Reference Points in the Housing Market*

Steen Andersen†   Cristian Badarinza‡   Lu Liu§
Julie Marx¶   Tarun Ramadorai‖

August 19, 2019

Abstract

Using comprehensive and granular Danish data, we revisit the determinants of decisions to list, and listing premia in the housing market. Nominal losses and down-payment constraints both affect the gap between listing prices and hedonic valuations; we discover that these determinants have interactive effects on household behavior. To explain these facts, we adopt a structural approach—sellers optimize expected utility from property sale, subject to down-payment constraints, and taking as given the “concave demand” of buyers (the probability of sale more steeply declines with positive listing premia than it rises with negative premia). A model with reference-dependent—but not necessarily loss-averse—preferences combined with penalties associated with down-payment constraints fits best, but cannot fully explain the new facts that we uncover.

*We thank Jan David Bakker, Pedro Bordalo, John Campbell, Joshua Coval, Andreas Fuster, Arpit Gupta, Adam Guren, Chris Hansman, Andrei Shleifer, Jeremy Stein, Ansgar Walther, Joshua White, and seminar participants at the FCA-Imperial Conference on Household Finance, the CBS Doctoral Workshop, the Bank of England, and the King’s College Conference on Financial Markets for useful comments.

†Copenhagen Business School, Email: san.fi@cbs.dk.
‡National University of Singapore, Email: cristian.badarinza@nus.edu.sg
§Imperial College London, Email: l.liu16@imperial.ac.uk.
¶Copenhagen Business School, Email: jna.fi@cbs.dk.
‖Corresponding author: Imperial College London, Tanaka Building, South Kensington Campus, London SW7 2AZ, and CEPR. Tel.: +44 207 594 99 10. Email: t.ramadorai@imperial.ac.uk.
1 Introduction

Housing is typically the largest household asset, and mortgages, typically the largest liability (Campbell, 2006, Badarinza et al. 2016). The size and importance of housing transactions for the economy has motivated much work on the drivers of household decisions in this market. On the one hand, Stein (1995) puts forward a rational theory which explains household listing and selling decisions using mortgage market frictions. He notes that down-payment constraints on mortgages create incentives for households to “fish,” listing their houses at speculative, high prices during housing downturns. This is because household leverage magnifies the effect of declines in collateral value, severely compressing the size of houses into which households can move. On the other hand, Genesove and Mayer (2001) provide highly-cited evidence that listing prices rise sharply when households face nominal losses, controlling for household leverage. They interpret this as high-stakes field evidence of households exhibiting reference-dependent loss-averse preferences (Kahneman and Tversky, 1989, Köszegi and Rabin, 2006, 2007).\footnote{Genesove and Mayer (1997, 2001) also provide evidence in support of the Stein (1995) model, but Genesove and Mayer (2001) highlight the relatively more important empirical role of loss aversion. More recent work by Ferreira et al. 2010, Anenberg, 2011, Schulhofer-Wohl, 2012, Hong et al. 2016, and Bracke and Tenreyro 2018 provides evidence consistent with the importance of both downpayment constraints and loss aversion.}

A deeper understanding of these issues requires granular data on property listings, combined with detailed information on household characteristics and financial circumstances. In this paper, we revisit the topic using a dataset which tracks the universe of Danish listings and housing transactions between 2009 and 2016, matched to household demographic characteristics and financial information. Using these data, we reconfirm that both nominal losses and down-payment constraints affect households’ listing and selling decisions, and document the relative importance of these factors. A new finding from our empirical work is that home equity and losses have interactive effects on listing prices in this market, affecting household behavior both independently and jointly.

To be more specific, we find evidence that listing premia (listing prices less hedonic
values) are substantially higher when households face nominal losses than when they face nominal gains. However, this observation varies with the level of households’ home equity. When home equity levels are low, i.e., when down-payment constraints are expected to be tighter, households set high listing prices that vary little around the reference point at which they would face a nominal loss. In contrast, households that are relatively unconstrained by down-payment considerations exhibit listing prices that are significantly steeper in expected losses than in expected gains.

We also find that households’ listing prices respond strongly to down-payment constraints, rising significantly when home equity falls. Once again, this behavior is modified by the interaction with nominal losses. Mortgages in Denmark are limited by law to an LTV of no greater than 80% (though both formal and informal unsecured borrowing can be used to smooth downsizing). The effect of the down-payment constraint reference point of 20% on listing premia is clear when households face nominal losses, with listing premia rising visibly for every unit decline in home equity below this point. In contrast, for households expecting nominal gains, we find evidence of a strong upward shift in this constraint reference point (i.e., to points greater than 20%) in the level of home equity at which they raise listing prices.

These findings hold when we account for unobservable house quality or selection, an important confound in analyses of the effect of nominal losses on listing prices (e.g., Clapp et al., 2018). We check robustness to using Genesove and Mayer’s (2001) bounding approach, as well as to the use of a regression kink design (RKD) (Card et al., 2015a). The RKD reveals that small movements in nominal gains and losses around a reference point of zero generate sharp changes in the slope of listing premia, consistent with a causal impact on behavior. However, we find no similar (unconditional) impact around the down-payment constraint reference point of 20%, a fact that we rationalize in our theoretical work.

DellaVigna (2018) rightly cautions that list prices and the decision to list are household
choices, so moving from facts to interpretations without an underlying structural model of behavior is difficult. We therefore explore the extent to which leading theoretical explanations of household behavior in housing markets can rationalize the patterns in the data. Our approach is to assume that the seller optimizes expected utility from the final sale of the property, facing disutility when listing fails to convert to final sale, and taking as given the impacts of the chosen listing price on both the probability of sale and the final sale price. We estimate functions that connect observed listing premia with final sale outcomes in the Danish data; these functions strongly confirm evidence that Guren (2018) documents in the US market. He shows that buyers react to sellers’ posted listing prices in a fashion that he terms “concave demand.” In our setup, these estimated functions serve as reduced-form approximations for demand, which the household/seller takes as given when optimally choosing listing premia.

In the model, we evaluate the following sets of preference specifications: (i) utility of the final sale price (the rational benchmark), (ii) a “pure” reference dependence model in which final sale price utility receives an additional utility kick from gains or losses relative to the historical purchase price of the house, (iii) a model in which the additional reference-dependent utility is piecewise linear, i.e., the disutility kick from losses is 2.25 times greater than the utility kick from gains (Tversky and Kahneman, 1992), and finally, (iv) a realization utility model à la Barberis and Xiong (2012). We also assess the importance of assuming that the seller faces concave demand rather than simply assuming that TOM and the final sales price are linear functions of listing prices. Finally, we check whether down-payment constraints are better modelled as (i) nonexistent, (ii) a monetary penalty incurred for every unit that realized home equity after mortgage repayment drops below 20% of the final sale price, or (iii) as a threshold below which households receive a fallback level of utility associated with not moving.

In all cases, our evaluation procedure is to require the models to match the conditional

\textsuperscript{2}Namely, above average list prices increase time-on-the market or TOM (i.e., they reduce the probability of final sale), while below average list prices reduce seller revenue with little effect on TOM.
shapes in empirically-observed listing premia as functions of home equity and gains. Using this procedure, we conclude in this draft of the paper that the model which best explains listing premia in the data requires concave demand à la Guren (2018), “pure” reference dependence, and a monetary penalty for every percent that home equity drops below the 20% level. Moving from utility of final sale price to reference-dependent preferences delivers the largest increase in the ability of the model to match the data, a smaller, but still large increase arises from modelling demand as concave rather than linear in listing premia, and a smaller, but still significant increase comes from adding in the effects of down-payment constraints.\(^3\)

An important finding from our analysis is that explaining the asymmetry in listing premia across gains and losses does not necessarily require asymmetric preferences such as loss aversion or realization utility. “Pure” reference dependent preferences are statistically significantly and quantitatively better than realization utility, and quantitatively better at matching observed listing premia profiles than loss averse preferences.\(^4\) This finding can be explained by the role of concave demand. To see why, consider a seller facing a nominal loss on the property. To make up for this, they wish to set a high listing premium to benefit from the higher realized sale premium, but balance this against the resultant decline in the probability of sale. In contrast, when sellers face large gains, it is optimal for them to choose lower listing premia to avoid the pain of not selling at all. However, the tradeoff in the gain domain is very different, since the flattening out of the sale probability as a function of listing premia (i.e., concave demand) means that reducing listing premia

\(^3\)We also evaluate whether a pure selection story on the extensive margin (i.e., the decision to list being driven by the expected level of gains or home equity) can explain our results; to do so, we compute the fraction of the housing stock in Denmark that lists at each level of gains and home equity. We find slight declines in listing propensities for properties valued below their nominal purchase price, but conclude that the magnitudes are small, and far from able to explain the large changes in observed listing premia in the loss domain.

\(^4\)We find quantitative improvements over the loss aversion model, but not statistically significant ones in our current empirical specifications. We are currently working on a more granular evaluation approach, i.e., with a finer discretization grid, and potentially matching the whole listing premium surface. As a result, our conclusions at this stage are less precise than we expect they will be in future versions of this paper.
past a certain point doesn’t help much at avoiding the feared outcome. This generates a relatively flatter profile of listing premia as gains increase.

We validate this model insight in the data, showing that in segments of the market in which there is greater concavity of demand (i.e., pronounced nonlinearity in the function connecting sale probabilities with listing premia), listing premia also exhibit a greater asymmetry in behavior across the gain and loss domains. While this is of course a reduced-form for the underlying search and matching problem of sellers and buyers in this market, we view this finding as intriguing, and intend to explore it more fully in future drafts of this paper.

While the model does a reasonable job at matching aspects of the data, it is unable to match the new facts that we uncover in our empirical work. Most importantly, the model cannot match the conditional variation observed in the slope of the listing premium-gains relationship, nor is it able to match the variation in the down-payment constraint point as gains and losses vary. While we have not explored these possibilities in detail by positing a model that is capable of explaining these facts in this draft of the paper, we believe that these new findings potentially have implications for both microeconomic models of behavior and macroeconomic aggregates in the housing market.

In micro terms, the interaction between reference dependence and constraints could have implications for the way we model behavior. We tend to assume that agents optimize their (potentially behavioral) preferences subject to constraints, and in numerous models, agents may also wish to impose constraints on themselves to “meta-optimize” (Gul and Pesendorfer, 2001, 2004, Fudenberg and Levine, 2005, Ashraf et al. 2006, DellaVigna and Malmendier 2006). However, if constraints affect the incidence of behavioral biases, or indeed, if being in a zone that is more prone to bias affects the response to constraints, our models must of necessity become more complicated to accommodate such behavior.

Taking a more macroeconomic perspective, reference points appear important for understanding aggregate housing market dynamics. The housing price-volume correlation
tends to fluctuate, and especially during housing market downturns, prices and liquidity can move in lockstep. This has important implications for labor mobility, which responds strongly to housing “lock” (Ferreira et al., 2012). Interaction effects such as the effect of expected losses on the household response to constraints could help to make sense of the seemingly extreme reactions of housing markets to apparently small changes in underlying prices, and inform mortgage market policy (Campbell, 2012, Piskorski and Seru, 2018).

The paper is organized as follows. Section 2 discusses the construction of our merged data set, and provides simple summary statistics about the variables that we construct and use in our analysis. Section 3 estimates a set of facts about the behavior of listing premia and their variation with gains and home equity. Section 4 estimates models with different preference and constraint specifications in an attempt to explain the facts uncovered in Section 3. Section 5 validates some of the predictions of the preferred model, and discusses where the class of models that we evaluate falls short in explaining features of the data. Section 6 concludes.

2 Data

2.1 Data Sources

Our data cover the details of all electronic listings and transactions in owner-occupied real estate in Denmark from 2009 to 2016. Electronic listings comprise the overwhelming majority of listings in Denmark over the period. In addition to listing information, we also acquire information on property sales dates and sales prices, the previous purchase price of the sold or listed property, hedonic characteristics of the property, and a range of demographic characteristics of the households engaging in these listings and transactions, including variables that accurately capture households’ financial position at each point in

---

5Other work in housing that takes a behavioral approach includes Armona et al. (2019) and Bailey et al. (2018, 2019), who attempt to uncover the factors driving house price expectations.
time. We link data from various sources; all data other than the listings data are made available to us by Statistics Denmark.

2.1.1 Property Listings Data

Property listings are captured and provided to us by RealView (http://realview.dk/en/), who attempt to be comprehensive at capturing all electronic listings of owner-occupied housing in Denmark over our sample period between 2009 and 2016. RealView captures the universe of listings in the portal www.boligsiden.dk, in addition to collecting data directly from brokers. The data does include properties that have been privately listed, but does not include properties that have not been on the market, i.e., direct private transfers between households. Of the total number of cleaned/filtered sale transactions in the official property registers (described below), 76.56 percent have associated listing data. For each property listing, we know the address, listing date, listing price, size and time of any adjustments to the listing price, changes in the broker associated with the property, and the sale or retraction date for the property. The address of the property is de-identified by Statistics Denmark, and used to link these listings data to administrative property transactions data.

2.1.2 Property Transactions and Other Property Data

We acquire administrative data on property transactions, property ownership, and housing characteristics from the registers of the Danish Tax and Customs Administration (SKAT). These data are available from 1992 to 2016. SKAT receives information on property transactions from the Danish Gazette (Statstidende). By law, registration of any transfer

---

We more closely investigate the roughly 25% of transactions that do not have an associated electronic listing. 10% of the transactions can be explained by the different (more imprecise) recording of addresses in the listing data relative to the registered transactions data. The remaining 15% of unmatched transactions can be explained by: (a) off-market transactions (i.e., direct private transfers between friends and family, or between unconnected households); and (b) broker errors in reporting non-publicly announced listings (“skuffesager”) to boligsiden.dk. We find that on average, unmatched transactions are more expensive than matched transactions. Sellers of more expensive houses tend to prefer the skuffesalg option for both privacy and security reasons.
of ownership must be publicly announced in the Danish Gazette, ensuring that these data are comprehensive. The registered transaction data report the sale price of the property, the date of the transaction, and a property identification number which we use to link these data to the Danish housing register.

Loss aversion and down-payment constraints were originally proposed as explanations for the puzzling aggregate correlation between house prices and measures of housing liquidity, such as the number of transactions, or the time that the average house spends on the market. In the online appendix, we show the price-volume correlation in Denmark over a broader period containing our sample period. The plot looks very similar to the broad patterns observed in the US.

The Danish housing register (Bygnings- og Boligregister, BBR) contains detailed characteristics of all Danish houses, such as size, location, and other hedonic characteristics, which we use to estimate a predicted price for each individual property. When estimating our hedonic model, we also include on the right-hand-side the (predetermined at the point of inclusion in the model) biennial assessed value of the property that is provided by SKAT, which assesses property values every second year for the purpose of property taxation. SKAT also captures the personal identification number (CPR) of the owner of every property in Denmark. This enables us to identify the property seller, since the seller is the owner at the beginning of the year in which the transaction occurred.

Later in our analysis, we combine the data in the housing register with the listings data to assess the determinants of the decision to list for any given property. We also use this approach to assess the fraction of the housing stock that is listed, conditional on functions of the hedonic value such as gains or losses since previous purchase, or the level of home equity.

---

7As we describe later, this is the same practice followed by Genesove and Mayer (1997, 2001); it does not greatly affect the fit of the hedonic model, and barely affects our substantive inferences when we remove this variable.
2.1.3 Mortgage Data

To establish the level of the owner’s home equity in each property at each date, we require the size of the mortgage attached to each property. We obtain mortgage data from the Danish central bank (Danmarks Nationalbank), which collects these data from mortgage banks through Finance Denmark, the business association for banks, mortgage institutions, asset management, securities trading, and investment funds in Denmark. The data are available annually for each owner from 2009 to 2016, cover all mortgage banks and all mortgages in Denmark and contain information on the mortgage principal, outstanding mortgage balance, loan-to-value ratio, and the mortgage interest rate. The data contain the personal identification number of the borrower as well as the property number of the attached property, allowing us to merge data sets across all sources. If several mortgages are outstanding for the same property, we simply sum them, and calculate a weighted average interest rate and loan-to-value ratio for the property and mortgage in question.

2.1.4 Owner/Seller Demographics

We source demographic data on individuals and households from the official Danish Civil Registration System (CPR Registeret). In addition to each individual’s personal identification number (CPR), gender, age, and marital history, the records also contain a family identification number that links members of the same household. This means that we can aggregate individual data on wealth and income to the household level. We also calculate a measure of households’ education using the average length of years spent in education across all adults in the household. These data come from the education records of the Danish Ministry of Education.

Individual income and wealth data also come from the official records at SKAT, which hold detailed information by CPR numbers for the entire Danish population. SKAT

---

Footnote: 8Households consist of one or two adults and any children below the age of 25 living at the same address.
receives this information directly from the relevant third-party sources, e.g., employers who supply statements of wages paid to their employees, as well as financial institutions who supply information on their customers' balance sheets. Since these data are used to facilitate taxation at source, they are of high quality.

2.1.5 Final Merged Data

Our analysis depends on measuring both nominal losses and home equity. This imposes some restrictions on the sample. We have transactions data available from 1992 to the present, meaning that we can only measure the purchase price of properties that were bought during or after 1992. Moreover, the mortgage data run from 2009 to 2016. In addition, the sample is restricted to properties for which we know both the ID of the owner, as well as that of the owner's household, in order to match with demographic information.

For listings that end in a final sale, we drop within-household transactions and transactions that Statistics Denmark flag as anomalous or unusual. We flag (but do not drop) listings by households that do not have a stable structure, that is, we create a dummy for those listings for which the household ceases to exist as a unit in the year following the listing owing to death or divorce. We also flag households with missing education information. We restrict our analysis to residential households, in our main analysis dropping listings from households that own more than three properties in total, as they are more likely property investors than owner-occupiers.

Once all these filters have been applied, our sample contains 240,825 listings of Danish owner-occupied housing in the period between 2009 and 2016, for both sold (69.8%) and retracted (30.2%) properties, matched to mortgages and other household financial and demographic information. These listings correspond to a total of 212,181 unique households, and 200,960 unique properties. Most households that we observe in the data sell one house during the sample period, but roughly 9% of households sell two houses
over the sample period, and roughly 1.5 percent of households sell three or more houses.

For our main analysis we study the 180,114 households that have a mortgage, but we return to the 60,711 with no mortgage as a robustness check. In addition, we use the entire housing stock (13,305,501 observations of 1,736,172 unique properties) to understand the extensive margin decision of whether to list the properties for sale. In the online appendix, we describe the data construction filters and their effects on our final sample in more detail.

2.2 Hedonic Pricing Model

To calculate expected losses relative to a reference point, as well as to calculate the level of home equity, we require an estimated price for each property for each household-year observation in the data. We therefore estimate a standard hedonic pricing model on our sample of sold listings and subsequently use the model to predict prices for the entire sample of listed properties, including those that are not sold.\footnote{Later in the paper, we also assess the extent to which gains, losses and home equity determine the decision to list. We estimate a separate hedonic model for all properties, including unlisted properties, in order to conduct these additional tests.}

The hedonic model predicts the log of the sale price $P_{it}$ of all sold properties $i$ in each year $t$, using a set of property characteristics:

$$
\ln(P_{it}) = \delta + \delta_t + \delta_m + \delta_{tm} + \beta_{ft} \mathbb{1}_{i=f} \mathbb{1}_{t=t_f} + \beta X_{it}
+ \beta_{fx} \mathbb{1}_{i=f} X_{it} + \Phi(v_{it}) + \mathbb{1}_{i=f} \Phi(v_{it}) + \varepsilon_{it},
$$

(1)

where $X_{it}$ is a vector of property characteristics, namely $\ln($lot size$)$, $\ln($interior size$)$, number of rooms, bathrooms, and showers, a dummy variable for whether the property was unoccupied at the time of sale or retraction, the age of the building, dummy variables for whether the property is located in a rural area or a historic area, and $\ln($distance of the property to the nearest major city$)$.

$\delta$ is a constant, $\delta_t$ are year fixed effects, $\delta_m$ are fixed effects for different municipalities
(there are 98 municipalities in Denmark), $\delta_{tm}$ are year cross municipality fixed effects, and $\mathbb{1}_{i=f}$ is an indicator variable for whether the property is an apartment (denoted by $f$ for flat) rather than a house.\footnote{In the online appendix, we also include cohort effects $\delta_c$ in the hedonic regression, and continue to find robust evidence of all patterns uncovered in our empirical analysis, showing that intra-cohort variation in gains and losses is also associated with changes in listing premia.} $\Phi(v_{it})$ is a third-order polynomial of the previous-year tax assessor valuation of the property.\footnote{Genesove and Mayer (1997, 2001) also consider tax assessment data in their hedonic model. Importantly, the tax assessment valuation is carried out before the time of the transaction, in some cases even many years before. Until 2013, the tax authority re-evaluates properties every second year. The assessment, which is valid from January 1st each year, is established on October 1st of the prior year. In the years between assessments, the valuation is adjusted by including local-area price changes. This adjustment has been frozen since 2013, recording such price changes as of 2011. Only in the case of significant value-enhancing adjustments to a house or apartment would a re-assessment have taken place thereafter—and once again, is pre-determined at the point of property sale.} We interact the apartment dummy with time dummies as well as with the hedonic characteristics and the tax valuation polynomial to allow for a different relationship between hedonics and apartment prices.

When we estimate the model, the $R^2$ statistic equals 0.86 in the full sample.\footnote{The $R^2$ when we eliminate the tax assessor valuation from the hedonic characteristics is 0.73.} The large sample size and precise fit of the model helps to ameliorate concerns of noise in our estimate of the expected price of properties, an important concern when estimating the effects of both loss aversion and home equity (Genesove and Mayer, 1997, 2001). We also adopt more rigorous approaches to deal with the important issue of unobserved quality \cite{Clapp2018} and its effects on our inferences later.\footnote{The online appendix contains several details about the hedonic model and estimates. We also estimate the model in levels rather than logs, with an $R^2$ of 0.88. Our results are qualitatively, and for the most part, quantitatively unaffected by the use of either model.}

### 2.3 Gains and Losses

Armed with the hedonic pricing model, we estimate percentage nominal gains (denoted by $G$) as the difference between the fitted values from the hedonic model (we denote this as $\hat{\ln P}$) and the log nominal price paid for the property ($\ln R$ for “reference” price). We also estimate percentage home equity (denoted by $H$) as the difference between $\hat{\ln P}$ and the log mortgage amount $\ln M$ reported by the mortgage bank each year.
The online appendix plots the distribution of \( G \) observed in the data, winsorized at the 1% and 99% percentile points as there are several very large values of both gains and losses given the substantial time elapsed since the purchase of several properties. The mean gain experienced in the data is 34% and the median gain is 26%. Over the sample period, several properties exhibit losses, so the distribution, while not symmetric, does have mass on either side of zero—25% of the properties in the sample exhibit nominal losses, while 75% exhibit gains.

### 2.4 Home Equity

The online appendix also shows the distribution of home equity values. Once again, this distribution is winsorized at the 1% and 99% percentile points of the distribution. In addition, home equity is winsorized at 100% to restrict it to this level for tiny mortgages, given the log difference approach that we use to compute it. The mean level of home equity is 28% and the median level is 26%, though we do see a number of household-year observations with negative equity—77% of the properties in the sample have positive home equity and 23% have negative home equity. The modal home equity value is close to 26%. Numbers close to 20% home equity are to be expected, as Denmark has a very tight legal constraint on mortgages at issuance. The Danish Mortgage Act specifies that mortgage banks can lend up to a maximum of 80% of the value of the property, i.e., LTV at issuance is restricted to be 80% or lower. This constraint does not change over our sample period.\(^\text{14}\)

\(^\text{14}\)The online appendix documents the changes in the Act over our 2009 to 2016 sample period. While the constraint does not move during this period, there are a few changes in the wording of the act, a change in the maximum maturity of certain categories of loans in February 2012 from 35 to 40 years, and the revision of certain stipulations on the issuance of bonds backed by mortgage loans. None of these materially affect our inferences.
2.4.1 Liquid Financial Wealth

There are at least two ways in which households can attempt to relax down-payment constraints. The first is that households can engage in unsecured borrowing. A common approach is to borrow from a bank or occasionally from the seller of the property to bridge the funding gap between 80% and 95% LTV, with a spread of between 200 and 500 bp over the mortgage rate.\textsuperscript{15} A second (typically unobservable) possibility is that households can bring additional funds to the table by liquidating other assets.\textsuperscript{16}

The online appendix shows the distribution of liquid financial assets in the sample. The wealthiest households in the sample have above 2 million DKK, which is roughly US$300,000 in liquid financial assets (cash, stocks, and bonds). The median level of liquid financial assets is 71,000 DKK and the mean in the sample is 247,000 DKK. When we divide financial assets by mortgage size, we find that households, at the median, could relax their constraints by around 6.25 percent if they were to liquidate all financial asset holdings. However, the right-hand side of the top panel of the figure in the online appendix shows that this would be misleading. Looking at net financial assets, once short-term non-mortgage liabilities (mainly unsecured debt) are accounted for, substantially changes this picture. The median level of net financial assets in the sample is -106,000 DKK and the mean is -136,000 DKK, and the picture shows that households’ available net financial assets actually effectively tighten constraints for around 60 percent of the households in our sample. When we divide net financial assets by mortgage size we find, for households with seemingly positive levels of financial assets, that the constraints are in fact tighter by 9.3% at the median. Put differently, if households were to liquidate all financial asset holdings and attempt to repay outstanding unsecured debt, at the median, they would fall short by 9.3%, rather than be able to use liquid financial wealth to augment their

\textsuperscript{15}For reference, see categories DNRNURI and DNRNUPI in the Danmarks Nationalbank’s statistical data bank.

\textsuperscript{16}We note that Stein (1995) stipulates in his model that \(M\) refers to mortgage debt aggregated with other resources that households can bring to the table.
down payments. We therefore control for the amount of net financial assets in several of our specifications to ensure that we accurately measure the impact of these constraints on household decisions. This is a significant advance, given the measurement concerns that have affected prior work in this area (e.g., Genesove and Mayer, 1997, 2001, and Bracke and Tenreyro, 2018).

### 2.4.2 Age and Education

Given the natural reduction in labor income generating opportunities as households approach retirement, we might also expect that mortgage credit availability reduces as households age. And both age and education have been shown in prior work to affect the incidence of departures from optimal household decision-making (e.g., Agarwal et al., 2009, Andersen, et al., 2018), meaning that we might expect preference-based heterogeneity across households along these dimensions. The online appendix shows the age and education distributions of households in the sample. As expected, home-owning households with mortgages are both older and more educated than the overall distribution of households.

### 2.5 Gains, Losses and Home Equity

There are several challenges associated with estimating the independent and joint effects of down-payment constraints and gains on households’ listing decisions. One important challenge is that home equity and expected gains/losses are likely to be highly correlated with one another, mainly because of their joint dependence on $\ln P$. Other factors that influence this correlation are the LTV ratio at origination, and households’ decisions to remortgage to higher levels or to engage in subsequent “cash-out” refinancing after the initial issuance of the mortgage. A second challenge in cleanly estimating the effects of both constraints and gains on household behavior is that their effects could interact in complex ways. This means that sufficient independent variation is necessary to be able
to estimate any interaction effects with reasonable precision.

We therefore document the extent to which there is independent variation in gains and home equity in the data. We first provide a simple classification of the household-years in the data into four groups, based on estimated $\ln P$, the purchase price of the home $R$, and the mortgage amount $M$. The groups are:

1. Unconstrained Winners (50.2%): $H \geq 20\%$ and $G \geq 0$.
2. Constrained Winners (24.9%): $H < 20\%$ and $G \geq 0$.\(^{17}\)
3. Unconstrained Losers (6.7%): $H \geq 20\%$ and $G < 0$
4. Constrained Losers (18.2%): $H < 20\%$ and $G < 0$

The density of the data in each of the four groups is shown in Figure 1. We show a vertical line at zero gains, and a horizontal line at 20\% home equity. Under the assumption that households wish to move into a house of at least the same size as they currently own, and do not possess additional resources that they can bring to bear to augment the down payment, 20\% current home equity is the constraint point, rather than zero home equity.\(^{18}\)

The figure shows that, as expected, there is a high correlation between the extent of home equity constraints and the gains and losses experienced by households. However, in our sample, there is considerable density off the principal diagonal of the plot. While this is reassuring, it could well be the case that this variation is confined to one particular part of the sample period, i.e., driven by time-variation in Danish house prices.

\(^{17}\) $M > R$ is frequently observed in the data (44.8\% of observations). This is primarily because of households’ subsequent actions to remortgage to higher levels than their mortgage at issuance. This generally arises from “cash-out” refinancing, but could also arise from disadvantageous subsequent re-financing by homeowners, or fluctuations in adjustable rate mortgage payments causing households to increase mortgage principal to reduce monthly payment volatility.

\(^{18}\) In the online appendix, we show, using a subsample of 14,939 households for which we can find two subsequent housing transactions and mortgage down-payment data, that there is a high correlation between the current house value, and the price of the next home that these households purchase. The price of the next home is virtually always above the price of the current home.
To check this, in the online appendix we plot the shares of seller groups in the data across each of the years in our sample. The figure shows that aggregate price variation does shift the relative shares in each group across years, with price rises increasing the fraction of unconstrained winners relative to losing and constrained groups. However, the relative shares still look fairly stable over the sample period, alleviating concerns that different groups simply come from different time periods, i.e., identification of any effects is likely to arise mainly from the cross section rather than the time series.

### 2.6 Listing Premia

To understand the effects of gains/losses and down-payment constraints on household listing behavior, we adopt a similar approach to Genesove and Mayer (2001). They focus on the impacts of gains/losses and LTV on the difference between the price (in logs) at which a household lists a house, \( \ln L \), and the expected price of the house, \( \hat{\ln P} \). For a number of reasons, they adopt the approach of regressing \( \ln L \) on \( \hat{\ln P} \). To simplify our analysis, we simply focus on explaining the difference, i.e., \( \ln L - \hat{\ln P} \). We term this difference the “Listing Premium,” and denote it as \( LP \) in what follows.\(^{19}\) The online appendix shows the distribution of \( LP \) in the data. There is significant variation in this variable—mean \( LP \) is 13.6% and median \( LP \) is 11.6%, meaning that households list their houses, on average, at considerably higher levels than the hedonic pricing model would predict. There is also appreciable mass in the distribution of \( LP \) below zero—75% of the properties in the sample are listed above the hedonic price, while 25% are below.

\(^{19}\)We confirm, estimating their specifications on our data (see online appendix), that the coefficient on \( \ln P \) in such a regression, controlling for a range of other determinants, is close to 1. We discuss below how our results are also robust to using the alternative approach of Genesove and Mayer (2001), and discuss identification and measurement concerns in greater detail there as well.
2.7 Time-on-the-Market

The online appendix also shows the distribution of another quantity of interest, namely, the time that a property spends on the market once it has been listed. This “time-on-the-market” (denoted by $TOM$) is an important measure of liquidity in this market. We winsorize this distribution at 200 weeks, viewing the properties that spend roughly 4 years on the market as essentially retracted. Mean $TOM$ in the data is 38 weeks and median $TOM$ is 25 weeks.

3 Facts: Listing Premia, Time-on-the-Market, and Sales Prices

Listing premia have been extensively studied in the literature. An early and important set of studies was conducted by Genesove and Mayer (1997, 2001). They estimate a piecewise linear specification, conditioning the seller’s listing price on the nominal purchase price, to check whether listing prices exhibit a steeper relationship with estimated $\ln P$, when $\ln P$ is lower than the nominal purchase price $R$. They do so using data from downtown Boston between 1990 and 1997 ($N = 5,792$), and find evidence that listing prices increase 2.5 to 3.5% for every 10% increase in expected loss (i.e., the difference between the hedonic price and the reference price). They also acknowledge that LTV is a possible confound, and control for “excess” LTV (i.e., the difference between measured LTV and 80%) in their specifications. They find that excess LTV has only a small effect on the listing price over and above nominal losses. Their work on excess LTV and the effect of down-payment constraints is motivated by Stein (1995), who informally discusses search with “fishing” behavior by down-payment constrained households—speculative listing at high prices in hopes of relaxing the constraint.

This early evidence was followed by confirming evidence in many subsequent papers,
including Anenberg (2011, 2015), Hong et al. (2016), and Bracke and Tenreyro (2018). These papers conclude that a combination of loss-averse or realization-utility preferences and down-payment constraints are needed to rationalize the evidence on the behavior of listing premia. While the evidence on the observed nonlinearity in list prices is striking, DellaVigna (2018) cautions that list prices and the decision to list are household choices, so moving from facts to interpretations without an underlying structural model of behavior is difficult.

In the remainder of this section, we first verify previously established facts in our data, and then identify new facts about the behavior of listing premia. The next section takes a more structural approach, and explores which combination of model features is best able to explain the collection of empirical observations.

3.1 Listing Premia, Gains/Losses, and Home Equity

Figure 2 takes a first look at the effects of gains on listing premia in the data. The plot in Panel A plots $LP$ against the nominal gain $G$ on the property. Clearly $LP$ responds to $G$, increasing substantially more with losses ($G < 0$) than it declines with gains ($G > 0$). There is also some visual evidence of a kink in the relationship, which suggests without further interrogation at this stage that a value close to the purchase price of the property might serve as a reference point for households. Panel B shows that there is also a strong negative relationship between $LP$ and the level of home equity ($H$), but shows little evidence of a kink in this plot at the $H = 20\%$ mark.

3.1.1 Unobserved Quality

Before we can conclusively declare that constraints and losses affect behavior in both simple and more complex ways, however, we must confront several challenges. First, Genesove and Mayer (2001) highlight that hedonic prices $\hat{P}$ are estimated with error stemming from two sources, namely, unobservable property quality, and the possibility...
that the seller over- or under-paid at the time of purchase. They show that both of these possibilities can bias inferences, and suggest a bounding strategy. In the online appendix, we verify that our use of their suggested approach yields virtually identical results to our unconditional results, assuaging concerns of such bias affecting our inferences. We also note that these concerns are potentially more muted in our setting since our hedonic model is estimated with greater precision given the larger sample of transactions in our data, and the consequent ability to utilize a range of fixed effects. Finally, on this point, we note that we continue to find the patterns in listing premia when controlling for detailed demographic characteristics and households’ financial circumstances (see online appendix), which have been considered unobservables in much previous work on the topic.

Second, an important issue in this literature is that the results of such regressions have implicitly been assumed to arise from a causal model. That is, both down-payment constraints and expected gains and losses are assumed to drive households to behave in particular ways. However, we might still be interested to know whether the thresholds that we detect in the data are causal, or simply evidence of self-selection into different groups. Endogenous self-selection into home equity and gain groups could clearly arise from multiple sources, and we list a few below:

1. Different types of households pick mortgages of different types and may have preferences for different amounts of leverage, refinancing strategies, or cash-out refinancing (e.g., Campbell and Cocco, 2003, Hurst and Stafford, 2004, Koijen et al., 2009, Badarinza et al., 2016).

2. There may be varying skill in timing house purchases (e.g., Bach et al. 2017).

3. Households may have unobserved preferences for house sizes or types that are correlated with house purchase prices (e.g., Humphreys et al. 2019).

To dig deeper and to uncover whether reference points are indeed causal, we therefore
utilize insights from modern microeconometrics and estimate a Regression Kink Design (RKD) (Card et al., 2015b), as we describe below.

### 3.1.2 Regression Kink Design

Card et al. (2015b) suggests a new approach to identification that relies on quasi-random assignment at thresholds of particular “running variables”. The idea is that if there are clear thresholds in these running variables that induce kinks in agents’ responses, then we should be able to detect a clear difference in the slope of the relationship between the outcome variable and the running variable estimated at these thresholds. As long as households can only imperfectly manipulate on which side of the threshold they are, the resulting differences in behavior above and below the threshold can be interpreted as causal. This research design is known as an RKD, and has been used in a number of applied microeconomics papers (e.g., Landais, 2015, Nielsen et al. 2010, Card et al. 2015a).

Card et al. (2015b, 2017) outline several conditions that need to be satisfied for the appropriate use of this technique. First, the technique requires that the running variable density is smooth (rather than bunched) at the relevant thresholds, as evidence that manipulation of the running variable is limited. Second, that there should be a clear difference in policy (i.e., incentives) that affects behavior at the relevant threshold. Third, that other relevant covariates are also smooth around the threshold. In the online appendix, we show that these conditions are met in our sample, for the case of both running variables (H and G) considered below.

Following Card et al. (2017), we compute the RKD estimate of a given running variable \( V \) as follows:

\[
\tau = \lim_{v \to v_+} \frac{dE[LP_{it}|V_{it} = v]}{dv} \bigg|_{V_{it}=v} - \lim_{v \to v_-} \frac{dE[LP_{it}|V_{it} = v]}{dv} \bigg|_{V_{it}=v},
\]  

(2)
based on the following RKD specification (Landais 2015):

\[
E[LP_{it}|V_{it} = v] = \kappa_m + \kappa_t + \xi X_{it} + \left[ \sum_{p=1}^{P} \gamma_p(v - \overline{v})^p + \nu_p(v - \overline{v})^p I_{V \geq \overline{v}} \right].
\]

(3)

where \(|v - \overline{v}| < b\).

As before, we include time (\(\kappa_t\)) and municipality (\(\kappa_m\)) fixed effects, and controls \(X_{it}\). These include household characteristics (age, education length, and net financial assets), as well as the previous purchase year, which we include to ensure that households are balanced along the dimension of housing choice, and is predetermined at the point of inclusion in this specification. \(V\) is the assignment variable, \(\overline{v}\) is the kink threshold, \(I_{V \geq \overline{v}}\) is an indicator whether the experienced property return is above the threshold, and \(b\) is the bandwidth size.

To estimate the gains effect, we choose \(V = G\) as the assignment variable, and \(\overline{v} = 0\) as the kink point. To estimate the effect of down-payment constraints, \(V = H\), with a baseline kink threshold of \(\overline{v} = 20\%\), under the assumption that the desired home has a roughly similar value as the current home and mortgages are unavailable beyond an 80% LTV (by law). We show results across bandwidths \(b \in \{b^*, 15, 20\}\) around each of the running variables to estimate the effects of the RKD. \(b^*\) denotes the mean-squared-error optimally chosen bandwidth and we further optimally chose polynomial order \(p = 2\), leading to a local quadratic function, both following Calonico et al (2014).\(^{20}\) In the online appendix, we further show that the estimated effect is robust to a wide range of bandwidths.

\(^{20}\)The precision but not the size of the estimate for unconstrained households depends on the use of a local linear compared to a local quadratic function. Hahn et al. (2001) show that the degree of the polynomial is critical in determining the statistical significance of the estimated effects. In particular, the second-order polynomial needed to identify derivative effects leads to an asymptotic variance of the estimate that is larger by a factor of 10 relative to the first-order polynomial. We verify that the qualitative patterns that we detect are broadly unaffected by the use of either polynomial order, but that the standard errors, consistent with Hahn et al. (2001), are substantially higher for the second-order polynomial. A comparison of results is available in the online appendix.
The results summarized in Table 1 confirm that several of our results continue to hold in a causal identification setup. The gains effect (reported in the first three columns of the table) is pronounced, and indicates a statistically significant slope difference around a value of experienced returns $G = 0\%$. The marginal effect of each additional percentage point of price appreciation on the chosen listing premium ($LP$) is around 0.4 percentage points greater when the household experiences losses as opposed to when it experiences gains.

Second, the causal evidence based on the RKD for the down-payment constraint on listing prices is substantially weaker. The result is insignificant at the optimally chosen bandwidth, which is perhaps not surprising given that the financial constraint can be overcome using more expensive unsecured credit or by downsizing, making the exact level of the constraint effectively a choice, thus blurring the 20% threshold.

### 3.1.3 Interaction Effects

Figure 3 looks more closely at the relationship between $LP$ and both $G$ and $H$. This is a 3-dimensional plot where the two horizontal axes are $H$ and $G$, and $LP$ is on the vertical axis. As in Figure 2, the plot shows that there is a pronounced increase in $LP$ for $G < 0$, and shows a similar increase in $LP$ when $H$ declines. What is striking about the plot is that it suggests that the position of any reference point is not uniquely determined by $G$ or $H$ alone. Visually, there seems to be considerable variation in the slope of the relationship between $LP$ and both $G$ and $H$ that depends on the level of the other variable. Put differently, it appears as if the effects of losses and constraints interact with one another, and that the factors affecting household behavior are neither one nor the other variable in isolation.
3.1.4 Generalized Logistic Functions

This rich set of interactions calls for a flexible and parsimonious model capable of capturing the observed shapes of the $LP-G$ and $LP-H$ relationships. To better document the facts about these patterns in the data, we estimate a simple model of reference points, borrowing a function commonly used in the biology literature to model the growth of organisms and populations. This is the generalized logistic function, also known as a Richards curve (Richards, 1959, Zwietering et al., 1990, Mead, 2017):

$$ E[LP(V)] = A + \frac{K - A}{(1 + Qe^{-BV})^{1/\nu}} $$ (5)

Here, the parameters $A$ and $K$ control the lower and upper asymptotes of the sigmoid function, and the parameters $Q$, $B$ and $\nu$ control the position of the reference (i.e. inflection) point as well as the slope of the sigmoid curve at the reference point.

Figure 4 plots the relationships estimated using the model in equation (5). We set $V$ first as gains ($V = G$), and next, as the level of home equity $V = H$. Panel A of the figure has $G$ along the x-axis, and $LP$ along the y-axis. However, we now condition on three levels of $H$: the blue line shows the $LP-G$ relationship for households with levels of $H$ between 20 and 40% (i.e., effectively unconstrained households), while the red lines show the same relationship when households are increasingly constrained (the dashed red line when $H$ is between -5% and 20%, and the solid line when $H$ is between $-15\%$ and $-5\%$).

To better understand these plots, we note that the average level of $LP$ declines substantially as households become less constrained, and increases substantially as households become more constrained—this is simply the unconditional relationship between $LP$ and $H$, seen in a different way in this plot. (Panel B of the figure shows the level differences that reflect the $LP-G$ relationship, i.e., higher levels of $LP$ for those with high realized losses (in red) relative to those experiencing gains (blue)).
What is more interesting here is that controlling for this change in level, the slope of \(LP\) as a function of \(G\) is also affected by the level of \(H\). The important new fact is that down-payment-unconstrained households exhibit seemingly greater levels of reference dependence along the gain/loss dimension, exhibiting a pronounced increase in the slope to the left of \(G = 0\). In contrast, down-payment constrained households exhibit a flatter \(LP\) across the \(G\) dimension.

The bottom panel shows another interesting fact—along the home equity dimension, while the slope around the threshold does not change, the position of the kink in the listing premium increases with the level of past experienced gains.

### 3.1.5 Conditional Effects on Listing Premia

Of course, these observations could simply be capturing the effect of other potential determinants for which the plots do not control, and indeed, we may be concerned yet again about the independent effects of \(G\) and \(H\) on \(LP\). To check whether these conditional effects do indeed exist controlling for one another, and for a range of other determinants, and to verify whether they are statistically significant, we estimate the following piecewise-linear specification:

\[
LP_{it} = \mu_t + \mu_m + \xi_0 X_{it} + \xi_1 B_{it} + \alpha_1 \mathbb{I}_{G_{it} < 0} + \alpha_2 \mathbb{I}_{H_{it} < 20\%} \\
+ (\beta_0 + \beta_1 \mathbb{I}_{G_{it} < 0} + \beta_2 B_{it} + \beta_3 \mathbb{I}_{G_{it} < 0} B_{it}) G_{it} \\
+ (\gamma_0 + \gamma_1 \mathbb{I}_{H_{it} < 20\%} + \gamma_2 B_{it} + \gamma_3 \mathbb{I}_{H_{it} < 20\%} B_{it}) H_{it} \\
+ \varepsilon_{it}.
\]  

Equation (6) allows \(LP\) to depend (piecewise) linearly on both home equity \(H\) and gains \(G\) (through \(\beta_0, \gamma_0\)). We include time (\(\mu_t\)) and municipality (\(\mu_m\)) fixed effects, and
controls $X_{it}$ (household age, years of education, and net financial assets). The piecewise linear specification also allows for kinks in the linear relationship at a reference point of 0 for nominal gains, and 20% for home equity through $\beta_1$ and $\gamma_1$—these coefficients capture the “unconditional” effects of gains and home equity on household behavior. To capture the conditional behavior seen in Figure 4, we bin both home equity and gains (as well as the other conditioning variables) and introduce dummy variables $B$ into the regression of the respective other dimension to capture the different $LP-G$ (and $LP-H$) relationships for these groups. We allow for $B$ to modify both the unconditional relationship with $G$ and $H$ ($\beta_2$, $\gamma_2$), as well as any slope differential at the reference points ($\beta_3$, $\gamma_3$).\footnote{Since we do not want to model any higher-order effects in this context, we exclude the respective gains bins from $B$ when interacted linearly with the gains variable, and home equity bins when interacted linearly with the home equity variable. That is, we allow only for “cross-effects” in this specification.}

Despite the considerable number of parameters in equation (6), the estimates verify the conditional variation seen in Figure 4. The y-axis of Panel A of Figure 5 shows the point estimate for the slope of the $LP-G$ relationship for the different bins of $H$ shown on the x-axis. The three bins in the centre correspond to the bins used in Figure 4. For example, the (linear) slope of the relationship is highest for the least constrained households (a roughly 0.6 point estimate), and monotonically declining as constraints become increasingly tight, up to a level of -15% home equity (a roughly 0.27 point estimate). For households that are severely constrained, i.e., at levels below -15% home equity, there is a rise in the slope once again.

Panel B of Figure 5 investigates the effect of down-payment constraints, conditioning the $LP-H$ relationship on the level of $G$. The intriguing finding, confirming the earlier analysis, is that there appears to be evidence of a shifting constraint reference point. Households experiencing nominal losses seem to raise their $LP$ at a lower level of $H$, while households experiencing nominal gains seem to raise $LP$ at levels of $H$ that are higher. The relationship also appears monotonic—the higher the gains, the higher the reference level of home equity at which households raise $LP$. Put differently, as $G$ rises,
there is a monotonic increase in the point (which we term the H-reference point) at which
the slope of the LP-H relationship changes. For those facing losses, the H-reference point
appears closer to the 20% mark, while it climbs steadily for those expecting gains.\textsuperscript{22} The
right plot in panel B shows, confirming visual evidence, that once the position of the
reference point is accounted for, there is no significant difference in the slope of the LP-H
relationship at the reference point across different G-groups.

Numerous potential interpretations of these intriguing patterns come to mind at this
stage, but mindful of DellaVigna’s (2018) exhortation about the complexity of moving
to more structural interpretations from reduced-form empirical observations, we defer
discussion and interpretation to the next (model) section of the paper. As a precursor
to doing so, we discuss additional important facts about the relationship between listing
premia and final market outcomes, namely, time-on-the-market and final sales prices.

### 3.2 Listing Premia, Time-on-the-Market, and Sale Prices

In recent work, Guren (2018) emphasizes an important aspect of the demand for housing.
He shows that buyers react to sellers’ posted listing prices in a manner that he terms
“concave demand.” In particular, he documents that above average list prices increase
TOM (i.e., reduce sale probability), while below average list prices reduce seller revenue
with little effect on TOM. We reproduce these patterns in the Danish data, estimating
similar relationships to those documented by Guren (2018) in the US market.

#### 3.2.1 Time-on-the-Market

The left plot in Panel A of Figure 6 shows how TOM relates to LP in the data using
a simple binned scatter plot. When LP is below 0, TOM barely varies with LP; how-
ever, TOM moves roughly linearly with LP when LP is positive and moderately high.

\textsuperscript{22}The H-reference point is calculated using a simple manual grid search procedure. We repeat our
estimation of the coefficient $\beta_3$ for different home equity cut-offs in the interval [-50%-100%]. We identify
the reference point as the home equity cut-off which corresponds to the largest value of $\beta_3$.  

27
Interestingly, we also observe in our data that the relationship between \( LP \) and \( TOM \) flattens out as \( LP \) rises to very high values above 40%. This behavior is mirrored in the right-hand side of Panel A of Figure 6, which shows the share of seller retracted listings, which also rises with \( LP \).

Panel B of the figure simply converts the two plots in Panel A into a single number, which is the probability of house sale within six months on the y-axis as a function of the listing premium on the x-axis. The plot smooths the average point estimate at each level of the listing premium, once again using a generalized logistic function. The solid line in the centre of the plot is this smoothed point estimate, while the two dashed lines on either side simply add and take away one (unconditional) standard deviation of the point estimate of the six-month sale probability as a crude confidence interval for the point estimate. We will return to this estimated sale probability in the model section; for now, it simply serves as a reduced-form approximation of the impacts of the listing premium on the probability that a buyer swiftly purchases the property.

### 3.2.2 Sale Prices

Figure 7 shows how the final sales price (i.e., the premium of the final sales price over the hedonic value) relates to \( LP \). Panel A shows that the pricing error from the hedonic model, i.e., \( \ln P - \ln \hat{P} \), which we term the “realized premium” or \( RP \), rises virtually one-for-one with \( LP \) at low levels of \( LP \), but flattens out at higher levels of \( LP \). Akin to Guren (2018), low list prices appear to reduce seller revenue with little corresponding decline in \( TOM \), and akin to Genesove and Mayer (2001), the Danish data also reveals that sellers who set high \( LP \) suffer longer \( TOM \), but ultimately achieve higher prices on these sales as reflected in \( RP \).

Once again, Panel B of the figure simply smooths the average point estimate of \( RP \) at each level of \( LP \) using a generalized logistic function, and a one-standard-deviation confidence interval constructed similarly to the previous case, to facilitate structural estimation.
of the models that we evaluate in the next section of the paper.

4 Modelling Household Listing Behaviour

To explain the facts uncovered in the previous section, we consider a wide set of different preferences and constraints that have commonly been used to explain patterns in listing premia and embed them in a simple model. Our approach is to assume that the seller optimizes their expected utility from the final sale of the property. When doing so, the seller takes as given the impacts of the chosen listing price on both the probability of sale and the final sale price from the reduced-form functions that we estimate from the data in Figures 6 and 7. These “market constraints” serve as a reduced form for the buyer’s problem, which the seller internalizes when optimizing utility.

In addition to these “market constraints,” sellers also face down-payment constraints à la Stein (1995), which we model variously as hard constraints which prevent the household from purchasing a new house, resulting in a (lower) outside option value, or as smooth penalty functions which impose financial penalties on households from exceeding the maximum LTV on a subsequent house purchase.

The seller preference specifications that we consider include the simple utility of the final sale price (i.e., a baseline “rational” preference specification); a “pure reference dependence” addition to this final sale utility that delivers an additional boost (or penalty) to utility from final sale prices that exceed or fall short of the nominal purchase price reference point; a loss averse utility function with a kink at gains of zero, and a greater weight on losses than gains à la Kahneman and Tversky (1979); and finally, realization utility à la Barberis and Xiong (2012).
4.1 Setup

The market consists of a continuum of sellers and buyers of residential property. For simplicity, we consider a model with two periods. In period 0, a subset of property owners receive a moving shock, put a property up for sale on the market and decide on the optimal listing price. In period 1, buyers visit properties that are up for sale. If negotiations succeed, the ownership title of the property is transferred to the new owner, for a resulting equilibrium price. If they fail, the seller continues to hold on to the property.

Equilibrium quantities and prices in this market result from the interaction between buyers (the demand side) and sellers (the supply side). Since the focus of the paper is on seller preferences and constraints, we start with a set of reduced-form assumptions about buyer decisions and equilibrium negotiation outcomes.

In particular, let $\alpha$ denote the probability that a willing buyer will be found, and $P$ the price resulting from the negotiation. Guren (2018) shows that a sufficient statistic determining equilibrium outcomes in this market is the listing premium, i.e. the difference between the listing price and the buyer’s reference property value.

For our purposes, we define this premium as the difference between the listing price ($L$) and the rational-expectations hedonic value of the property ($\hat{P}$):

$$\ell = L - \hat{P}.$$  \hfill (7)

---

23 We start with a version of the model which abstracts from the decision to list (i.e. the extensive margin of residential property transactions), and solely focuses on the optimal behaviour of sellers in terms of their choice of listing premia (i.e. the intensive margin). Later on, we also explore the implications of decisions along the extensive margin, i.e., whether or not to decide to list.

24 In the model solution and calibration exercise, we normalize property values to 1. All model quantities can therefore be thought of as being expressed in logs, consistent with the definitions of gains/losses and home equity used in the empirical sections above.

25 Guren (2018) assumes that the buyer’s reference value is given by the average listing price in a given zip code and year. This allows for more flexibility, allowing listing prices to systematically deviate from hedonic property values across time and locations. Instead, we prefer to start with a simpler benchmark, since this allows the model to be more internally consistent. We note that this distinction does not play a significant role empirically, especially given that Denmark has a rather homogenous and liquid housing market.
Under the assumption that sellers take $\alpha(\ell)$ and $P(\ell)$ as given, these functions capture equilibrium outcomes in the negotiation process in period 1. This greatly simplifies the model.

In the rest of the paper, we refer to these two functions as market constraints, because they restrict the seller’s action space, and capture the fundamental tradeoff that sellers face: a larger listing premium leads to a higher ultimate transaction price, while at the same time it decreases the probability that a willing buyer will be found within a reasonable time frame. This latter point is essential, capturing the tight link between listing behavior and time-on-the-market.\footnote{In our estimation, we define a \textit{period} as equal to six months. In this case, the function $\alpha(\ell)$ captures the probability that the transaction goes through within a time frame of six months after the initial listing.}

We are now ready to specify a typical seller’s decision in period 0:

$$
\ell^* = \max_{\ell} E \left[ U(P(\ell)) \right].
$$

In period 1, we distinguish between two possible outcomes, conditional on the level of the listing premium:

$$
U(P(\ell)) = \begin{cases} 
\overline{u}(P(\ell)), & \text{Prob. } = \alpha(\ell) \\
\hat{P} - \theta, & \text{Prob. } = 1 - \alpha(\ell)
\end{cases}
$$

With probability $\alpha(\ell)$, a willing buyer is found, and the seller receives utility $\overline{u}(P(\ell))$ from selling the property for an equilibrium price $P(\ell)$. With a probability $1 - \alpha$ the listing fails to result in a sale, in which case the seller falls back to their outside option level of utility, suffering costs $\theta$ from engaging in a failed search and not being able to move to a new house.\footnote{Our model is a two-period version of the sales process. We seek to extend it to distinguish between the utility cost of failed searches and those from deciding not to list in the first place. In this simple version of the model, all utility costs (regret, search, listing, nonmoving, and transaction costs) are captured by a single parameter.}
4.2 Utility functions

Equation (8) illustrates one tradeoff that sellers face when choosing optimal listing premia. A higher listing premium results in longer TOM, i.e., lower sale probability, but on the other hand, conditional on a willing buyer being found, high listing premia deliver ultimately higher sales prices, and greater utility from trade $u$. We now turn to specifying the exact form that this utility will take.

4.2.1 Baseline Utility of Final Sale Price

We consider the baseline case in which the seller’s utility takes a simple terminal-value form, depending strictly on the final price realized from the sale of the house:

$$u(P(\ell)) = P(\ell).$$

(9)

4.2.2 Reference Dependence

We next consider the case in which the seller has reference-dependent preferences, with the reference level given by $R$. Defining the realized gains relative to this reference level as $G(\ell) = P(\ell) - R$, the seller’s utility is then given by:

$$u(P(\ell)) = P(\ell) + G(\ell).$$

(10)

It is important to note that this specification is not just a transformation of utility or a scaling factor, but closer to the spirit of state-dependent utility and external habit formation (e.g., Arrow, 1974, Campbell and Cochrane, 1999). Cross-sectional variation across sellers arises from differences in reference levels, i.e., variation in initial prices paid for the property.
4.2.3 Reference Dependent Loss Aversion

Reference dependent loss-aversion is an integral component of prospect theory (Kahneman and Tversky, 1979). We model loss averse preferences as:

\[
u(P(\ell)) = \begin{cases} 
P(\ell) + G(\ell), & \text{if } G(\ell) \geq 0 \\
P(\ell) + \lambda G(\ell), & \text{if } G(\ell) < 0 \end{cases}
\]

(11)

where the parameter \(\lambda > 1\) governs the degree of loss aversion. This specification of the problem assumes that utility is piecewise linear in nominal gains and losses relative to the reference point, with a kink at zero, which approximates most specifications used to estimate this effect in the literature.

4.2.4 Realization Utility

Finally, a seller with realization utility will only ever sell the property if the transaction price (weakly) lies above the reference level \((G = 0)\), and she will otherwise fall back on the outside option:

\[
u(P(\ell)) = \begin{cases} 
\hat{P} - \theta, & \text{if } G(\ell) < 0 \\
P(\ell) + G(\ell), & \text{if } G(\ell) \geq 0 \end{cases}
\]

(12)

The utility specification (12) is an interpretation of Barberis and Xiong (2012)—the assumption we make is that sellers will wait to see if the final transaction price delivers positive gains. If so, they will complete the transaction and realize these gains, and if not, they will choose the outside/fallback option.

4.3 Financial Constraints

We distinguish between two ways of modelling the down-payment constraint faced by households. To establish notation, let \(M\) be the level of the outstanding mortgage,\(^{28}\) and

\(^{28}\)In our empirical work, we confirm that the patterns in listing premia hold when we control for net liquid financial assets of the household as a robustness check. In the model and our structural estimation,
the necessary down-payment on any new mortgage origination. For a given price level
$P(\ell)$, we then define the “realized” home equity position of the household as $H(\ell) = P(\ell) - M$, which allows us to distinguish between constrained households ($H(\ell) < \gamma$) and unconstrained ones ($H(\ell) > \gamma$).

### 4.3.1 “Threshold” Constraint

For the case in which the home equity constraint is strictly imposed, and only unconstrained sellers would be able to move, we have:

$$\bar{u}(P(\ell)) = \begin{cases} \hat{P} - \theta, & \text{if } H(\ell) < \gamma \\ u(P(\ell)), & \text{if } H(\ell) \geq \gamma \end{cases}$$

(13)

In this case, sellers facing binding borrowing constraints will fall back on their outside option $\hat{P} - \theta$, i.e., failing to secure the necessary down-payment for a planned move entails the disutility of continuing to own the current property despite any utility from moving that motivated the decision to list in the first place.

### 4.3.2 Penalties for Falling Short

An alternative is that violating the down-payment constraint does not lead the seller to withdraw their sale offer. Instead, they incur a monetary penalty for every unit by which realized home equity drops below the constraint threshold (this might arise from incurring higher interest rates on the additional borrowing required, from renting rather than new purchases, or from downsizing in response to the constraint). We model this as:

$$\bar{u}(P(\ell)) = \begin{cases} u(P(\ell)) + \eta(H - \gamma), & \text{if } H(\ell) < \gamma \\ u(P(\ell)), & \text{if } H(\ell) \geq \gamma \end{cases}$$

(14)

we currently match patterns in listing premia along the home equity dimension without applying these controls. We intend to rectify this in future drafts of this paper.
where $\eta$ is the per unit penalty.

### 4.4 Calibration and Model Fit

To match the model with the data, we first estimate the market constraints $\alpha(\ell)$ and $P(\ell)$ as shown in Panels B of Figures 6 and 7. In addition, we allow for a certain degree of uncertainty in terms of the actual realizations of these market constraints by using a discretized probability distribution where we attach a 60% probability to a realization of the mean, and 20% each for realizations one standard deviation above and below the mean. For simplicity, we use the in-sample observed unconditional standard deviations of selling probabilities and realized market premia as crude proxies for the uncertainty that sellers face when estimating market constraints in the data.

We set $\lambda = 2.25$ for loss aversion in the reference-dependent utility function, a standard value in the literature. Since households in Denmark can use mortgage financing up to loan-to-value ratios of 80%, we set the down-payment constraint limit $\gamma = 20\%$.

We normalize all quantities in the model in terms of the property’s hedonic value $\bar{P} = 1$. We define the variables $G_0 = \bar{P} - R$ and $H_0 = \bar{P} - M$ as the model equivalents of the levels of gains and home equity for which we calculate listing premia in the data. We solve the model numerically in each case, obtaining policy functions $\ell^* = LP_{\text{model}}$ for given values of market constraints, parameters, and tracing loci of the optimal listing premium as the two variables $G_0$ and $H_0$ vary in the model. We choose the value of $\theta = 0.46$ to match the observed magnitude of the unconditional average listing premium in the data, and the value of $\eta = 0.87$ which minimizes the distance between the average model-implied listing premium as a function of home equity and its empirical counterpart.\(^{29}\)

To assess the goodness of fit for each alternative combination of model features, we compare the policy function $LP_{\text{model}}$ with its counterpart in the data $LP_{\text{data}}$, using the bins seen in the conditional plots in Figure 4. For each point in these figures, we calculate

\(^{29}\)We currently estimate $\theta$ and $\eta$ using the pure reference dependence model.
the mean absolute error, i.e., the absolute difference between $LP^{\text{model}}$ setting $(G_0, H_0)$ to the values in the data, and $LP^{\text{data}}$ at the same point. To avoid irregular solutions for listing premia that lie in a domain for which estimation uncertainty is very large (especially as concerns market constraints—where irregular slope changes massively tilt behavior in one direction or the other), we restrict our focus to the range [-20\%,40\%] for both gains and home equity. To summarize, we ask each model to match the listing premia-gains relationship in these ranges conditional on three different bins of home equity and vice versa, a total of six shapes, and 78 bins of data in total per model. We then run a pooled regression across all combinations of grid points and model specifications, to estimate the associated mean and standard error for each model, and to compute t-statistics to assess the relative performance of the models.

4.5 Results

Table 2 summarizes absolute mean prediction errors for model variants spanning our different model features. The rows show different combinations of utility functions and down-payment constraints. The columns correspond to two cases of estimated market constraints: a linear version, and a non-linear one.\textsuperscript{30}

For example, consider the model variant with the lowest prediction error—resulting from a combination of non-linear market constraints, reference dependent utility, and down-payment constraints modelled using a penalty function. With this particular model specification, we are able to match the listing premia with an average error of 2.9 percentage points across 78 bins of gains and home equity. For the case of a model without reference-dependent utility and linear market constraints, the average prediction error reaches 34.2\%. It reduces to 23.8\% if we assume non-linear market constraints, 7.5\% when we add reference dependence, and to 5.3\% if we assume a hard financial constraint

\textsuperscript{30}In the online appendix, we illustrate the model predictions vs. their counterparts observed in the data. That is, we plot $LP^{\text{model}}$ vs $LP^{\text{data}}$ for each model.

36
around the down-payment threshold.

### 4.5.1 Reference Dependence

The first important message is that we can reject the null of no reference dependence in this market. A model featuring a simple terminal wealth utility function is not able to match the patterns in the data. The prediction errors associated with this case are significantly (roughly 2-3 times) larger than the case of reference dependence. That said, the results suggest that asymmetry in reference dependence across gain and loss domains is not necessary to match the observed patterns in the data. While we cannot statistically exclude the fact that sellers are loss averse, we also do not find any supporting evidence for either loss aversion or realization utility.\textsuperscript{31} Put differently, even without asymmetry in the utility function, the model is still able to capture the asymmetry of the listing premium around the nominal purchase price reference point. To better understand this result, we need to look at the role of market constraints in more detail.

### 4.5.2 Market Constraints

Optimal listing behavior arises from the tradeoff between the expected utility of a higher realized transaction price and the possibility that the transaction will fail. To illustrate the impact of these quantities on the seller’s decision, we answer two questions.

The first is why loss aversion by itself is not sufficient to generate non-linear patterns in the listing premium. Consider a model with linear market constraints and loss averse preferences. In this case, the optimal listing premium is given by the interplay between the marginal cost (which is constant), and the marginal benefit (which is not). However, the marginal benefit only changes sharply around the seller’s reference point, so loss aversion can only generate a discrete jump, i.e., a discontinuity in the seller’s choice of listing.

\textsuperscript{31}We note that the inability of the model to distinguish between pure reference dependence and loss aversion may also be because of an estimation power issue, related to the relatively low density of the discretization grid in the data and the model (78 bins of gains and home equity in total, for each model variant).
premium, but not a change of listing premium slopes (this is the same point made by DellaVigna (2009, 2018)).

The second is why the situation is different when market constraints are non-linear. Consider the case of a seller facing losses. Such a seller will set a premium that is as high as possible to benefit from the fact that aggressive listing does pay off conditional on a willing buyer being found. This is traded off against a lower probability that such a buyer will be found at all. The tradeoff faced by sellers facing gains is different—it is optimal to choose low listing premia to avoid hitting the fallback utility from a failed listing. Concave demand means that lowering listing premia past a point does not boost the sale probability, but does continue to have adverse effects on realized sale premia. This leads to a dulling of the effect of gains on listing premia, i.e., a lower slope in this domain.

To better understand this, consider a simple local linear approximation of the market constraints \( \alpha(\ell) = \alpha_0 - \alpha_1 \ell \) and \( \beta(\ell) = \beta_0 + \beta_1 \ell \) in a “pure” reference-dependent utility model without financial constraints. The optimal listing premium in this model is:

\[
\ell^* = \frac{1}{2} \left( \frac{\alpha_0}{\alpha_1} - \frac{\beta_0 + \theta}{\beta_1} - \frac{1}{\beta_1} G \right). \tag{15}
\]

Equation (15) shows how market constraints affect \( \ell^* \). In particular, the less sensitive the probability of sale is with respect to the listing premium (i.e. the lower \( \alpha_1 \)), the higher the listing premium that the seller will optimally choose. Sellers experiencing gains would be perfectly happy to set a low listing premium, but they end up not doing so, because the market does not reward low listing premia with substantially higher probabilities of sale. In the online appendix, we provide a graphical illustration of this mechanism, showing how variation in the slope \( \alpha_1 \) as listing premia rise above and fall below zero translates into slope differentials in the listing premia in the gain and loss domains.

\[^{32}\text{In the data, we do not find evidence for such a discontinuity. Similarly, in the model, given the calibration of structural parameters, the implied magnitude of this discontinuity is essentially zero.}\]
Finally, another perspective on the role of market constraints is to think of our approach as a test of seller rationality. Put differently, the approach can be used to assess whether sellers’ decisions are consistent with the constraints that they should expect to face in the market, estimated from the data.

4.5.3 Down-payment Constraints

The final model variations that we consider address the modelling of down-payment constraints. The data seem to favour a model of financing constraints which impose smooth penalties around the 20% legal down-payment threshold, as opposed to a hard binding limit. A value of $\eta = 0.87$ is preferred to match the average listing premium profile with respect to home equity, i.e., there is an 87 bp penalty (as a fraction of the mortgage amount) for every percent that home equity drops below the 20% amount. This number can be contrasted with an average of roughly 50 bp on the whole loan arising from the unsecured Danish lending market in which households can borrow additional amounts beyond the legal loan-to-value limits. The relatively larger number that we estimate may capture the significant rise past 95% LTV, and/or other financial constraints that prevent households from borrowing significant sums in this market, including the results on net liquid financial wealth that we documented earlier.

4.5.4 Preferred Model

Figure 8 compares the model-implied patterns of optimal listing premia (solid lines) with those observed in the data (dotted lines), for the preferred model specification with estimated non-linear market constraints, pure reference dependence, and financial constraints which take the form of a penalty associated with the down-payment threshold of 20%.

Panel A of the figure plots listing premia for different levels of gains. For levels of gains

---

33 Households in this market face 200-500 basis points increases in interest rates for every percentage point of borrowing in this market between 80 and 95 LTV. Taking 450 bp as the point estimate within this range, at an 80% LTV an additional ten percent borrowing at 400 bp adds roughly 50 bp to the overall loan.
and home equity around their respective thresholds, the model captures both the magnitudes and the size of the non-linearities well, but it misses two central features of the data: first, the flattening out of listing premia for higher levels of gains, and second, the observation that decisions of more constrained sellers (e.g. those with a level of home equity around 0%) are substantially less likely to depend on their property’s gains since purchase.

Panel B of the figure plots listing premia for different levels of home equity. In this case, the model matches the slope differences around the down-payment threshold, as well as the overall magnitudes. However, it misses the magnitude of interaction effects, in particular the observation that financial reference points depend on realized market gains in non-trivial ways. Importantly, the model does not capture the flattening out of listing premia for negative levels of home equity, suggesting that the penalty function should take a more strongly non-linear form, reflecting pronounced increases in borrowing costs for households which are underwater.

4.6 The Extensive Margin

The realized gains or losses on a given property and the household’s home equity position might reasonably be expected to influence the decision to list the property for sale in the first place. If so, the seller faces a two-stage optimal choice problem, in which the utility gains from listing the property are weighed against the outside option of the status quo:

\[
V^S = \max \{ \max_{\ell} E[U(P(\ell))] , \hat{P} - \theta \}.
\]

Here, \( \hat{P} - \theta \) is the outside option for the case in which the seller decides not to list, which reduces the market value of the property by a penalty for foregone opportunities from not being able to put the property up for sale. Rather than solving a more involved version
of the model,\textsuperscript{34} in this draft, we focus on a particular dimension of the extensive margin decision which potentially affects our inferences on the intensive margin.\textsuperscript{35}

Suppose that owners observing losses on their property or facing potentially binding down-payment constraints can decide whether or not to list in the first place. Self-selection of a particular type could deliver the results we observe on the intensive margin, if the decision to list is correlated with the premium. In particular, if those that decide not to list are more conservative (i.e., set lower listing premia), and those who decide to list are more aggressive (i.e., set higher listing premia) the resulting selection effect would lead to a higher observed non-linearity in listing premia around reference points. Panel A of Figure 9 takes a first look at the data, plotting the share of listed properties as a fraction of all properties in Denmark over the sample period, across bins of gains (the online appendix plots the same pattern with home equity on the x-axis instead of gains). The figure does show a modest decrease in selling probabilities just below the threshold of zero gains, which could be cause for concern.\textsuperscript{36}

How much of the observed variation in listing premia could such selection effects generate? Our approach to bound the bias is to estimate the counterfactual under the assumption that the distribution of observed listing premia for properties with greater than zero gains is a fair representation of the (potentially selected) distribution of listing premia of those below this threshold. We therefore obtain the distribution of listing premia for gains between 0\% and 20\% as the “baseline distribution” for the counterfactual.\textsuperscript{37} We then compute counterfactual average listing premia in the loss domain under the

\textsuperscript{34}Importantly, in this model, we have to assume that for the majority of sellers $\theta$ is negative, i.e. they strongly prefer to continue to occupy their present residences as opposed to moving. This creates an additional layer of structural estimation involving strong distributional assumptions, which we defer to future drafts of this paper.

\textsuperscript{35}We thank Jeremy Stein for highlighting this potential issue with our inferences on the intensive margin.

\textsuperscript{36}Since no such effect obtains with respect to home equity, we restrict the remaining analysis to selection effects along the gains dimension.

\textsuperscript{37}We test through a number of alternative balance statistics that sellers and properties just above and below the threshold do not differ materially, along a wide range of observable characteristics. The associated test statistics are in all cases well below standard critical values.
assumption that only the most conservative sellers drop out, trimming the “baseline
distribution” of listing premia from below by the fraction implied by the reduction in the
selling probability observed in Panel A Figure 9. Panel B of Figure 9 reports the average
listing premia computed from this exercise. The results suggest that only a very modest
part of the observed variation in listing premia can be attributed to effects along the
extensive margin.

5 Validation of Structural Mechanism and Open Questions

5.1 Out-of-sample Validation

Sellers’ responses to “concave demand” play an important role in the model. In the
current version of this paper, we abstract from equilibrium considerations regarding buyer
behavior, and the way in which buyers react to seller’s listing decisions, instead using a
reduced-form approach to approximating the demand-side using estimated functions in
the data. Nevertheless, our partial equilibrium framework delivers a clear prediction that
can be tested in the data, namely that the non-linearity of the market constraint is tightly
linked with the non-linearity in the choice of the listing premium around seller reference
points.

To test this prediction, we exploit the variation in demand concavity across segments of
the Danish housing market. Within each such segment (e.g., a given year or a given price
category), we estimate two quantities. The first, which we label “non-linearity of market
constraint” is given by the slope difference above and below zero for the relationship
between the selling probability and the listing premium. From Figure 6 we know that

---

38 Assuming that the behavior of these sellers is representative for those immediately below the re-
spective thresholds of 0% for gains, the distribution of observed listing premia should not differ above
and below the threshold. Indeed, under the null of no intensive margin effects, different levels of listing
premia should only materialize because of owners selectively dropping out from listing.
the selling probability profile flattens out for levels of the listing premium close to and below zero, while it is strongly downward-sloping for listing premia above zero. A larger positive value of the kink that we estimate implies a greater degree of non-linearity in the market constraint.

The second, which we label “non-linearity of listing premium” is given by the slope difference above and below zero for the relationship between listing premia and gains. We know that the listing profile is flat for gains above zero, and strongly kinked around zero, with larger negative gains leading to increasingly larger listing premia. A larger positive value of the slope difference that we estimate indicates a more pronounced non-linearity of listing premia around the reference point.

While only a rough approximation of both demand concavity and listing behavior, these simple measures seem to carry enough information for us to observe variation across market segments that is consistent with the model’s predictions. We bin houses into six equal-sized bins sorted by hedonic value, and estimate the two kinks (demand concavity and listing premia wrt gains) within each bin. When plotted against each other, Figure 10 shows that the non-linearity in listing behavior around gains is substantially larger in higher price segments, in which there is more pronounced demand concavity (indicated by points located in the South-West quadrant of the scatter plot). Analogously, both the non-linearity in listing behavior and the concavity of demand are less pronounced in lower price segments (indicated by points located in the North-East quadrant).

5.2 Open Questions

The main findings that the preferred model is unable to match is the interaction effects; i.e., the change in the slope of the $LP-G$ relationship as home equity varies, and the change in the kink point in the $LP-H$ relationship as expected gains and losses vary. This new set of facts appears to require a more intricate model of preferences and/or constraints than the literature has thus far proposed. We briefly speculate on the possible types of
models that may rationalize these findings here, with a view towards enlarging the set of preference and constraint specifications that we consider in future drafts of this paper.

One interpretation of the finding of a changing slope in the $LP-G$ relationship as the level of home equity changes is that constrained households seem to simply set a high $LP$, without responding greatly to the nominal reference point separating gains from losses. In contrast, unconstrained households respond substantially more to nominal losses—the luxury of being unconstrained appears to cause more psychological motivations such as loss aversion to come to the fore. Put differently, unconstrained households seem constrained by their loss aversion à la Genesove and Mayer (2001), while constrained households respond to their real constraints by engaging in “fishing” behavior à la Stein (1995). It may also be that this finding can be rationalized by a more complex specification of reference points à la Köszegi and Rabin (2006, 2007).

One interpretation of the change in the position of the kink in the $LP-H$ relationship is that a household’s propensity to engage in “fishing” behavior kicks in at a level of home equity that is strongly influenced by their expected nominal gains on the property they will sell. Households facing nominal losses feel constrained at levels of home equity (i.e., $H = 20\%$) that would force them to downsize, while those enjoying nominal gains may have in mind a larger “reference” level of housing into which they would like to upsize (or indeed, a larger fraction of home equity in the next house). To achieve this larger reference level of housing, they begin “fishing” at levels of $H > 20\%$ in hopes of achieving the higher down payment on the new, larger house. To provide suggestive evidence on this story, in the online appendix we focus on a sample of 14,440 households for which we can find two subsequent housing transactions and mortgage down payment data. For this limited subsample, we show a binned scatter plot of the $LP$ on the subsequently sold listing against the realized down payment on the subsequent house, controlling for the level of home equity on the subsequently sold listing. We find evidence that the down-payment on the new house is correlated with the $LP$, which, given our evidence of $G$
predicting $LP$, is consistent with the idea of households shifting their reference level of housing on the basis of expected gains.

6 Conclusion

Using comprehensive Danish data on the housing market, we show that both nominal losses and down-payment constraints strongly affect households’ listing and selling decisions. More importantly, we show how these two factors driving seller behavior in the housing market interact with one another.

We find evidence that the reference dependent behavior is less evident when households are facing more severe constraints, and most pronounced for unconstrained households. We also find that home equity constraints loom larger for households facing nominal losses. However, for households facing nominal gains, we find evidence consistent with an upward shift in the point at which they feel constrained. This can be explained by households resetting their desired size or quality of housing upwards in response to experienced gains.

We employ an increasingly standard tool to establish causality, i.e., the regression kink design, to provide evidence that reference points appear to causally affect behavior, rather than these nonlinearities operating solely through the unobserved correlation between household skill at picking houses or mortgages and their propensity to engage in particular types of behavior in the housing market.

We consider various types of preferences that have commonly been used to explain patterns in listing premia, and embed them in a model of listing behavior. The model which best explains listing premia in the data requires concave demand a la Guren (2018), reference dependence, and a penalty on levels of realized home equity below the 20% level. One striking result that we find from this analysis is that nonlinearity in the demand response to listing premia alone can deliver nonlinearity in listing premia profiles with respect to expected gains. No further nonlinearity in preferences is necessary to help
explain this often-cited fact.

Finally, we conclude that the widely-adopted sets of preference specifications that we consider cannot explain some of the new evidence that we uncover about seller behavior in the housing market. In future drafts of this paper, we intend to explore the types of preferences that can rationalize these new facts.
References


Figure 1
Gains and home equity

This figure plots the joint distribution of the experienced gain and home equity position of households, at the time of listing. The color scheme refers to the relative frequency of observations in gain and home equity bins of 10 percentage points, where each color corresponds to a decile in the joint frequency distribution. The darker shading indicates a higher density of observations. Gain-home equity bins that did not have sufficient observations are shaded in white. The dotted blue lines separate the joint distribution in four groups: (1) Unconstrained Winners ($H \geq 20\%$ and $G \geq 0$) covering 50.2% of the sample, (2) Constrained Winners ($H < 20\%$ and $G \geq 0$) with 24.9%, (3) Unconstrained Losers ($H \geq 20\%$ and $G < 0$) with 6.7%, and (4) Constrained Losers ($H < 20\%$ and $G < 0$) accounting for 18.2% of the sample.
Figure 2

Gains, home equity and the listing premium

This figure reports equally-spaced, binned average values for the listing premium \( LP \) along levels of experienced gains (Panel A) and home equity (Panel B), respectively.

Panel A

![Graph showing the relationship between gain and listing premium.]

Panel B

![Graph showing the relationship between home equity and listing premium.]

53
Figure 3
Listing premium by gains and home equity bins

This figure reports binned average values for the listing premium ($LP$) along both levels of experienced gains and home equity.
Figure 4
Estimation of Generalized Logistic Functions (GLF)

This figure shows the effect of experienced gains (Panel A) and home equity (Panel B) on the listing premium ($LP$). We report estimated relationships which follow a non-linear model specified in the form of a generalized logistics function $E[LP(V)] = A + \frac{K - A}{1 + Qe^{-BV/\nu}}$, for which the underlying parameters $A, K, Q, B, \nu$ are estimated through a non-linear least squares procedure, and the assignment variables are $V = G$ and $V = H$ respectively. The solid dots indicate bin scatter points, for equally spaced bins of experienced gains and home equity.

Panel A

Panel B
Figure 5
Estimated conditional coefficients

This figure shows the conditional effects of loss aversion and home equity constraint, across bins of the respective other dimension. Panel A reports the effect of experienced gains on the listing premium ($LP$) for bins within each home equity group (constrained vs. unconstrained), corresponding to the estimated coefficients $\beta_1 + \beta_3$ from equation (6) which reflect the slope across the loss domain ($G < 0$) for different bins of home equity, but with additional controls for home equity, and time and municipality fixed effects. The sign for $\beta_1 + \beta_3$ is reversed such that an increase in the coefficient can be read as an increase in the effect. Panel B reports the effect of home equity on the listing premium ($LP$) for bins within each experienced gain group (winners vs. losers), corresponding to the estimated coefficients $\gamma_1 + \gamma_3$ from equation (6). The sign for $\gamma_1 + \gamma_3$ is reversed such that an increase in the coefficient can be read as an increase in the effect. The left plot in Panel B shows the home equity cut-off points identified from the data. To calculate these cut-off points, we repeat our estimation of the coefficient $\beta_3$ for different home equity cut-offs in the interval [-50%,100%]. For each gain bin, we select the optimal cut-off point as the one with the largest value of $\beta_3$. The slope coefficients reported in the right plot correspond to these cut-off points.

Panel A

Panel B
Figure 6
Time-on-the-market, retraction rate and probability of sale

This figure shows the relationship between time-on-market (TOM) and the retraction rate (Panel A) and the probability of sale (Panel B) with the listing premium (LP). Time-on-the-market is measured as weeks between initial listing and date of sale or retraction. The retraction rate is the share of listings that does not result in a sale. The probability of sale is measured as the probability to sell within 6 months of the initial listing.

Panel A

Panel B
Figure 7
Realized premium

This figure shows the relationship between the realized premium ($RP$) and the listing premium ($LP$). The realized premium is measured as the difference between the log realized sales price and log hedonic price. We use a discretized probability distribution where we attach a 60% probability to a realization of the mean, and 20% each for realizations one standard deviation below and above the mean. We use the in-sample observed standard deviation of selling probabilities and realized market premia as proxies for the uncertainty that sellers face when estimating market constraints in the data.

Panel A

Panel B
Figure 8
Interaction effects between gains and home equity in the model and the data

This figure reports model-implied patterns of listing premia, for different levels of gains and home equity (solid lines) alongside their data counterparts (dotted lines). The model corresponds to a specification with non-linear market constraints, reference dependent utility and financial constraints taking the form of a penalty function around the down-payment threshold of 20%.

Panel A

Listing premium in the model and in the data

Panel B

Listing premium in the model and in the data
Figure 9
Understanding the extensive margin

Panel A of this figure reports the share of listed houses relative to the stock of all houses, across 5% bins of gains. Panel B reports counter-factual calculations for upper bounds on the component of the listing premium that could be driven by selection effects. We assume that the listing behaviour of sellers just above the threshold should be representative for those just below, and compute counter-factual average listing premia implied by a situation in which the most conservative sellers drop out. We use the observed distribution of listing premia for the gains interval [0%, 20%] and the distribution of shares of listings for the gains interval [-40%,0%].

Panel A

Panel B
This figure reports the relationship between two measures of non-linearity, estimated separately within market segments. We measure the ‘non-linearity of market constraint’ as the slope difference above and below zero for the relationship between the selling probability and the listing premium. We measure the ‘non-linearity of listing premium’ as the slope difference below and above zero for the relationship between listing premia and realized property value gains. We divide the observed distribution of prices in six equal-sized bins and estimate the two variables separately in each such segment.
The table shows results from sharp RKD tests of loss aversion, using the 0% gain cutoff, and down-payment constraints, using the 20% home equity cutoff, for varying bandwidths $b \in \{b^\star, 15, 20\}$ and optimally chosen polynomials (in this case, a local quadratic regression). $b^\star$ refers to the optimally chosen bandwidth using a MSE-optimal bandwidth selector from Calonico et al. (2014). The control variables are year fixed effects, household controls (age, education length and net financial wealth) and year of previous purchase. *, **, *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Gains/Losses</th>
<th>Home Equity</th>
</tr>
</thead>
<tbody>
<tr>
<td>RKD estimation result</td>
<td>0.417**</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>(0.197)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Cutoff</td>
<td>0%</td>
<td>20%</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>14%</td>
<td>26%</td>
</tr>
<tr>
<td>Polynomial order</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>N below cutoff</td>
<td>44,413</td>
<td>77,158</td>
</tr>
<tr>
<td>N above cutoff</td>
<td>133,864</td>
<td>101,119</td>
</tr>
</tbody>
</table>

* *, **, *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively.
Table 2
Overview of model fit

This table reports mean absolute prediction errors between model-implied listing premia and their data counterparts. For each point in a grid spanning the intervals [-0.2, 0.4] of gains and home equity, respectively, we calculate the mean absolute error as the absolute difference between the model-implied listing premium and the one observed in the data. We run a pooled regression across all combinations of grid points and model specifications to estimate the associated mean and standard error for each modeling choice. † indicates the model variant with the lowest mean absolute prediction error. *, **, *** indicate statistical significance at the 10%, 5% and 1% confidence level, respectively. This inference is based on t-statistics computed with OLS standard errors, testing the Null hypothesis that the absolute mean error of the respective model is not different from the lowest mean absolute prediction error (indicated by †).

<table>
<thead>
<tr>
<th></th>
<th>Linear market constraints</th>
<th>Non-linear market constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Utility of final wealth</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained</td>
<td>0.342***</td>
<td>0.238***</td>
</tr>
<tr>
<td>Threshold constraint</td>
<td>0.185***</td>
<td>0.062***</td>
</tr>
<tr>
<td>Penalty function</td>
<td>0.154***</td>
<td>0.084***</td>
</tr>
<tr>
<td><strong>Reference dependence</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained</td>
<td>0.135***</td>
<td>0.075***</td>
</tr>
<tr>
<td>Threshold constraint</td>
<td>0.088***</td>
<td>0.053***</td>
</tr>
<tr>
<td>Penalty function</td>
<td>0.052***</td>
<td>0.029†</td>
</tr>
<tr>
<td><strong>Loss aversion</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained</td>
<td>0.135***</td>
<td>0.076***</td>
</tr>
<tr>
<td>Threshold constraint</td>
<td>0.089***</td>
<td>0.059***</td>
</tr>
<tr>
<td>Penalty function</td>
<td>0.053***</td>
<td>0.040</td>
</tr>
<tr>
<td><strong>Realization utility</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unconstrained</td>
<td>0.135***</td>
<td>0.080***</td>
</tr>
<tr>
<td>Threshold constraint</td>
<td>0.089***</td>
<td>0.066***</td>
</tr>
<tr>
<td>Penalty function</td>
<td>0.053***</td>
<td>0.052***</td>
</tr>
</tbody>
</table>
REFERENCE POINTS IN THE HOUSING MARKET
Online Appendix

Steffen Andersen*    Cristian Badarinza†    Lu Liu‡
Julie Marx§    Tarun Ramadorai¶

August 19, 2019

*Copenhagen Business School and CEPR, Email: san.fi@cbs.dk.
†National University of Singapore, Email: cristian.badarinza@nus.edu.sg
‡Imperial College London, Email: l.liu16@imperial.ac.uk.
§Copenhagen Business School, Email: jma.fi@cbs.dk.
¶Corresponding author: Imperial College London, Tanaka Building, South Kensington Campus, Lon-
don SW7 2AZ, and CEPR. Tel.: +44 207 594 99 10. Email: t.ramadorai@imperial.ac.uk.
This figure shows quarterly average realized house sales prices (in DKK per square meter) on the right-hand axis, and the number of houses sold in Denmark on the left-hand axis, between 2004Q1 and 2018Q2. The sample period for our analysis covers the years 2009 to 2016. Aggregate housing market statistics are provided by Finans Danmark, the private association of banks and mortgage lenders in Denmark.
Figure A.2
Summary statistics: Transaction characteristics

This figure shows four histograms of main variables of interest. Gain (G) is computed as the log difference between the estimated hedonic price ($\hat{P}$) and the previous purchase price ($R$), i.e. $G = \ln \hat{P} - \ln R$, in percent. Home equity (H) is computed as the log difference between the estimated hedonic price and the current mortgage value ($M$), i.e. $H = \ln \hat{P} - \ln M$, in percent. $H$ is truncated at 100 in order to avoid small mortgage balances leading to log differences greater than 100. The listing premium (LP) measures the log difference between the ask price and estimated hedonic price, in percent. All are winsorized at 1 percent in both ends. Time on the market (TOM) measures the time in weeks between when a house is listed and recorded as sold. Each listing spell is restricted to 200 weeks.

Panel A

Panel B
Figure A.3
Summary statistics: Household characteristics

This figure shows four histograms of household characteristics. Panel A shows the distribution of available liquid assets. Liquidity is measured as liquid financial wealth (deposit holdings, stocks and bonds). Net financial wealth is measured as liquid financial wealth net of bank debt. Panel B shows household characteristics. Age measures the average age in the household, and education length measures the average length of years spent in education across all adults in the household.

Panel A

Panel B
This figure shows a binned scatter plot of the estimated log hedonic price $\ln(P_{it})$ versus the realized log sales price, for the sample of listings that resulted in a sale ($N = 90,535$). The hedonic model is as follows: $\ln(P_{it}) = \delta + \delta_t + \delta_m + \delta_{tm} + \beta_{i=}f\mathbb{1}_{t=\tau} + \beta_{X_{it}} + \beta_{fx}\mathbb{1}_{i=\tau}X_{it} + \Phi(v_{it}) + \mathbb{1}_{i=\tau}\Phi(v_{it}) + \varepsilon_{it}$, where $X_{it}$ is a vector of property characteristics, namely $\ln(\text{lot size})$, $\ln(\text{interior size})$, number of rooms, number of bathrooms, number of showers, a dummy variable for whether the property was unoccupied at the time of sale or retraction, $\ln(\text{age of the building})$, a dummy variable for whether the property is located in a rural area, a dummy for whether the building is in a historic area, and $\ln(\text{distance of the property to the nearest major city})$. $\delta$ is a constant, $\delta_t$ are year fixed effects, $\delta_m$ are fixed effects for different municipalities (98 municipalities in total), and $\mathbb{1}_{i=\tau}$ is an indicator variable for whether the property is an apartment (denoted by $f$ for flat) rather than a house. $\Phi(v_{it})$ is a third-order polynomial of the previous-year tax assessor valuation of the property. The $R^2$ of the regression is 0.86.
This figure shows the relative share of each seller group over time. The four groups are defined as follows: I) Unconstrained Winners ($H \geq 20\%$ and $G \geq 0$), II) Constrained Winners ($H < 20\%$ and $G \geq 0$), III) Unconstrained Losers ($H \geq 20\%$ and $G < 0$), IV) Constrained Losers ($H < 20\%$ and $G < 0$).
Figure A.6
Loss aversion: Understanding heterogeneity

This figure shows the effect of experienced gains on the ask-market-premium (AMP) across quantile bins of covariates (age, education length and net financial wealth). It reports estimated coefficients across different bins of covariates, which corresponds to the slope across the loss domain ($G < 0$), conditional on additional controls for home equity, and time and municipality fixed effects. The sign for $\beta_1 + \beta_3$ is reversed such that an increase in the coefficient can be read as an increase in the effect.
Figure A.7
Down-payment constraints: Understanding heterogeneity

This figure shows the effect of home equity on the ask-market-premium (AMP) across quantile bins of covariates (age, education length, and net financial wealth). It reports the estimated coefficients across different bins of covariates, which corresponds to the slope across the constrained domain \((H < 20\%)\), conditional on additional controls for experienced gains, and time and municipality fixed effects. The sign for \(\gamma_1 + \gamma_3\) is reversed such that an increase in the coefficient can be read as an increase in the effect.
This figure shows the relationship between residual list premium and gains or home equity, respectively. The residual list premium is computed with household controls (age, education length, net financial assets) and municipality and year fixed effects partialled out.
Figure A.9
Non-mortgage sample

This figure shows the relationship between list premium and gains for the sample of households with no mortgage ($N = 60,711$).
Figure A.10
RKD validation: Smooth density of assignment variable

This figure shows the number of observations in bins of the assignment variable, gain and home equity, respectively. It provides visual evidence for a lack of bunching and potential manipulation of the assignment variable around the relevant RK cutoff. Following Landais (2015), the results for the McCrary (2008) test for continuity of the assignment variable and a similar test for the continuity of the derivative are further shown on the figure. We cannot reject the null of continuity of the derivative of the assignment variables at the kink at the 5% significance level.¹
This figure shows binned means of covariates (home equity/gain, age, length of education, liquidity, bank debt, financial wealth) over bins of the assignment variable, gain and home equity, respectively. It provides visual evidence for these covariates evolving smoothly around and not having a kink at the cutoff point.
Figure A.12
RKD robustness: Estimates for different bandwidths (Gain)

This figure plots the range of RKD estimates and 95% confidence intervals across bandwidths ranging from 5 to 50, using a local quadratic regression. The optimal bandwidth is indicated based on the MSE-optimal bandwidth selector from Calonico et al. (2014).
This figure compares RK estimates using a local linear regression with estimates using a local quadratic regression, across different bandwidths $b \in \{b^*, 10, 20\}$. $b^*$ refers to the MSE-optimal bandwidth selector from Calonico et al. (2014), which is 11.4 (10.9) for gains (home equity) and the local linear regression, compared to 13.9 (25.2) for the local quadratic regression.

![Figure A.13](image-url)
Figure A.14

List premium predicts down payment

This figure shows a binned scatter plot of the ask-market-premium against the down-payment of a seller’s next house, controlling for current home equity ($H$), based on a sub-sample of the data for which we have information on the next house purchase price and mortgage value ($N = 14,440$).
This figure shows a binned scatter plot of the current home price against the next house price (in 2015 DKK), based on a sub-sample of the data for which we have information on the next house purchase price and mortgage value ($N = 14,440$).
Understanding the role of market constraints in the model

This figure reports model-implied listing premia for different levels of gains, obtained from a model specification without down-payment constraints.
Figure A.17
Understanding the role of down-payment constraints in the model

This figure reports model-implied listing premia for different levels of gains and home equity, obtained from a model specification without a hard down-payment constraint threshold (Panel A) and one with a smooth penalty function around the down-payment constraint threshold (Panel B). The solid lines indicate model quantities and the dotted lines estimated quantities in the data. The profiles reported correspond to a level of home equity of 15% and a level of gains of 20%.

Panel A

Panel B
Figure A.18
Illustration of economic mechanism in the model
Figure A.19
Understanding the extensive margin: Home equity

This figure reports the share of listed houses relative to the stock of all houses, across 5\% bins of home equity.
Table A.1
Construction of main dataset

This table describes the cleaning and sample selection process from the raw listings data to the final matched data, with $N = 180,114$.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All listings</strong></td>
<td><strong>614,801</strong></td>
</tr>
<tr>
<td>Unmatched in registers(^a)</td>
<td>-107,471</td>
</tr>
<tr>
<td></td>
<td><strong>507,330</strong></td>
</tr>
<tr>
<td><strong>Cleaning</strong></td>
<td></td>
</tr>
<tr>
<td>Owner ID not determined(^b)</td>
<td>-71,881</td>
</tr>
<tr>
<td>Owners not found(^c)</td>
<td>-4,028</td>
</tr>
<tr>
<td>Error in listing or purchase date(^d)</td>
<td>-1,516</td>
</tr>
<tr>
<td>No purchase price(^e)</td>
<td>-167,942</td>
</tr>
<tr>
<td>No ask price</td>
<td>-893</td>
</tr>
<tr>
<td>No predicted purchase price</td>
<td>-137</td>
</tr>
<tr>
<td>No hedonic price</td>
<td>-16</td>
</tr>
<tr>
<td></td>
<td><strong>260,917</strong></td>
</tr>
<tr>
<td><strong>Selecting</strong></td>
<td></td>
</tr>
<tr>
<td>Investors(^f)</td>
<td>-20,092</td>
</tr>
<tr>
<td>No mortgage</td>
<td>-60,711</td>
</tr>
<tr>
<td><strong>Final data</strong></td>
<td><strong>180,114</strong></td>
</tr>
</tbody>
</table>

\(^a\) Reasons could be misreported addresses or not ordinary owner-occupied housing.

\(^b\) E.g. properties with several owners from different households.

\(^c\) No owner ID in registers

\(^d\) Listing date is before purchase date

\(^e\) Purchased before 1992

\(^f\) Seller owns more than 3 properties
Table A.2
Amendments to the Danish Mortgage-Credit Loans and Mortgage-Credit Bonds Act in the period from 2009 to 2016

<table>
<thead>
<tr>
<th>Date</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>May 2009</td>
<td>Allows a bankruptcy estate to make changes to fees in special circumstances</td>
</tr>
<tr>
<td>June 2010</td>
<td>Adjustments about bankruptcies</td>
</tr>
<tr>
<td>June 2010</td>
<td>Change of wording</td>
</tr>
<tr>
<td>December 2010</td>
<td>Change of wording</td>
</tr>
<tr>
<td>February 2012</td>
<td>Maximum maturity for loans to public housing, youth housing, and private housing cooperatives is extended from 35 to 40 years</td>
</tr>
<tr>
<td>December 2012</td>
<td>Elaboration of the rules on digital communication with the FSA</td>
</tr>
<tr>
<td>December 2012</td>
<td>Elaboration on the opportunity for mortgage credit institutions to take up loans to meet their obligation to provide supplementary collateral.</td>
</tr>
<tr>
<td>March 2014</td>
<td>Establish the terms under which the mortgage-credit institution can initiate sale of bonds if the term to maturity on a mortgage-credit loan is longer than the term to maturity on the underlying mortgage-credit bonds.</td>
</tr>
<tr>
<td>March 2014</td>
<td>Implements EU regulation. Change of wording on the definition of market value.</td>
</tr>
<tr>
<td>December 2014</td>
<td>Small additions to the terms under which the mortgage-credit institution can initiate sale of bonds if the term to maturity on a mortgage-credit loan is longer than the term to maturity on the underlying mortgage-credit bonds.</td>
</tr>
<tr>
<td>April 2015</td>
<td>Changes to the terms under which the mortgage-credit institution can initiate sale of bonds if the term to maturity on a mortgage-credit loan is longer than the term to maturity on the underlying mortgage-credit bonds.</td>
</tr>
</tbody>
</table>
Table A.3
Replicating main results from Genesove and Mayer (2001)

This table replicates Table 2 from Genesove and Mayer (2001) using our main dataset. The dependent variable is the log ask price. LOSS is the previous log selling price less the expected log selling price, truncated from below at 0, and LOSS (squared) is the term squared. LTV if \( \geq 80 \) is the current LTV of the property if the LTV is greater equal to 80 and 0 otherwise. Estimated hedonic house prices are assumed to be additive in baseline value and market index, where baseline value captures the value of hedonic characteristics of the property and the market index reflects time-series variation in aggregate house prices. Residual from last sales price is the pricing error from the previous sale and months since last sale counts the number of months between the previous and current sale.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ask</td>
<td>Loss</td>
<td>Loss</td>
<td>Loss</td>
<td>Loss</td>
<td>Loss</td>
<td>Loss</td>
</tr>
<tr>
<td>LOSS</td>
<td>0.523***</td>
<td>0.435***</td>
<td>0.490***</td>
<td>0.323***</td>
<td>0.544***</td>
<td>0.459***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>LOSS (squared)</td>
<td>0.084**</td>
<td>0.282***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.037)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LTV if ( \geq 80 )</td>
<td>0.002***</td>
<td>0.002***</td>
<td>0.002***</td>
<td>0.002***</td>
<td>0.002***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Baseline value</td>
<td>0.983***</td>
<td>0.980***</td>
<td>0.983***</td>
<td>0.980***</td>
<td>0.984***</td>
<td>0.981***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Market index at listing</td>
<td>0.980***</td>
<td>0.977***</td>
<td>0.980***</td>
<td>0.977***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residual from last sales price</td>
<td>-0.082***</td>
<td>-0.084***</td>
<td>-0.078***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Months since last sale</td>
<td>-0.000***</td>
<td>-0.000***</td>
<td>-0.000***</td>
<td>-0.000***</td>
<td>0.000</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.505***</td>
<td>0.534***</td>
<td>0.506***</td>
<td>0.538***</td>
<td>76.785***</td>
<td>76.574***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.073)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Year-Quarter FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>180114</td>
<td>180114</td>
<td>180114</td>
<td>180114</td>
<td>180114</td>
<td>180114</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.870</td>
<td>0.872</td>
<td>0.870</td>
<td>0.872</td>
<td>0.874</td>
<td>0.875</td>
</tr>
</tbody>
</table>
Table A.4
Loss Aversion and Down-Payment Constraints: Baseline results

This table reports results for four regressions. Column (4) represents the estimated coefficients from the saturated regression

$$
\ell_{it} = \mu_t + \mu_m + \xi_0 X_{it} + \alpha_1 \mathbb{1}_{G_{it} < 0} + \alpha_2 \mathbb{1}_{H_{it} < 20\%} + (\beta_0 + \beta_1 \mathbb{1}_{G_{it} < 0}) G_{it} + (\gamma_0 + \gamma_1 \mathbb{1}_{H_{it} < 20\%}) H_{it} + \epsilon_{it},
$$

where $\ell_{it}$ is the list premium, $\mu_t$ and $\mu_m$ are year and municipality fixed effects, respectively, and $\mathbb{1}_{G_{it} < 0}$ and $\mathbb{1}_{H_{it} < 20\%}$ are indicator functions for losing and constrained households, respectively. Column (1) and (2) report results for specifications with only gain or home equity coefficients separately, and column (3) corresponds to column (4) but excludes household controls (age, liquid financial wealth and bank debt). Standard errors are clustered by year and municipality. */**/*** denote $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LP</td>
<td>LP</td>
<td>LP</td>
<td>LP</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.860**</td>
<td>-0.174</td>
<td>-0.227</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.344)</td>
<td>(0.245)</td>
<td>(0.233)</td>
<td></td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>-0.038***</td>
<td>-0.012**</td>
<td>-0.017***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>-0.474***</td>
<td>-0.364***</td>
<td>-0.356***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.027)</td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>8.644***</td>
<td>6.831***</td>
<td>6.730***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.720)</td>
<td>(0.706)</td>
<td>(0.687)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>-0.089***</td>
<td>-0.077***</td>
<td>-0.081***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>-0.104***</td>
<td>-0.085***</td>
<td>-0.081***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td>Household controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Year FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Observations</td>
<td>178273</td>
<td>178273</td>
<td>178273</td>
<td>178273</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.176</td>
<td>0.227</td>
<td>0.260</td>
<td>0.265</td>
</tr>
</tbody>
</table>