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Hans Koster and Jan Rouwendal

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
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Abstract

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JEL Classification: H43, R21, R30

Keywords: Home seller behaviour, List price, Sales price, Sales time, Time preference, Bidding wars, Undervaluation

Hans Koster - h.koster@vu.nl
Vrije Universiteit Amsterdam

Jan Rouwendal - j.rouwendal@vu.nl
Vrije Universiteit Amsterdam

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Housing market discount rates: Evidence from bargaining and bidding wars*

Hans R.A. Koster[†] Jan Rouwendal[‡]

February 16, 2023

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[†]Corresponding author. Department of Spatial Economics, Vrije Universiteit Amsterdam, De Boelelaan 1105 1081HV Amsterdam, email: h.koster@vu.nl. Hans is also a research fellow at Tinbergen Institute and research affiliate with the Centre for Economic Policy Research.

[‡]Department of Spatial Economics, Vrije Universiteit Amsterdam, De Boelelaan 1105 1081 HV Amsterdam, email: j.rouwendal@vu.nl. Jan is also a fellow at the Tinbergen Institute and the Amsterdam School of Real Estate.

1 Introduction

When selling a house, homeowners face a fundamental trade-off between setting a relatively low list price to quickly sell the property at a lower price, or choosing a higher list price and waiting longer to potentially receive a better offer. While a low list price may reduce uncertainty and costs associated with the sales process, it also increases the risk of missing higher bids. Research shows that sellers who set relatively high list prices tend to achieve both a higher sales price and a longer time-on-the-market (Genesove and Mayer, 2001). This suggests that the choice of list price is closely related to the seller's time preference (Cohen et al., 2020).

In this paper, we show that seller behaviour can be characterised by a discount rate that can be computed as a function of parameters estimated from data. Using data on list prices, sales times, and sales prices, we calculate housing market discount rates. Because sales times are on average about five months and rarely exceed three years, we interpret these as short-run discount rates.

We start by setting up a parsimonious model of selling a house through bargaining between the seller and one prospective buyer, referred to as a 'buyers' market' (Zorn and Sackley, 1991). In this model, the markup plays a key role, capturing the difference between the chosen list price and the expected list price in the neighbourhood at the time of listing (Guren, 2018). In conventional bargaining situations, buyers are unlikely to bid above the list price. We can determine the implied discount rate by analysing the relationship between the elasticity of sales prices and the markup, the elasticity of sales times and the markup, and the expected sales time. It is important to note that the discount rate we identify is considered as a 'gross' discount rate as it takes into account not only the pure rate of time preference, but also factors such as listing costs and the seller's aversion to risk and potential losses.

Next, we expand our analysis to include scenarios where bidding wars occur and homes sell for prices above the listed price. Our data reveal that the frequency of bidding wars has been increasing, with as many as 80% of all sales in the Netherlands in 2021 involving bidding wars.[1] When multiple buyers compete for a property, this is referred to as a 'seller's market' (Zorn and Sackley, 1991). Our extension of the list price-setting theory aligns with previous research in Albrecht et al. (2016) and Han and Strange (2016). We posit that the likelihood of a bidding war is influenced by the chosen markup. A bidding war premium suggests that sellers may benefit from setting a lower list price in order to spur competition and potentially earn higher revenues. However, if a bidding war does not take place, the seller may receive a lower sales

[1] Han and Strange (2014) also document the increasing frequency of bidding wars and sales prices exceeding list prices in North America.

price. Our research demonstrates that in the presence of bidding wars, the discount rate can still be determined using data on sales prices, time-on-the-market, and list prices.

We estimate the empirical parameters necessary to compute the gross discount rate using a unique dataset on housing transactions, including withdrawals, occurring between 1985 and 2021 from the Netherlands. To account for the endogeneity of the markup (as it is correlated with the unobserved quality of a home), we adopt a similar approach as previous research Guren (2018).[2] This includes controlling for a variety of time-varying housing attributes and property fixed effects to capture observed and unobserved housing quality, as well as including neighbourhood-by-quarter or street-by-quarter fixed effects to account for changes in unobserved neighbourhood quality. Additionally, to further address concerns about endogeneity, we use an instrument proposed by Guren (2018), which is the price appreciation in the neighbourhood since the seller has moved into the property. This is based on the idea that due to sellers' aversion to absolute losses and fewer liquidity constraints, the list price will be set lower when sellers have experienced more price growth (see Genesove and Mayer, 1997, 2001).

The paper presents the following findings. Our research shows that conventional bargaining results in high discount rates ranging from 15% to 50%, which is consistent with previous experimental studies that used hypothetical money rewards as a measure (see Frederick et al., 2002). Additionally, we find that the gross discount rates in the presence of bidding wars fall within the same range. These estimated short-term discount rates are significantly higher compared to long-term discount rates based on housing market data (Giglio et al., 2015; Bracke et al., 2018; Gautier and Van Vuuren, 2019; Koster and Pinchbeck, 2022). Additionally, there is considerable heterogeneity in the implied gross discount rate through the choice of the markup. For example, we find that sellers who have already moved before putting their property on the market have considerably higher discount rates (nearly 8 percentage points) which highlights the importance of seller 'desperation'. Furthermore, we find that sellers with a bachelor's degree or higher have discount rates that are around 4 percentage points lower than those with only primary education, although this effect becomes somewhat smaller when other household characteristics are also considered.

How to interpret these discount rates? The findings of our study unequivocally suggest that sellers tend to set list prices that are too low in order to quickly sell their properties, which results in the *undervaluation* of future financial flows. The high implied discount rates we observe may be attributed to several factors, including loss aversion (Genesove and Mayer, 2001),

[2] If not all relevant housing attributes are controlled for, a higher markup will be associated with a higher sales price and a shorter sales time. Hence, the elasticities of sales times and prices with respect to the markup will be biased downwards.

liquidity constraints (Genesove and Mayer, 1997), and listing costs associated with inspections (Guren, 2018; Ngai and Sheedy, 2020). Furthermore, we argue that the stress associated with the unfamiliar and uncertain process of selling a property. in which a large share of one's wealth is at stake, is likely to strongly contribute to the high discount rates that are significantly higher than market-based interest rates.

Related literature. Our paper contributes to several strands of literature. First, our paper adds to a literature estimating (gross) discount rates in housing markets. The use of data on housing transactions offers a unique advantage in identifying discount rates, as participation rates are high (with more than 55% of properties in the Netherlands being owner-occupied) and the high-stakes nature of the transaction means that individuals are likely to pay attention to trade-offs between money and time. Previous research has found that long-run discount rates in the housing market are between 2% and 5% (Do and Sirmans, 1994; Palmon and Smith, 1998; Giglio et al., 2015; Bracke et al., 2018; Gautier and Van Vuuren, 2019; Koster and Pinchbeck, 2022). However, our paper differs in that it focuses on estimating short-run discount rates in the housing market, rather than long-run rates.

Our paper draws on a second strand of literature concerning list price-setting and time preferences. The models used in this literature generally assume that the seller aims to maximize a target function, typically the expected present value of the sales price, which is a product of the expected discount factor and the expected price.[3] Several studies assume values for discount rates (see *e.g.* Arnold, 1999, who chooses a value between 11 and 25%). Others implicitly estimate discount rates. Carrillo (2012), for example, develops an equilibrium search model for the housing market, but allows for idiosyncratic variation in gross discount rates, which are estimated to be between 10% and 33%.[4] The study by Carrillo (2012) thus suggests that the (idiosyncratic) discount rates relevant for home seller behaviour are considerably higher than the long-term discount rates estimated using data on leaseholds (see Giglio et al., 2015; Bracke et al., 2018). Similarly, Guren (2018) finds high implicit discount rates, assuming an annual rate of 5% while estimating monthly search costs to be 2.1% of the housing value, equivalent to a gross annual discount rate of approximately 30%. Additionally, the results of Genesove and

[3] An exception is the recent paper by Andersen et al. (2022) where the time-on-the-market does not play a role in the seller's utility function.

[4] Carrillo (2012) distinguishes between the median discount rate – which is fixed a priori – and 'seller motivation'. Together they form the individual-specific discount rate. To be more specific, he models the discount rate of the sellers who are active on the market as a logistic transformation of a normally distributed random variable that is estimated to have a mean of 8.58 and a standard deviation 1.125. For the median seller, this gives an annual discount factor that equals 0.93. The logistic transformation changes the symmetric normal distribution into a highly asymmetric distribution of discount factors that equals 0.89, on average. There is considerable variation in this variable. In 20% of the cases, it is smaller than 0.84, implying a discount rate of about 20%, in 10% of the cases it is smaller than 0.75, implying a discount rate of at least 33%.

Mayer (1997) imply an annualized return of over 20%, even though they do not provide specific numbers.[5] In contrast to those papers, our paper makes time preferences explicit and at the same time imposes relatively mild assumptions on seller's behaviour. Our gross discount rates include sellers' motivation to sell and listing costs.

The third literature to which our paper contributes is that on bidding wars. We build on previous research by Horowitz (1992), who first identified that some houses sold for prices exceeding the list price, a phenomenon that cannot be explained by traditional theories (see Chen and Rosenthal, 1996; Arnold, 1999; Carrillo, 2012). Han and Strange (2014) later observed a significant increase in the frequency of sales prices exceeding list prices after 2000. They also document that during the subsequent housing market downturn, the percentage of homes sold above the list price did not return to its pre-peak levels. One possible explanation for this is that real estate agents were more successful in creating situations where multiple buyers could submit offers, even in a weaker market. The recent literature on bidding wars suggests that the simultaneous presence of multiple bidders can drive up the sales price to exceed the list price. This idea was formalized by Albrecht et al. (2016) in their housing market search model, in which they proposed that when prospective buyers arrive at a house at the same time, the sales process becomes a second-price auction in which the reservation prices of the competing bidders provide relevant lower bounds for the price. Empirical studies, such as Han and Strange (2016), have shown that in situations where two or more bidders are present, *the sales price typically exceeds the list price*. We take a somewhat different approach by using a stock-flow matching approach (see *e.g.* Coles and Muthoo, 1998) in which a house can be sold immediately to searchers present in the market at the time the house is posted, or later through conventional bargaining with newly arriving searchers. In this way, we address both buyers' markets with conventional bargaining and sellers' markets with bidding wars. Our theory also considers the role of list prices in these different market situations, and how it affects the optimal pricing strategy for sellers.

The paper unfolds as follows. Section 2 discusses the theoretical framework to derive the gross discount rate derivation, followed by a discussion in Section 3 on the data. Section 4 presents the econometric framework to identify the effects of interest and Section 5 shows the results. Section 6 concludes.

[5] They do not provide numbers but relate that for low equity sellers 10 weeks extra on the market yields a 4% higher price, which implies an annualised return of more than 20% (Genesove and Mayer, 1997, p. 267).

2 Theoretical framework

2.1 Buyers' markets: conventional bargaining

In this section, we will develop a model describing the choice of list prices, which is in line with those used in the existing literature. We will not construct an explicit model of the bargaining process but use a 'reduced-form' specification that states that the expected sales price is a function of the list price. At the core of our model is the expected present value of the sales price, for which we use the conventional exponential discounting formula with a constant discount rate. As indicated above, this parameter characterises optimal list price-setting behaviour and our estimation results allow us to recover it for individual home sellers.

The model we propose is standard in the literature on list pricing and it can be embedded in a more general framework of intertemporal utility maximisation. We consider a homeowner who attempts to maximise the expected discounted revenues of selling her property through bilateral bargaining, which is specified as the integral over time of instantaneous utilities discounted by the household's rate of time preference. The intertemporal budget constraint specifies that the difference between the integrals over time of income and expenditure discounted by the interest rate must be equal to the household's wealth. Hence:

$$R = \int_0^\infty f(t, P^\ell) e^{-rt} P(P^\ell) \mathrm{d}t. \tag{1}$$

In this equation $f(t, P^\ell)$ is the density function of time t at which the house is sold and $P = P(P^\ell)$ the sales price. r is the seller's rate of time preference, or rate of discount. The expected sales time T is:

$$T(P^\ell) = \int_0^\infty f(t, P^\ell) t \mathrm{d}t, \tag{2}$$

which is an increasing function of the list price.

A useful context for this set-up are models of intertemporal utility-maximizing behaviour. In Appendix A.1 we write down a simple model of lifetime utility-maximizing behaviour subject to an intertemporal budget constraint. In this model, the expected contribution of selling the house to wealth is indicated by our target function (1).

The density function $f(\cdot)$ and the expected sales price P may depend on the characteristics of the house and on the circumstances prevailing at the local housing market at the time of the sale, while the discount rate r may differ among sellers. For notational simplicity this heterogeneity is not made explicit in the equations, but it will be taken into account in the empirical work reported below.

In line with the extant literature, in (1) we assume that conditional on the list price, the expected sales price is independent of the time at which the sale occurs.[6] We can therefore write the expected present value of the revenues as the product of the expected sales price and the expected value of the discount factor:

$$R = \int_0^\infty f(t, P^\ell) e^{-rt} \mathrm{d}t P(P^\ell). \tag{3}$$

At least since Horowitz (1992), the list price has been regarded as a signal of the seller's reservation price. It is, therefore, natural to assume that a higher list price implies that only the searchers with the strongest interest in the house will pay a visit. This increases expected sale times, while at the same time increases the expected sales price. We, therefore, assume the sales time as well as the sales price to be increasing in the list price.

A constant arrival rate of bidders considerably simplifies the analysis and implies an exponential distribution of the sales time t:[7]

$$f(t) = \theta \mathrm{e}^{-\theta t}. \tag{4}$$

The arrival rate θ is a decreasing function of the list price. Substitution and integration gives:

$$\begin{aligned} R &= \frac{\theta(P^\ell)}{\theta(P^\ell) + r} P, \\ &= \frac{1}{1 + r/\theta(P^\ell)} P, \\ &= \frac{1}{1 + rT} P, \end{aligned} \tag{5}$$

where $T = T(P^\ell)$ denotes the *expected* sales time, which is given by $1/\theta(P^\ell)$.[8]

The first-order condition for optimal list price-setting ($\partial \log R / \partial \log P^\ell = 0$) is:[9]

$$\frac{\partial \log P}{\partial \log P^\ell} - \frac{rT}{1 + rT} \frac{\partial \log T}{\partial \log P^\ell} = 0. \tag{6}$$

[6] Also in line with the literature is the absence of costs incurred by the seller in selling the house. It is easy to check that subtraction of such (discounted) costs from the expected returns will not affect the implied discount rate unless they depend on the list price, which appears unlikely. Indeed, for a seller, search costs are small as almost all houses on sale are advertised on the website `Funda.nl`, which is not expensive. Other than providing clear pictures and a promotional text, there is not much sellers can do to attract more prospective buyers. In other words, while search costs are high for prospective buyers, they are likely negligible for sellers (see Koster and Van Ommeren, 2020).

[7] We consider that elapsed time-on-the-market may have a direct impact on sales prices in Appendix C.5.

[8] We obtain exactly the same expression if we instead adopt a discrete time framework and assume a given probability that a potential buyer visits the house in each period as *e.g.* in Horowitz (1992).

[9] Note that $\partial \log R / \partial \log P^\ell = 0$ and $\partial \log R / \partial P^\ell = 0$ are equivalent. To show this, it suffices to observe that $\partial \log P^\ell = (1/P^\ell) \partial P^\ell$. Substitution then gives $P^\ell \partial \log R / \partial P^\ell = 0$. This is true if *(i)* either $\partial \log R / \partial P^\ell = 0$, or *(ii)* $P^\ell = 0$. However, the latter possibility is excluded by the fact that we use the log of P^ℓ.

In Appendix A.3 it is shown that the second-order condition is satisfied when the elasticity of the sales time with respect to the list price exceeds $1 + rT$, which holds for empirically relevant values.

If the elasticities of the sales price and the sales time with respect to the list price are both positive, as is expected, we need a positive value of the discount rate to validate this condition. Note that since $rT/(1+rT)$ is between 0 and 1, the elasticity of the sales time with respect to the list price must be larger than the elasticity of the sales price. Optimal list price-setting implies that the discount rate can be computed as:

$$r = \frac{\varepsilon_{P\ell}^{P}}{T\left(\varepsilon_{P\ell}^{T} - \varepsilon_{P\ell}^{P}\right)}. \tag{7}$$

In this equation we use the symbol ε to denote the elasticities of price and time on the market (indicated by a superscript) with respect to the list price (indicated by a subscript). An attractive feature of this expression is that the elasticities on the right-hand side can be estimated, while the expected sales time can be obtained from the data. This makes the equation suitable for empirically investigating the discount rates used by home sellers. With sales times considerably smaller than one year, equation (7) then indicates that high elasticities of the sales time with respect to the list prices are necessary to make seller behaviour compatible with a discount rate of the same order of magnitude as, say, the mortgage interest rate.

Our estimation of the discount rate does not intend to capture pure time preference. Our idea is that the discount rate that we estimate provides a summary measure of the strategy used by the seller. Time preference is one of the considerations of this seller, but there are others, which is the reason why we refer to the rate in (7) as a 'gross' discount rate. For instance, Genesove and Mayer (2001) show that many sellers are loss averse and that this implies posting a high list price and accepting the implied longer sales time in order to realise at least the price they paid themselves. Hence the desire to realise at least their reference price affects the trade-off such sellers are willing to make between the sales time and the revenues, and this is reflected in the discount rate we find. We could, alternatively, have assumed a discount rate of, say, 5% and interpret any difference with the rate we measure as 'seller motivation' as Carrillo (2012) and others have done. However, we prefer to avoid making a priori assumptions of the value of the rate of time preference and start by measuring the gross discount rate, while looking for plausible interpretations afterwards.

The advantage of our approach is that we characterise seller behaviour with a single parameter. The drawback is that our approach does not immediately reveal what is behind this parameter.

In this sense, we adopt a partial equilibrium approach rather than, for instance, the structural model of reference-dependence in Andersen et al. (2022). Their model allows them to investigate this aspect of seller behaviour in great detail, but they do not pay much attention to the longer time on the market that may be the result of reference dependence.

In keeping with the existing literature on discount rates, we first focus on obtaining an estimate of the average discount rate. However, the discount rate is based on the expected sales time T. To the extent the expectations on T differ between home sellers due to higher or lower markups, this may lead to heterogeneity in the implied discount rate. We will therefore provide an heterogeneity analysis where we relate demographic characteristics to the choice of markup, which in turn affects the implied discount rates.

List prices and markups. So far, the choice variable of the seller is the list price P^ℓ. However, in the extant literature, one has primarily focused on 'markups', which are deviations of list prices from the prevailing list prices in the neighbourhood of otherwise identical properties. Let us therefore decompose the list price into an expected sales price $\mathbb{E}[\log P^\ell]$ and a markup. Following Guren (2018), we then define the markup as the percent deviation from the expected list price: $m = \log P^\ell - \mathbb{E}[\log P^\ell]$.

The seller observes the expected sales price from recent listings on the local housing market and takes it as given, while the markup is the true choice variable. The first-order condition is $\partial R/\partial m = 0$, which is equivalent to:[10]

$$\frac{\partial \log P}{\partial m} - \frac{rT}{1+rT}\frac{\partial \log T}{\partial m} = 0. \tag{8}$$

Optimal list price-setting then implies that the discount rate can be computed as:

$$r = \frac{\varepsilon_m^P}{T\left(\varepsilon_m^T - \varepsilon_m^P\right)}. \tag{9}$$

Note that this equation is equivalent to (7). This is the formula we will use in the empirical work. We have slightly abused the notation for elasticities by denoting $\partial \log P/\partial m$ as ε_m^P and similar for the elasticity of the sales time. Because using the markup or the list price as the choice variable is equivalent, in what follows we focus on the markup.

[10] To verify this, note first that maximization of R with respect to m is equivalent to maximization of $\log R$ with respect to m since $\partial \log R/\partial m = (1/R)(\partial R/\partial m)$. Hence we can write the first-order condition as $\partial \log P/\partial m - (rT/(1+rT)(\partial \log T/\partial m = 0)$. Second, $\partial \log P/\partial m = (\partial \log P/\partial P^\ell)(\partial P^\ell/\partial m)$ which is equal to $(\partial \log P/\partial \log P^\ell)$ since $\partial P^\ell/\partial m = P^\ell$, while a similar derivation holds for $\partial \log T/\partial m$.

2.2 *Seller's markets: bidding wars*

As discussed above, in recent years the sales prices of many houses exceeded the list price (Leib et al., 2020). This particularly occurs when the housing market is booming, but there is also an underlying upward trend, irrespective of price fluctuations. We include this feature into the model by assuming that there is a probability π that a house will be sold in a 'bidding war'; otherwise it will be sold via conventional bargaining. The probability of a bidding war depends on the list price: we assume that a higher list price decreases the probability of a bidding war, whereas the sales price when a bidding war occurs is increasing in the list price.

Albrecht et al. (2016) assume that bidders arrive at houses for sale with a constant arrival rate, while there is also a constant probability that two or more bidders arrive. This means that the probability of a bidding war is independent of the elapsed time-on-the-market. Our data indeed indicate that bidding wars usually occur shortly after a house is posted for sale. To capture this empirical fact, we adopt a stock-flow matching framework (see *e.g.* Coles and Muthoo 1998; Taylor 1999 for the labour market, and Smith et al. 2022 for the housing market), in which a house for sale can be either matched immediately with searchers already present in the market or with newly arriving searchers later on.[11] As in the previous subsection, we will not construct a fully-fledged bargaining model but concentrate on reduced-form equations that can be linked to the empirical work reported later.

Formally, we assume that a house is sold either in a bidding war occurring immediately after it has been posted or through bilateral bargaining afterwards. For bilateral bargaining, the model of the previous subsection is still valid. Bidding wars occur with a probability π that is decreasing in the list price P^ℓ, so $\pi = \pi(P^\ell)$. The expected revenues are, therefore:

$$R^{\mathcal{B}} = \pi P^{\mathcal{B}} + (1 - \pi)R. \tag{10}$$

In this equation $P^{\mathcal{B}} = P^{\mathcal{B}}(P^\ell)$ is the expected sales price if a bidding war occurs when the list price is P^ℓ, and $R = R(P^\ell)$ the expected revenues when the house is sold through conventional bargaining as in (5).

[11] Our setup is similar to Coles and Muthoo (1998), who study a stock-flow market equilibrium in which sales either take place immediately via competitive bidding – if searchers in the existing pool are interested – or after some time via bilateral bargaining with a searcher who arrives later. The authors show, among other things, that the option to sell the house later through conventional bargaining imposes a lower bound on the price the seller is willing to accept in the initial auction. However, Coles and Muthoo (1998) do not consider the role of the list price, which is key in the current paper.

Optimal list price-setting requires:

$$\frac{\partial \pi}{\partial m}\left[P^{\mathcal{B}} - R\right] + \pi\left(\frac{\partial P^{\mathcal{B}}}{\partial m} - \frac{\partial R}{\partial m}\right) + \frac{\partial R}{\partial m} = 0, \tag{11}$$

The second-order condition for the optimal list price is discussed in Appendix A.4. The expression in square brackets in (11) is the *bidding war premium*. Since the seller of a house always has the option to wait and sell the house through conventional bargaining, the bidding war premium must be non-negative. The expression in parentheses is the first derivative of the bidding war premium. Its sign is determined by the relative impact of a higher list price on the revenues from selling in a bidding war versus selling in conventional bilateral bargaining. In both cases the reservation prices of bidders that are attracted to the house are important. It seems reasonable to consider these reservation prices as random draws from a given distribution that is equal for all searchers. Bidding wars have some similarity with auctions and the sales price may be the second-highest reservation price of the competing bidders, provided it exceeds or is not far below the list price.

To find the discount rate implied by the first-order condition in the presence of bidding wars, we rewrite (11):

$$\begin{aligned} \underbrace{\left[\frac{\partial \pi}{\partial m}P^{\mathcal{B}} + \pi\frac{\partial P^{\mathcal{B}}}{\partial m}\right]}_{\mathcal{X}} + \frac{1}{1+rT}\underbrace{\left[-\frac{\partial \pi}{\partial m}P + (1-\pi)\frac{\partial P}{\partial m}\right]}_{\mathcal{Y}} - \\ \frac{rT}{(1+rT)^2}\underbrace{\left[(1-\pi)P\frac{\partial \log T}{\partial m}\right]}_{\mathcal{Z}} = 0, \end{aligned} \tag{12}$$

This is a quadratic equation in r that can be solved as:

$$\begin{aligned} r_1 &= -\frac{2\mathcal{X} + \mathcal{Y} - \mathcal{Z} + \sqrt{(\mathcal{Y}-\mathcal{Z})^2 - 4\mathcal{X}\mathcal{Z}}}{2\mathcal{X}T} \\ r_2 &= -\frac{2\mathcal{X} + \mathcal{Y} - \mathcal{Z} - \sqrt{(\mathcal{Y}-\mathcal{Z})^2 - 4\mathcal{X}\mathcal{Z}}}{2\mathcal{X}T} \end{aligned} \tag{13}$$

where $\mathcal{X}$, $\mathcal{Y}$ and $\mathcal{Z}$ are the first, second and third expressions in square brackets in (12) respectively. It is easy to verify that $\mathcal{Y}$ and $\mathcal{Z}$ are both positive. The first derivative of the left-hand side of (12) with respect to r is negative if $0 < rT < 1$. Since the expected sales time is smaller than 1 year, the implication is that there can be only one interest rate between 0 and 100% that is consistent with the first-order condition. We therefore can disregard r_2 because it always leads to a negative implied discount rate r.

3 Data and descriptives

3.1 Data

3.1.1 Listings data.

Our analysis is based upon several datasets. The dataset that is central to our analysis is from the NVM (Dutch Association of Real Estate Agents) and contains listings of properties, including withdrawals. It contains about 75% of all housing transactions for 35 years; between 1985 and 2021. For 4,188,576 transactions, we know the sales price (if it has been sold), the first list price, the final list price, the time-on-the-market, the exact location, and a wide range of housing attributes such as size (in m^2), house type, and construction year. We exclude transactions with sales prices that are above €10 million or below €10,000 or a m^2 price below €250 or above €5,000. Furthermore, we exclude homes smaller than $25m^2$ or larger than $750m^2$. We also drop a few properties that have a negative time-on-the-market and exclude observations for which the sales to list price ratio is below 0.5 or above 2. These selections comprise less than 5% of our data and do not impact our results.

Interestingly and uniquely, our dataset also provides information on retracted listings, which are listings that do not lead to a sale. This applies to 11% of the listings so this is a non-negligible share. To calculate the time-on-the-market we merge each withdrawal to subsequent sale of the property. We then add the time-on-the-market of the different retracted listings, and take the list price of the first retraction.[12]

In our analysis, we focus on repeated sales, so properties that are sold at least twice. It appears that 28% of the transactions in the full sample refer to properties that are sold at least twice. This share is somewhat low because we only focus on properties that do not change type, and have differences in size over the years that are less than 20% of the mean size of the property.

Further, one key variable of interest is whether a bidding war has occurred. Following Han and Strange (2014), we then define a dummy to be equal to one when the sales price exceeds the final list price.

We will include neighbourhood-by-quarter fixed effects in most specifications. Neighbourhoods are defined by Statistics Netherlands and are small; on average the number of households is 822, while the median is just 290 households.

[12]One may also calculate the time-on-the-market as the elapsed time between the first listing and the eventual sale. Although we think this will overestimate time-on-the-market, we will show robustness of our results to this alternative way of calculating time-on-the-market.

3.1.2 Demographic data.

We enrich the listings data by obtaining data from Statistics Netherlands, which entails the universe of people and households in the Netherlands between 1995 and 2021. Hence, our regressions will be based on matched listings from 1995-2021. Based on address identifiers from GBA-Adresobject, we obtain information on sellers' characteristics from GBA-persoon and GBA-huishoudens, such as household size and type, the average age of adults, the share of people that are non-western immigrants, and the average age of adults in the household. Furthermore, for about 60% of the data, we obtain information on the highest acquired level of education from Hoogsteopltab.

More importantly, for the instrument, to be introduced later, we calculate price appreciation since the seller moved into the property until it is listed. To calculate how long someone lived in the property, we obtain the date of entry from GBA-Adresobject. We further use the date of moving out to determine whether the household moved before it listed the property on the market.

3.1.3 Land registry.

For some ancillary analyses, we match housing transactions from the NVM to the universe of housing transactions in the Kadaster, *i.e.* the Land Registry. The Land Registry data are inferior to the NVM data because the former data provide no information on list prices and sales time, but the data do provide information on the seller type. More specifically, for a subset of the transactions we know whether the seller was a owner-occupier, a private landlord, or housing corporation.

3.2 Price appreciation and markup

For our instrument, to be discussed later, we use the full span of the data (1985-2021) to calculate price appreciation in each neighbourhood, following Guren (2018). More specifically, we calculate the predicted sales price using data on properties i located in neighbourhood n in month t, by regressing $\log P_{ijt} = x_{ijt}'\beta + \mu_i + \mu_{jt} + \epsilon_{ijt}$, where x_{ijt} are time-varying housing characteristics, μ_i are property fixed effects, μ_{jt} are neighbourhood-by-year fixed effects and ϵ_{ijt} is a random error. Our interest is in the estimate of μ_{jt}, which is the relative price level in a neighbourhood in year t. We calculate price appreciation as

$$z_{ijt} = \mu_{jt} - \mu_{j\tilde{t}}, \tag{14}$$

where $\tilde{t}$ denotes the month of the previous sale.[13]

[13]To achieve cleaner identification, Guren (2018) considers to exclude certain groups from the data (such as investors and properties with a large negative appreciation.) We consider to exclude similar groups in Appendix

To calculate markups, we use list prices and estimate $\log P^{\ell}_{ijt} = x'_{ijt}\beta^{\ell} + \mu^{\ell}_i + \mu^{\ell}_{jt} + \epsilon^{\ell}_{ijt}$, where t now denotes quarters. The markup is then given by

$$m_{ijt} = \log P^{\ell}_{ijt} - \mathbb{E}[\log P^{\ell}_{ijt}], \tag{15}$$

where the expected list price is given by $\mathbb{E}[\log P^{\ell}_{ijt}] = x'_{ijt}\hat{\beta}^{\ell} + \hat{\mu}^{\ell}_i + \hat{\mu}^{\ell}_{jt}$.

3.3 Descriptives

Table 1 reports the key descriptive statistics. For the full statistics we refer to Appendix B.1. PANEL A focuses on the full sample. The average sales price is about €250 thousand.

On average, the sales price is about 5% lower than the list price. Furthermore, the average time-on-the-market is almost 5 months. In line with Han and Strange (2016), we also observe that for a reasonable share of the transactions (9.1%), the list price is exactly equal to the sales price. It appears that 14.2% of the transactions are sold above the list price. We re-emphasise that we use this variable as a proxy for the occurrence of a bidding war, following Albrecht et al. (2016) and Han and Strange (2014). We show later that the share of bidding wars may be considerably higher in certain years. We also report characteristics of the seller, which seem to consists of a representative sample of the Dutch population, with an average age of 47 and a share of the population that has a bachelor's degree or higher of 37.5%

In PANEL B of Table 1 we focus on the repeat-sales sample, which appears to be in many ways comparable to the full sample. For example, the share of properties that have been sold above the list price is very similar (14.6%). Still, the average sales price is about 15% lower because somewhat cheaper and smaller flats are overrepresented in the repeat-sales sample.[14]

In Figure 1 we plot trends for four important housing market indicators for the period 1995-2019. In Figure 1a we show the development of sales prices since 1995. It is striking that after 2012, houses quickly became much more expensive when the housing market recovered from the economic crisis. The average house price in 2021 exceeded €400 thousand

In Figure 1b we look at the sales time. The time-on-the-market peaked just after 2012 when prices declined. Surprisingly, increases in prices do not always imply reductions in time-on-the-market. For example, between 1999 and 2005, sales price increases were not associated with shorter sales times. On the other hand, after 2012 prices and sales times moved in the opposite direction.

C.4. Because the results do not change much we not exclude these observations in the baseline specifications.

[14] We have made sure that our results are not driven by repeat-sales observations. The results, where we include local area (postcode) instead of property fixed effects, are available upon request.

TABLE 1 – DESCRIPTIVE STATISTICS FOR THE NVM DATA

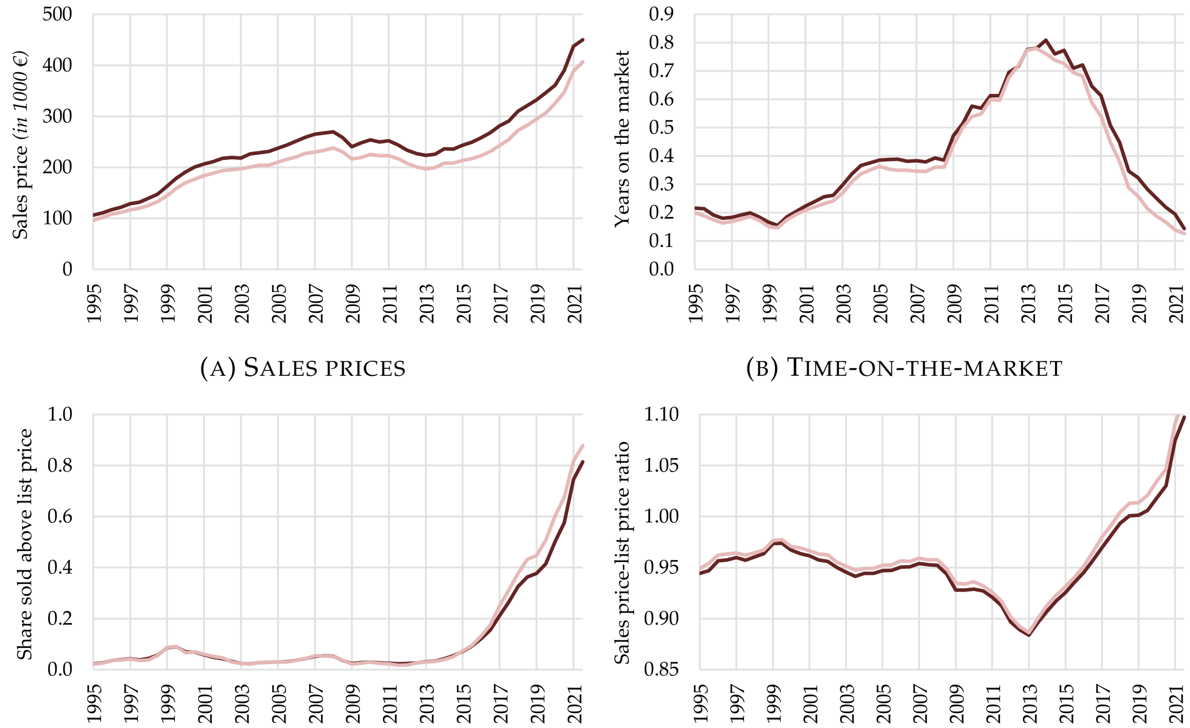
PANEL A: Full sample	(1) mean	(2) sd	(3) 5th perc.	(4) median	(5) 95th perc.
Sales price *(in €)*	249,217	185,223	83,949	202,000	565,000
List price *(in €)*	261,296	199,674	87,580	212,500	595,000
Years on the market	0.403	0.716	0.0192	0.156	1.558
Sold above list price	0.142	0.349	0	0	1
Markup	0	0.0466	-0.0737	0	0.0736
Price appreciation since purchase	0.272	0.345	-0.129	0.187	0.966
Size of property *(in m^2)*	122.8	56.05	61	115	210
Apartment	0.126	0.331	0	0	1
Maintenance state is good	0.855	0.352	0	1	1
Construction year <1945	0.241	0.428	0	0	1
Moved before listing	0.192	0.394	0	0	1
Household size	2.203	1.854	1	2	4
Household – single without kids	0.318	0.466	0	0	1
Non-western foreigner	0.0411	0.177	0	0	0.333
Age	46.55	18.26	24.67	41	83
Education – bachelor's degree	0.375	0.457	0	0	1

PANEL B: Repeated-sales sample	(1) mean	(2) sd	(3) 5th perc.	(4) median	(5) 95th perc.
Sales price *(in €)*	208,531	131,743	82,000	178,000	428,000
List price *(in €)*	216,058	137,388	85,764	185,000	439,000
Years on the market	0.367	0.651	0.0192	0.145	1.394
Sold above list price	0.146	0.353	0	0	1
Markup	0	0.0459	-0.0727	0	0.0728
Price appreciation since purchase	0.218	0.286	-0.131	0.156	0.768
Size of property *(in m^2)*	105.8	38.23	57	101	165
Apartment	0.155	0.362	0	0	1
Maintenance state is good	0.902	0.297	0	1	1
Construction year <1945	0.215	0.411	0	0	1
Moved before listing	0.141	0.348	0	0	1
Household size	2.188	1.365	1	2	4
Household – single without kids	0.318	0.466	0	0	1
Non-western foreigner	0.0447	0.184	0	0	0.500
Age	40.93	15.22	24.50	36	75
Education – bachelor's degree	0.400	0.461	0	0	1

Note: The number of observations is 2,848,857 for the full sample and 808,241 for the repeated-sales sample. For confidentiality reasons, we cannot report minimum and maximum values. Descriptive statistics for the full set of variables are reported in Tables B1 and B2 in Appendix B.1.

In Figure 1c we show that until 2015, bidding above the list price was a rare phenomenon. Since 2016 we witness an unparalleled share of transactions sold above the list price: in 2021 this is about 80%. Note that the share of bidding wars is also unprecedentedly high in comparison with housing markets in the U.S. in 'boom' periods.[15] In line with this observation, in Figure 1d we plot the ratio of the sales price to the list price. For the most part, this is well below 1 and around 0.95, suggesting that conventional bargaining, where one seller and one prospective

[15] The increasing frequency of bidding wars may be facilitated by the emergence of websites (most notably: `Funda.nl`) on which essentially all houses for sale in a given area are advertised. Prospective buyers regularly visit such websites and notice houses of potential interest soon after they are posted. In tight markets, this can easily result in two or more interested parties visiting a given house, which may result in a bidding war.



(A) SALES PRICES

(B) TIME-ON-THE-MARKET

(C) SHARE SOLD ABOVE LIST PRICE

(D) RATIO SALES TO LIST PRICE

FIGURE 1 – TRENDS IN VARIABLES OF INTEREST

Notes: The dark red line refers to all observations, whether the light red line refers observations in the repeat-sales sample.

buyer bargain over the price is the default. However, in recent years, the ratio of sales prices to list prices exceeds one.

4 Econometric framework

4.1 *Buyers' markets: conventional bargaining*

The main equation to be estimated – equation (7) – shows that the discount rate of a seller occupying a property i is determined by two elasticities and the expected sales time.[16] We need to estimate *(i)* the elasticity of the sales price with respect to the markup $(\partial \log P_{ijt}/\partial m_{ijt})$, *(ii)* the elasticity of sales time with respect to the markup $(\partial \log T_{ijt}/\partial m_{ijt})$ and *(iii)* the expected sales time $T_{ijt} = T(m_{ijt})$.

4.1.1 The effect of the markup on time-on-the-market and sales prices

We assume the elasticities of interest are determined by the following relationship between the sales price and the markup:

$$\{\log T_{ijt}, \log P_{ijt}\} = \alpha m_{ijt} + x'_{ijt}\beta + \mu_i + \mu_{jt} + \epsilon_{ijt}, \tag{16}$$

[16]Our notation does not distinguish between the seller and the house sold. We refer to both with the same subscript i.

where T_{ijt} denotes the sales time of property i in neighbourhood j in year t, while P_{ijt} denotes the sale price. m_{ijt} is the markup as defined in (15). Further, x_{ijt} are housing controls that change over time, μ_i are property fixed effects, μ_{jt} are neighbourhood$\times$quarter fixed effects, and ϵ_{ijt} denotes the error term.

The main issue in identifying the causal effect of the markup on the time-on-the-market or sales price is that properties with a shorter time-on-the-market or higher sales price are likely more attractive in unobserved characteristics (see Guren, 2018). To mitigate this issue, we include a vector of housing characteristics x_{ijt}, capturing for example house size, insulation quality and the listed building status. However, it is unlikely that x_{ijt} will capture all attributes related to housing quality. We therefore will also include property fixed effects μ_i. This is a very effective way to control for all time-invariant housing (and location) attributes, such as construction year, architectural quality, *etc.* One still may argue that α may not capture a causal effect of the markup because properties that have higher markups are more likely to have become more attractive (*e.g.* due to extensions). We therefore will control for neighbourhood$\times$quarter fixed effects μ_{jt}. Note that because we include both fixed effects for each property and each neighbourhood-by-quarter combination, we only use variation between houses that were sold in the same neighbourhood in the same quarter and then compare the *change over time* in the markup and time-on-the-market/sales prices.

4.1.2 An instrumental variables strategy.

One may still be concerned that detailed fixed effects may not completely address endogeneity issues. We, therefore, follow the instrumental variables strategy adopted by Guren (2018). As an instrument for markups, we calculate the amount of appreciation z_{ijt} in the house price since the time the seller has moved in the property. This implies that we compare different sellers at the same moment, but they bought their property at different times. Hence, as appreciation since the moment of purchase may be different between different sellers, their marginal utility of cash on hand may be different. The instrument takes advantage of two sources of variation in the marginal utility in cash at hand that are independent of unobserved quality. The first source is liquidity constraints that may be different. When the total price appreciation is low, it is more likely that sellers can extract less equity and each euro is required to invest in the next property. Hence, the marginal utility is high. Sellers that can extract more equity from the property have less binding down-payment constraints, have a lower marginal utility of cash on hand, and therefore set lower markups (Genesove and Mayer, 1997; Anenberg, 2011; Andersen et al., 2022). The second source of variation in the marginal utility is due to loss aversion, which has been shown to be very important in the housing market (Genesove and Mayer, 2001; Engelhardt, 2003; Anenberg, 2011; Andersen et al., 2022). If house prices have decreased since the moment of buying, the seller is more likely to set a high markup to sell above her initial purchase price.

4.1.3 Non-linearity in the markup.

Another issue stipulated by Guren (2018) is that the effect of the markup is likely non-linear because of concave demand. In other words, properties with a too high markup may not be frequented by prospective buyers because they do not consider the property to be attractive. On the other hand, when the markup is low, this may not attract much more prospective buyers than if the markup would have been somewhat higher. We note that we can find the probability that a house sells within a particular time interval from our model, which assumes an exponential distribution of the sales time with a parameter θ. That parameter equals the inverse of the expected sales time, which we estimate as a function of the markup, and therefore of the list price. This function turns out to be flat at a value close to 1 for small markups, then becomes concave and it ultimately flattens of for very high markups, when the probability of a sale within the chosen period is already low. The latter, non-concave part of the curve is an implication of the non-negativeness of the probability that a house sells within the chosen period.

Hence, our implied demand curve is concave for the empirically relevant range of markups. It is nevertheless possible that our log-linear equations underestimate the amount of concavity that is present in the data. To investigate this, we add a quadratic term for markups. We also do this in the sales price equation, because it is also possible that the impact of a higher list price on the sales price gets smaller when the markup is increased. We therefore estimate:

$$\{\log T_{ijt}, \log P_{ijt}\} = \alpha_1 m_{ijt} + \alpha_2 m_{ijt}^2 + x_{ijt}'\beta + \mu_i + \mu_{jt} + f(\hat{\xi}_{ijt}) + \epsilon_{ijt}. \tag{17}$$

Because the endogenous variable is non-linear, we cannot use a standard two-stage least squares approach. Instead, use use a control function approach in which first-stage errors, denoted by $\hat{\xi}_{ijt}$ are inserted as a second-order polynomial in the second stage (Blundell and Powell, 2003).

4.1.4 Heterogeneity in the markup

Initially, we will focus on measuring the average gross discount rate, assuming that the expected time-on-the-market equals the average time-on-the-market. However, given that we have data on the characteristics of the seller, we can see how sellers with different characteristics choose different markups, which in turn will lead to differences in the discount rate. In principle, seller characteristics are suitable instruments for the markup, as they affect the markup through differential time preferences, but should not affect sales prices directly. We think the exclusion restriction is satisfied because prospective buyers typically do not know the characteristics of the seller as the real estate agent handles the sale. Our adjusted first-stage then entails:

$$m_{ijt} = \gamma_1 z_{ijt} + \gamma_2 z_{ijt}^2 + \delta h_{ijt} + x'_{ijt}\zeta + \lambda_i + \lambda_{jt} + \xi_{ijt}, \tag{18}$$

where z_{ijt} captures price appreciation, while h_{ijt} is a a range of household characteristics, such as the education level, age and household composition. We then control for housing quality, captured by x_{ijt} and the fixed effects λ_i an λ_{jt}. Like in the above, we will insert the first-stage error ξ_{ijt} as a control function in (17). Based on the estimated parameters $\hat{\gamma}_1$, $\hat{\gamma}_2$, and $\hat{\delta}$ we can predict the markup, which in turn will be used to calculate the household-specific expected time-on-the-market and the implied discount rates.

4.2 Sellers' markets: bidding wars

In sellers' markets where bidding wars are important, we need to estimate additional semi-elasticities. That is, we need to know the response of the bidding war probability once the markup is higher. Moreover, we aim to estimate the effects of bidding wars on sales prices and time-on-the-market.

Following Han and Strange (2014), our proxy for bidding wars, denoted by b_{ijt}, is a dummy variable that equals one when the property is sold above the last list price observed. To understand how the markup affects bidding wars, we estimate:

$$b_{ijt} = \zeta m_{ijt} + x'_{ijt}\eta + \upsilon_i + \upsilon_{jt} + \chi_{ijt}, \tag{19}$$

where ζ and η are parameters to be estimated, υ_i are fixed effects for each property and υ_{jt} are neighbourhood$\times$quarter fixed effects. χ_{ijt} captures the unexplained part of the variation in bidding wars, which is assumed to be uncorrelated to the markup m_{ijt}. Following the previous specifications, we instrument for m_{ijt} with the price appreciation since the seller moved in the property. A higher price appreciation is expected to lead to lead to lower markups.

The price and time-on-the-market equations are then given by:

$$\{\log T_{ijt}, \log P_{ijt}\} = \alpha_0 b_{ijt} + \alpha_1 m_{ijt} + x'_{ijt}\beta + \mu_i + \mu_{jt} + \epsilon_{ijt}, \tag{20}$$

where β_0 is an additional parameter to be estimated.[17]

An issue in the above equation may be that the bidding war dummy may also be endogenous: properties that are sold via a bidding war may have a higher unobserved quality, leading to a

[17]For convenience, we initially assume that $\hat{\alpha}_B^P = \hat{\alpha}^P$, so that the markup has the same effect on sales prices in bidding wars as without bidding wars. We will provide evidence that $\hat{\alpha}_B^P$ and $\hat{\alpha}^P$ are actually statistically significantly different from each other, but this will not materially influence the implied discount rate.

shorter time-on-the-market and a higher sales price. We, therefore, need to find an instrument that is uncorrelated to unobserved quality and should not directly influence time-on-the-market or prices. Leib et al. (2020) provide evidence that rounded (rather than precise) list prices attract higher offers, *but only in sellers' markets*. The idea is that rounded list prices attract more potential buyers, which increases the chances on a bidding war. We will use a dummy indicating whether the list price is set according to notches at `Funda.nl`, which is by far the largest online platform providing an overview of properties on sale in the Netherlands. When selecting the list price in the search criteria, prospective buyers select prices within certain ranges (rather than typing the exact list prices themselves). We use these notches to indicate 'rounded' list prices.[18] By controlling for property and neighbourhood-by-quarter fixed effects, we expect that rounded list prices are not correlated to the unobserved quality and do not impact sales prices and time-on-the-market other than via increasing the probability of a bidding war.

5 Results

5.1 *Buyers' markets: conventional bargaining*

5.1.1 Baseline results

In Table 2 we report the baseline results of the effects of the markup on sales prices (PANEL A), time-on-the-market (PANEL B). Based on the estimated elasticities, we recover gross discount rates (PANEL C).

In column (1) we include property fixed effects and quarter fixed effects. The results indicate that a 10% increase in the markup is associated with a 6.8% increase in the sales price. Similarly, a 10% increase in the markup is associated with a 38.4% increase in the time-on-the-market. Unsurprisingly, choosing a higher markup leads to a higher sales price, but unintentionally also implies that the time-on-the-market is longer. These estimates lead to very high discount rate of 52%. Column (2) improves on the identification by including neighbourhood-by-quarter fixed effects, which should further control for unobserved quality of houses and time-varying trends in small neighbourhoods. The coefficients are not materially influenced so the gross discount rate is in the same ballpark.

To the extent unobserved quality is correlated to the markup in the previous specification, we would expect to see a somewhat lower effect of the markup on sales prices, but a higher effect of the markup on time-on-the-market. This is exactly what we find in column (3) where we include street-by-year fixed effects: the effect of the markup on sales prices is reduced by about

[18] `Funda.nl` uses the following notches: €50,000, €75,000, €100,000, €125,000, €150,000, €175,000, €200,000, €225,000, €250,000, €275,000, €300,000, €325,000, €350,000, €375,000, €400,000, €450,000, €500,000, €550,000, €600,000, €650,000, €700,000, €750,000, €800,000, €900,000, €1,000,000, €1,250,000, €1,500,000, and €2,000,000.

TABLE 2 – RESULTS WITH CONVENTIONAL BARGAINING

	Property f.e.	*+ N'hood ×quarter f.e.*	*+Street× ×quarter f.e.*	*Instrument: Price appreciation*		*Instruments: + Seller demographics*
PANEL A: Sales prices *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	0.6785***	0.7022***	0.6290***	**0.8112*****	**0.8122*****	**0.8821*****
	(0.0040)	(0.0035)	(0.0110)	**(0.0584)**	**(0.0825)**	**(0.0761)**
(Markup)^2					**-0.3499**	**-0.4735**
					(0.2317)	**(0.3519)**
Housing controls	✓	✓	✓	✓	✓	✓
First-stage residuals					✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓					
Neighbourhood×quarter fixed effects		✓		✓	✓	✓
Street×quarter fixed effects			✓			
Number of observations	570,039	415,660	53,249	52,589	52,589	30,888
R^2	0.9788	0.9951	0.9964			
Kleibergen-Paap F-statistic				99.29	99.29	15.77
PANEL B: Time-on-the-market *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	3.8427***	3.7292***	4.2592***	**7.8356*****	**7.8528*****	**8.9764*****
	(0.0350)	(0.0426)	(0.1488)	**(1.0740)**	**(1.5104)**	**(1.2940)**
(Markup)^2					**4.6854**	**9.4220****
					(2.9166)	**(3.9738)**
Housing controls	✓	✓	✓	✓	✓	✓
First-stage residuals					✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓					
Neighbourhood×quarter fixed effects		✓		✓	✓	✓
Street×quarter fixed effects			✓			
Number of observations	570,039	415,660	53,249	52,589	52,589	30,888
R^2	0.5911	0.7853	0.8500			
Kleibergen-Paap F-statistic				99.29	99.29	15.77
PANEL C: Implied discount rates	(1)	(2)	(3)	(4)	(5)	(6)
Gross discount rate, r	0.5212***	0.5638***	0.4212***	0.2807***	0.2804***	0.2649***
	(0.0069)	(0.0086)	(0.0193)	(0.0485)	(0.0692)	(0.0525)
	[0.5078, 0.5347]	[0.5469, 0.5808]	[0.3833, 0.4590]	[0.1857, 0.3757]	[0.1448, 0.4159]	[0.1620, 0.3678]

Notes: **Bold** indicates instrumented. In columns (4)-(6) we instrument list price by price appreciation since the seller moved in the property. In column (6) we also use seller demographics as additional instruments. In columns (5) and (6) we adopt a control-function approach in which we insert the first-stage errors as a control function in the second stage. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. Standard errors are cluster-bootstrapped (250 replications) in columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

11%, while the effect on time-on-the-market is approximately 14% higher. These estimates lead to a gross discount rate of 42%.

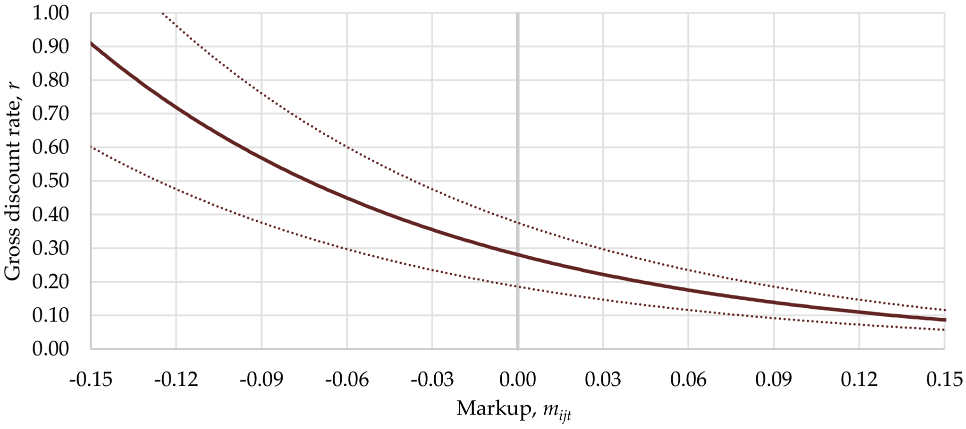
To the extent one is concerned that detailed fixed effects do not capture unobserved housing quality fully, we apply an instrumental variables strategy using the price appreciation in the neighbourhood since the last sale. We first include property and neighbourhood-by-quarter fixed effects in column (4). The first-stage results reported in Appendix C.1 indeed indicate that a higher appreciation is associated with a lower markup. Going back to Table 2, one may see that the instrument is sufficiently strong as the Kleibergen-Paap *F*-statistic is almost 100. We find that the impact of the markup on sales prices is somewhat stronger; the estimated elasticity implies that a 10 percentage point increase in the markup is associated with a 8.1% increase in sales prices. The effect on time-on-the-market is considerably higher: the coefficient implies that a 10% increase in the markup increases the time-on-the-market by 78%. Given the stronger estimated elasticity of time-on-the-market with respect to the markup, the gross discount rate is reduced to 28%.

In column (5), we consider the non-linear effects of the markup on prices and time-on-the-market to see if we find evidence for concave demand (Guren, 2018). As indicated before, we use a control function approach where first-stage errors are inserted as a second-order polynomial in the second stage. Although our framework already implied concavity, we indeed find weak evidence for a non-linear effect of markups. However, the coefficients have the expected signs but are not statistically significant. For sales prices, we find that the marginal impact of markup decreases once the markup is set higher, in line with the idea that when the markup is very high, prospective buyers will not be interested. Similarly, we find that a higher markup increases time-on-the-market at an increasing rate. The gross discount rate for the average markup in our sample is 28%, which is very close to the previous estimates.

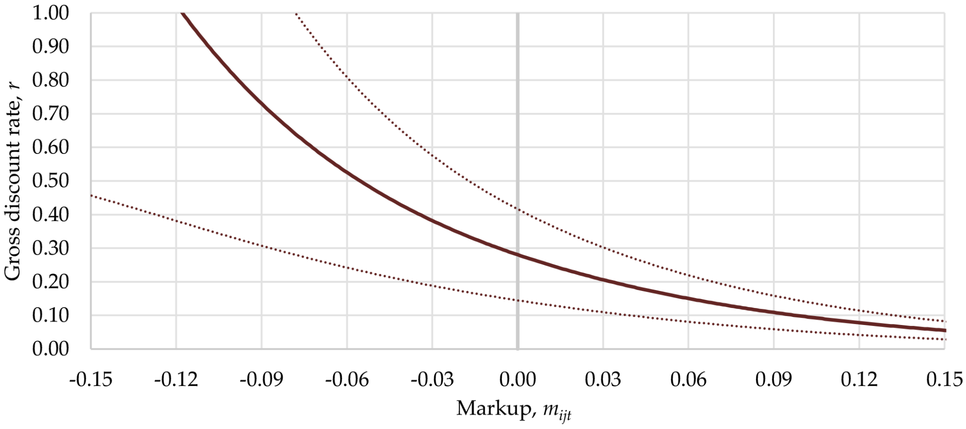
Column (6) focuses on a subsample of the listings for which we have detailed characteristics on sellers, such as the level of education, age, and household size. In principle, seller's characteristics are valid instruments for the markup, as they affect the markup through differential time preferences, but should not affect sales prices directly. This is particularly so because prospective buyers typically do not know who is the seller because the real estate agent deals with inspections. In Appendix B.1 we display the first-stage results. We show that sellers that already have moved before listing their property set higher markups. Also sellers with a higher level of education and elderly people choose higher markups. Going back to Table 2 we show that using seller characteristics as additional instruments does not materially change the results. The average implied gross discount rate is 26%. However, the quadratic term for time-on-the-market is now twice as high and statistically significant at the 5% level.

5.1.2 Heterogeneity in gross discount rate

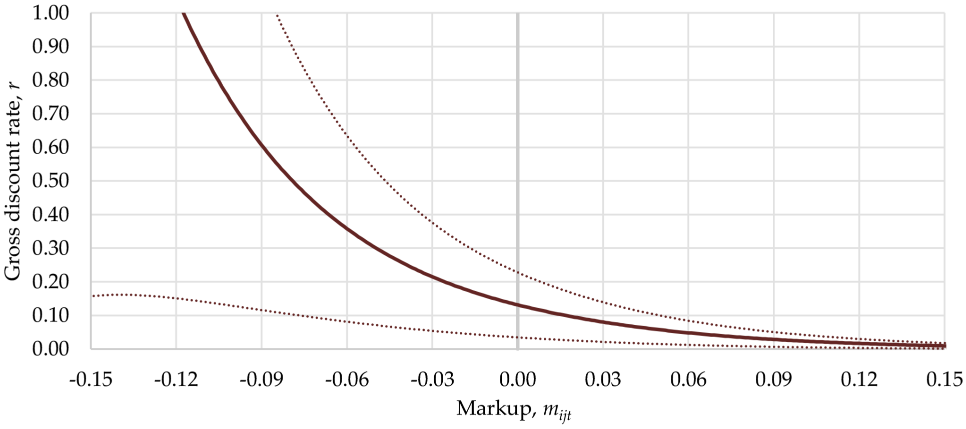
To investigate how the discount rate relates to the markup, in Figure 2 we plot the gross discount rates for different levels of the markup. We use the coefficients as estimated in column (4) (*i.e.*, a



(A) SPECIFICATION BASED ON ESTIMATES IN COLUMN (4), TABLE 2



(B) SPECIFICATION BASED ON ESTIMATES IN COLUMN (5), TABLE 2



(C) SPECIFICATION BASED ON ESTIMATES IN COLUMN (6), TABLE 2

FIGURE 2 – IMPLIED DISCOUNT RATES FOR DIFFERENT MARKUPS

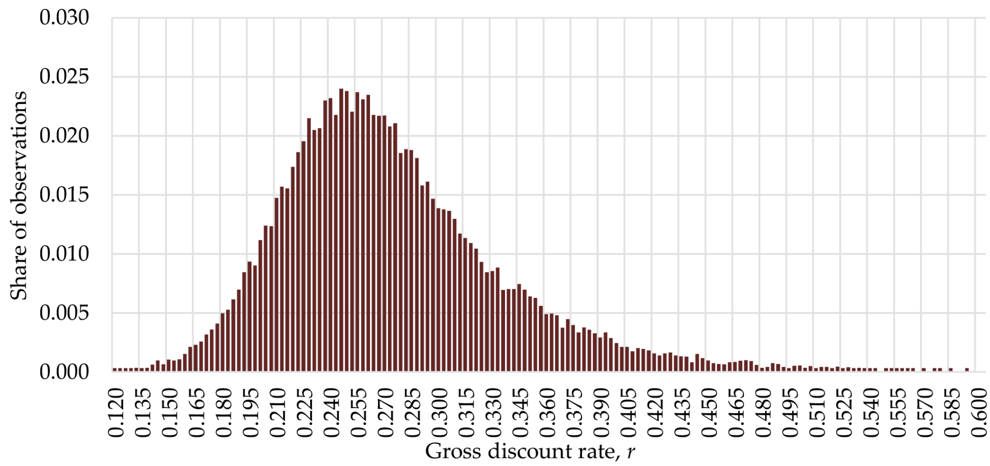


FIGURE 3 – THE DISTRIBUTION OF GROSS DISCOUNT RATES

linear specification) and columns (5) and (6) (*i.e.*, the non-linear specifications). We find that for negative markups, discount rates are very high, while discount rates become progressively smaller once the markup is set higher. This is particularly so for the non-linear specifications (see Figures 2b and 2c). The general pattern makes sense: more impatient people will choose relatively low markups to sell the home quickly. For high markups (exceeding 10%), we find implied discount rates that are close to prevailing market interest rates.

To further investigate heterogeneity we calculate the implied gross discount rates using the first-stage in equation (18), corresponding to the specification listed in column (6). We use the variation in the markup between sellers with different characteristics to obtain a distribution of discount rates, which we report in Figure 3. We show that gross discount rates range from 12% to 50%, which is in line with the confidence bands estimated in column (6). Hence, there is sizeable heterogeneity. To examine how different seller's characteristics are associated with gross discount rates, we regress gross discount rates on those characteristics and show the results in Table 3.[19]

In column (1) we only include price appreciation and whether the sellers already have moved out before the listing. We find that sellers that have experienced more price appreciation since the previous purchase have somewhat higher implied discount rates because they choose lower markups. For example, discount rates are 24% at the 5^{th} percentile of the price appreciation distribution, while 29% at the 95^{th} percentile. Interestingly, sellers that already have moved out before they put their property on the market have considerably higher discount rates (almost 8

[19]To obtain standard errors, we use the following bootstrap procedure. We first estimate the first stage that includes seller's characteristics (see equation (18) and column (2), Table C1, in Appendix B.1). Second, given the seller's characteristics we obtain the markup for each seller. Third, using the specification in column (6), Table 2, we calculate the seller-specific gross discount rate. Fourth, we regress the estimated gross discount rates on household characteristics. We repeat these steps 250 times for randomly drawn samples of properties with replacement.

TABLE 3 – HETEROGENEOUS DISCOUNT RATES
(Dependent variable: the implied gross discount rate)

	Baseline	*Education*	*Baseline+education*	*All*
	(1)	(2)	(3)	(4)
Price appreciation since purchase	0.1150***		0.1160***	0.1193***
	(0.0227)		(0.0228)	(0.0232)
(Price appreciation since purchase)^2	-0.0723***		-0.0740***	-0.0819***
	(0.0196)		(0.0197)	(0.0205)
Moved before listing	0.0798***		0.0786***	0.0752***
	(0.0149)		(0.0147)	(0.0138)
Education – secondary		-0.0260	-0.0225	-0.0171
		(0.0161)	(0.0159)	(0.0158)
Education – vocational		-0.0383**	-0.0324**	-0.0240
		(0.0169)	(0.0165)	(0.0161)
Education – bachelor's degree		-0.0409**	-0.0348**	-0.0233
		(0.0165)	(0.0161)	(0.0158)
Western foreigner				0.0146
				(0.0133)
Non-western foreigner				0.0218*
				(0.0127)
Male				0.0043
				(0.0051)
Age 26-40				-0.0220***
				(0.0076)
Age 41-55				0.0052
				(0.0103)
Age 56-70				0.0236
				(0.0203)
Age >70				-0.1361***
				(0.0486)
Household size				-0.0079
				(0.0061)
Household – single with kids				0.0269*
				(0.0155)
Household – couple without kids				-0.0115
				(0.0083)
Household – couple with kids				-0.0070
				(0.0171)
Household other				0.0156
				(0.0217)
Constant	0.2495***	0.3085***	0.2796***	0.3022***
	(0.0767)	(0.0731)	(0.0757)	(0.0769)
Number of observations	30,768	30,768	30,768	30,768
R^2	0.960	0.948	0.960	0.965

Notes: Bootstrapped standard errors (250 replications) are clustered at the property level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

percentage points).

Column (2) investigates differences between sellers with different education levels. Because sellers with higher levels of education set higher markups, their discount rates are considerably lower. For example, compared to people with primary education, a seller with a bachelor's degree or higher has a discount rate that is about 4 percentage points lower. In column (3) we add both price appreciation and the level of education leading to similar results.

Column (4) in Table 3 adds many more household characteristics, showing that the effect of education becomes somewhat smaller. Younger as well as elderly people have lower discount rates, which is intuitive as they have a lower opportunity cost of time. Further, we find suggestive evidence that foreign-born sellers have a higher gross discount rate (about 1.5-2.2 percentage points).

5.1.3 Interpretation of the gross discount rate

The estimates reported above are generally between 15-50%, which strongly suggests that sellers are impatient and undervalue future money flows.

Although the discount rates we find are an order of magnitude higher than market-based interest rates, they are not much higher than the idiosyncratic discount rates reported by Carrillo (2013), who attributes them to seller motivation, and Genesove and Mayer (1997), who compute a discount rate of 20% for sellers that are presumably more patient than on average. Nevertheless, the high values we find raise questions about the interpretation of our findings in terms of target function (1), if it is interpreted as the change in the intertemporal budget constraint of the home seller.

In Appendix A.2 we discuss several possible micro-foundations of this target function in a model of intertemporal utility maximization. We start with a simple version that supports the interpretation of (1) as the change in the intertemporal budget constraint. As noted, the discount rates we find are too high to be easily compatible with such a model. We then show that the presence of a mortgage on the house offered for sale cannot explain our high discount rates we find, but would imply a lower discount rate if sellers are impatient (see Appendix A.2.1). Intuitively, the reason is that for impatient sellers, the presence of a mortgage that has a lower interest rate than their rate of time preferences makes it less problematic that the house is sold later.

If household consumption is restricted by a borrowing constraint that is binding up to the point the house is sold (for instance because temporarily two mortgages are present), we must look directly at the change in utility associated with selling the house to derive the seller's target function. In Appendix A.2.2 we consider the simple case in which instantaneous utility is constant over time and shifts to a higher level at the time of selling the house, due to consumption possibilities that are constrained until the house is sold. Then, we show that borrowing constraints do not necessarily imply high discount rates. However, strong borrowing constraints are likely to imply a strong desire to sell the house quickly, even at the cost of lower revenues, which suggests a higher discount rate. This is confirmed in our empirical results for seller who have already left the house, that were discussed above. Related to this finding, the discount rate may also capture 'seller motivation'. Some sellers may have a necessity to move to another location, leaving the house behind, and, hence, gain a low utility flow during the sales time. A young professional, for example, may need to move to another city due to a job relocation. Other sellers may stay in the house and have a relatively high utility flow during the sale time. In principle, the discount rate should include the average seller motivation, but in the empirical section we will allow discount rates to be heterogeneous across different types of sellers.

Further, seller search or listing costs will be reflected in the discount rate that we find. High costs of keeping the house available for sale and being prepared for visits of prospective buyers naturally lead to a stronger desire to sell quickly. In Appendix A.2.3 we present a formal model with three types of seller costs: *(i)* a fixed cost C^0 at the start (making the house available for sale) *(ii)* a flow cost c as long it is on the market and *(iii)* a share of the C^S of the sales price. We derive an adapted expression for the rate of discount:

$$r = \frac{\varepsilon^P_{P^\ell} - \varepsilon^T_{P^\ell}\left(\frac{cT(P^\ell)}{(1-C^S)P(P^\ell)}\right)}{T(P^\ell)\left(\varepsilon^T_{P^\ell} - \varepsilon^P_{P^\ell}\right)}. \tag{21}$$

The second term in the numerator is negative and it shows that ignoring search costs will lead to an upward bias in the computed rate of discount. Alternatively, the equation can be interpreted as suggesting that the rate of discount we compute on the basis of (7) includes the impact of search costs.

The additional term in the numerator is the product of the elasticity of the sales time with respect to the list price and the ratio of the expected total variable search cost to the net sales price. The expected sales time is about five months. We have no direct information about the variable search cost c. Guren (2018) assumes monthly costs of 2.1% of the value of the house. Combined with an expected sales time of five months and an elasticity $\varepsilon^T_{P\ell}$ around 6, as we find in our empirical work, this would suggest a value of the second term on the numerator of approximately 0.6. Since we find a price elasticity $\varepsilon^P_{P\ell}$ of approximately 0.9, this would suggest that two thirds of the value of the discount rate we compute is attributable to search costs.

However, monthly search costs in the order of 2% of the value of the house appear to be unrealistically high in the Dutch context. In the Netherlands, the cost for making use of the listing website `Funda.nl` is fixed, while real estate agents charge a commission of around 1% of the sales price (which are both part of C^S). Most of the examples of listing costs discussed by (Guren, 2018) to motivate the search cost of 2.1% are thus excluded from the flow cost variable c.

The main remaining source of flow costs c is to keep the house available for inspection visits of prospective buyers. These appear unlikely to exceed more than a few hundred euros per month. The only attempt to estimate the flow cost c of selling a house reported in the literature that we are aware of is that in Ngai and Sheedy (2020), who approach them as the opportunity costs of the time spent on inspections. They use an average number of 10 visits per house sale and a cost of one day's income per visit.[20] Their estimate is 2.5% of the value of the house as 'the hypothetical cost of spending a whole year searching' (Ngai and Sheedy, 2020, p. 2518). Since the average time on the market in our data is less than half a year, this suggests a value of cT of approximately 1.25% of the value of the house. All in all, this suggests that 10-15% of the value of the discount rate that we estimate is due to listing costs. This is non-negligible, but does not qualitatively change our conclusion that home seller are on average very impatient.

We think that there is one remaining explanation that may rationalise why gross discount rates are a magnitude higher than the prevailing market interest rates. We refer to this explanation as 'seller stress'. The presence of stress is likely because a large share of the seller's wealth is at stake in an unfamiliar process with uncertain outcomes. Such stress may imply a substantial loss of instantaneous utility that cannot be compensated by adjusted consumption of other goods and makes it desirable to close the sales process as soon as possible. In Appendix A.2.4 we develop a simple model that motivates that it may cause higher discount rates. The model that is relevant in this case differs from that with a borrowing constraint because the loss in utility due to stress is not necessarily related to the size of the revenues (as is the loss in consumption possibilities). Moreover, the loss in instantaneous utility may increase over time if anxiousness increases with the elapsed time on the market. We show in Appendix A.2.4 that both factors lead to a higher value of the discount rate implied by (7).

In sum, we think that listing costs and stress are likely to be simultaneously present, and our impression is that the latter may particularly contribute to the high estimated gross discount rates. We recognise and have provided empirical evidence, that other aspects play a role as well and cannot always be clearly distinguished from each other. Household who have already left the house may feel more stressed than other, many of them have double mortgage payments, and keeping the house in good condition for inspection by prospective buyers may be more costly, while they may at the same time be trying to realise a sales price that is at least equal to the amount they paid for the house themselves. Our approach, covering all these considerations simultaneously, delivers a discount rate that is an order of magnitude higher than interest rates.

[20] This is motivated by referring to data of Genesove and Han (2012) for the U.S. and from Hometrack for the U.K.

5.1.4 Robustness

We subject the estimates of discount rates to a range of robustness checks, which we discuss in detail in Appendix C.2. First, we include (even) more detailed fixed effects leading to virtually the same estimates, albeit less precise. Second, we show that gross discount rates are somewhat lower if we use all housing transactions, rather than just repeated sales, and include local area instead of property fixed effects. Third, we show that estimates are reasonably robust if we only include data from before 2005, when bidding wars essentially did not occur, or when we use adjusted list prices to calculate the markup. We further investigate temporal differences in the coefficients but we only find suggestive evidence that discount rates have been higher in early years and were the lowest between 2010 and 2018, while they have been increasing since.

In Appendix C.3 focuses on how to deal with listing retractions. First, we may simply exclude them. Unexpectedly, this leads to a lower sensitivity of time-on-the-market towards higher markups, implying higher gross discount rates. Conversely, if we use the total elapsed time from the first listing to the eventual sale (including the time in which the house was not actually offered for sale at the listing website `Funda.nl`), sales times are much more sensitivity to higher markups implying lower discount rates. Both approaches imply somewhat unrealistic assumptions on what the time-on-the-market is, but they provide useful bounds and show that gross discount rates are likely somewhere in between 15% and 50%. We also show that discount rates are similar if we include sales that are immediately sold and estimate Poisson regressions in order to deal with a zero time-on-the-market.

In line with Guren (2018), in Appendix C.4 we exclude a couple of groups for which the exclusion restriction is less likely to hold. We exclude transactions that are likely done by investors, we exclude properties that experience a large negative price appreciations, and we remove properties that have experienced extensions and improvements. The estimated discount rates are robust.

Appendix C.5 studies whether a direct impact of sales time on sales prices may affect the estimated discount rates. For example, if a property sits longer on the market, prospective buyers may potentially incorrectly think that this property has a lower quality (Taylor, 1999). We show that sales time has a small negative effect on sales prices, and – using the appropriately adjusted formula for the implied discount rate – that this does not materially influence the estimated discount rates.

All in all, these robustness checks confirm the finding of high gross discount rates.

5.2 *Sellers' markets: bidding wars*

5.2.1 Baseline results

In Table 4 we report the results when we allow for the a positive probability on bidding wars. PANEL A focuses on the probability that a bidding war occurs. PANEL B and PANEL C of Table 4 investigate the impact of bidding wars and the markup on sales prices and time-on-the-market respectively. Finally, in PANEL D we compute implied discount rates as per equation (13).

In column (1) we start with the baseline equation where we do not instrument for bidding wars or the markup and only include property and neighbourhood-by-quarter fixed effects. We find that lower markups trigger lower bidding wards. The coefficient indicates that a 10 percentage point increase in the markup decreases the probability on a bidding war by 4.1 percentage points so this effect is substantial. At the same time, we find evidence that bidding wars lead to higher sales prices ($(\exp(0.0644) - 1) \times 100\% = 6.9\%$) and a shorter time-on-the-market ($(\exp(-0.4707) - 1 \times 100\%) = 37.5\%$). However, because we do not address endogeneity issues properly, the implied discount rate is still high (*i.e.*, more than 60%). In column (2) we aim to mitigate endogeneity concerns by including street$\times$quarter fixed effects, which should further control for unobserved location quality. The estimates are similar.

In column (3) we address the potential endogeneity of the bidding war dummy, by instrumenting for it with an indicator of whether the list price is rounded. In line with Leib et al. (2020), in PANEL A it is shown that this has a positive effect on the probability of a bidding war: a rounded list price increases the probability of a bidding war by 4.5 percentage points. Given an average bidding war probability of 14.2%, this effect is substantial. When looking at the Kleibergen-Paap *F*-statistic in PANELS B and C, this instrument is strong. However, because we do not address the endogeneity of markups yet, the gross discount rate is still on the high side (*i.e.*, 65%).

Column (4) instead addresses the endogeneity of the markup by using price appreciation since the seller moved as the instrument. We find that the markup has a strong negative effect on the probability of a bidding war; however, the coefficient is imprecisely estimated: the coefficient in PANEL A indicates that a 10 percentage point increase in the markup is associated with a 3.9 percentage point decrease in the bidding war probability. The coefficients regarding the markup in PANELS B and C are similar to the results with conventional bargaining. Moreover, the estimated implied discount rate of 33% is very close to the comparable specification with conventional bargaining.

In column (5) we report the preferred specification where we instrument for both the bidding war dummy as well as the markup. We find that higher markups decrease the probability on a

TABLE 4 – RESULTS FOR PROBABILITY ON BIDDING WARS, PRICES AND TIME-ON-THE-MARKET

	+ N'hood ×quarter f.e.	+Street× ×quarter f.e.	Instrument for bidding wars	Instrument for markup	Instrument both	Varying markup effect
PANEL A: Sold above list price	(1)	(2)	(3)	(4)	(5)	(6)
Markup	-0.4105***	-0.3938***	-0.4079***	**-0.3899**	**-0.3713**	**-0.3713**
	(0.0109)	(0.0359)	(0.0109)	(**0.2626**)	(**0.2630**)	(**0.2630**)
Rounded list price			0.0446***		0.0535***	0.0535***
			(0.0027)		(0.0076)	(0.0076)
Housing controls	✓	✓	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Street×quarter fixed effects		✓			✓	
Neighbourhood×quarter fixed effects	✓		✓	✓	✓	✓
Number of observations	415,660	53,249	415,660	52,589	52,589	52,589
R^2	0.8435	0.8964	0.8439			
Kleibergen-Paap F-statistic				99.29	99.29	99.29
PANEL B: Sales prices *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	0.7286***	0.6504***	0.7357***	**0.8396*****	**0.8506*****	**1.0337*****
	(0.0034)	(0.0108)	(0.0061)	(**0.0559**)	(**0.0584**)	(**0.0825**)
Markup× Sold above list price						**-1.1008***** (**0.3263**)
Sold above list price	0.0644***	0.0544***	**0.0817*****	0.0720***	**0.0987*****	**0.0609*****
	(0.0006)	(0.0019)	(**0.0122**)	(0.0024)	(**0.0279**)	(**0.0043**)
Housing controls	✓	✓	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Street×quarter fixed effects		✓			✓	
Neighbourhood×quarter fixed effects	✓		✓	✓	✓	✓
Number of observations	415,660	53,249	415,660	52,589	52,589	52,589
R^2	0.9955	0.9966				
Kleibergen-Paap F-statistic			271.2	98.39	16.33	8.990
PANEL C: Time-on-the-market *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	3.5360***	4.1241***	3.4569***	**7.7049*****	**7.6879*****	**7.6879*****
	(0.0423)	(0.1490)	(0.0975)	(**1.0809**)	(**1.1170**)	(**1.1170**)
Sold above list price	-0.4707***	-0.3431***	**-0.6632*****	-0.3160***	**-0.3275**	**-0.3275**
	(0.0103)	(0.0362)	(**0.2140**)	(0.0462)	(**0.5218**)	(**0.5218**)
Housing controls	✓	✓	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Street×quarter fixed effects		✓			✓	
Neighbourhood×quarter fixed effects	✓		✓	✓	✓	✓
Number of observations	415,660	53,249	415,660	52,589	52,589	52,589
R^2	0.7882	0.8509				
Kleibergen-Paap F-statistic			271.2	98.39	16.33	16.33
PANEL D: Implied discount rates	(1)	(2)	(3)	(4)	(5)	(6)
Gross discount rate, r	0.6289***	0.4690***	0.6446***	0.3254***	0.3294***	0.3331***
	(0.0098)	(0.0219)	(0.0212)	(0.0610)	(0.0656)	(0.0622)
	[0.6096, 0.6481]	[0.4260, 0.5119]	[0.6030, 0.6863]	[0.2058, 0.4450]	[0.2008, 0.4580]	[0.2112, 0.4550]

Notes: **Bold** indicates instrumented. In column (4) we instrument 'sold above list price' by a dummy indicating whether the list price is rounded. In column (5) we instrument for the list price by price appreciation since the seller moved in the property. In column (6) we instrument both 'sold above list price' and the log list price. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

bidding war, while rounded list prices increase chances. We further find a robust bidding war premium: when a property is sold above the list price, the sales price is 10.5% higher. We do not find statistically significant evidence that bidding wars reduce time-on-the-market, but this mostly an issue of precision, as standard errors are quite large, while point estimates are very robust across specifications. The coefficient implies that a bidding war reduces time-on-the-market by 31%. The implied discount rate is again very similar and 34%.

Finally, column (6) in Table 4 allows the effect of markups on sales prices to vary between properties that are sold via conventional bargaining and via bidding wars, so $\alpha^P_{\mathcal{B}} \neq \alpha_P$. In PANEL B we show that the interaction effect is statistically significantly different from the baseline effect. The magnitude of the point estimate is sizeable and suggest that the markup does not directly affect the sales prices, only via the impact of changing the probability on a bidding war. However, we run also into problems of weak instruments (the Kleibergen-Paap F-statistic is about 8) and therefore standard errors are larger. More importantly, the implied gross discount rate is essentially the same (*i.e.*, 33.3%) and not statistically significantly different from the previous specifications.

In sum, the results where we allow for the presence of bidding wars does not alter the conclusion that gross discount rates are way above the market interest rates, suggesting that sellers are impatient.

5.2.2 Do sellers provoke bidding wars?

Our theory suggests that the choice of markup interacts with the occurrence of bidding wars. To investigate this we compare the markups chosen under conventional bargaining – when a bidding war occurs with probability 0 – with that when bidding wars may occur.

The first-order condition in the model with bidding wars is given in (11), which we repeat here in slightly different form:

$$\frac{\partial \pi}{\partial m}\left[P^{\mathcal{B}} - R\right] + \pi P^{\mathcal{B}} \frac{\partial \log P^{\mathcal{B}}}{\partial m} + (1-\pi)\frac{\partial R}{\partial m} = 0. \tag{22}$$

Without bidding wars, the first order condition is $\partial R/\partial m = 0$. Since the first two terms on the left-hand side of (22) @@will only be exactly zero by coincidence, the presence of bidding wars will induce sellers@@ to change their list prices, thereby affecting the probability of its occurrence.

The first term on the left-hand side of (22) refers to the decrease in the probability of a bidding war that results from a higher markup, while the second term refers to the increasing revenues that will be realised if it occurs. @@Choosing a higher markup@@ than in the absence of bidding wars, and thereby decreasing the probability that a bidding war occurs, is in the interest of sellers if the absolute value of second term is exceeds that of the first one, whereas in the opposite situation sellers have an interest in provoking bidding wars by deliberately choosing low markups.

To consider what our model suggests has happened in the Netherlands in recent years we compute the value of the first wo terms on the left-hand side of (22) using the estimation results reported in column (5) in Table 4. These suggest that $\partial\pi/\partial m = -0.3717$, and that the sales price is 9.9% higher in a bidding war. Using the discount rate of 33% and a sales time of 5 months if no bidding war occurs, we find that the first term is equal to -0.081 times the sales price under bilateral bargaining. The second term is equal to $\partial P^{\mathcal{B}}/\partial m = 0.8506$ times the product of the sales price and the probability of a bidding war. It follows from these results that the sum of the first two terms will be positive if the probability on a bidding war occurs exceeds 9.6%. The actual frequency of bidding wars was much higher in Amsterdam and many other places in the Netherlands in the most recent years to which our data refer. Our model and estimation results thus suggests that *sellers should increase their list prices relative to the situation without bidding wars*. Hence, even with the very high discount rates that we find, the effect of a higher list price on the expected bidding war premium exceeds that of the lower probability of a bidding war. It seems therefore unlikely that the frequent occurrences of bidding war is explained by rational home sellers deliberately choosing low markups.

6 Conclusions

In this paper, we argue that the trade-off between higher revenues and a fast realisation of the sale is the key determinant of list price-setting behaviour. A feature that has been currently overlooked in the literature is that one can characterise this trade-off by a gross discount rate that is a function of variables observed in the data. We derive these discount rates in buyers' markets (with conventional bargaining) and in sellers' markets (with bidding wars).

This study exploits data on more than 1 million housing sales in the Netherlands with information on list prices and time-on-the-market. We address endogeneity concerns by instrumenting the endogenous markup by price appreciation since the seller purchased the property, following Guren (2018). When considering bidding wars, we instrument for the probability of a bidding war with a dummy indicating whether the list price is rounded, which in turn may attract more prospective buyers because of the particular features of the listing website on which buyers search.

We show that the implied short-run discount rates are in between 15% and 40%. These results are robust to various alternative specifications.

In particular, we find the elasticity of the markup – both in cases with and without a bidding war – to be around 0.8, whereas the elasticity of the sales time with respect to the markup is about 7. As the average realised sales time is around 5 months, this implies that it would be attractive to increase the markup because the additional waiting time is well rewarded by the higher revenues, unless the seller is very impatient.

It seems likely that the high gross discount rates we find are related to restrictions experienced or perceived by the seller during the sales process. Temporary owners of two houses may feel pressure to end this situation as soon as possible because their consumption budget (for non-housing goods) is decreased by double mortgage payments. Even without this pressure, the fact that a large part of one's wealth is at stake in an unfamiliar and to a large extent uncontrollable sales process may imply a considerable decrease in instantaneous utility that becomes even more substantial when it lasts longer. The 'stress' associated with the selling process, together with listing costs may explain why discount rates are high. However, it is important to recognise that listing costs only account for a minor part (10-15%) of gross discount rates.

We further show that list price-setting behaviour interacts with bidding wars (*i.e.* in sellers' markets) in a non-trivial way. Choosing a higher markup decreases the probability of a bidding war and its associated premium, but it also increases the revenues from selling the house. The latter effect is more important when the baseline probability of a bidding war is already high – for instance because of a large pool of prospective buyers present in the market – and may dominate the former. According to our estimates, this happens when more than approximately 10% of the houses is sold for more than the list price. This makes it unlikely that the exceptionally high share of bidding wars in the Netherlands in recent years is caused by sellers strategically setting low markups to realise high sales prices by triggering a bidding war.

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Appendix A Theory

A.1 Intertemporal utility maximisation

The model of Section 2.1 is standard in the literature on list price-setting. It can be embedded in a more general framework of intertemporal utility maximisation. To do so, assume that consumers derive utility from housing and other consumption. Utility experienced at time τ is $u(c_\tau, h_\tau)$ and consumers maximise the present value of expected lifetime utility U:

$$U = \mathbb{E}\left[\int_0^\infty u(c_\tau, h_\tau)e^{-\rho\tau}\mathrm{d}\tau\right]. \tag{A.1}$$

In this equation ρ is the household's time preference. Assume that the household owns a house in which they don't live. That house therefore does not contribute to utility, but the revenues from selling it affect the intertemporal budget constraint.

Consider the simple case in which the household has purchased and is the outright owner of another house. Then the housing services offered by that house occur in the utility function and there are no expenses related to the house in which it lives. The intertemporal budget constraint, imposes that current wealth A plus the expected value of all future incomes y and the present value of selling the house in which it doesn't live must be equal to the present value of all consumption expenditure. Let P denote the revenues of selling the house and t the time at which it is sold. The intertemporal budget constraint can then be written as:

$$\int_0^\infty c_\tau e^{-r\tau} = A + \int_0^\infty y_\tau e^{-r\tau} + Pe^{-rt} \tag{A.2}$$

where r is the relevant rate of discount. It is in this household's interest to maximise the present value Pe^{-rt} of the revenues of selling the house. Introducing uncertainty concerning the realised sales time t implies that expected revenues R, as formulated in equation (1), replaces the last term in the above wealth equation. Target function (1) in Section 2.1 may therefore be interpreted as the change in the intertemporal budget implied by the sale of the house. This conclusion does not change if we allow the household to have financed the house in which it currently lives by a mortgage loan, to change housing consumption in the future, or to rent instead of own. What is important, as will be further discussed below, is that the house offered for sale does only affect utility via the intertemporal budget constraint (A.2).

In this simple model, one expects the seller's discount rate to be equal to the interest rate at which she can transfer money over time.

A.2 *Why do home sellers undervalue future money flows?*

In this Appendix, we consider some extensions of the model introduced in Section 2.1 to investigate its sensitivity for alternative assumptions.

A.2.1 A mortgage associated with the house for sale

Let us now consider the case where a mortgage is associated with the house offered for sale. We can still work with the intertemporal budget constraint, but now have to take into account the mortgage payments M that continue up to the time the house is sold and the outstanding amount of the mortgage at the time of sale $L(t)$. If the house is sold at time t the associated financial flows are:

$$-\int_0^t M(s)e^{-rs}\mathrm{d}s + e^{-rt}(P - L(t)). \tag{A.3}$$

The three most popular mortgage loan types in the Netherlands in the period to which our data refer were *(i)* the annuity mortgage, *(ii)* an investment mortgage that uses life insurance to save for repayment, and *(iii)* the interest-only mortgage. For all three types, mortgage payments are constant over time when the interest rate is fixed, implying that the integral in the above equation simplifies to $(M/r)(1-e^{-rt})$. With an interest-only loan, which was by far the most popular mortgage type until 2013, the amount to be repaid is independent of the sales time. For this loan type, the mortgage payments are equal to μL where μ is the (net) mortgage interest rate. For the interest-only mortgage, we find that the expected revenues of selling the house for the intertemporal budget constraint are:

$$R = \int_0^t f(t)\left[-\frac{\mu L}{r}(1-e^{-rt}) + e^{-r(t)}(P - L)\right]\mathrm{d}t. \tag{A.4}$$

It is readily verified that this simplifies to equation (1) if $L = 0$. The first-order condition now implies:

$$r = \frac{\partial \log P/\partial \log P^{\ell} - \mu T \frac{L}{P}(\partial \log T/\partial \log P^{\ell})}{T\Big((1-\frac{L}{P})(\partial \log T/\partial \log P^{\ell}) - (\partial \log P/\partial \log P^{\ell})\Big)}. \tag{A.5}$$

which simplifies to (7) for $L = 0$, as expected. This equation implies that the discount rate is increasing in the size of the mortgage loan L if the discount rate exceeds the mortgage interest rate for $L = 0$ ($r > \mu$) as we find empirically. Hence we will *underestimate* the actual discount rate if a mortgage is present.

A.2.2 Borrowing restrictions

If a household experience borrowing constraints, smoothing consumption over time becomes more difficult. There are now two binding constraints and the change in the intertemporal budget constraint does not longer contain sufficient information for the change in the consumer's optimum. For instance, with two mortgage loans and no possibility to take an additional loan, a household can be forced to hand-to-mouth consumption of what remains of its income after debt service until the house is sold, even if the intertemporal budget constraint would be compatible with much higher levels of consumption during the period the house is unsold. In such a case, we have to look at the realised values of the instantaneous utility function $u(c_\tau, h)$.

We aim to get some relevant insights by considering the stylised situation in which utility is constant before and after the sale of the house and jumps to a higher level, which is dependent on the sales price at the moment of sale. The benefits of selling the house at time t are then equal to the higher utility experienced by the household from the moment at which the house is sold:

$$\Delta U = \int_t^\infty (u_a - u_b) e^{-\rho\tau} \mathrm{d}\tau. \tag{A.6}$$

In this equation u_a denotes instantaneous utility after the sale and u_b utility before the sale. Again, we assume a constant hazard rate, that depends on the list price. @@Note that the relevant discount rate is @@[HK: 'the r of the budget constraint is a bit awkward:]@@ no longer the r of the budget constraint, but the time preference ρ from the utility function.

From the first-order condition for optimal list price-setting, we can derive the following expression for the rate of discount, which turns out to be similar to (7):

$$\rho = \frac{\omega(\partial \log P / \partial \log P^\ell)}{T\Big(\partial \log T / \partial \log P^\ell - \omega(\partial \log P / \partial \log P^\ell)\Big)}. \tag{A.7}$$

with:

$$\omega = \frac{\partial \log(u_a - u_b)}{\partial \log P^\ell} = \frac{P}{u_a - u_b} \frac{\partial(u_a - u_b)}{\partial P}. \tag{A.8}$$

More specifically ω differs only from r in that the elasticity of the sales price with respect to the list price is now multiplied by the elasticity of the *jump* in utility at the time of selling the house with respect to the sales price, captured by ω.

The difference in utility before and after the sale is determined by the increased consumption possibilities associated with the net revenues of the sale. With a concave utility function it is not difficult to verify that with a value of ω larger than 1, the discount rate implied by (7) is smaller than the seller's rate of time preference ρ while the reverse is the case for a value of ω that is smaller than 1.

In the latter case, the relative impact of a higher sales price on utility is smaller than that on the sales price and this induces the seller to attach less weight to the sales price than is suggested by (7). Following Carrillo (2012) we may depict the implied difference between the actual rate of time preference and the one implied by (7) as 'seller motivation'. The seller is more impatient than appears to be justified by the monetary revenues from selling the house; and the reason suggested by our model is that the increase in instantaneous utility associated with the sale is inelastic with respect to the revenues.

We think it is instructive to consider an example. If preferences are Cobb-Douglas in housing and other consumption, utility is $u = kc^{\beta}$ wit k a constant reflecting housing consumption. Assuming that the net revenues of selling the house, $P - M$, with M the outstanding amount of the mortgage at the time of the sale, are completely used to reduce the mortgage on the seller's current house, we have $c_a = c_b + \mu(P - M)$ with μ the mortgage interest rate, implying:

$$\omega = \beta \frac{\mu P}{c_a} \frac{c_a^{\beta}}{c_a^{\beta} - c_b^{\beta}}. \tag{A.9}$$

Each of the three terms on the right-hand side of (A.9) can be smaller than 1, but none of them is necessarily so. β can be interpreted as the product of the share of other consumption than housing in total consumption multiplied by the inverse of the intertemporal rate of substitution. Since the latter is usually estimated as being smaller than 1, β may be larger than 1. The product of the interest rate and the price of the house – the interest to be paid with a loan-to-value ratio equal to 1 – is probably, but not necessarily, smaller than non-housing consumption. Moreover, the ratio of utility after the sale to the utility difference caused by the sale may also be larger than 1. It seems therefore that borrowing constraints do not provide a very strong argument for the high discount rates implied by (7).

A.2.3 Listing costs

We introduce three types of listing costs: *(i)* initial costs C^0, associated with making the house available for sale, *(ii)* flow costs c associated with keeping the house available for sale, which we assume to be constant over time, and *(iii)* cost associated with selling the house, which we assume to be a fraction C^s of the sales price. The target function (2) now becomes:

$$R = -C^0 + \int_0^{\infty} f(t, P^{\ell})[\int_0^t ce^{-ru}\mathrm{d}u + e^{-rt}(1 - C^s)P(P^{\ell})]\mathrm{d}t. \tag{A.10}$$

Elaboration of this equation gives:

$$R = -C^0 - \frac{c}{r} + \int_0^{\infty} f(t, P^{\ell})e^{-rt}P^*(P^{\ell})\mathrm{d}t. \tag{A.11}$$

with $P^*(P^\ell) = (1 - C^s)P(P^\ell) + \frac{c}{r}$. With a constant arrival rate θ of prospective buyers, the first-order condition becomes:

$$\frac{\partial \log P}{\partial \log P^\ell} - \frac{rT}{1+rT}\frac{\partial \log T}{\partial \log P^\ell}\left(1 + \frac{c}{r(1-C^S)P(P^\ell)}\right) = 0, \tag{A.12}$$

which is similar to (6), with an additional term appearing on the right-hand side. The implied equation for the rate of discount is:

$$r = \frac{\varepsilon^P_{P^\ell} - \varepsilon^T_{P^\ell}\left(\frac{cT(P^\ell)}{(1-C^S)P(P^\ell)}\right)}{T(P^\ell)\left(\varepsilon^T_{P^\ell} - \varepsilon^P_{P^\ell}\right)}. \tag{A.13}$$

In this equation we use the symbol ε to denote the elasticities of price and time on the market (indicated by the superscript) with respect to the list price (indicated by a subscript). If $c = 0$ this is equal to (7). The additional term in the numerator is the product of the elasticity of the time-on-the-market with respect to the list price and the ratio of the expected variable listing cost to the net sales price.

A.2.4 Seller motivation: stress

The seller's motivation to sell a house may be influenced by the stress selling a house may cause. We consider two ways in which seller 'stress' can affect the target function. The first is that it can cause impatience that differs from the usual time preference. Stress implies a desire to end the process of selling the house as soon as possible. We model this by a multiplicative additional discount function $e^{\alpha t}$. The second effect is that sellers' utility goes down by an amount a as long as the selling process continues. Using the same approach as for the analysis of borrowing restrictions the target function now becomes:

$$\Delta U = \int_t^\infty [u_a - (u_b - a)]e^{-(\rho+\alpha)\tau}\mathrm{d}\tau. \tag{A.14}$$

We now find that the left-hand side of (A.7) becomes equal to $\rho + \alpha$ while ω on the right hand side will be smaller (see equation (A.8)). Both changes imply that (7) returns a higher discount rate. Hence, seller stress could be a reason why implied discount rates exceed conventional values of time preference or prevailing market interest rates.

A.3 The second-order condition under bilateral bargaining

To verify the second-order condition we rewrite the target function as (5):

$$\log R = -\log(1 + rT) + \log P \tag{A.15}$$

The first derivative is:

$$\frac{\partial \log R}{\partial \log P^{\ell}} = -\frac{r}{1+rT}\frac{\partial T}{\partial \log P^{\ell}} + \frac{\partial \log P}{\partial \log P^{\ell}}. \tag{A.16}$$

and the second derivative:

$$\frac{\partial^2 \log R}{\partial (\log P^{\ell})^2} = \frac{r^2}{(1+rT)^2}\left(\frac{\partial T}{\partial \log P^{\ell}}\right)^2 - \frac{r}{1+rT}\frac{\partial^2 T}{\partial (\log P^{\ell})^2} + \frac{\partial^2 \log P}{\partial (\log P^{\ell})^2}. \tag{A.17}$$

The second-order condition is satisfied if this second derivative is negative. We assume that the sales price is a concave function of the list price and that the sales time is a convex function of the list price. A sufficient condition for the validity of the second-order condition is:

$$\frac{r^2}{(1+rT)^2}\left(\frac{\partial T}{\partial \log P^{\ell}}\right)^2 < \frac{r}{1+rT}\frac{\partial^2 T}{\partial (\log P^{\ell})^2}. \tag{A.18}$$

Our empirical specification of the relationship between the sales time and list price is:

$$T = \mathrm{e}^{\nu+\gamma \log P^{\ell}} \tag{A.19}$$

Using this, we find that the sufficient condition is equivalent to $\gamma > 1 + rT$, which is the case for the empirically relevant values of γ, r and T

A.4 The second-order condition in the presence of bidding wars

To consider the second-order condition when bidding wars occur, we first rewrite (11) as:

$$\frac{\partial \pi}{\partial \log P^{\ell}}\mathrm{BWP} + \pi\frac{\partial \mathrm{BWP}}{\partial \log P^{\ell}} + \frac{\partial R}{\partial \log P^{\ell}} = 0, \tag{A.20}$$

where $\mathrm{BWP} = P^{\mathcal{B}} - R$ denotes the bidding war premium. The second-order condition is:

$$\frac{\partial^2 \pi}{\partial (\log P^{\ell})^2}\mathrm{BWP} + 2\frac{\partial \pi}{\partial \log P^{\ell}}\frac{\partial \mathrm{BWP}}{\partial \log P^{\ell}} + \pi\frac{\partial^2 \mathrm{BWP}}{\partial (\log P^{\ell})^2} + \frac{\partial^2 R}{\partial (\log P^{\ell})^2} < 0. \tag{A.21}$$

We know that R is a convex function of the list price, hence the last term is negative. We assume that the bidding war premium is a concave function of the list price.[21] The third term is then also negative.

The probability of a bidding war is decreasing in the list price. This leaves us with the first two terms. The probability of a bidding war is decreasing in the listed price, bounded below by zero.

[21] This is true if the expected sales price realised in a bidding war is a more concave function of the list price than the expected sales price realised in bilateral bargaining. This seems plausible if reservation prices of bidders are random draws from a given distribution and the sales price realised with a bidding war is the second-highest reservation price of the bidders, while Nash bargaining determines the price with bilateral bargaining. This will imply that bidding wars result in higher sales prices but if the list price gets higher, the difference becomes smaller.

This makes it likely that it is a convex function of the list price, implying that the first term is positive. The bidding war premium is decreasing in the list price, which tells us that the second term is also positive. Hence what we find is that the target function is now the weighted sum of the concave function giving the expected revenues from bilateral bargaining and a decreasing convex function of the bidding war premium. The result can be a function that is still globally concave, but it is also possible that for low list prices the function is convex and that it reaches a minimum.

The sign of the expression on the left-hand side of (A.20) thus depends on the relative magnitudes of the various terms. We have checked the validity of the second-order condition based on our empirical estimates.

Appendix B Data

B.1 *Other descriptive statistics*

In Tables B1 and B2 we show the descriptive statistics for the full set of variables we have in our data for, respectively, the full sample and the repeated-sales sample. The final list price is on average about 2% lower than the first list price.

There is some variation in the time-on-the-market, dependent on how we measure it. Our preferred measure adds the time-on-the-market of any previously retracted listings. Then, the time-on-the-market is almost 21 weeks. If we just ignore previously retracted listings, the time-on-the-market is on average 19 weeks. Alternatively, if we also count the time in between

TABLE B1 – FULL DESCRIPTIVE STATISTICS, FULL SAMPLE

	(1) mean	(2) sd	(3) 5^{th} perc.	(4) median	(5) 95^{th} perc.
Sales price *(in €)*	249,217	185,223	83,949	202,000	565,000
List price *(in €)*	261,296	199,674	87,580	212,500	595,000
Adjusted list price *(in €)*	256,215	193,515	86,218	209,000	580,000
Years on the market	0.403	0.716	0.0192	0.156	1.558
Years on the market (without retractions)	0.365	0.638	0.0192	0.148	1.374
Years on the market (long) long	0.525	1.275	0.0192	0.156	2.012
Sold above list price	0.142	0.349	0	0	1
Mark-up	3.33e-05	0.0466	-0.0737	1.67e-09	0.0736
Price appreciation since purchase	0.272	0.345	-0.129	0.187	0.966
Rounded list price	0.116	0.320	0	0	1
Size of property *(in m^2)*	122.8	56.05	61	115	210
Apartment	0.126	0.331	0	0	1
Number of layers of insulation	2.122	1.738	0	2	5
Property has central heating	0.916	0.278	0	1	1
Property is (part of) listed building	0.00816	0.0899	0	0	0
Historic property	0.00782	0.0881	0	0	0
Maintenance score of the outside	0.754	0.119	0.500	0.750	1
Maintenance score of the inside	0.750	0.135	0.500	0.750	1
Construction year <1945	0.241	0.428	0	0	1
Moved before listing	0.192	0.394	0	0	1
Household size	2.203	1.854	1	2	4
Household – single without kids	0.318	0.466	0	0	1
Household – single with kids	0.0506	0.219	0	0	1
Household – couple without kids	0.340	0.474	0	0	1
Household – couple without kids	0.272	0.445	0	0	1
Household – other	0.0192	0.137	0	0	0
Male	0.497	0.441	0	0.500	1
Western-foreigner	0.0555	0.206	0	0	0.500
Non-western foreigner	0.0411	0.177	0	0	0.333
Age	46.55	18.26	24.67	41	83
Education – primary	0.0526	0.207	0	0	0.500
Education – secondary	0.288	0.418	0	0	1
Education – vocational	0.285	0.421	0	0	1
Education – bachelor’s degree	0.375	0.457	0	0	1

Note: The number of observations is 2,848,857 for the full sample. For confidentiality reasons, we cannot report minimum and maximum values. To save space, we do not report 7 construction decade dummies.

TABLE B2 – FULL DESCRIPTIVE STATISTICS, REPEATED SALES

	(1) mean	(2) sd	(3) 5^{th} perc.	(4) median	(5) 95^{th} perc.
Sales price *(in €)*	208,531	131,743	82,000	178,000	428,000
List price *(in €)*	216,058	137,388	85,764	185,000	439,000
Adjusted list price *(in €)*	212,843	134,256	85,084	182,500	429,000
Years on the market	0.367	0.651	0.0192	0.145	1.394
Years on the market (without retractions)	0.330	0.571	0.0192	0.137	1.210
Years on the market (long) long	0.487	1.192	0.0192	0.148	1.856
Sold above list price	0.146	0.353	0	0	1
Mark-up	0.000160	0.0459	-0.0727	1.04e-07	0.0728
Price appreciation since purchase	0.218	0.286	-0.131	0.156	0.768
Rounded list price	0.110	0.313	0	0	1
Size of property *(in m^2)*	105.8	38.23	57	101	165
Apartment	0.155	0.362	0	0	1
Number of layers of insulation	2.066	1.693	0	1	5
Property has central heating	0.933	0.250	0	1	1
Property is (part of) listed building	0.00637	0.0795	0	0	0
Historic property	0.00579	0.0759	0	0	0
Maintenance score of the outside	0.761	0.0990	0.625	0.750	1
Maintenance score of the inside	0.763	0.114	0.500	0.750	1
Construction year <1945	0.215	0.411	0	0	1
Moved before listing	0.141	0.348	0	0	1
Household size	2.188	1.365	1	2	4
Household – single without kids	0.318	0.466	0	0	1
Household – single with kids	0.0485	0.215	0	0	0
Household – couple without kids	0.344	0.475	0	0	1
Household – couple without kids	0.277	0.447	0	0	1
Household – other	0.0129	0.113	0	0	0
Male	0.507	0.437	0	0.500	1
Western-foreigner	0.0561	0.205	0	0	0.500
Non-western foreigner	0.0447	0.184	0	0	0.500
Age	40.93	15.22	24.50	36	75
Education – primary	0.0438	0.188	0	0	0.500
Education – secondary	0.268	0.406	0	0	1
Education – vocational	0.288	0.421	0	0	1
Education – bachelor's degree	0.400	0.461	0	0	1

Note: The number of observations is 808,241 for the repeated-sales sample. For confidentiality reasons, we cannot report minimum and maximum values. To save space, we do not report 7 construction decade dummies.

retraction and listing again, the average time-on-the-market is 27 weeks, which is likely an overestimate of the true time-on-the-market.

Price appreciation since the previous sale is generally positive. On average, prices since the previous sale have increased by 27%, which is substantial. Our other instrument is the rounded list price. In 12% of the cases, list prices are rounded to the notches reported on `Funda.nl`.

Interestingly, most sellers still live in the property when listing the property. Still, almost 20% of the sellers have already moved out once listing the property.

For a subset of the data, we have information on the type of seller. Table B3 shows that home sales are typically sold by owner-occupiers. For 84% of the sales, there is a singly owner-occupier

TABLE B3 – DESCRIPTIVE STATISTICS, SELLER TYPE

PANEL A: Full sample	(1) mean	(2) sd	(3) 5^{th} perc.	(4) median	(5) 95^{th} perc.
Seller – owner-occupier	0.842	0.365	0	1	1
Seller – landlord	0.0343	0.182	0	0	0
Seller – housing corporation	0.00759	0.0868	0	0	0
Seller – unknown	0.116	0.320	0	0	1
PANEL B: Repeated-sales sample	**(1) mean**	**(2) sd**	**(3) 5^{th} perc.**	**(4) median**	**(5) 95^{th} perc.**
Seller – owner-occupier	0.859	0.348	0	1	1
Seller – landlord	0.0367	0.188	0	0	0
Seller – housing corporation	0.00525	0.0723	0	0	0
Seller – unknown	0.0993	0.299	0	0	1

Note: The number of observations is 1,252,721 for the full sample and 377,008 for the repeated-sales sample. For confidentiality reasons, we cannot report minimum and maximum values.

that aims to sell the property. Given that for 12% of the sales, the seller is unknown, this share likely exceeds 90%. Private landlords sell another 3.4%. Sales by housing corporations, owning a large public housing stock comprising 40% of the total housing stock, are uncommon, as only 0.8% of the sales are by housing corporations.

B.2 Retracted listings

In Figure B1 below we show the share of retracted listings over the years. It is shown that the share of retracted listings is on average 11%, but has been considerably higher during the housing crisis of 2009-2012, when the share of retractions exceeded 25%. This is in line with an increased time on the market observed in Figure 1. More specifically, the trend in time-on-the-market is highly correlated to the share of retractions ($\rho = 0.675$). In recent times, the share of retractions has essentially reduced to zero, as the increased demand pressure meant that essentially all houses were sold, often very quickly.

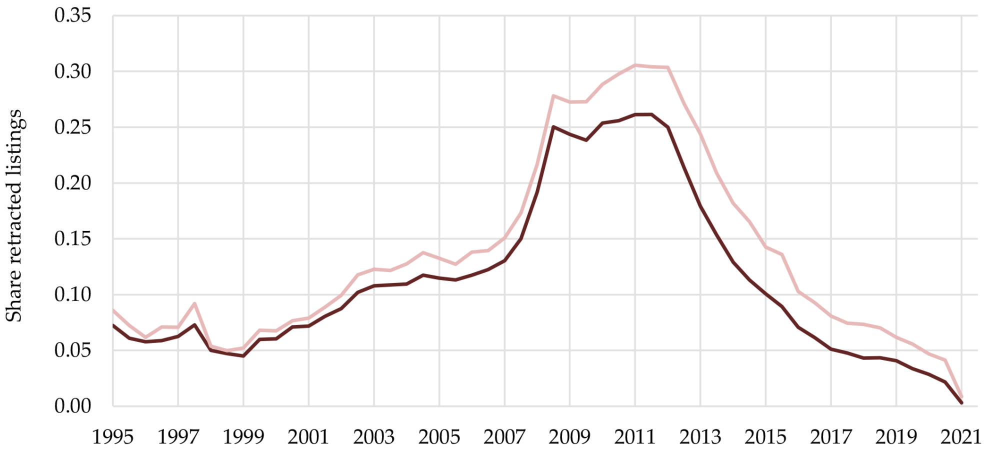


FIGURE B1 – RETRACTED LISTINGS

Appendix C Other results

C.1 First-stage results

We report first-stage in Table C1. In column (1) we show that price appreciation since the previous purchase generally has a negative effect on the markup. An increase from 0 to 25% increase in price appreciation (about the average appreciation in the sample) changes the markup by $(0.25 \times -0.0460) \times 100\% = -1.2$ percentage points. An increase from 25 to 50% implies an decrease in the markup of -0.8 percentage points. Column (2) adds a range of seller characteristics as additional instruments. Interestingly, we find that if the seller already has moved out before listing the property, the markup is 2.3 percentage points lower. Generally, we find that households with higher levels of education set higher markups, although the effect is not large (about 0.7 percentage points). Foreign-born people set lower markups. For example, non-western foreigners set markups that are 0.7 percentage points lower. We also find that elderly people set higher markups, which may be because they do not have a strong incentive to move so their opportunity costs of waiting for the right bid are lower.

In columns (3) and (4) in Table C1 we add respectively street-by-quarter and even building-by-quarter fixed effects (which corresponds to columns (1) and (2) in Table C3). We show that this does not affect much the magnitude of the first-stage coefficients. However, the coefficients are less precisely estimated, which is unsurprising given the much lower number of observations in these more restrictive specifications.

In the first two columns of Table C2 we report the first-stage estimates for the dummy indicating whether the property has been sold above the list price. As hypothesised, we find that rounded list prices have a strong positive effect on the probability that a bidding war occurs. More specifically, the probability increases by about 4.5-5.5 percentage points when using rounded list prices, which is a substantial effect. Unsurprisingly, a higher markup is also associated with a lower probability on a bidding war (see column (1))

In columns (3) and (4) the dependent variable is the markup. The coefficients related to price appreciation are similar to previous specifications. Rounded list prices are associated with slightly lower markups (*i.e.*, -0.5 percentage points), which may mean that people round list prices down to the nearest notch.

C.2 Robustness

Table C3 provides a range of robustness checks if we assume that there is conventional bargaining between a seller and one prospective buyer. In column (1) we add street-by-quarter fixed effects to further control for unobservable time-varying property and location attributes.

TABLE C1 – CONVENTIONAL BARGAINING: FIRST-STAGE RESULTS

(Dependent variable: the markup)

	N'hood× quarter f.e.	*+Seller demographics*	*Street× quarter f.e.*	*Building× quarter f.e.*
	(1)	(2)	(3)	(4)
Price appreciation since purchase	-0.0460***	-0.0429***	-0.0513***	-0.0517**
	(0.0043)	(0.0058)	(0.0114)	(0.0201)
(Price appreciation since purchase)^2	0.0203***	0.0313***	0.0253**	0.0099
	(0.0044)	(0.0065)	(0.0103)	(0.0182)
Moved before listing		-0.0228***		
		(0.0023)		
Education – secondary		0.0050		
		(0.0044)		
Education – vocational		0.0073*		
		(0.0044)		
Education – bachelor's degree		0.0079*		
		(0.0043)		
Western-foreigner		-0.0047		
		(0.0040)		
Non-western foreigner		-0.0073*		
		(0.0037)		
Male		-0.0010		
		(0.0016)		
Age 26-40		0.0079***		
		(0.0022)		
Age 41-55		-0.0006		
		(0.0029)		
Age 56-70		-0.0070		
		(0.0055)		
Age >70		0.0557***		
		(0.0167)		
Household size		0.0031*		
		(0.0019)		
Household – single with kids		-0.0092**		
		(0.0043)		
Household – couple without kids		0.0037		
		(0.0024)		
Household – couple without kids		0.0021		
		(0.0050)		
Household – other		-0.0053		
		(0.0068)		
Housing controls	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓
Neighbourhood×quarter fixed effects	✓	✓		
Street×quarter fixed effects			✓	
Building×quarter fixed effects				✓
Number of observations	52,589	30,888	5,496	1,676
R^2	0.4524	0.5301	0.7431	0.8044

Notes: Standard errors are clustered at the property level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE C2 – BIDDING WARS: FIRST-STAGE RESULTS

	Dependent variable: sold above list price		*Dependent variable: the markup*	
	(1)	(2)	(3)	(4)
Price appreciation since purchase		0.0183	-0.0454***	-0.0460***
		(0.0167)	(0.0043)	(0.0043)
(Price appreciation since purchase)^2		-0.0093	0.0200***	0.0203***
		(0.0173)	(0.0044)	(0.0044)
Rounded list price	0.0446***	0.0551***		-0.0048***
	(0.0027)	(0.0076)		(0.0019)
Markup	-0.4079***			
	(0.0109)			
Sold above list price			-0.0336***	
			(0.0021)	
Housing controls	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓
Neighbourhood×quarter fixed effects	✓	✓	✓	✓
Number of observations	415,660	52,615	52,589	52,589
R^2	0.8439	0.8334	0.4613	0.4526

Notes: Standard errors are clustered at the property level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Although the standard error of the estimates goes up, the point estimate of the gross discount rate is virtually identical to the baseline estimate, albeit statistically insignificant at conventional levels.

Column (2) pushes the limits further by including building×quarter fixed effects. This implies that we focus on transactions occurring in the same building in the same quarter, but with different markups. This very restrictive specification leads to slightly lower estimates for the effect of the markup on time-on-the-market and sales prices. In the former case, the estimate is statistically insignificant, which is unsurprising given the low number of observations left. Still, albeit imprecise, the gross discount rate is very close to our baseline estimate.

In column (3) we test whether focusing on repeat sales matters for the results. Hence, to also include non-repeat sales we include postcode fixed effects. Postcodes contain about 15 properties so are very small. Somewhat surprisingly, we find that the impact of the markup on time-on-the-market is about twice as strong. The implied discount rate is then 15%. The lower discount rate is particularly caused by a higher elasticity of the time-on-the-market with respect to the markup. However, one may argue that the price appreciation is less convincing without property fixed effects.

Column (4) in Table C3 addresses the concern that people that have lived in the property for a long time have higher price appreciation, but at the same time may be different from people that move in quickly and may have very different time preferences so that our IV strategy identifies

TABLE C3 – ROBUSTNESS WITH CONVENTIONAL BARGAINING

	+Street× quarter f.e.	*+Building× quarter f.e.*	*Postcode f.e.*	*Years lived in the property*	*Adjusted list price*	*1985-2005*
PANEL A: Sales prices *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	**0.7641***** **(0.1749)**	**0.5516***** **(0.2002)**	**0.7382***** **(0.0762)**	**0.6418***** **(0.0970)**		**1.1240***** **(0.2822)**
Markup (adjusted)					**0.3569***** **(0.0320)**	
Years lived in the property				-0.0012*** (0.0003)		
(Years lived in the property)^2				0.0000 (0.0000)		
Housing controls	✓	✓	✓	✓	✓	✓
Property fixed effects	✓	✓		✓	✓	✓
Postcode fixed effects			✓			
Street×quarter fixed effects	✓					
Building×quarter fixed effects		✓				
Neighbourhood×quarter fixed effects			✓	✓	✓	✓
Number of observations	5,496	1,676	113,824	46,665	52,589	7,588
Kleibergen-Paap F-statistic	14.35	10.40	213.5	29.43	259.2	5.483
PANEL B: Time-on-the-market *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	**7.1157**** **(3.5695)**	**6.2718** **(4.9603)**	**12.4670***** **(0.9602)**	**6.1263***** **(1.7736)**		**8.8703*** **(4.9575)**
Markup (adjusted)					**4.8155***** **(0.5580)**	
Years lived in the property				0.0025 (0.0058)		
(Years lived in the property)^2				0.0001 (0.0003)		
First-stage errors	No	No	No	No	No	No
Housing controls	Yes	Yes	Yes	Yes	Yes	Yes
Property fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Street×half-year fixed effects	No	No	No	No	Yes	No
Neighbourhood×quarter fixed effects	No	No	No	Yes	No	No
Neighbourhood×half-year fixed effects	Yes	Yes	Yes	Yes	No	Yes
Number of observations	5,496	1,676	113,824	46,665	52,589	7,588
Kleibergen-Paap F-statistic	14.35	10.40	213.5	29.43	259.2	5.483
PANEL C: Implied discount rates	(1)	(2)	(3)	(4)	(5)	(6)
Gross discount rate, r	0.2924 (0.1806) [-0.0616 - 0.6464]	0.2344 (0.2236) [-0.2038 - 0.6726]	0.1530*** (0.0209) [0.1119 - 0.1940]	0.2844*** (0.1038) [0.0811 - 0.4878]	0.1946*** (0.0308) [0.1342 - 0.2549]	0.3527 (0.2474) [-0.1323 - 0.8376]

Notes: **Bold** indicates instrumented. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

only a local (average) treatment effect. We see that this is not an issue as the direct impact of years lived in the property is statistically insignificant for time-on-the-market, while it has a slight negative effect on sales prices (about 0.1% per year). The gross discount rate is hardly affected.

In the main analyses, the markup is defined as the difference between expected list prices and the first list price. Alternatively, in column (5), we consider to use the last list price before selling the property. We do not prefer this approach because the final list price may have been adjusted as a response to the time-on-the-market and (lack of) bids received by prospective buyers. Hence, the final list price is likely endogenous. Still, it is shown that this leads to somewhat lower coefficients, but to a very similar estimated of the gross discount rate. Hence, we think it is safe to conclude that using final list price does not materially affect our conclusions.

One may argue that in the previous analyses we include sales in buyer's markets (with conventional bargaining) and seller's markets (where bidding wars may take place). To be entirely sure that bidding wars do not affect our estimates we only include sales that are listed between 1995 and 2005, which is way before bidding wars became an issue. Column (6) shows that the coefficients capturing the impacts of the markup on time-on-the-market and sales prices are slightly higher so that the implied gross discount rate is similar to our baseline estimate. However, because we exclude so many observations, the discount rate is imprecisely estimated.

We further investigate temporal differences in the coefficients by re-estimating the baseline specification in column (4) in Table 2, but now we let the coefficients vary over time. Unfortunately, such an approach implies t endogenous variables, which would require too much from the data and we do not obtain meaningful results. Hence, we make the simplifying assumption that the first-stage has time-invariant coefficients (so $\gamma_{1t} = \gamma_1$ and $\gamma_{12t} = \gamma_2$, $\forall t$), which in principle yields consistent outcomes but is considerably more efficient (see Levkovich et al., 2019). We think this assumption is pretty innocuous: we just assume that sellers respond similarly to previous price appreciation over time, without making assumptions on how buyers respond to markups. We report the results in Figure C1. We find that the elasticities of the sales price with respect to the markup bump around a bit (see Figure C1a), but are always positive and are on average close to our baseline estimates. The same holds for the elasticities of the time-on-the-market with respect to the markup in Figure C1b. Using these elasticities, we seem to find weak evidence that implied gross discount rates have decreased somewhat over the years. Particularly in early years the gross discount rates are imprecisely estimated so we should refrain from drawing strong conclusions (see Figure C1c). Overall, we think that assuming constant elasticities is defensible given that we do not find clear patterns in these

TABLE C4 – CONVENTIONAL BARGAINING – MEASURING TIME-ON-THE-MARKET

	Exclude retractions	*Long sales time*	*Incl. zero sales time*	*Excl. zero sales time*
PANEL A: Time-on-the-market *(log)*	(1)	(2)	(3)	(4)
Markup	**3.0334*****	**13.7468*****	**8.1469*****	**7.8453*****
	(0.9762)	**(1.3667)**	**(1.7963)**	**(1.6641)**
First-stage errors			✓	✓
Housing controls	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓
Neighbourhood×quarter fixed effects	✓	✓	✓	✓
Number of observations	5,496	1,676	113,824	46,665
Kleibergen-Paap F-statistic	14.35	10.40	213.5	29.43
PANEL B: Implied discount rates	(1)	(2)	(3)	(4)
Gross discount rate, r	0.9158**	0.1557***	0.2527***	0.2820***
	(0.4133)	(0.0203)	(0.0690)	(0.0745)
	[0.1058, 1.7258]	[0.1159, 0.1955]	[0.1174, 0.3880]	[0.1360, 0.4279]

Notes: **Bold** indicates instrumented. Column (3) and (4) are estimated obtained by PPML. We then insert first-stage errors as a control function in the second stage. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. Standard errors are bootstrapped in columns (3) and (4) (250 replications). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

figures.

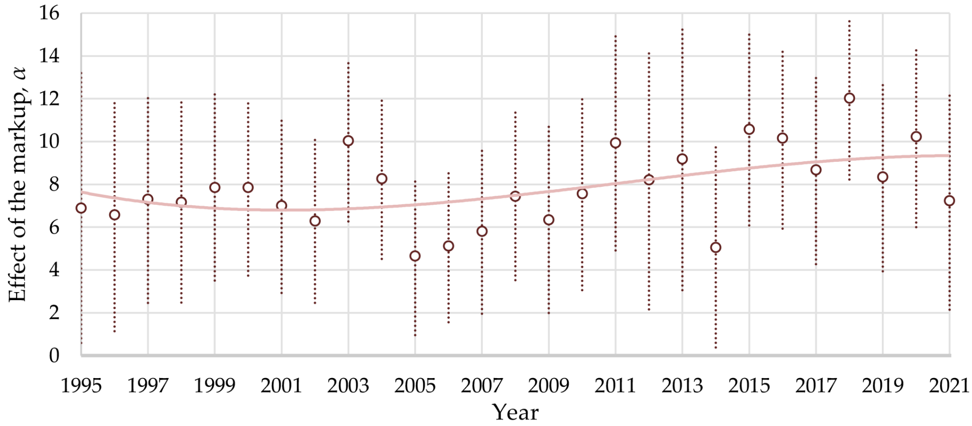
C.3 *Robustness – measuring time-on-the-market*

In the baseline analyses we include sales that have been retracted. The time-on-the-market used there is the sum of the lengths of previous time intervals during which the house was offered for sale on `Funda.nl` but not actually sold. In Table C4 we show robustness to alternative assumptions.[22]

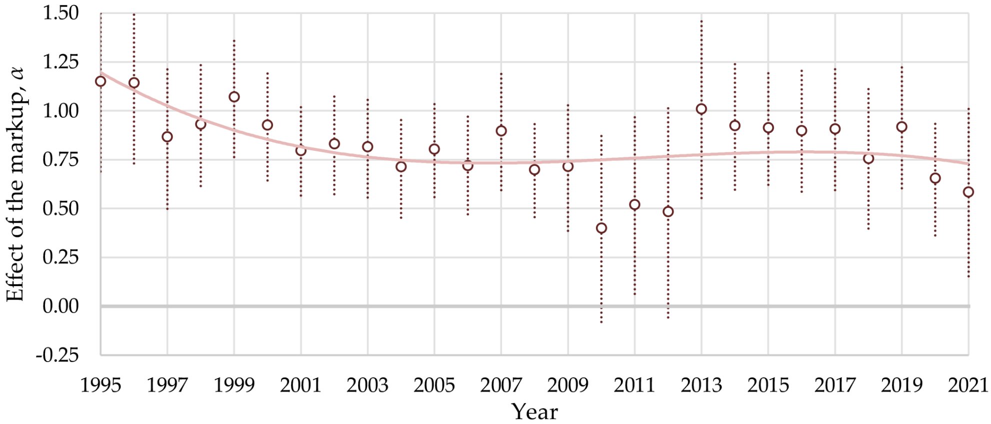
Alternatively, in column (1) we exclude retracted listings and only use the time intervals that ended with sales. Unexpectedly, this leads to a lower sensitivity of time-on-the-market regarding markups, implying higher gross discount rates. The gross discount rate is then 92%, which overestimates the true discount rate. However, given the implied 95% confidence interval, our baseline estimate falls well within this band.

By contrast, in column (2) we use the total elapsed time from the first retracted listing until the eventual sale. Then, sales times are much more sensitive to higher markups, which in turn implies lower discount rates. The gross discount rate is now 15.6%, which is about half of the baseline estimate. Hence, we think this estimate serves as a useful lower bound estimate of the discount rate given assumptions on how time-on-the-market is measured.

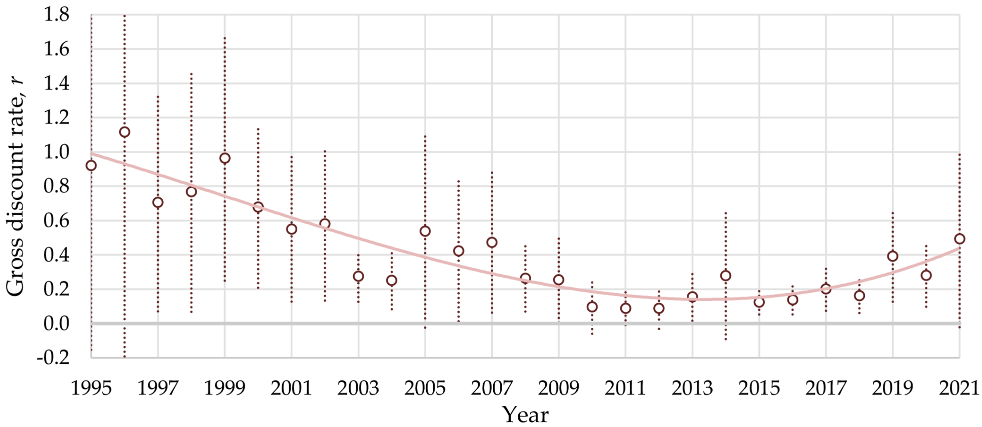
[22]We do not report results for sales prices, which are identical to the results reported in column (4), Table 2.



(A) SALES PRICE



(B) TIME-ON-THE-MARKET



(C) IMPLIED GROSS DISCOUNT RATE

FIGURE C1 – HETEROGENEITY OVER TIME IN THE EFFECTS OF INTEREST

Notes: The vertical dotted lines denote 95% confidence bands, while the light red line refers to a trend line. To estimate the gross implied discount rate in each year we use the average time-on-the-market to proxy for the expected time-on-the-market.

In column (3) we consider to include sales that are immediately sold, *i.e.*, have a zero time-on-the-market. The reason to drop listings with a zero sales time is that these observations may be mismeasured. The listing date was unknown in a few cases so realtors may have put in the same sales date as the listings date. Still, when we include sales with a zero sales time, this increases our number of observations by about 3.5%.

Because we cannot take the log of zero, we use Poisson-Pseudo Maximum Likelihood (PPML) to obtain the parameters of interest. Because PPML is somewhat more sensitive to outliers, we remove all listings that are more than two standard deviations away from the mean of time-on-the-market or sales prices. We find a very similar estimate for the discount rate in column (3) of Table C5.

We also obtain a similar gross discount rate in column (4) in Table C5 if we exclude zero time-on-the-market sales, but still estimate the coefficients by PPML. Hence, the omission of zero time-on-the-market sales does not materially affect our estimates.

C.4 Robustness – excluding IV groups

Here we subject the results with respect to conventional bargaining to a number of additional robustness checks. As an instrument for the markup we use instruments in the spirit of Guren (2018), who makes selections in the IV samples to achieve cleaner identification. In this subsection we run similar checks. We display the results in Table C5. We compare our estimates to the baseline estimate reported in column (4) in Table 2.

First, we exclude properties that are explicitly listed as; an investment target; for which tenants are still renting the property; which are sold because of foreclosures; or which will not be inhabited by the buyer. Hence, by these selections we essentially exclude large investors. Because of the nature of the data (*i.e.* `NVM` focuses on standard real estate sales rather than including sales of large investors), these selections comprise just over 1% of the sales. It is then not surprising that the estimated discount rate is very close to the comparable specification in column (6), Table 2.

Second, like Guren (2018), we drop observations with an unusually low depreciation of less than -25% as these home buyers are likely to have needed unusual initial mortgages to move on to the next property. We show that the effect of the markup on prices is somewhat stronger, while the impact on time-on-the-market is somewhat smaller. Hence, the calculated gross discount rate is somewhat higher (*i.e.*, 42%) than the baseline estimate. Still, the estimate of 28% falls well within the confidence band.

Third, we remove transactions for which a remodelling has taken place. More specifically, we

Table C5 – Conventional bargaining – excluding IV groups

	No investors	*Appreciation $>-25\%$*	*No extensions*	*Only owner-occupiers*	*All selections*
Panel A: Sales prices *(log)*	(1)	(2)	(3)	(4)	(5)
Markup	**0.8238***** **(0.0593)**	**0.8989***** **(0.0624)**	**0.8909***** **(0.0698)**	**0.8478***** **(0.1266)**	**0.8634***** **(0.1331)**
Housing controls	✓	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓	✓
Neighbourhood×quarter fixed effects	✓	✓	✓	✓	✓
Number of observations	51,954	51,404	44,157	6,751	4,934
Kleibergen-Paap *F*-statistic	95.75	85.95	71.42	17.35	16.31
Panel B: Time-on-the-market *(log)*	(1)	(2)	(3)	(4)	(5)
Markup	**7.7166***** **(1.0872)**	**6.0789***** **(1.1153)**	**7.0330***** **(1.2559)**	**8.6732***** **(2.4223)**	**6.9025***** **(2.4071)**
Housing controls	✓	✓	✓	✓	✓
Property fixed effects	✓	✓	✓	✓	✓
Neighbourhood×quarter fixed effects	✓	✓	✓	✓	✓
Number of observations	51,954	51,404	44,157	6,751	4,934
Kleibergen-Paap *F*-statistic	95.75	85.95	71.42	17.35	16.31
Panel C: Implied discount rates	(1)	(2)	(3)	(4)	(5)
Gross discount rate, r	0.2905*** (0.0515) [0.1896, 0.3913]	0.4218*** (0.0971) [0.2315, 0.6121]	0.3526*** (0.0787) [0.1983, 0.5068]	0.2633*** (0.0924) [0.0822, 0.4445]	0.3475** (0.1514) [0.0507, 0.6443]

Notes: **Bold** indicates instrumented. As instrument, we use price appreciation since the seller moved in the property. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

exclude transactions for which the house size changes by more than 5 m^2 – implying that we remove extensions. This implies that we drop about 15% of the transactions. The effect of the markup on sales prices is now somewhat higher, while the effect of the markup on time-on-the-market is essentially the same. The estimate of the discount rate is therefore therefore a bit higher, although it is not much different from the preferred estimate of the discount rate.

Fourth, using ancillary data from the Land Registry, we obtain information on whether the seller was an owner-occupier, a private landlord or housing corporation. We then focus only on sellers that are owner-occupiers. Because the Land Registry data are only available for a portion of the data the number of observations drop by about 87%. Still, it is reassuring that this does not change much our estimates, although the impact of the markup on sales times is somewhat higher. A caveat is that with the low number of observations, the coefficient is not statistically significantly higher than the baseline estimate. The gross discount rate is very similar to our baseline estimate.

In column (5) we apply all the above-mentioned selections to obtain a somewhat imprecise but very similar estimate of the discount rate. Hence, sample selections that further strengthen the validity of the instrument will not materially affect our results.

C.5 Robustness – time-on-the-market as a sign of quality

In line with Taylor (1999), one may argue that properties that sit longer on the market may be viewed by prospective buyers as having a lower quality, although this may be incorrect. In this case, the sales price may depend on the elapsed time on the market (which also depends on the markup).

Let us consider to include this in our model of conventional bargaining. Please recall that the the expected revenues of selling the house is given by:

$$R = \int_0^\infty f(t, m) e^{-rt} P(m) \mathrm{d}t. \tag{C.1}$$

Consider the situation that the sales price is given by $P(0, m)e^{\lambda t}$, with $\lambda < 0$, implying that properties that sit longer on the market have a lower expected sales price. Then:

$$R = \int_0^\infty f(t, m) e^{(\lambda - r)t} P(0, m) \mathrm{d}t. \tag{C.2}$$

The discount rate is given by:

$$r = \frac{\partial \log P / \partial m}{T\Big((\partial \log T / \partial m) - (\partial \log P / \partial m) \Big)} + \lambda. \tag{C.3}$$

We can easily estimate the above relationship by expanding the sales price equation (16):

$$\log P_{ijt} = \alpha m_{ijt} + x'_{ijt}\beta + \lambda T_{ijt} + \mu_i + \mu_{jt} + \epsilon_{ijt}. \tag{C.4}$$

An issue is that T_{ijt} may be endogenous and correlated to unobserved quality of homes so that λ also capture that houses that sit on the market for longer have lower quality. We think this is not much of an issue because this will bias the coefficient downwards (*i.e.* making it more negative), and implying a lower discount rate. We show that the estimated discount rates will actually be slightly higher than the baseline estimates. Moreover, with neighbourhood-by-year fixed effects and instrumenting for the markup, we expect the issue of unobserved quality to be limited.

We replicate the baseline results for conventional bargaining, but include sales time as an

TABLE C6 – CONVENTIONAL BARGAINING – TIME ON THE MARKET AS A SIGN OF QUALITY

	Property f.e.	*+ N'hood ×quarter f.e.*	*+Street× ×quarter f.e.*	*Instruments: Price appreciation*		*Instrument: + Seller demographics*
PANEL A: Sales prices *(log)*	(1)	(2)	(3)	(4)	(5)	(6)
Markup	0.7329***	0.7463***	0.6715***	**0.9032*****	**0.9047*****	**1.0058*****
	(0.0039)	(0.0034)	(0.0111)	**(0.0567)**	**(0.0790)**	**(0.0706)**
(Markup)^2					**-0.3230**	**-0.3578**
					(0.2238)	**(0.3390)**
Years on the market	-0.0390***	-0.0336***	-0.0247***	-0.0424***	-0.0424***	-0.0433***
	(0.0004)	(0.0004)	(0.0009)	(0.0017)	(0.0024)	(0.0024)
Housing controls	✓	✓	✓	✓	✓	✓
First-stage residuals					✓	✓
Property fixed effects	✓	✓	✓	✓	✓	✓
Quarter fixed effects	✓					
Neighbourhood×quarter fixed effects		✓		✓	✓	✓
Street×quarter fixed effects			✓			
Number of observations	570,039	415,660	53,249	52,589	52,589	30,888
R^2	0.9800	0.9956	0.9966			
Kleibergen-Paap F-statistic				94	94	94
PANEL B: Implied discount rates	(1)	(2)	(3)	(4)	(5)	(6)
Gross discount rate, r	0.5801***	0.6150***	0.4580***	0.3186***	0.3184***	0.3084***
	(0.0077)	(0.0096)	(0.0211)	(0.0546)	(0.0784)	(0.0600)
	[0.5651, 0.5951]	[0.5963, 0.6337]	[0.4166, 0.4995]	[0.2116, 0.4256]	[0.1647, 0.4722]	[0.1908, 0.4260]

Notes: **Bold** indicates instrumented. In columns (4)-(6) we instrument list price by price appreciation since the seller moved in the property. In column (6) we also use seller demographics as additional instruments. In columns (5) and (6) we adopt a control-function approach in which we insert the first-stage errors as a control function in the second stage. Standard errors are clustered at the property level and in parentheses, while 95% confidence bands are in brackets. Standard errors are cluster-bootstrapped (250 replications) in columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

additional control in Table C6. We do not report the results for time-on-the-market, as these are identical to those reported in Panel B in Table 2

In all specifications we find a consistent negative effect of years on the market on sales price. One additional year in sales time is associated with a sales price decrease of 2.5-4.5%. Hence, it seems that properties that sit long on the market are considered to be less attractive, as hypothesised by Taylor (1999). The impact of the markup on sales prices is now somewhat stronger than reported in Table 2. For example, the coefficient of the markup in column (4) is 0.903, while it was 0.811 in the baseline specification.

In Panel B of Table C6 we then investigate whether observed gross discount rates are similar if we use the adjusted formula (C.3). Fortunately, the gross discount rates are not materially different from the baseline estimates. For example, when instrumenting for the markup with price appreciation in column (4) we find a discount rate of 32%, while it is 28% in the comparable baseline specification. Column (6) shows a discount rate of 31%, which is only slightly higher than the 28% found earlier. Hence, allowing sales times to have a direct impact on sales prices does not alter our conclusion that home sellers undervalue future money flows.