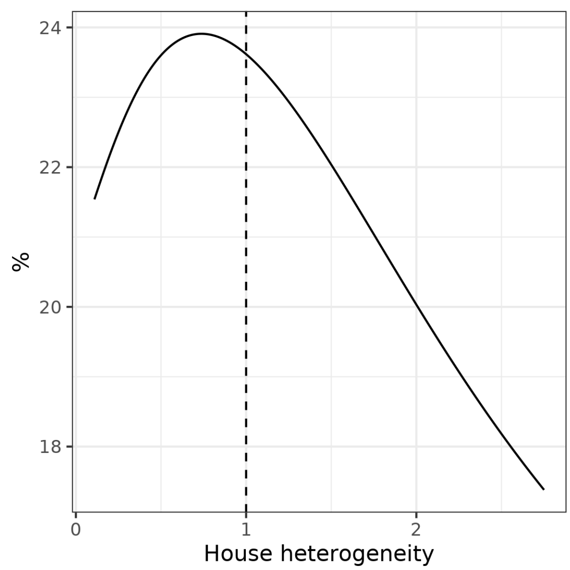
This figure examines robustness around the assumed impatient share (a recalibrated model with 33% impatient rather than the baseline 50%) and illustrates the iBuyer market share under varying key economic factors, when we set disutility from accessing iBuyer technology to zero, which could be viewed as an upper bound on the full market adoption. Panel (a) shows the iBuyer market share as the signal noise in the iBuyer algorithmic valuation technology increases. Panel (b) shows the effect of increased time on the market (liquidity) in the regular transaction market. Panel (c) depicts the impact of dispersion in private values of homes across individuals. The dashed line represents the baseline market share, derived from the estimation of our model.



(a) Accuracy of algorithmic pricing



(b) Underlying market liquidity



(c) Dispersion of private values

Appendix A.9: Model Validation

We undertake two model validation exercises: First, we examine the equilibrium impact on prices and liquidity following iBuyer entry. Second, at the individual level, we explore why consumers transacting with iBuyers may value selling their home quickly.

Equilibrium Evidence

First, the model's equilibrium predictions are shown in Table A.10.1. Next, we examine the elasticities of price and liquidity to iBuyer entry using a difference-in-difference style analysis in the data. We utilize the following empirical design to generate elasticities that map to the model-implied elasticities reported above:

$$Liquidity_{zt} = \beta iBuyerShare_z \times Post_t + \gamma_z + \gamma_t + \epsilon_{zy}$$

$$\log(\text{Price})_{\text{izt}} = \beta iBuyerShare_z \times Post_t + X'_{izt}\mathbf{\Gamma} + \gamma_{\text{i}} + \gamma_\tau^i + \gamma_z + \epsilon_{izt}$$

$Liquidity_{zt}$ is the fraction of listings in zip z at year t selling within two weeks. $\log(Price)_{izt}$ is the log sale price of property i in zip z at time t. γ_* are fixed effects at the zip, time, property, or ownership tenure (τ)[41] level. X'_{izt} is time-varying characteristics of the house (in particular, age fixed effects). $iBuyerShare_z$ is the iBuyer Market share in 2018, $Post_t$ is an indicator for post 2018. Since iBuyer entry may be endogenously correlated with changes in time on the market—indeed, our model suggests that iBuyer is related to liquidity of the market -- 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 2018:

$$iBuyer_{izt} = H'_i\mathbf{B} + \epsilon_{izt}$$

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

$$\%\ \widehat{\imath Buyer}_z = \frac{1}{N_z} \sum_{i \in z; t \in (2011-2014)} \widehat{\imath Buyer}_{\imath zt}$$

As before, $\widehat{\imath Buyer}_{\imath zt}$ 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 2013. We use this measure to instrument for $iBuyer\ Share_z$. Thus, our instrument for iBuyer market share in 2018 is the predicted iBuyer share based on the physical homes transacted between 2011 and 2014. Figure A.10.2 shows the empirical first stage relationship.

The first stage effect is very strong: A 1% increase in predicted share based on the physical characteristics of houses transacting in 2011-2013 is associated with a 0.964% increase in actual iBuyer market share in 2018 (this regression omits Phoenix, which is used to fit the hedonic model) (shown in Table A.10.3 Column (1)). Columns (2)-(4) show the results for log prices, and Columns (5)-(7) show the results for the fraction of listings sold within two weeks. Columns (2) and (5) are the OLS, (3) and (6) are the reduced form, and (4) and (7) are the IV estimates. Broadly, we find that a 1% increase in iBuyer share is associated with a 1.4% increase in prices (Column (4)) and a 1.6% increase in the fraction of listings sold within two weeks (Column (5)).

Consistent with the model's predictions, results in Appendix Table A.10.1 show that we find a positive elasticity of price to iBuyer market share, typically close to the model's prediction within standard error bounds, and a similarly positive relationship for fraction of houses selling within two weeks of listing. The regression coefficient is a semi-elasticity of prices to iBuyer share, with an instrumental variable coefficient of 1.4, and a standard error of 0.27. The model provides a similarly positive, although slightly larger semi-elasticity. Similarly, our model predicts a lower time-to-sale for iBuyer transactions, which is consistent with the increased probability

[41] That is, for the property-level regression, the number of years between the current sale and previous sale to account for house wear-and-tear or renovations.

of a home selling within two weeks shown in the reduced form analysis. Broadly, our model makes predictions that are qualitatively and quantitatively consistent with this reduced form exercise.

Individual-level evidence

We next 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.

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:[42]

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

Here i indexes an individual in zip code 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. $\widehat{\imath Buyer}_{\imath zt}$ 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.

We construct $\widehat{\imath Buyer}_{\imath zt}$ 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 $\widehat{\imath Buyer}_{\imath zt}$ to be one if house i is predicted to be above median based on the probability that the home would be targeted by iBuyers.

Table A.10.4 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

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

are increasing the rate of sales. We find a strong effect among low LTV individuals -- those with LTVs below the 75th 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:

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

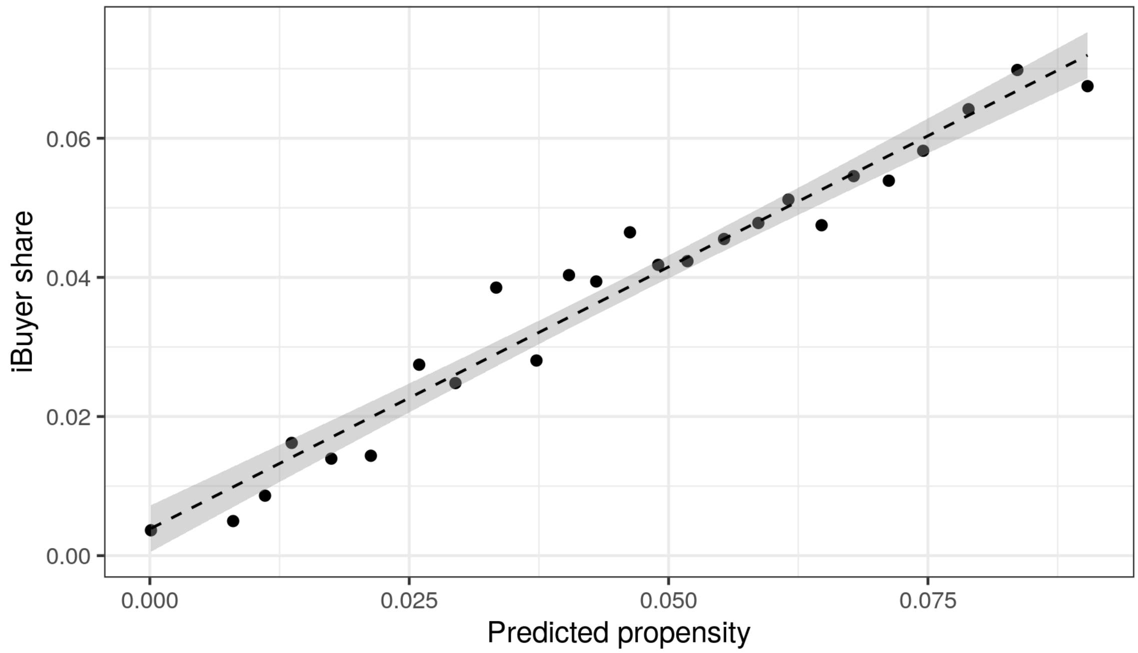
$Price\ Imputed_{it}^{Old}$ represents the estimated value of the sold house *i* at time *t* based on local price appreciation in the market between the time of purchase and the time of sale. In particular, $Purchase\ Price_{it_0}^{Old}$ is the original purchase price of property i at original purchase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

Figure A.10.5 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.

Appendix A.9.1: Instrument for 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.9.2: Model Validation: iBuyer Entry and Regional Outcome Variables

This table shows the association between iBuyer entry and regional outcome variables using the zip-code level data from deeds records, column (1), house-level transaction data, columns (2)-(4), and zip-year level Redfin data, columns (5)-(7). *iBuyer Share* is the change in iBuyer share in the zip code in 2018. *Log sale amount* is the log of the sale price as recorded in the deeds records. *% Sold in 2 weeks* is the change in houses sold within two weeks of listing and measured at the zip-code level by Redfin. *Propensity* is the instrument used to predict iBuyer market share, calculated by first fitting a hedonic model of iBuyer propensity to purchase a house based on physical characteristics of the house, and then using the model to predict iBuyer market share based on the ex-ante physical characteristics of the housing stock represented by transactions occurring between 2011 and 2013. Column (1) is the first stage regression, regressing the endogenous iBuyer share on the instrument. Columns (2)-(4) examine changes in sale prices for identical homes in areas with high and low iBuyer presence before and after iBuyer entry, excluding homes that iBuyers actually purchase. Columns (5)-(7) examine changes in sale speeds after listing in areas with high and low iBuyer presence. Columns (2) and (5) are the OLS regressions; (3) and (6) are the reduced form regressions using predicted propensity, and (4) and (7) are the IV regressions. Standard errors are shown in parentheses.

	Dependent variable:						
	iBuyer share	log(Sale amount)			% listings sold in two weeks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	OLS	OLS	RF	IV	OLS	RF	IV
Propensity	0.964	-	-	-	-	-	-
	(0.070)	-	-	-	-	-	-
Post x Share	-	0.451	-	1.405	-0.007	-	1.579
	-	(0.156)	-	(0.266)	(0.157)	-	(0.306)
Post x Propensity	-	-	1.824	-		1.457	-
	-	-	(0.303)	-		(0.233)	-
Unit of observation	Zip	Property sale	Property sale	Property sale	Zip-Year	Zip-Year	Zip-Year
Zip FE	N	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y	Y
Property FE	N	Y	Y	Y	N	N	N
House Age & Tenure FE	N	Y	Y	Y	N	N	N
N	348	959,408	959,408	959,408	662	662	662
R^2	0.352	0.946	0.946	0.946	0.680	0.711	0.591

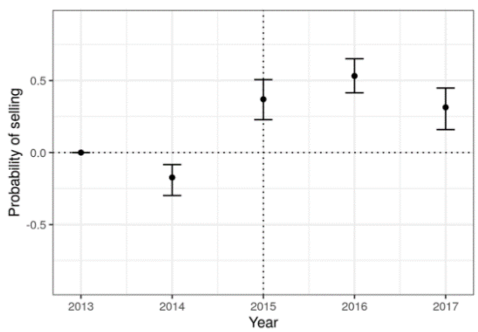
Appendix A.9.3: Model Validation: iBuyer Entry and Homeowner Mobility

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 story (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.

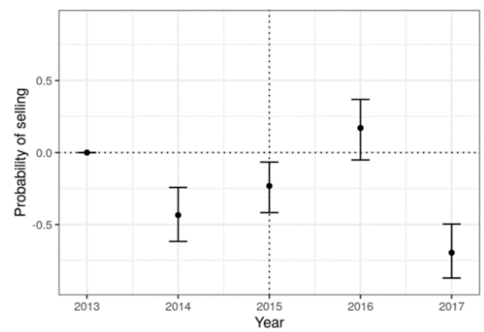
	Dependent variable:					
	Sells			Remains in Market	ΔBuy Price (imputed)	ΔLTV (imputed)
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\iota Buyer}$	1.677	1.720	1.556	-2.212	-0.543	-0.404
	(0.046)	(0.055)	(0.081)	(0.243)	(0.753)	(0.296)
$\widehat{\iota Buyer} \times Post$	0.490	0.622	-0.032	-0.809	-1.854	-0.572
	(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

Appendix A.9.4: Model Validation: iBuyer Entry and Homeowner Mobility

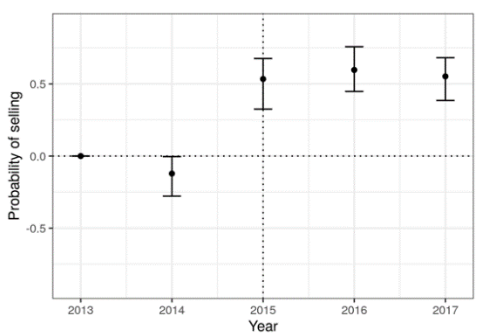
This figure shows the estimated differential change in individuals' selling, moving, and downsizing propensities around the iBuyer entry time of more exposed homeowners to iBuyer entry (treatment) relative to less exposed ones (control). We define treatment and control based on whether the individual's 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.



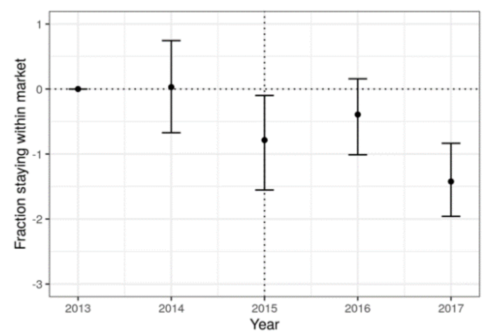
(a) Selling, all iBuyer homes



(b) Selling, high-LTV iBuyer homes



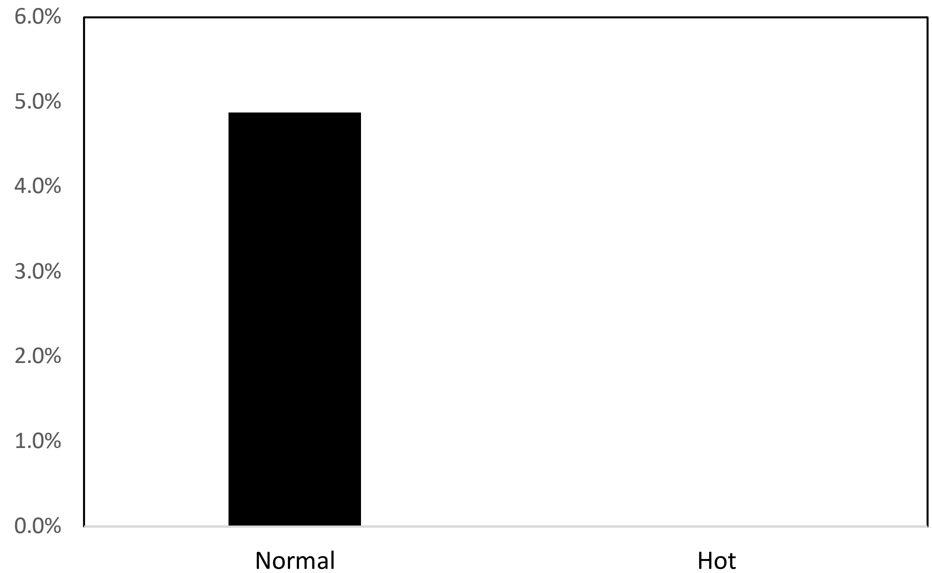
(c) Selling, low-LTV iBuyer homes



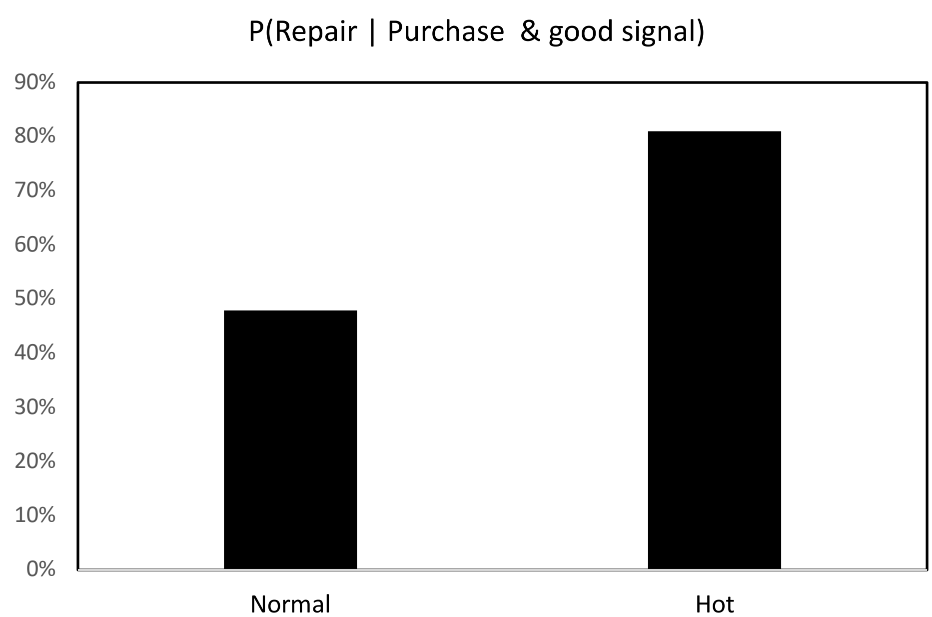
(d) Staying in market, all iBuyer homes

Appendix A.10: iBuyers in "Hot" Markets

This figure shows iBuyers in a "hot" market, where the matching rate is set to generate a time to sale of roughly 30 days. Panel (a) shows iBuyer market share. Note that in the "hot" market, iBuyer market share is close to, but not exactly zero. Panel (b) shows iBuyer pricing mistakes, defined as the fraction of houses that iBuyers purchase that require repairs despite having good signals.



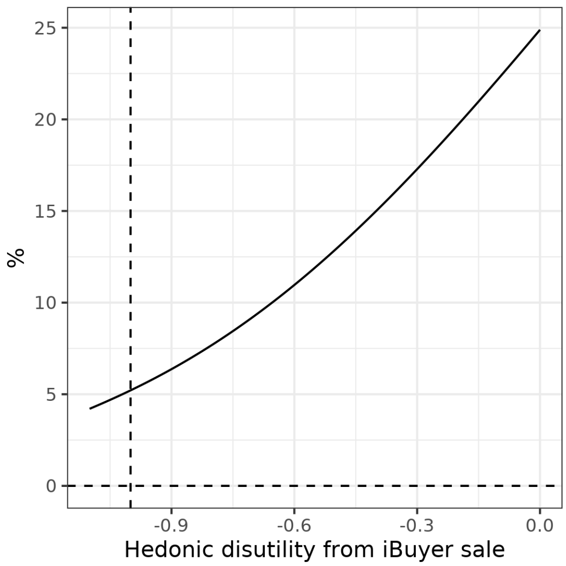
(a) iBuyer market share



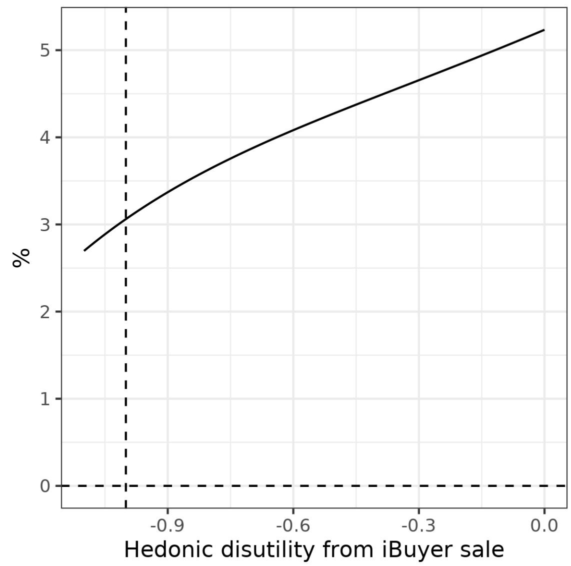
(b) iBuyers and pricing mistakes

Appendix A.11: Hedonic Preference for Transacting with Intermediary

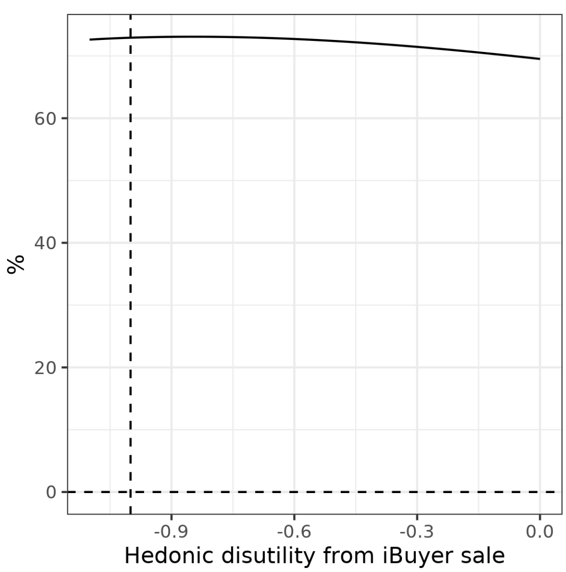
This figure shows how iBuyer outcomes vary as the hedonic value of transacting with iBuyers varies. Hedonic utility increases (disutility decreases) moving from left-to-right and is shown in multiples of the estimated value (so that negative one is the baseline). The vertical dashed line shows the baseline value. Dispersion increases from left to right. Panel (a) shows the iBuyer share of transactions. Panel (b) shows the iBuyer per-transaction gross spread (average sale price minus purchase price). Panel (c) shows the share of sellers to iBuyers who are impatient sellers. Panel (d) shows the share of houses that iBuyers buy that are lower-quality types.



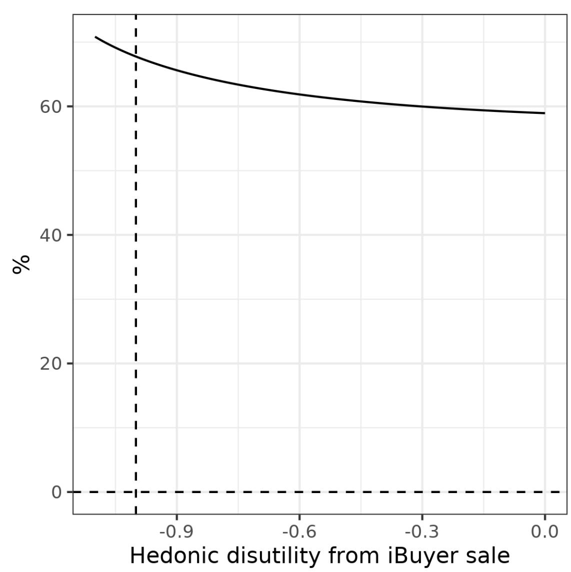
(a) iBuyer market share



(b) iBuyer per-transaction gross spread



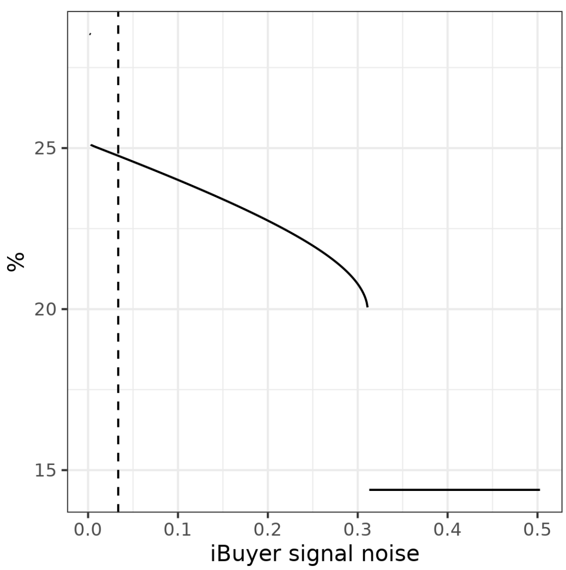
(c) Impatient share of iBuyer customers



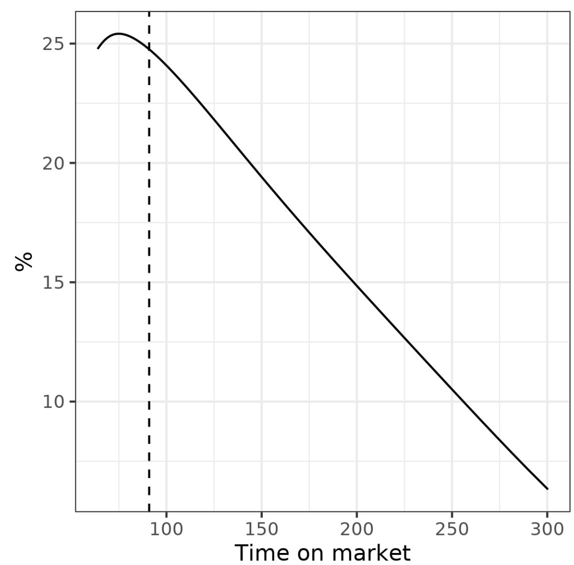
(d) Lower-quality share of iBuyer purchases

Appendix A.12: Full Technology Adoption: Key Frictions and iBuyer Market Share

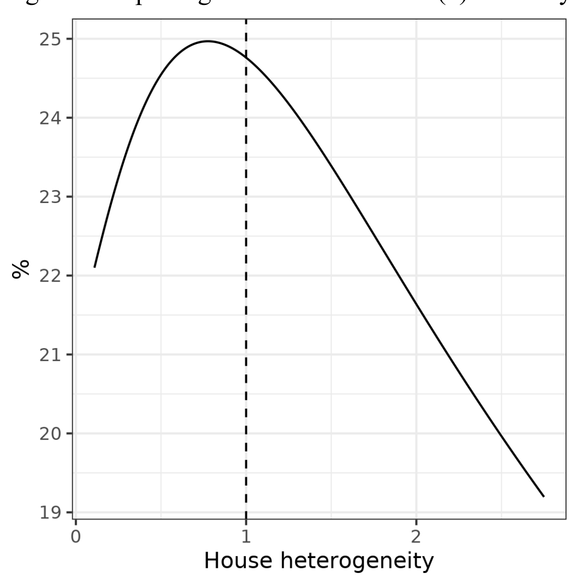
This figure illustrates the iBuyer market share under varying key economic factors, when we set disutility from accessing iBuyer technology to zero, which could be viewed as an upper bound on the full market adoption. Panel (a) shows the iBuyer market share as the signal noise in the iBuyer algorithmic valuation technology increases. Panel (b) shows the effect of increased time on the market (liquidity) in the regular transaction market. Panel (c) depicts the impact of dispersion in private values of homes across individuals. The dashed line represents the baseline market share, derived from the estimation of our model.



(a) Accuracy of algorithmic pricing



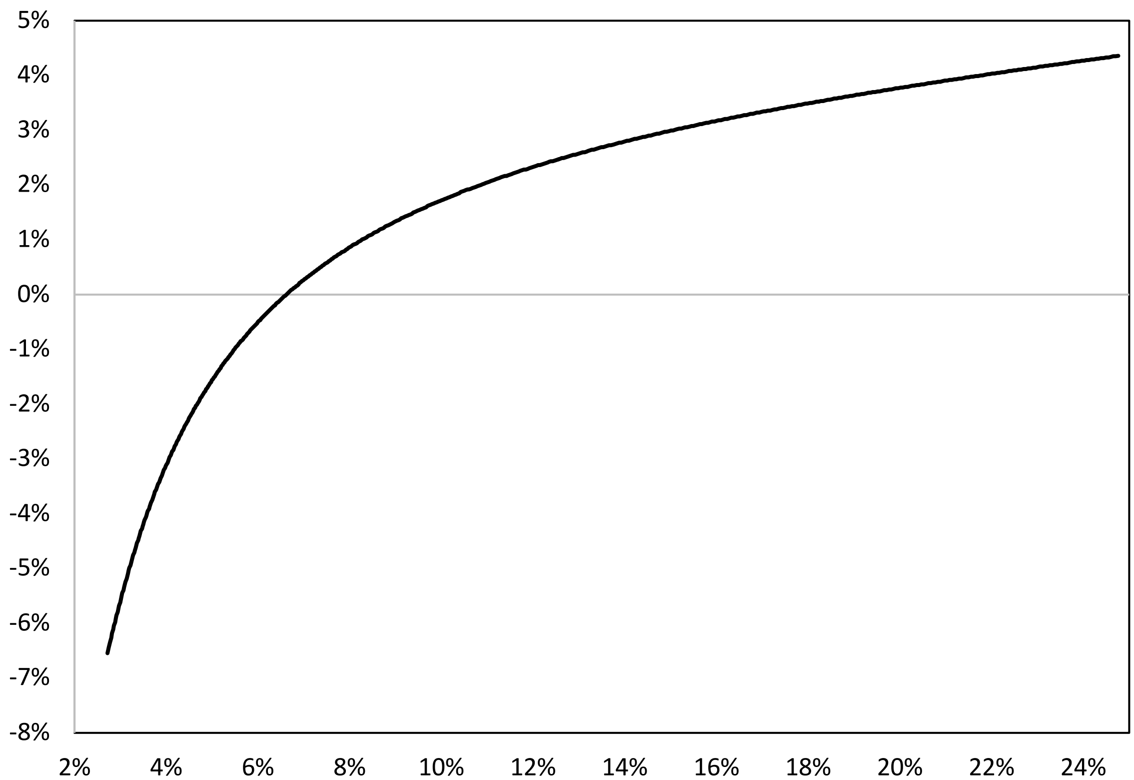
(b) Underlying market liquidity



(c) Dispersion of private values

Appendix A.13: Gross Spread and Fixed Operating Costs as % of Home Price

In this figure, we decrease the cost of accessing iBuyer technology (hedonic disutility of transacting with intermediary), which leads to a rise in iBuyer market share (shown on the x-axis). This figure displays the gross iBuyer spread associated with each of these market shares, less the fixed operating costs (corporate overhead), expressed as a percentage of the average home acquisition price. We assume that the fixed operating cost is about 1% of the average home acquisition price at the maximum market share of around 24.7%. For market shares below this level, the cost is correspondingly higher; for example, at half of this maximum market share, the fixed operating cost will be 2% of the average home acquisition price. The gross iBuyer spread is just enough to cover the fixed operating cost at the market share of 6.6%.



Appendix A.14: Speed of Traditional Listing

This figure uses data from Zillow.com and shows the fraction of US metropolitan areas where the median days-to-pending (i.e., the number of days between when a listing appears and when it is marked as a pending sale) is below 30 days. Data are weekly and shown over the entire available date range.