Deal or no Deal? The Time-on-Market, Time-to-Close, and Residential Transaction Prices

Marc Francke[a,b,*], Yumei Wang[a], Martijn Dröes[a,c]

[a] *University of Amsterdam, Amsterdam Business School, Plantage Muidergracht 12, Amsterdam, 1018 TV, North-Holland, the Netherlands*
[b] *Ortec Finance, Naritaweg 51, Amsterdam, 1043 BP, the Netherlands*
[c] *Amsterdam School of Real Estate, Jollemanhof 5, 1019 GW, the Netherlands*

Abstract

Unlike many other major asset classes, when purchasing a property, a lot of time can pass between the date of purchase and the date when ownership is formally transferred from the seller to the buyer. Using detailed housing transactions data from the Netherlands, we find that this period, the time-to-close, has a positive effect on transaction prices. These results are in line with a micro-economic bargaining model in which the seller wants to be compensated by the buyer for the additional costs associated with a longer time-to-close. Further results show that ignoring the time-to-close leads to estimation bias in the effect of time-on-market on transaction prices.

Keywords: transfer of ownership, residential real estate, time-to-close

JEL classification: C21, C31, R32

Declarations of interest: none

*Corresponding author

Email addresses: m.k.francke@uva.nl (Marc Francke), y.wang7@uva.nl (Yumei Wang), m.i.droes@uva.nl (Martijn Dröes)

Preprint submitted to Elsevier *December 13, 2023*

1. Introduction

Unlike many other major asset classes, such as stocks and bonds, a lot of time can pass between buying a piece of real estate and the legal transfer of ownership. In case of of a home, for example, the time period before ownership is actually transferred – commonly known as the time-to-close (TTC) – can easily be a couple of months. Although the TTC potentially plays an important role in the transaction process of real estate, it has received little attention in the literature.

The purpose of this paper is twofold. First, we want to highlight the importance of TTC when buying or selling real estate. We focus on residential real estate because we have a detailed dataset of housing transactions for several regions in the Netherlands, covering both the purchase date and the legal transfer date. We discuss that the TTC has a distinct purpose – among others, for the buyer to arrange a mortgage, and the seller to find a new home. Besides the amount of time necessary to get a mortgage, the actual length of the TTC is negotiable between the buyer and seller. It differs from the more commonly studied time-on-market (TOM) as this period is before TTC and is used to market the property.

Second, we examine what the effect of TTC is on house prices. Although the sign and size of the effect is ultimately an empirical question, as there are different channels through which TTC can effect transaction prices, we develop several hypotheses using a micro-economic bargaining model based on the costs faced by a buyer or seller when the TTC becomes longer or shorter. The model is based on the idea that sellers of properties want to be compensated, at least partially, by the buyer for the additional costs related to a longer TTC, and that these costs are capitalized in the transaction price. These costs include double mortgage costs, temporary rental costs, and the loss of foregone house price appreciation (depending on the housing cycle). Based on a calibrated version of the model, we hypothesize that TTC most likely has a positive effect on house prices. We further argue that the required compensation is higher during booms since, among others, the seller's Nash bargaining power is larger and the expected capital appreciation is higher.

We empirically examine the effect of TTC on transaction prices using housing transactions data from four regional housing markets in the Netherlands in the period from 2006 to 2016. We examine these four region as we were allowed to merge realtor data (purchase agreement date) with official land registry data (data of legal transfer) for those four regions. This is rather unique because both the Dutch brokerage organization and the land registry are separate organizations that are to some extent competitors of each other, both providing pricing services to Dutch consumers.

Based on this data, we estimate several hedonic price models that include both TOM and TTC. There are two key identification challenges when examining the effect of TTC on transaction prices. The TTC is likely influenced by household characteristics, something that our data do not allow us to directly control for. To mitigate this issue we employ an instrumental variable (IV) approach proposed by Engelhardt (2003) and also later applied by Dubé and Legros (2016). The idea is to use spatio-temporal lagged averages of TTC as instrumental variable. The identifying assumption is that an individual household cannot affect the average market outcome, certainly not in the past, but that market conditions over time are correlated. In addition, to cover for unobserved housing characteristics and amenities, we control for a substantial amount of housing characteristics, location-specific trends and fixed effects, and also employ a repeat sales methodology. It becomes therefore less likely that our results are just due to variations in types of houses sold, unobserved local market factors, or local policies. The second identification issue is that prices, TTC, and TOM are interdependent. To cover for the fact that these are correlated processes, we employ a seemingly unrelated regression (SUR) approach.

Our results show that TTC indeed has a positive effect on house prices. Focusing on the IV results, an increase of TTC by one standard deviation (about one and a half months) increases transaction prices by 2.4 percent. This is economically sizeable. The effect is larger during booms and we find some evidence that the effect is also larger in a tight regional market such as Amsterdam. In contrast, TOM has a negative effect on transaction prices, which is consistent with previous empirical studies (Benefield et al., 2014). Ignoring the TTC leads to an overestimation (bias) in the price effect of TOM of 6.3 percent, which is reasonable in terms of size. Incorrectly incorporating the TTC into the TOM period leads to a more modest bias of 1.3 percent. Importantly, a change in this joint measure has a negative effect on prices while it leads to an increase if TTC and TOM are treated separately. These results highlight that TTC is an important part of the transaction process and should be modelled separately when examining house prices.

This paper relates to several strands of the literature. TOM has received quite some attention in the literature, including its impact on house prices (Haurin, 1988; Wheaton, 1990; Genesove and Mayer, 2001; Genesove and Han, 2012; Han and Strange, 2015, 2016; Hayunga and Pace, 2019), and commercial property returns (Cheng et al., 2013). Benefield et al. (2014) summarize an extensive literature on the simultaneous modeling of the transaction price and TOM. They reviewed estimation results from 197 price and 232 TOM models, and find ambiguous relations. However, in most cases in the transaction price model TOM has a negative impact. This is in line with for example Dubé and Legros (2016).[1]

Yet, there is very little consensus about how to exactly measure the time-on-market (see Benefield and Hardin, 2015). In particular, in some cases the date of signing the purchase and sale agreement is used, while in others the time-on-market is determined based on the actual date of legal transfer (closure date). Benefield and Hardin (2015) distinguish several different measures of TOM, based on multiple listing service (MLS) data from the Charleston metropolitan statistical area. They provide evidence that the effect of housing characteristics on TOM crucially depends on the definition of TOM, with many effects changing sign and magnitude as TOM is being differently defined. Although some of their TOM measures do include TTC, they do not analyze the TTC and its impact on prices separately, but particularly focus on the role of relisting of properties. Staying with the same broker after relisting results in a higher price than changing broker.

Although the TTC plays an important role in the transaction process of physical assets, research on the TTC itself is, as far as we know, relatively scarce. A notable exception is

[1] Han and Strange (2015) provide a good overview of factors impacting price and TOM. They distinguish between subject and house characteristics, market conditions, and seller's strategy.

the work by Han and Hong (2020). Han and Hong show that TTC and transaction prices are lower in case a house is bought by cash. The argument is that paying cash reduces uncertainty for the seller because the buyer no longer has to take out a mortgage. As a result, homeowners selling their homes accept a lower price. Han and Hong (2020) find support for this effect using data for the Los Angeles county between 2002–2016. In our paper, we focus on another source of uncertainty related to the mismatch between selling one's current home and buying a new one. Moreover, we essentially center the discussion on financially constrained homeowners, as most homeowners are financially constrained, which explains why the TTC on average is a couple of months. In addition, buying by cash is far less common in the Netherlands. Only 2.4% of the transactions in our dataset have a TTC smaller than or equal to ten days while between 5% to 20% of transactions are cash buys in the Los Angeles county.[2]

Our research further relates to the paper by Moen et al. (2021). They show that buying first rather than selling first is more likely to occur during a boom and that this has an important impact on house price dynamics. We argue that in this case the effect of TTC on prices is largely driven by capital appreciation, which is higher during booms. In addition, Moen et al. present the buying first and selling first timing difference based separately on the sales agreement date and closure date. However, they do not explore the impact of these dates on transaction prices in further detail. The specific purpose of our paper is to highlight that the TTC period is an important part of the transaction process of buying and selling real estate and as such affects its price.

This paper is structured as follows. Section 2 discusses the Dutch institutional context. Section 3 elaborates on the bargaining model which is used to develop several hypotheses. Section 4 and 5 describe the data and empirical methodology, respectively. Section 6 presents the empirical results and Section 7 concludes.

[2] At a more aggregate level Lyons (2019) discusses that TTC is related to prices by decomposing price index changes into different factors, but mainly focuses and finds effects of the list price. In our paper we use micro level data and estimate the causal impact of TTC on prices.

2. Institutional Context

This section briefly discusses the specific Dutch institutional context to provide insight into the possible channels through which the TTC can have an effect on transaction prices and what are the key elements of the transaction process in the Netherlands. We focus the discussion on the secondary market because most sales are secondary and we have data on those sales.

After a successful (closed) bid on the house the buyer and seller sign a purchase agreement. This agreement is immediately binding for the seller, and for the buyer after three days, at least two of which are working days. The purchase agreement contains the agreed transaction price and the date on which the house legally changes hands. It typically includes that the buyer can cancel the agreement if the bank does not provide a mortgage or if, after a formal building inspection, it is found that there are hidden defects in the home's construction. If the buyer (or seller) otherwise would like to cancel the agreement a penalty of ten percent of the agreed transaction price needs to be paid. Given the size of the fine, this is relatively rare though. The buyer also makes a deposit at the notary of his or her choice, this can also be a (provisional) guarantee by a bank. On the agreed date of legal transfer, the final purchase agreement is signed at the notary and the transaction price (usually paid with a mortgage) is transferred to the seller's account, and the buyer receives the keys of the house.

The buyer typically uses the time until the legal transfer of ownership (TTC) to obtain a mortgage (non-recourse loan) and if the buyer still needs to sell his current house or is expecting that his next house will take a long time to obtain, he can negotiate for a longer TTC. The same applies to the seller. Thus, the final TTC depends on the bargaining power of both buyer and seller. The loan-to-value (LTV) ratio's in the Netherlands are one of the highest in the world, with LTV's up to 100 percent. In more recent times, however, banks have become more cautious about making large loans. There are no down-payment constraints in the Netherlands. It could be argued then that the TTC is just a reflection of the amount of time it takes to obtain a mortgage. Although this certainly plays an important role, it does not explain the considerable cross-sectional variation in the TTC, even within neighborhoods. We will elaborate more on this in Section 4.

Although the evidence is largely anecdotal, the process to get a mortgage has also become more easy over time and it is also more easy to compare mortgage providers. Some twenty years ago, the advice was to take at least eight weeks to apply for a mortgage. Nowadays there are many online mortgage providers and many providers have a digital system to submit the appropriate documentation. The valuation process has also been expedited, in part through the use of automated valuation models. According to the Dutch mortgage data society (HDN), the current mortgage application time is 33 days. This can vary over time, depending on mortgage lender backlogs. This implies that we should carefully control for local trends in the data (see This means that we must carefully control for local trends in the data (see Section 5) and also that the bargaining perspective we will focus on in this article has likely gained and will likely continue to gain importance with future financial innovations.

3. A Bargaining Model

In this section, we present a bargaining model that helps us formulate two key hypotheses regarding the effect of the time-to-close (TTC) on the transaction price of residential real estate. The basic idea is that house prices are a reflection of the additional costs a home-owner faces as a results of a longer TTC. This section then mainly elaborates on those costs and the shape of the homeowner's cost function.

3.1. Timing of Events: Time-on-market and Time-to-close

We consider the situation of an owner-occupier who lists his house at t_0 and sells it at t_1, the date the purchase and sale agreement is signed, see Figure 1. The time-on-market (TOM) in days is thus $t_1 - t_0$. The purchase and sale agreement stipulates the final transaction price P and the date of legal transfer t_2, with $t_0 \leq t_1 \leq t_2 < \infty$. The time-to-close ($TTC$) is defined as $t_2 - t_1$ and it is, like the time-on-market, non-negative. We consider that the homeowner buys his next house at t_{next}, i.e., it is legally in its possession at this date and

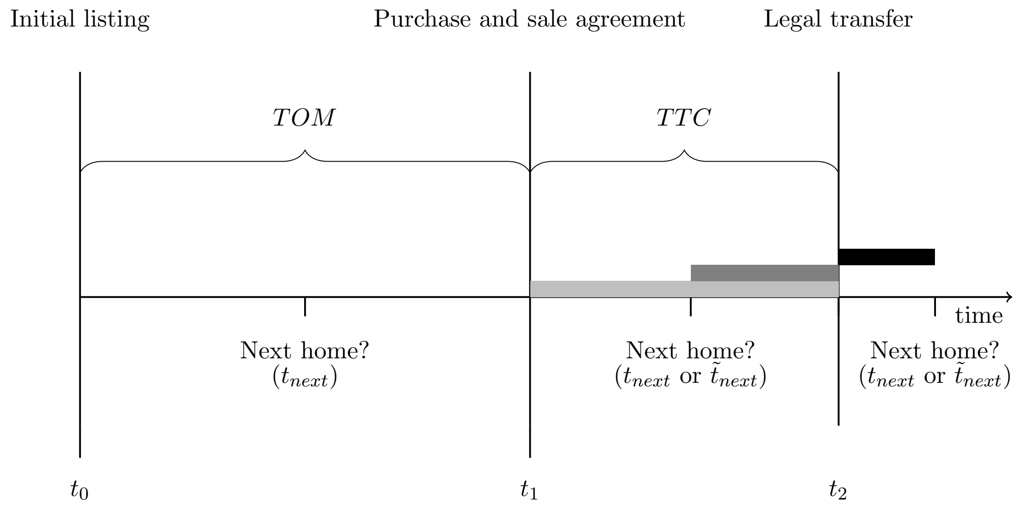


Figure 1 – The transaction process: time-on-market and time-to-close.

This figure shows the transaction process from the perspective of the seller. At t_0 the house is listed, at t_1 the purchase agreement is reached with a buyer, and at t_2 ownership of the property is legally transferred to the buyer. At t_1 the seller has to set t_2. Depending on whether the homeowner has already bought a new house to live in at t_{next} the homeowner may experience — besides the opportunity costs of price appreciation of the current home (light grey bar) — double mortgage costs (dark grey bar) or short-term rental costs (black bar). At t_1, t_{next} might be known or not, which is indicated by the tilde.

he can start living in it.[3] The date t_{next} is particularly important as it influences the seller's costs, i.e. double mortgage costs or temporary rental costs, see next subsection.

3.2. Economic Rationale: The Seller's Cost Function

We consider the choice of the homeowner regarding t_2 at time t_1, as at t_1 the homeowner together with the buyer of the property has to formally decide to set t_2. We argue that from the perspective of the homeowner there are three main costs associated with a change in t_2.[4] These costs are highlighted as different colored bars in Figure 1). First, setting t_2 at a later date implies that the homeowner faces an opportunity cost in terms of missing out on

[3]We thus abstract from a homeowner who becomes a renter. This is not unreasonable as there is typically a high persistency in home-ownership status. Turner and Smith (2009), for example, show that about 61 percent of U.S. households (with a moderate degree of income) are still a homeowner after 18 years, even if they moved house. We also abstract from investors, who buy a property to rent it out.

[4]In essence, the sale of a property resembles a forward contract with its price depending on the expected costs incurred by the homeowner.

any additional price appreciation (or depreciation) of the house (light gray bar).[5] We model this by denoting the expected daily price appreciation rate as g and the opportunity costs as $(t_2 - t_1) * g$. Second, in case $t_{next} < t_2$, the homeowner has double mortgage costs (dark grey bar), which is financed via a bridge loan. The expected additional cost associated with such a loan is $(t_2 - t_{next}) * m$, where m is the daily mortgage rate of a bridge loan. Finally, in case $t_{next} > t_2$, the homeowner faces a short-term rental cost $(t_{next} - t_2) * r$ at a daily rate of r (black bar). These three costs components can be interpreted as a present value at time t_1 where, for simplicity, the discount rate is set at 1. The total sum of these cost components (i.e., related to g, m, and r) is denoted as C^S which represents the homeowner's (seller's) cost function.[6]

Consider a successful bid as

$$P = P^* + \beta C^S - (1 - \beta) C^B \tag{1}$$

$$P \geq P^R, \tag{2}$$

where P is the final transaction price. The transaction is only successful when the price is larger than the seller's reservation price, P^R. The base price of the bid is P^* which captures the price given that the property has been properly marketed (i.e., given TOM) and is immediately sold and transferred to the buyer at t_1 (i.e., $t_1 = t_2 = t_{next}$). The term C^B is the buyer's cost function and the scalar β is a Nash bargaining parameter between the seller and buyer of the current property, with $\beta \in (0, 1)$. The term $P^* + \beta C^S - (1 - \beta) C^B$ constitutes a successful bid conditional on the (optimal) choice of t_2. The transaction price is then thus the results of a Nash bargaining solution that is a weighted average between the buyer's and seller's costs and captures the minimum cost the seller would be willing to

[5]Note that we ignore the price appreciation of the next home, so homeowners are assumed to be not perfectly hedged against price increases of the current home. For a discussion on hedging demand, see Han (2008, 2010).

[6]We abstract from search and other costs (e.g., brokerage fees, transfer tax, moving costs), as these costs are typically not related to the duration of TTC

accept and the maximum cost the buyer is willing to pay.[7]

For simplicity, we will assume that the buyer's cost is a fixed amount, $C^B = F$. That is, the buyer is a TTC-taker (much like a price-taker in a competitive production equilibrium). In Appendix C, we explore a version of the model under symmetric bargaining power, where the buyer's cost function is not fixed. Given the fixed buyer's cost, we can focus the discussion on the shape of the seller's cost function. Given the way prices are set, the idea then is that the seller wants to be, at least partly (depending on β), compensated by the buyer for the additional costs associated with a longer TTC. The question is then to what extent C^S varies with TTC; does a higher TTC lead to a higher C^S, and thus to a higher transaction price?

Before we examine this question in further detail, we make two additional simplifying assumptions:

Assumption A1: *C^S and C^B are known to both the seller and buyer.*

Assumption A2: *The agents in this model are risk neutral.*

The implication of the first assumption is that there is no information asymmetry between the buyer and seller in terms of the expected costs. For example, the seller does not know his own cost better or can hide his costs and use this to his advantage.[8] The implication of the second assumption is that both the buyer and seller ignore uncertainty when evaluating expected costs. If the seller would for example be risk averse he would like to avoid the mismatch between selling his current home and buying a new one. Also, and in line with Han and Hong (2020), the seller would prefer cash payments to avoid that the buyer cancels the deal because he could not get a mortgage.[9]

As the effect of TTC on prices (i.e., cost components), evaluated at t_1, is partly due to

[7]For an example on wage bargaining, see Mumford and Dowrick (1994).

[8]In the residential real estate market the information asymmetry between buyers and sellers might be less pronounced than in commercial real estate markets as most homeowners move within the same municipality or MSA, also most buyers and sellers use a realtor. For a discussion on information asymmetry in commercial real estate markets, see Garmaise and Moskowitz (2003).

[9]For a further discussion about the role of uncertainty in the real estate transaction process, see Lin and Vandell (2007) and Lin and Liu (2008).

variation in t_{next}, we consider two cases with respect to t_{next}:

Case 1: t_{next} is known to the homeowner at t_1, and

Case 2: t_{next} is not yet known at t_1, i.e. $t_{next} = \tilde{t}_{next}$.

Regarding **Case 1**, t_{next} can be before or after t_1, as long as the next home was already formally purchased before t_1. This is typical for a buyer's market, i.e., easy to buy, difficult to sell. From an economic point of view it is not meaningful to model this case explicitly, as due to the lack of uncertainty regarding t_{next} the outcome is already fixed. For example, if $t_{next} < t_1$ (again, see Figure 1) the homeowner, from the perspective of t_1, will face foregone capital appreciation g and double mortgage costs m over the time-to-close period. The homeowner can avoid those costs by setting $t_2 = t_1$. In case $t_1 < t_{next} < t_2$, there is again the foregone capital appreciation g between t_1 and t_2 and double mortgage costs m between t_{next} and t_2. The homeowner can avoid the double mortgage costs by lowering t_2 such that $t_2 = t_{next}$. As long as the short-term rental costs r are larger than g (and they typically are, see subsection 3.3) the homeowner will not reduce t_2 any further as this would create a wedge between t_2 and t_{next} resulting in the homeowner having to pay relatively high short-term rental costs. The only cost left is that related to g. Vice versa, if $g > r$, the homeowner sets $t_2 = t_1$ as reducing t_2 allows the homeowner to avoid the costs related to foregone capital appreciation.[10] To conclude, Case 1 contains several corner solutions. Either the TTC is zero or there is no mismatch between buying his next home and selling his current one. In the latter case, the homeowner still faces costs related to foregone capital appreciation. So, if anything, it seems that the costs in **Case 1** are determined by g, but there is not much more to analyze.

In **Case 2**, it holds that $\tilde{t}_{next} > t_1$, where the tilde indicates that t_{next} is unknown at t_1. In essence, the homeowner would like to time the purchase of his next home to avoid the potential mismatch that occurs when he has to leave his current home. However, matching this perfectly is difficult in practice. To capture this notion, assume that $\tilde{t}_{next}$ is a random

[10]Alternatively, when the capital appreciation is high, the homeowner might decide not to list his house in the first place (i.e. postponing t_1) as long as the double mortgage costs are not too high.

variable following the exponential distribution, $\tilde{t}_{next} \sim \exp(\lambda) = f_{\tilde{t}_{next}}(t)$, where λ is the hazard rate. Then the cumulative probability that the next home is bought before t_2 is equal to $1 - e^{-\lambda t_2}$ (*double mortgage costs*), and after t_2 equal to $e^{-\lambda t_2}$ (*short-term rental costs*), where $t_2 \geq 0$ and normalizing $t_1 = 0$. In this case, the expected cost function for the seller can be defined as

$$\begin{aligned} C^S(t_2; g, m, r, \lambda) &= \underbrace{\int_0^{t_2} f_{\tilde{t}_{next}}(t)\left(gt_2 + m(t_2 - t)\right) dt}_{\tilde{t}_{next} < t_2} \\ &+ \underbrace{\int_{t_2}^{\infty} f_{\tilde{t}_{next}}(t)\left(gt_2 + r(t - t_2)\right) dt}_{\tilde{t}_{next} > t_2} \\ &= -\frac{m}{\lambda} + (g + m)t_2 + \frac{m + r}{\lambda} e^{-\lambda t_2}. \end{aligned} \tag{3}$$

The question then is to examine how this cost function changes with respect to t_2.

3.3. Calibrated Cost Function

In Figure 2, we plot the cost function as stated in Eq. (3). For the baseline scenario, we assume that $\lambda = 0.0137$ (i.e., $1/\lambda = 73$, in line with an average $t_2 - t_1$ of 73 days, see Section 4). We further assume that the quality-adjusted annualized price appreciation (i.e. in line with the time fixed effects in our hedonic pricing models) g is 4.0% and the annual average mortgage interest rate m is 3.5% (20-year mortgage over the last 15 years according to the Dutch Central Bank). Furthermore, the annual short-term rental costs r are 9% (about €2,000 per month) of average house prices. The costs are normalized to be 100 at 73 days of t_2.

The results in Figure 2 clearly show that a larger t_2 has a positive effect on prices over a normal range of t_2 (i.e., as soon as TTC is larger than 36 days). Given that it typically can take two or more months to obtain a mortgage, and before that time ownership cannot be transferred, it seems that t_2 is always sufficiently large under normal conditions. As most households are financially constrained, we would thus expect that on average TTC has a positive effect on transaction prices. At about 60 days of TTC (median in our sample) the slope is about 0.34 in index terms per day, at 90 days (75^{th} percentile) the slope is about 1.9 times as much. The effect for $TTC > 36$ is approximately linear, at least in this setup. We summarize the above discussion in the following hypothesis:

Hypothesis 1. *On average, TTC has a positive effect on transaction prices.*

Before 36 days the slope is negative. There is an interesting additional channel for a potential negative effect in case TTC is relatively low and that is in contrast to that suggested by Han and Hong (2020). Besides that paying with cash (i.e., low TTC) could reduce the uncertainty for sellers and lead to a discount on prices, as TTC becomes smaller it also becomes more likely that a homeowner has to arrange a rental house to live in, which can be quite expensive. A larger TTC thus reduces the expected costs for the seller and would lead to a discount on prices. This also suggests that financially constrained homeowners might avoid getting into a situation where TTC becomes too low to begin with.

Next, Figure 2 also shows the costs function in case of booms and busts. We assume that the opportunity costs in terms of capital appreciation g, the daily mortgage rate m, and short-term rents r are higher during booms. That is, a seller stands more to lose in terms of foregone capital appreciation and costs related to mismatch. This is amplified by the fact that the bargaining parameter β is most likely also higher during booms than during busts (i.e., a seller's market). That is, the seller is expected to get more compensation from the buyer for the expected costs related to a longer TTC. Figure 2 clearly shows that, besides a higher level of the costs, the slope of the costs function is more positive for booms.[11] This leads to the following hypothesis:

Hypothesis 2. *TTC has a larger effect on house prices during booms than during busts.*

[11] We also explored moderate decreases in prices ($g < 0$). In this case, the cost function becomes smaller, flatter, and the inflection point goes to the right. However, the mismatch costs are so substantial that the slope remains positive if TTC is sufficiently large. Importantly, our key hypothesis that the effect of TTC is larger during booms than busts still holds.

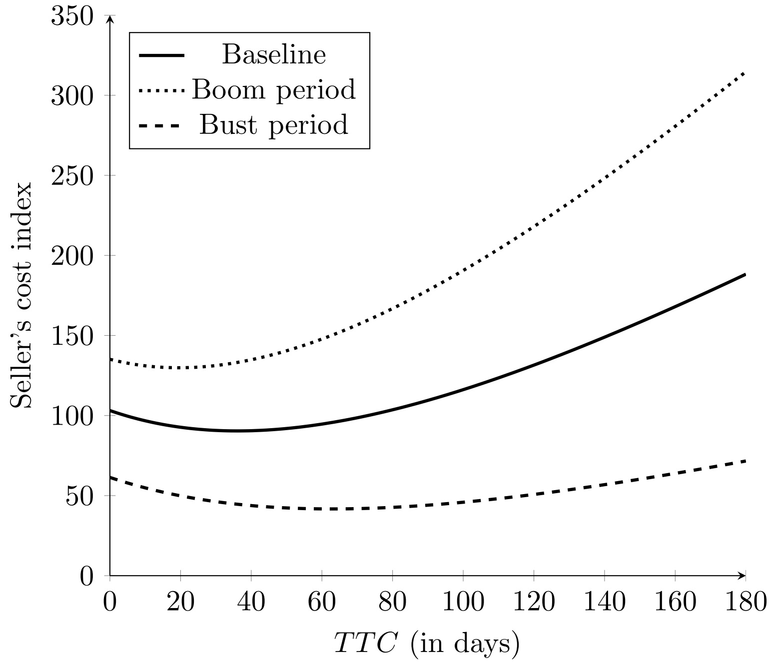


FIGURE 2 – CALIBRATED SELLER'S COST FUNCTION.

This figure plots the seller's cost function as stated in Eq. (3). Our baseline annualized parameter values are $\lambda = 1/73$, $g = 0.04$, $m = 0.035$, $r = 0.09$. For the boom period we use $\lambda = 1/77$, $g = 0.075$, $m = 0.05$, $r = 0.113$ and for the bust period $\lambda = 1/68$, $g = 0.01$, $m = 0.02$, $r = 0.0566$. Note that g, m, and r are annual figures and are converted to daily rates. We normalize the seller's cost index to 100 for $TTC = 73$ (i.e. our sample average, see Section 4).

From a regional perspective, we would expect something similar in areas where housing markets are relatively tight, something we will empirically investigate later on.

Finally, we performed two additional analyses. First, it could be argued that the results we find are just very specific to the parameters we put in. However, in Appendix B we explore the shape of the costs function more formally. It seems that the costs function is always positively sloping as long as $t_2 >> 0$. Of course, it could still be true that the calibrated results are very specific to our modeling framework, which is why we will also do an empirical analysis based on actual data. Second, in Appendix C we also explore a situation (symmetric Nash bargaining outcome) where the buyer's cost function is not fixed but contains similar elements as the seller's cost function. In this case, TTC in the baseline scenario still has a positive effect on transaction prices. An additional interesting aspect that comes out of this analysis is that the optimal TTC is lower during bust. This stands in contrast to what we would normally expect for TOM (i.e., see Krainer, 2001; Novy-Marx, 2009; Genesove and Han, 2012). This inverse relationship is something we also observe in the data.

4. Data

In this paper, we focus on the market for existing owner-occupied housing in the Netherlands. We use transactions data from four different regions of the Netherlands, namely the Achterhoek, Amsterdam, Hart van Brabant and Zwolle, see Figure 3. These regions are evenly spread across the Netherlands, reflecting tight (urban) markets like Amsterdam, and more peripheral markets such as the Achterhoek. More importantly, for these regions we could get both the realtors transactions data (purchase date) from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) and a matched set of administrative data (legal transfer date) from the Land Registry (Kadaster) over the period 2006-2016.

The NVM transaction data includes the transaction price, list price, and an extensive set of property characteristics. There is also information about the time-on-market (TOM). The Kadaster data contains the date of legal transfer such that we can calculate the time-to-close (TTC). We add the Kadaster data to the NVM data and use the price recorded in the official land registry as final transaction price. After merging and applying some filters to remove outliers we have 115,279 transactions in our database, see Appendix A for more details and a discussion about the representativeness of the dataset. Table 1 provides descriptive statistics for the dataset.

House Prices

The average house price is equal to about €265,000. There is also some information about the list price which we will use for one of the robustness checks in the empirical analysis. The list price is typically somewhat larger than the final transaction price and the average is about 281,000 euros. Figure 4 show the development of house prices over time. From

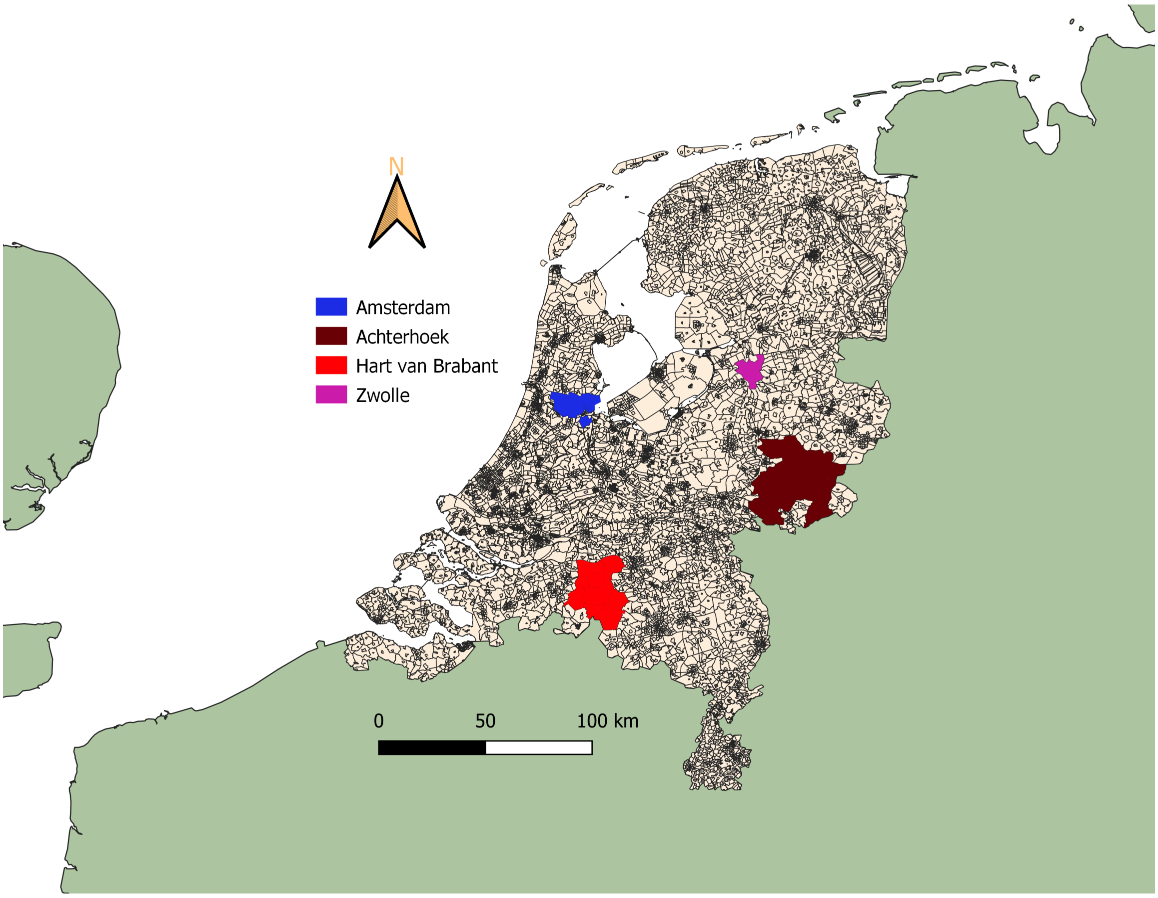


Figure 3 – The four analyzed regions in the Netherlands.

Note: This map shows the four regions for which we have transactions data: Achterhoek, Amsterdam, Hart van Brabant, and Zwolle.

the top of the market in 2008 to 2013, average prices decreased by 17%, on average 3.1% per year. From 2013 to 2016 prices increased sharply by 28%, on average 8.6% per year. This information is useful to define boom and bust periods to be used later on the empirical analysis.

Time-on-market and time-to-close

According to Table 1, the averages of TOM and TTC are 155 and 73 days, respectively. In addition, the standard deviation of the TTC is 47 days. The variation in TTC is such that this is not just a reflection of the necessity for most households to obtain a mortgage. The

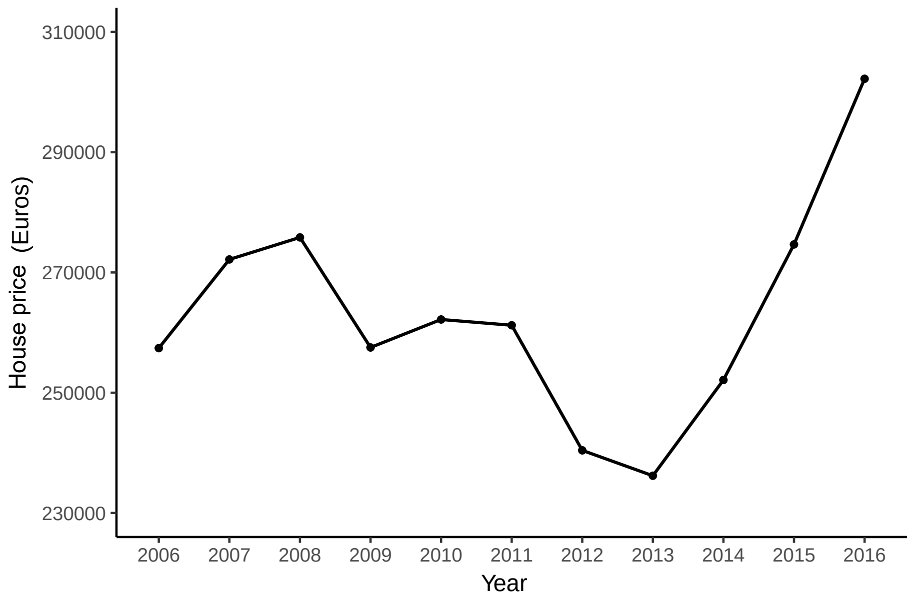


Figure 4 – House prices (2006-2016)

Note: This figure shows the average house price across the four analyzed regions between 2006 and 2016.

variation in TTC is smaller than that of TOM. This is also clearly visible in the kernel density plots reported in Figure 5, although the TTC seem to be more evenly spread out. About 2.4% of the transactions have a TTC of less than or equal to 10 days and 0.5% of the transactions have a TTC of zero. This implies that cash buys in the Netherlands during this period are maybe less frequent than in for example some parts of the U.S. (i.e., Han and Hong, 2020). Both the overall sample correlation between sale prices and TOM, and TOM and TTC are quite small, respectively -0.014 and -0.008. The correlation between house prices and TTC is somewhat larger, 0.160.

Although the purpose of this paper is not to explore the time series dynamics between TOM and TTC in detail, that is, we will mainly focus on the cross-sectional variation (except maybe for showing a seemingly unrelated regression analysis with lags as robustness), it is useful to see that TOM and TTC have an opposite time series pattern in Figure 5.[12]

[12]Figure D.1 in Appendix D shows the annual means of P, TOM, and TTC per region, having the same patterns as their aggregated counterparts. Note that the average transaction price in Amsterdam is much

Table 1 – Descriptive statistics (2006-2016)

Variables	Categories	Mean	Std.Dev.	Min	Max
Dependent Variable					
House price (in euros)		265,443	168,632	50,000	2,000,000
List price (in euros)		281,278	182,251	45,000	2,900,000
Independent Variables					
TOM (in days)		155	195	1	1,095
TTC (in days)		73	47	0	366
$TOM + TTC$ (in days)		229	200	1	1,361
Instrumental Variables					
P_{500m,t_1-90}		261,768	111,574	65,000	1,600,000
TOM_{500m,t_1-90}		156	112	1	1,095
TTC_{500m,t_1-90}		73	26	0	366
$(TOM + TTC)_{500m,t_1-90}$		229	117	21	1,303
Control variables					
Floor area (m^2)		102	46	25	500
Plot area (m^2)		139	337	0	5,000
Construction Period	<1500 (R)	0.02%			
	1500-1905	9.6%			
	1906-1930	20.4%			
	1931-1944	8.2%			
	1945-1959	5.7%			
	1960-1970	12.4%			
	1971-1980	9.5%			
	1981-1990	13.3%			
	1991-2000	13.5%			
	>2001	7.2%			
House Type	Apartment (R)	54.3%			
	Corner	7.6%			
	Detached	6.8%			
	Half of double	9.2%			
	Row house	20.6%			
	Semi-detached	1.5%			
Maintenance Condition	Below average (R)	9.7%			
	Average	74.0%			
	Above average	16.3%			
Monument	Yes	1.7%			
Parking	Garage and carport (R)	1.3%			
	Garage and no carport	13.4%			
	Garage for more cars	2%			
	Garport and no garage	4.3%			
	No parking	75%			
	Parking spot	4%			
Garden	Yes	49.9%			
Attic	Yes	18.7%			

Number of observations, $N = 115,279$. R denotes the reference group in case of a dummy variable.

In particular, the highest average TTC in our sample is in 2006, 84 days, and the lowest value in 2012, 60 days. Interestingly, the level of TTC is lower after 2012 than in the early part of our sample. This may have been caused by the fact that the process of obtaining mortgage financing has become more efficient. Instead, the highest TOM value is in 2013, 228 days, and the lowest value in 2016, 115 days. The opposite patterns of TOM and TTC are indicative that these are separate processes that need to be separately modeled. It also implies that we need to carefully control for trends in our analysis.

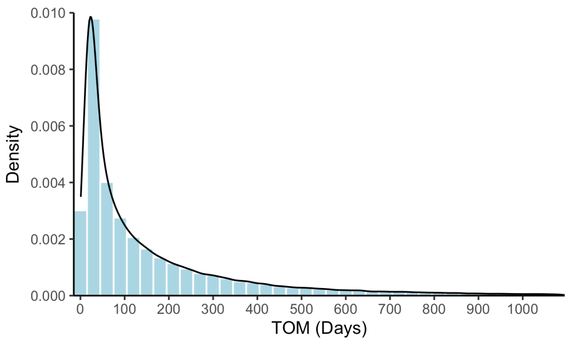
Although there is considerable temporal variation in TTC, it is useful to mention that when we regress $\log TTC$ on housing characteristics, (4-digit zip code) neighborhood fixed effects, annual time fixed effect and their interactions, ninety percent of the variation in TTC still remains unexplained $(1 - R^2)$. That is, there is considerable variation in TTC *within* neighborhoods, which is suggestive evidence that these might indeed be the result of different bargaining outcomes, implying that the analysis we intend to do seems to have some merits.

Table 1 also contains the descriptive statistics of the spatio-temporal lagged instrumental variables (IV's) for house prices, TOM, and TTC, using averages over transactions in the past 90 days and within a radius of 500 meters of a particular transaction (we will also explore other thresholds). Not surprisingly, the average of those averages is similar to those of the variables themselves. However, the standard deviations are smaller as some of the variation within neighborhoods is averaged out. There are on average 17 neighboring transactions used to create the average for a particular transaction. A more detailed discussion of the IV strategy is done in the empirical methodology section.

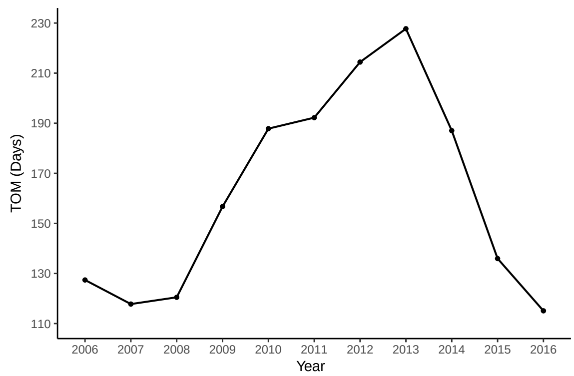
Finally, for a very limited subsample (18%) we also have some information about the legal transfer date of the seller's next house (i.e. t_{next}), although we do not have additional information like the address and the date of signing the sale contract. Although this is not sufficient to perform analysis on, the descriptive statistics are insightful. In most cases, about 60%, the seller sells his house first, before buying his next house ($t_{next} > t_1$). More-

higher compared to the other regions, and the average TOM and TTC much lower.

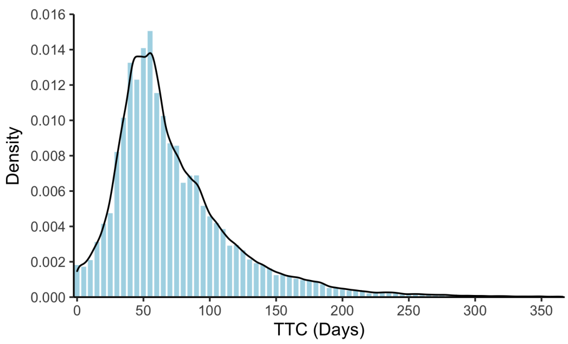
over, only in 26.3% of transactions, $t_{next} > t_2$, implying that the seller must temporarily find an alternative (rental) place to live. That is, a homeowner is more likely to face double mortgage costs than short-term rental costs. As part of the argument in this paper is about a mismatch between selling your current home and buying a new one, we also looked how many households perfectly match t_{next} and t_2. It seems that this only happens in 3% of the cases. It is 9% using a 7-day window before/after t_2. This suggests that double mortgage costs and short-term rental costs may actually be applicable for many homeowners.



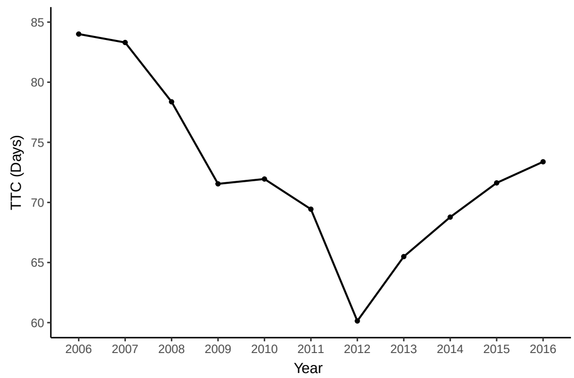
(A) Kernel density time-on-market



(B) Time series plot time-on-market



(C) Kernel density time-to-close



(D) Time series plot time-to-close

Figure 5 – The time-on-market and time-to-close

Note: This figure shows the kernel density plot and time series of TOM and TTC. The time series plots are based on the average per year.

Control variables

The control variables include floor and plot area, construction period, house type, maintenance condition (split up in below average, average, above average), monument, parking facilities, and the presence of a garden and an attic. The average floor size equals 102m^2, and the average plot (for single-family homes) is equal to 139m^2. More than half of the transactions involves apartments, and most transactions have a construction year in the period 1906–1930, about 20%. About 75% of the transactions have no parking place and 1.7% of the transactions have a historical character (have a monumental status) and are typically expected to sell for a higher price due to their historical character (Lazrak et al., 2014). In the analysis, we use 248 location (neighborhood) dummy variables based on the first four digits of the zip code. There are on average about 465 transactions per zip code and about 4,000 zip codes in the Netherlands. We also add year dummies using the date of signing the sale contract as basis.

5. Empirical Approach

To examine the effect of $TTC_{i,t}$ and $TOM_{i,t}$ on the transaction price P_i for house i sold at time t we use a hedonic approach:

$$\log P_{i,t} = \beta_{ttc} \log TTC_{i,t} + \beta_{tom} \log TOM_{i,t} + x'_{i,t}\beta_X + \alpha_j + \tau_t + \varepsilon^p_{i,t}, \tag{4}$$

where we use the natural logarithm of $P_{i,t}$, $TOM_{i,t}$ and $TTC_{i,t}$, $x_{i,t}$ is a vector of housing characteristics, α_j are a set of 4-digit zip code (neighborhood) fixed effects, τ_t are year fixed effects, and $\varepsilon^p_{i,t}$ is the error term. The parameter of interest is denoted by β_{ttc}. In accordance with **Hypothesis 1**, we expect this coefficient to be positive. We expect that the effect of $TOM_{i,t}$ is negative, see Dubé and Legros (2016) and Benefield and Hardin (2015). We will also estimate a version of Eq. (4) ignoring $\log TTC_{i,t}$ and a version using a combined measure $\log(TOM_{i,t} + TTC_{i,t})$ to examine whether in such a case the estimated effect of $TOM_{i,t}$ is biased. We also examine adding a quadratic term for $TTC_{i,t}$.

There are several identification issues when estimating Eq. (4). First, there are omitted house and household characteristics. Second, $P_{i,t}$, $TOM_{i,t}$, and $TTC_{i,t}$ are simultaneously determined. Various studies deal with the endogeneity of $TOM_{i,t}$ using two-stage least squares (2SLS), see among others Yavas and Yang (1995), Knight (2002), and Clauretie and Thistle (2007). In this paper, we will also use an instrumental variable approach and estimate:

$$\log P_{i,t} = \beta_{ttc} \log \hat{TTC}_{i,t} + \beta_{tom} \log \hat{TOM}_{i,t} + x'_{i,t}\beta_x + \alpha_j + \tau_t + \varepsilon^p_{i,t}, \quad (5)$$

where $\hat{TOM}_{i,t}$ and $\hat{TTC}_{i,t}$ are the predicted $TOM_{i,t}$ and $TTC_{i,t}$ and $\varepsilon^p_{i,t}$ is again the error term.

We follow the approach used by Engelhardt (2003) and Dubé and Legros (2016), using spatio-temporal lagged instrumental variables for the first-stage.[13] In particular, we take the average (log) $TOM_{i,t}$ and $TTC_{i,t}$ within 500 meters of a transaction and in the past 90 days as instruments (i.e. TOM_{500m,t_1-90} and TOM_{500m,t_1-90}). We also used other thresholds (i.e. 250m and 120 days, and 1km and 60 days) for the spatial and temporal lags showing that our results are robust. The identification strategy is based on the idea that it is virtually impossible for a homeowner (with some set of unobserved characteristics) to affect the aggregate market outcome (instrumental validity), particularly so in the past, but that this aggregate outcome does correlate (instrumental relevance) with the $TOM_{i,t}$ and $TTC_{i,t}$ of that particular house. In this setup, there are no overidentifying restrictions to allow for additional exogeneity testing, so the validity of the instruments mainly hinges on the assumption made above.

One issue with this approach is that there might be unobserved local changes in amenities or local policies that are correlated with the instrumental variables. In order to deal with this, we also show robustness using interactions of zip code and time fixed effects ($\alpha_j \times \tau_t$) as additional controls in Eq. (5). This also ensure that we are looking at the cross-

[13]We also considered using an alternative approach based on changes in transfer taxation over time. Unfortunately, during our sample period, there have not been large changes in transfer taxation.

sectional variation in TTC and the results are not just capturing unobserved trends. In addition, we employ a repeat sales methodology to filter out unobserved housing characteristics, estimating Eq. (5) using trading pairs in both the first- and second-stage regression. Alternatively, we use a differencing approach based on the transaction price and list price of the property. In addition, to test **Hypothesis 2** we also estimate Eq. (5) separately for boom and bust periods and, similarly, for different regions.

Although the IV approach might control for the endogeneity of $TOM_{i,t}$ and $TTC_{i,t}$, it is not explicit about the fact that $P_{i,t}$, $TOM_{i,t}$, and $TTC_{i,t}$ are simultaneously determined and potentially correlated. Therefore, as further robustness, we also reestimate Eq. (5) using a seemingly unrelated regression (SUR) approach:

$$\begin{bmatrix} \log P_{i,t} \\ \log TOM_{i,t} \\ \log TTC_{i,t} \end{bmatrix} = \begin{bmatrix} X_p & 0 & 0 \\ 0 & X_{tom} & 0 \\ 0 & 0 & X_{ttc} \end{bmatrix} \begin{bmatrix} \beta_p \\ \beta_{tom} \\ \beta_{ttc} \end{bmatrix} + \begin{bmatrix} \alpha_j^p \\ \alpha_j^{tom} \\ \alpha_j^{ttc} \end{bmatrix} + \begin{bmatrix} \tau_t^p \\ \tau_t^{tom} \\ \tau_t^{ttc} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t}^p \\ \varepsilon_{i,t}^{tom} \\ \varepsilon_{i,t}^{ttc} \end{bmatrix}, \tag{6}$$

where $X_p = [x'_{i,t}, \log \hat{TTC}_{i,t}, \log \hat{TOM}_{i,t}]$, $X_{tom} = [x'_{i,t}, \log \hat{P}_{i,t}, \log \hat{TTC}_{i,t}]$, and $X_{ttc} = [x'_{i,t}, \log \hat{P}_{i,t}, \log \hat{TOM}_{i,t}]$. We use the same instrumental variable approach as before, but we now also instrument house prices in the $TOM_{i,t}$ and $TTC_{i,t}$ equations using the average spatio-temporal lagged house price. The SUR approach allows for correlation between $\varepsilon_{i,t}^p$, $\varepsilon_{i,t}^{tom}$, and $\varepsilon_{i,t}^{ttc}$, and it allows for causal interference via a Granger causality argument using lagged version of $TOM_{i,t}$ and $TTC_{i,t}$ in the price equation.

We apply a 3SLS approach based on the generalized method of moments (3SLS-GMM) to estimate the system of equations. This method leads to an asymptotically more efficient estimator, compared to ignoring the correlations, and a consistent estimator even when the set of instruments differ between equations (Schmidt, 1990; Henningsen et al., 2007). Note that estimating this set of equations should not lead to any other results regarding the effect of $TTC_{i,t}$ on transaction prices, but we would expect it affects the standard errors. A potential concern might be that Eq. (6) allows $TTC_{i,t}$ to have an effect on $TOM_{i,t}$ while $TTC_{i,t}$ comes after $TOM_{i,t}$ in term of temporal ordering. However, note that this framework is measuring expectations and it seems reasonable that households thinking about $TOM_{i,t}$ and the eventual transaction price also have some idea about their desired (expected) $TTC_{i,t}$.

6. Empirical Results

6.1. OLS Results

Table 2 shows the estimates of Eq. (4) based on Ordinary Least Squares (OLS). Column (1) reports the main specification with both TTC and TOM included as variables. According to the results, the TTC has a positive and statistically significant effect on house prices, in line with **Hypothesis 1**. A one standard deviation increase in the TTC (47 days), evaluated relative to the average TTC (73 days), has an effect on house prices of 0.9 percent $((1+47/73)^{0.0181}-1)$. This is about €2,400 based on an average house price of €265,000.[14]

Instead, TOM has a negative effect on transaction prices. A one standard deviation increase in TOM, again evaluated against the average TOM, decreases house prices by 1.1 percent. This negative effect is in line with the previous literature (Benefield et al., 2014) and a bit larger than for example Dubé and Legros (2016) (OLS regression coefficient of -0.0141 versus -0.0044). Comparing the results to column (2) that excludes TTC from the equation, we find that the effect of a standard deviation change in TOM is now 1.3 percent, which is an (over)estimation bias of 9.2 percent.

Finally, in column 3, TOM and TTC are added as a joint variable. This leads to some sort of average effect. Overall, the effect is still negative as TTC is quantitatively smaller than TOM. The effect of a standard deviation change in the joint variable is -0.6 percent, so in this case we get an underestimation. Comparing the coefficient estimate in column (3) with that reported in column (1), the estimation bias in the marginal effect is now even more severe and close to thirty percent.[15]

[14] We also estimated a version of the model that includes both $\ln TTC$ and $\ln TTC$ squared, which resulted in coefficient estimates of -0.011 and 0.0053, respectively. So the effect below 3 days of TTC is negative – in line with the argument given by Han and Hong (2020) – but for the majority of households it is positive.

[15] Comparing the overall effects of a standard deviation change of TOM and $TOM + TCC$ suggests an

Table 2 – The effect of TTC on house prices (OLS)
(Dependent variable: log house price)

	(1)	(2)	(3)
$\log TTC$	0.0181***		
	(0.0007)		
$\log TOM$	−0.0141***	−0.0154***	
	(0.0004)	(0.0004)	
$\log(TOM + TTC)$			−0.0100***
			(0.0007)
Housing characteristics	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes
Fixed effects: Year_{t_1}	Yes	Yes	Yes
Observations	115,279	115,279	115,279
R^2	0.8723	0.8713	0.8710

Note: This table shows results based on merged realtor-land registry data for four regions in the Netherlands from 2006-2016. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

6.2. IV Results and other robustness checks

Table 3, columns (1) to (3) (Panel A), replicates the results of Table 2 using an instrumental variable (IV) approach, see Eq. (5). The first-stage regression results are reported in Table 4. The results in Table 3 clearly show that the IV estimates are larger than the OLS estimates, which is not that unusual. It usually implies that the instruments are not that strong. However, examining the results in Table 4 suggests that the spatial-temporal instruments are highly relevant, indicated by both the individual statistical significance and the joint significance (F-test) of the IV's. According to column (1), an increase in the average (based on nearby properties) TOM of one percent increase the TOM of a property by 0.84 percent. Similarly, an increase in the average TTC of one percent increases the TTC by 0.98 percent. We find similar results in columns (2) and (3). Interestingly, the average TTC seems to have a negative effect on TOM and the average TOM a negative effect on TTC. We will explore this more formally using the SUR approach in the next subsection.

Looking more closely at the second-stage results in Table 3, the Durban-Wu-Hausman

even larger estimation bias, but a standard deviation change in TOM is not the same as a standard deviation change in the joint variable, suggesting that it might be better to compare the marginal effects in this case.

test and individual t-tests suggest that both TOM and TTC are indeed endogenous. According to column (1) an increase in TTC of one standard deviation increases house prices by 2.4 percent, or about €6,400 relative to an average house price of €265,000. A standard deviation increase in TOM decreases house prices by 3.0 percent. This is in line with the results of Dubé and Legros (2016), although they find a somewhat stronger marginal effect, -0.0777.

Omitting TTC from the equation leads to an effect of TOM of -3.2 percent, an overestimation of 6.3 percent. Adding TTC to TOM leads to an overestimation of the marginal effect of 1.3 percent, which is not that sizeable. This is also in contrast to the OLS results which suggested a strong underestimation. What is interesting though is the economic interpretation. While for example a 20 percent increase in $TOM + TTC$ according to column (3) leads to a 0.7 percent *decline* in transaction prices, it leads to a 0.2 increase when considering the results in column (1). All of these results again illustrate the importance of separating TTC and TOM when examining their impact on house prices.

Next, we discuss several robustness checks that are reported in Panel B of Table 3. As both TOM and TTC are skewed to the left, there might be a concern that outliers in the tale of the distribution are influencing our results. As a consequence, in column (4) we have removed the top 1% of the data. In this case we find a marginal effect that does not differ much from our baseline estimate in column (1). Second, we control for unobserved housing characteristics via a repeat sales methodology, see column (5). Although there is potential sample selection, we still find a positive marginal effect of TTC of 0.0455 and the effect of TOM is still negative. Third, we use an alternative differencing approach by taking the (log) difference between the house price and list price as dependent variable. In addition, this also shows to what extent sellers already incorporate the (expected) TTC when listing their home. There is also some evidence that actually buyers and sellers negotiate about the price premium (or discount) relative to the listing price (e.g. Genesove and Mayer, 1997; McGreal et al., 2009). The results are reported in column (6). The effect of TTC on transaction prices is still positive and statistically significant but much smaller, suggesting

Table 3 – The effect of TTC on house prices (2SLS)

(Dependent variable: log house price)

	Panel A: IV approach			Panel B: Other robustness checks			
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) Outliers	(5) Repeat sales	(6) Price premium	(7) Zip code x Year FE
$\log TTC$	0.0479***			0.0493***	0.0455***	0.0065***	0.0376***
	(0.0024)			(0.0025)	(0.0054)	(0.0007)	(0.0022)
$\log TOM$	−0.0377***	−0.0401***		−0.0384***	−0.0507***	−0.0422***	−0.0146***
	(0.0012)	(0.0012)		(0.0012)	(0.0027)	(0.0004)	(0.0012)
$\log(TOM + TTC)$			−0.0382***				
			(0.0019)				
Durbin-Wu-Hausman χ^2-test	487.8***	602.6***	312.5***	468.3***	180.0***	463.1***	141.3***
t-test for endogeneity of $\log TOM$	23.5***			23.0***	16.0***	27.2***	−21.2***
t-test for endogeneity of $\log TTC$	−16.95***			−6.2***	−8.4***	−9.6***	13.7***
Housing characteristics	Yes	Yes	Yes	Yes	No	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes	Yes	No	Yes	Yes
Fixed effects: Year_{t_1}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115,279	115,279	115,279	113,009	15,166	115,279	115,279
R^2	0.8656	0.8683	0.8675	0.8650	0.1030	0.4883	0.8942

Note: The Durbin-Wu-Hausman χ^2-statistic is used to test for joint endogeneity of the endogenous variables. We also report a (individual) t-test based on a control function approach. Table 4 gives the first-stage results for Panel A. The repeat sales approach takes the log difference between the second and first sale price in a trading pair. The same is done for TTC, TOM, and the IV's. Column (6) uses the (log) difference between house prices and list prices as dependent variable. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

that indeed most of the effect is already incorporated by the seller, in line with the idea behind the baseline bargaining model presented earlier. Finally, an important concern is that our results might just be a reflection of unobserved local market trends, for example due to changes in local policy. Consequently, we re-estimate Eq. (5) with 4-digit zip code times year fixed effects, see column (7). The estimation results show that we still get a TTC effect of 0.0375 and a TOM effect of -0.0146. So although the effects are quantitatively somewhat smaller, the idea that there is cross-sectional variation in TTC within neighborhoods and that this affects transaction prices indeed seems to have some merit.

Table 4 – First-stage estimation results

	(1)		(2)	(3)
	$\log TOM$	$\log TTC$	$\log TOM$	$\log(TOM + TTC)$
IV: $\log TOM_{500m,t_1-90}$	0.8398***	−0.0271***	0.8415***	
	(0.0051)	(0.0034)	(0.0051)	
IV: $\log TTC_{500m,t_1-90}$	−0.1092***	0.9848***		
	(0.0102)	(0.0080)		
IV: $\log(TOM + TTC)_{500m,t_1-90}$				0.8432***
				(0.0051)
Weak IVs F-test	10,291.53***	6,987.96***	13,926.95***	23,409.48***
Housing characteristics	Yes	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes	Yes
Fixed effects: Year_{t_1}	Yes	Yes	Yes	Yes
Observations	115,279	115,279	115,279	115,279
R^2	0.2951	0.1893	0.2946	0.3469
Residual Std. Error	1.0499	0.7476	1.0503	0.6171
F-statistic	168.93***	94.20***	169.10***	215.11***

Note: The spatio-temporal lagged instrumental variables are defined based on a spatial radius of 500 meters and a temporal lag length of 90 days. Table D.3 provides first and second stage estimation results using a spatial radius of 250 and 1000 meters and a temporal lag length of 60 and 120 days. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

6.3. Seemingly Unrelated Regressions

As prices, TOM and TTC are not independent variables, Table 5 presents the estimation results using a seemingly unrelated regressions (SUR) framework, see Eq. (6). The equations are simultaneously estimated using 3SLS-GMM (i.e. using the spatial-temporal IV's) and takes into account the correlations between the error terms across equations. The first stage results are reported in Table D.1. As expected, the coefficient estimates by SUR for the price equation are identical to those from the previous 2SLS estimates, but the standard errors differ. In the TOM model (column 2), the marginal effects of prices and TTC are negative and statistically significant. The negative effect of prices is consistent with the results of Dubé and Legros (2016). If a homeowner sets a high reservation price, he will have to wait for a longer time to sell the property. An increase of TTC by 20%, decreases TOM by 2.5 percent and a one percent price increase, decreases TOM by 0.46 percent. Interestingly, the relationship between TOM and TTC is bi-directional. In particular, in the TTC model (column 3), the marginal effect of TOM is also negative, although its economic magnitude is small. Overall, these results suggest that TOM and TTC are inversely related. Instead, prices are positively related to TTC. Finally, it is useful to note that the coefficients of determination R^2 for TOM and TTC models are relatively low, compared to the price model, 0.18 and 0.10 versus 0.87. This is in line with previous studies showing that house and location variables have low explanatory power in models for TOM (Clauretie and Thistle, 2007). The same seems to hold for TTC.

6.4. Heterogeneity over Market Cycles and Regions

In this section we analyze whether the impact of TTC and TOM on house prices differs over the market cycle and over regions. Based on the longitudinal patterns of P, TOM and TTC, we use the years 2006–2008 and 2014–2016 as boom periods, and the years 2009–2013 as a bust period. Table 6 gives the 2SLS estimation output. Comparing columns 1 and 2, we find that the marginal effect of TTC on prices is lower (0.0380) in busts compared to the booms (0.0653). This is in line with **Hypothesis 2**. Both effects are still positive though, and statistically significant at the one percent level. The marginal effect of a 20% increase in TTC ranges between 0.7 (bust) and 1.2 (boom) percent. Similarly, the marginal effect of TOM is substantially lower in bust (−0.0061) than in boom periods (−0.0435).

Next, we analyze whether the marginal effects of TOM and TTC on house prices differ over regions. Columns 3–6 in Table 6 provide the second stage 2SLS estimation results for the four regions in our sample: Achterhoek, Amsterdam, Hart van Brabant, and Zwolle.

Table 5 – Joint estimation of price, TOM, and TTC equations (3SLS-GMM)

	Dependent Variable:		
3SLS-GMM:	$\log P$ (1)	$\log TOM$ (2)	$\log TTC$ (3)
$\log \hat{P}$		-0.4604^{***}	0.1912^{***}
		(0.0505)	(0.0359)
$\log T\hat{O}M$	-0.0377^{***}		-0.0431^{***}
	(0.0011)		(0.0055)
$\log T\hat{T}C$	0.0479^{***}	-0.1395^{***}	
	(0.0019)	(0.0127)	
Durbin-Wu-Hausman χ^2-test	487.81^{***}	10.09^{***}	48.03^{***}
t-test on endogeneity of $\log P$		-4.49^{***}	7.05^{***}
t-test on endogeneity of $\log TOM$	23.54^{***}		-4.61^{***}
t-test on endogeneity of $\log TTC$	-16.95^{***}	0.45	
Housing characteristics	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes
Fixed effects: Year$_{t_1}$	Yes	Yes	Yes
Observations	115, 279	115, 279	115, 279
Residual Std. Error	0.1683	1.1292	0.7859
R^2	0.8656	0.1847	0.1039

Note: The Durbin-Wu-Hausman χ^2-statistic is used to test for joint endogeneity of the endogenous variable variables (column 1: TOM, TTC; column 2: P, TTC; column 3: P, TOM). We also report a t-test based on a control function approach. The estimated correlations between the error terms are: $\text{cor}(\hat{\varepsilon}^P, \hat{\varepsilon}^{TOM}) = 0.2236$, $\text{cor}(\hat{\varepsilon}^P, \hat{\varepsilon}^{TTC}) = -0.1844$, and $\text{cor}(\hat{\varepsilon}^{TOM}, \hat{\varepsilon}^{TTC}) = 0.0638$. Table D.1 provides the first-stage results. *p<0.1; **p<0.05; ***p<0.01.

The average TTC varies from 63 days in Amsterdam to 87 days in Hart van Brabant, a difference of more than three weeks, see Figure D.1. The average TOM also varies, from 115 days in Amsterdam to 238 days in Achterhoek, a difference of more than four months, see Figure D.1. The marginal effect of TOM on prices is negative and statistically significant in all regions and is highest in Amsterdam (−0.0482), which is typically seen as a tight market. The marginal effect of TTC varies less over regions and is, except for Zwolle, around 0.04. The average house price in Zwolle is also lower (€223,000) than in Achterhoek (€237,000), Amsterdam (€289,000), or Hart van Brabant (€244,000). Even though the marginal effect for most regions is roughly the same, the economic magnitude is highest in Amsterdam as average prices are highest there. Although the evidence on boom-bust dynamics is clearer, these results still seem to support the underlying idea of **Hypothesis 2**.

Table 6 – Variation across market phases and regions (2SLS)

(Dependent variable: log house price)

	Market Phases		*Regional Markets*			
	Bust	Boom	Achterhoek	Amsterdam	Hart van Brabant	Zwolle
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \hat{TOM}$	-0.0061^{***}	-0.0435^{***}	-0.0065^{***}	-0.0482^{***}	-0.0066^{***}	-0.0138^{***}
	(0.0018)	(0.0017)	(0.0020)	(0.0020)	(0.0018)	(0.0030)
$\log \hat{TTC}$	0.0380^{***}	0.0653^{***}	0.0399^{***}	0.0421^{***}	0.0434^{***}	0.0272^{***}
	(0.0034)	(0.0034)	(0.0040)	(0.0037)	(0.0036)	(0.0056)
Durbin-Wu-Hausman χ^2-test	33.84^{***}	459.82^{***}	8.46^{***}	272.50^{***}	10.14^{***}	2.33^{*}
t-test on endogeneity of $\log TOM$	-0.52	19.69^{***}	-1.26	18.74^{***}	-1.91^{*}	1.71^{*}
t-test on endogeneity of $\log TTC$	-8.22^{***}	-19.05^{***}	-4.05^{***}	-11.49^{***}	-4.35^{***}	-1.07
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Year_{t_1}	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,456	73,823	13,703	62,559	28,449	10,568
Residual Std. Error	0.1497	0.1769	0.1517	0.1528	0.1370	0.1227
R^2	0.8852	0.8566	0.8568	0.9065	0.8821	0.8871

Note: The Durbin-Wu-Hausman χ^2-statistic is used to test for joint endogeneity of the endogenous variables. We also report a t-test based on a control function approach. Consistent with the results from the full sample, TOM and TTC are jointly endogenous for all subsamples. Table D.2 gives the first-stage estimation results. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

7. Conclusion

Unlike many other consumer and investment goods, when buying real estate there is usually a long time between the purchase and the final delivery of the property. For residential real estate, this period, the time-to-close (TTC), is necessary for the buyer to arrange financing, and for the seller to move to his next home. As such, its purpose is different from that of the time-on-market (TOM). The TTC is agreed upon between buyers and sellers when the purchase contract is signed, and varies over transactions.

In this paper, we have analyzed the relationship between the length of the TTC period and the transaction price for residential properties in the owner-occupied market. We argue that a seller wants to be compensated, at least partially, for the expected costs caused by the time between the signing of the purchase contract and the final delivery of the home. The seller's costs are a function of the expected price appreciation after signing the purchase agreement, any interest payments for a bridge loan when his next home is bought too soon, or any short-term rental costs when the next home is bought too late. We conclude that because of these costs the marginal effect of the TTC on transaction prices – in contrast to TOM – is positive.

Using transactions data for four regions within the Netherlands over the period 2006–2016 and a hedonic price model, we show that a standard deviation increase in TTC increases house prices by 2.4 percent. Instead, the effect of TOM is of opposite sign. Mainly if TTC is not controlled for we find a moderate overestimation bias of the marginal effect of TOM of 6.3 percent. When we combine TOM and TTC in a single measure the effect on prices is negative, while the overall effect is positive when we consider the same increase in TOM and TTC separately. These results illustrate the importance of modeling the price effect of both TOM and TTC separately. Further results show that the effects are stronger during booms and in tight markets such as Amsterdam.

The mismatch between selling your current home versus buying a new one is a key driver underlying the price effect of TTC. This mismatch varies over the market cycle and has important implications for house price dynamics as discussed by Moen et al. (2021).

It would be useful to investigate how TTC itself affects house price dynamics and how it relates to for example liquidity (i.e. commonly measure by TOM) and liquidity risk (Cheng et al., 2013). In addition, the TTC is affected by the ease at which mortgages are given. These days, a homeowner can fairly easily apply for a mortgage online, the procedure to get a mortgage has become less cumbersome, and as a result the TTC has decreased over the past decade. Finally, a framework that combines the uncertainty/cash buyer argument given by Han and Hong (2020) versus the expected cost argument in case of financially constrained homeowners, as argued in our study, would also be extremely useful. Keeping these considerations in mind though, our study highlights that the TTC is a fundamental part of the transaction process of real estate and, as such, has an economic meaningful effect on its price.

Acknowledgements

We would like to thank Jan Rouwendal, Matthijs Korevaar, Torsten Jochem, and participants of the Weimer School meeting (West Palm Beach, January 2019), seminar participants at the Dutch Central Bank (DNB), Ortec Finance, the University of Amsterdam, the 2019 International AREUEA conference (Milan), and the 2022 International AREUEA conference (Dublin) for valuable comments and advice. Yumei Wang has been funded by the China Scholarship Council (grant number 201508510080). Finally, we would like to thank the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) and the Land Registry (Kadaster) for providing us with the transactions data.

References

Benefield, J.D., Cain, C., Johnson, K., 2014. A review of literature utilizing simultaneous modeling techniques for property price and time-on-market. Journal of Real Estate Literature 22, 149–175.

Benefield, J.D., Hardin, W.G., 2015. Does time-on-market measurement matter? The Journal of Real Estate Finance and Economics 50, 52–73.

Cheng, P., Lin, Z., Liu, Y., 2013. Liquidity risk of private assets: Evidence from real estate markets. The Financial Review 48, 671–696.

Clauretie, T.M., Thistle, P.D., 2007. The effect of time-on-market and location on search costs and anchoring: the case of single-family properties. The Journal of Real Estate Finance and Economics 35, 181–196.

Dorinth, v.D., 2019. Local Constant-Quality Housing Market Liquidity Indices. Technical Report. Working paper.

Dröes, M.I., Koster, H.R., 2023. A world divided: refugee centers, house prices and household preferences. Journal of Economic Geography 23, 51–90.

Dubé, J., Legros, D., 2016. A spatiotemporal solution for the simultaneous sale price and time-on-the-market problem. Real Estate Economics 44, 846–877.

Engelhardt, G.V., 2003. Nominal loss aversion, housing equity constraints, and household mobility: evidence from the united states. Journal of Urban Economics 53, 171–195.

Garmaise, M.J., Moskowitz, T.J., 2003. Confronting information asymmetries: Evidence from real estate markets. The Review of Financial Studies 17, 405–437.

Genesove, D., Han, L., 2012. Search and matching in the housing market. Journal of Urban Economics 72, 31–45.

Genesove, D., Mayer, C.J., 1997. Equity and time to sale in the real estate market. American Economic Review 87, 255–269.

Genesove, D., Mayer, C.J., 2001. Loss aversion and seller behavior: Evidence from the housing market. The Quarterly Journal of Economics 116, 1233–1260.

Han, L., 2008. Hedging house price risk in the presence of lumpy transaction costs. Journal of Urban Economics 64, 270–287.

Han, L., 2010. The effects of price risk on housing demand: Empirical evidence from U.S. markets. Review of Financial Studies 23, 3889–3928.

Han, L., Hong, S.H., 2020. Cash Is King? Evidence from Housing Markets. Technical Report. Working paper.

Han, L., Strange, W.C., 2015. Chapter 13 - The microstructure of housing markets: Search, bargaining, and brokerage, in: Duranton, G., Henderson, J.V., Strange, W.C. (Eds.), Handbook of Regional and Urban Economics. Elsevier. volume 5, pp. 813–886.

Han, L., Strange, W.C., 2016. What is the role of the asking price for a house? Journal of Urban Economics 93, 115–130.

Harding, J.P., Knight, J.R., Sirmans, C., 2003. Estimating bargaining effects in hedonic models: Evidence from the housing market. Real Estate Economics 31, 601–622.

Haurin, D.R., 1988. The duration of marketing time of residential housing. Real Estate Economics 16, 396–410.

Hayunga, D.K., Pace, R.K., 2019. The impact of tom on prices in the us housing market. The Journal of Real Estate Finance and Economics 58, 335–365.

Henningsen, A., Hamann, J.D., et al., 2007. Systemfit: A package for estimating systems of simultaneous equations in R. Journal of Statistical Software 23, 1–40.

Knight, J.R., 2002. Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. Real Estate Economics 30, 213–237.

Krainer, J., 2001. A theory of liquidity in residential real estate markets. Journal of Urban Economics 49, 32–53.

Lazrak, F., Nijkamp, P., Rietveld, P., Rouwendal, J., 2014. The market value of cultural heritage in urban areas: An application of spatial hedonic pricing. J Geogr Syst 16, 89–114.

Lin, Z., Liu, Y., 2008. Real estate returns and risk with heterogeneous investors. Real Estate Economics 36, 753–776.

Lin, Z., Vandell, K.D., 2007. Illiquidity and pricing biases in the real estate market. Real Estate Economics 35, 291–330.

Lyons, R.C., 2019. Can list prices accurately capture housing price trends? insights from extreme markets conditions. Finance Research Letters 30, 228–232.

McGreal, S., Adair, A., Brown, L., Webb, J., 2009. Pricing and time on the market for residential properties in a major u.k. city. Journal of Real Estate Research 31, 209–234.

Moen, E., Nenov, P., Snieker, F., 2021. Buying first or selling first in housing markets. Journal of the European Economic Association 19, 38–81.

Mumford, K., Dowrick, S., 1994. Wage bargaining with endogenous profits, overtime working and heterogeneous labor. The Review of Economics and Statistics 76, 329–336.

Novy-Marx, R., 2009. Hot and cold markets. Real Estate Economics 37, 1–22.

Schmidt, P., 1990. Three-stage least squares with different instruments for different equations. Journal of Econometrics 43, 389–394.

Turner, T., Smith, M., 2009. Exits from homeownership: The effects of race, ethnicity, and income. Journal of Regional Science 49, 1–32.

Wheaton, W.C., 1990. Vacancy, search, and prices in a housing market matching model. Journal of Political Economy 98, 1270–1292.

Yavas, A., Yang, S., 1995. The strategic role of listing price in marketing real estate: Theory and evidence. Real Estate Economics 23, 347–368.

Appendix A. Data Merging and Filtering

This paper uses sales data from four different regions in the Netherlands: Achterhoek, Amsterdam, Hart van Brabant and Zwolle. The region Achterhoek consists of the municipalities Aalten, Berkelland, Bronckhorst, Doetinchem, Doesburg, Lochem, Montferland, Oost Gelre, and the region Hart van Brabant consists of the municipalities Dongen, Gilze en Rijen, Goirle, Heusden, Hilvarenbeek, Loon op Zand, Oisterwijk, Tilburg and Waalwijk.

As mentioned, the data come from two sources: the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) and the Dutch Land Registry (Kadaster). The NVM database includes about 160,000 transactions in the period 2006–2016 (measured by t_1). Although we have transactions data, we do adjust the TOM for potential withdrawals after listing.[16] For a good discussion on the role of withdrawals in the transaction process, see Dorinth (2019). The Kadaster database includes transactions in the period 2006–2017 (measured by t_2). We use the NVM database as our main database as it contains detailed housing characteristics and merge the Kadaster data to it based on the address (zip code, house number, house letter, and additions).

When merging the files, we require the following: (1) the address must be identical in the NVM and Kadaster database, corrected for possible different spellings; (2) the Land Registry transaction price must lie between 0.9 and 1.1 times the NVM transaction price; (3) the date of signing the sale contract t_1 must lie between the date of legal transfer t_2 minus 12 months and plus 2 months.

As the NVM data covers about 70% of the market (and more towards the end of the sample period, see Dröes and Koster, 2023) we do lose some observations. In addition, the NVM database includes newly built houses, the Kadaster data does not. So by merging we effectively exclude newly built houses from the analysis. To give some idea about the match quality, for 17% of the transactions in the NVM database we could not find a corresponding transaction in the land registry. So our focus lies on existing properties.

[16] If properties are withdrawn and put back on the market within three months, we consider the two marketing periods as one. So, we take t_0 from the first marketing period, and t_1 from the second.

After the merge, we filter the data and impose that: (i) $TTC \geq 0$; (ii) $0 < TOM < 3$ years (1,095 days). Transactions with TOM is equal to zero are excluded, because they typically have not been listed on the market; (iii) the price from the Kadaster must be between €50,000 and €2,000,000; (iv) the initial and final asking price must be between €45,000 and €3,000,000; (v) the floor area must be between $25m^2$ and $500m^2$; (vi) the plot area must be zero for apartments and between $25m^2$ and $5{,}000m^2$ for single family homes. After merging and filtering we have 115,603 transactions over the period 2006–2016.

There are two additional notes about this database. First, some transactions might ultimately fail because of for example the buyer not getting a mortgage. We cannot identify those failures. A failed transaction may not necessarily be registered in the NVM database, it depends also on the broker, and even if it is recorded the missing transaction in the Kadaster data can just be a reflection of a mismatch between both databases. Second, the merged database contains mainly transactions where the buyer is also the resident. It may include purchases by private investors, natural persons who own more than one home as an investment. Although we have no information about the buyer and seller, we expect the number of purchases by private investors to be relatively low.

Appendix B. A Formal Exploration of the Seller's Cost Function

To determine the effect of a change in TTC on prices we have to examine the cost function in Eq. (3) for a change in t_2, where we ignore the bargaining coefficient β, as it does not depend on t_2. Taking the partial derivative of $C^S(t_2; g, m, r, \lambda)$ with respect to t_2 gives

$$\frac{\partial C^S}{\partial t_2} = g + m(1 - e^{-\lambda t_2}) - re^{-\lambda t_2}. \tag{B.1}$$

The question is if, and when, this partial derivative is positive. We argue that under some basic economic restrictions it is positive, as summarized in the following proposition:

Proposition 1. *Given Assumptions A1 and A2, and $g, m, r > 0$, and $t_2 >> 0$, the marginal effect of TTC on the transaction price is positive.*

Proof. As mentioned, a homeowner wants to get (partially) compensated by the buyer for an increase in C^S leading to a higher transaction price P. Eq. (B.1) captures the change in C^S (**Case 2**) at point $t_1 = 0$ as a result of an increase in t_2, i.e. increase in TTC. The first two terms g and $m(1 - e^{-\lambda t_2})$ are positive as g and m are positive, and $e^{-\lambda t_2}$ is positive by definition as it is the (cumulative) probability that t_{next} occurs after t_2. The question then is whether these first two terms outweigh the third term $-re^{-\lambda t_2}$. This can be rewritten as

$$\frac{1}{e^{-\lambda t_2}}(g + m) - m > r.$$

This makes clear that if $t_2 \to \infty$, $e^{-\lambda t_2}$ will go to zero and the inequality holds. That is, if t_2 is sufficiently large, $t_2 >> 0$, TTC has a positive effect on price. This point is after $t_2 = 1/\lambda * \ln((r + m)/(g + m))$, when Eq. (B.1) is zero (i.e. at a minimum as $C'' > 0$). Regarding **Case 1**, as mentioned, the main cost (if any) is determined by g, which is here assumed to be positive. □

The intuition behind **Proposition 1**, particularly regarding **Case 2**, is straightforward. Due to the uncertainty in t_{next} the homeowner who sells his property, cannot perfectly match t_2 with t_{next} at point t_1 and, as such, faces expected costs from this mismatch, either in terms of double mortgage costs or short-term rental costs. This is on top of the opportunity cost in terms of g the homeowner always faces (also in **Case 1**) under normal market conditions.

An Additional Discussion about Booms and Busts and the Time-On-Market

During booms some key parameters of the model are different than during busts. As mentioned, the bargaining parameter β is most likely higher during booms than during busts (i.e., a seller's market). That is, the seller gets more compensation from the buyer for the expected costs related to a longer TTC. Also, the opportunity costs in terms of capital appreciation g, the daily mortgage rate m, and short-term rents r are higher during booms.

It is also useful to think what this implies for **Case 1** versus **Case 2**, something we do not do in the main text of this paper. In **Case 1**, the additional costs are mainly driven by g, so we would expect that during a boom the effect of TTC is larger in this case. In **Case 2**, the first-order derivative in Eq. (B.1) is dominated by g and m when $t_2 >> 0$. Moreover, an additional argument that is not explored in the main text is that during a boom it is more likely to be in **Case 1** where t_{next} is already known and the incentives of the homeowner are mostly driven by the capital appreciation g (e.g., see Moen et al., 2021).

Finally, the paper does not elaborate on the relationship between TOM and TTC much. In particular, TOM is assumed to be known information at t_1. That does, however, not imply that TTC and TOM are not correlated. They might well be (for example due to some unobserved factors that affect both). We simply do not theoretically model this relationship explicitly, but it does suggest that it will be important to capture such interdependencies in our empirical framework. In particular, it is well appreciated that TOM is lower during booms. Instead, we would expect that TTC is higher during booms as, among others, the bargaining power of the seller is higher. Our analysis in Appendix C that also includes the buyer's cost function suggests that TTC is indeed expected to increase during booms.[17]

[17] Another example may be when you already bought another home before you put your current home on

Appendix C. Symmetric Bargaining Equilibrium

Appendix C.1. The Buyer's Cost Function

So far we have assumed that the buyer's cost function is fixed, $C^B = F$, and the compensation of the seller's costs is driving the effect on house prices. In this appendix, we relax this assumption, which also allows us to explore the optimal TTC in more detail. Consider a buyer who has a former house, and he will sell it to buy the house of the seller. Here t_n denotes the delivery date of buyer's former house. The ordering of t_2 and t_n matters.

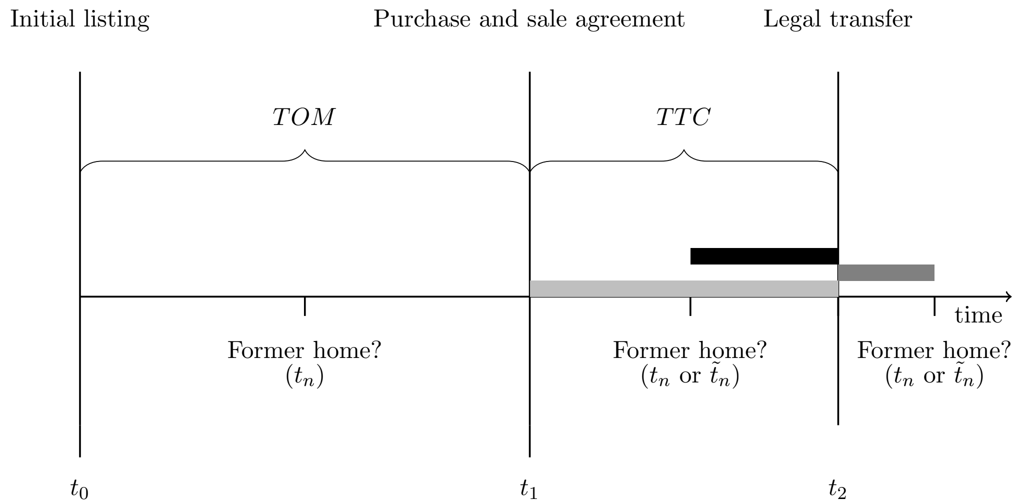


FIGURE C.6 – THE TRANSACTION PROCESS: TIME-ON-MARKET AND TIME-TO-CLOSE.

This figure shows the transaction process of buying a house from the perspective of the buyer at time t_1, the formal buying date (signing of the purchase and sale agreement). At this time the buyer and seller set t_2, the legal transfer date, and the transaction price of the house. The figure also shows the sell date of the former house, t_n. For simplicity, we only show the legal transfer date of the former house, because it determines whether the homeowner has to deal with the additional costs in terms of the opportunity costs of price depreciation of the current home (light grey bar), double mortgage costs (dark grey bar), or short-term rental costs (black bar). The date the homeowner can formally leave his former house, t_n, can be known at t_1 or not, which is indicated by the tilde.

In the same context as with the seller's cost function, we consider two cases with respect to t_n: **Case 1**, t_n is known to the home purchaser at t_1 and **Case 2**, t_n is not yet known

the market. In this case, it might well be that the relevant choice is based on TOM plus TTC. Also, as soon as TOM is relatively large your bargaining power might decrease (also see Harding et al., 2003) and in that case it might become more difficult to get a higher compensation for TTC. So there are multiple ways in which TOM and TTC can be related.

at t_1. In **Case 1**, the buyer cost function C^B is:

$$C^B = -gt_2 + Rt_2, \quad FTB \tag{C.1}$$

$$C^B = -gt_2 + m(t_n - t_2), \quad t_2 \leq t_n \tag{C.2}$$

$$C^B = -gt_2 + r(t_2 - t_n), \quad t_2 > t_n \tag{C.3}$$

where R is the long-term daily rent rate which is only relevant in case the buyer is living currently in a rental house (first-time buyer, FTB). Next, to the opportunity cost of price appreciation $-g * t_2$, a non-first time buyer faces in case of $t_2 \leq t_n$ a double mortgage cost $(t_n - t_2) * m$ at a daily rate of m and if $t_2 > t_n$ a short-term rental cost $(t_2 - t_n) * r$, where r is the daily rate. Taking the first derivative of C^B w.r.t. t_2 gives

$$\frac{\partial C^B}{\partial t_2} = R - g > 0, \quad \text{FTB} \tag{C.4}$$

$$\frac{\partial C^B}{\partial t_2} = -(g + m) < 0, \quad t_2 \leq t_n \tag{C.5}$$

$$\frac{\partial C^B}{\partial t_2} = r - g > 0, \quad t_2 > t_n \tag{C.6}$$

In **Case 1**, TTC has a negative effect on sale prices only if the buyer holds two properties at the same time (i.e., $t_2 \leq t_n$), otherwise its effect is positive. Also, the buyer would like to set $t_2 = t_n$ to obtain a minimum cost of $-gt_2$.

More interestingly is **Case 2**, where t_n is not yet known to the buyer at t_1. An illustration is provided in Figure C.6. Similarly to the seller side, let $\tilde{t}_n \sim \exp(\lambda)$ determine the probability that a non-first-time buyer sells his former house before the delivery of the house he has just bought.[18] The buyer cost function is determined by t_n and t_2 as follows:

$$\begin{aligned} C^B(t_2; g, m, r, \lambda) &= \underbrace{\int_0^{t_2} f_{\tilde{t}_n}(t)\,(-gt_2 + r(t_2 - t))\,dt}_{\tilde{t}_n < t_2} \\ &+ \underbrace{\int_{t_2}^{\infty} f_{\tilde{t}_n}(t)\,(-gt_2 + m(t - t_2))\,dt}_{\tilde{t}_n > t_2} \\ &= -\frac{r}{\lambda} + (r-g)t_2 + \frac{m+r}{\lambda}e^{-\lambda t_2}. \end{aligned} \tag{C.7}$$

This equation resembles that of the seller, however, price appreciation is beneficial for the buyer the longer the TTC (i.e. negative sign on g) and the higher the TTC, the more likely it is the buyer has to pay for rental costs as he might have already sold his former house.

Taking the first derivative of the buyer cost function w.r.t. t_2 and equating it to zero gives the minimum (optimal) cost point for the buyer, C_B^*, which is at the following TTC:

$$TTC^B = \frac{1}{\lambda}\ln(\frac{m+r}{r-g}). \tag{C.8}$$

Similarly, based on Eq. (3), the minimum of the cost function for the seller, C_S^*, is

$$TTC^S = \frac{1}{\lambda}\ln(\frac{m+r}{m+g}). \tag{C.9}$$

Although the seller would like to have the TTC at its own minimum cost, the bargaining solution also factors in the cost of the buyer. That is, the overall cost, C, is then defined as

$$\begin{aligned} C &= \beta C^S - (1-\beta)C^B \\ &= \frac{(r-m)}{2\lambda} + (g + \frac{m-r}{2})t_2. \end{aligned} \tag{C.10}$$

If it is positive, the seller wants to be compensated by the buyer. If it is negative, the buyer

[18] Assuming this distribution function implies that there is a period that the buyer will hold two properties simultaneously.

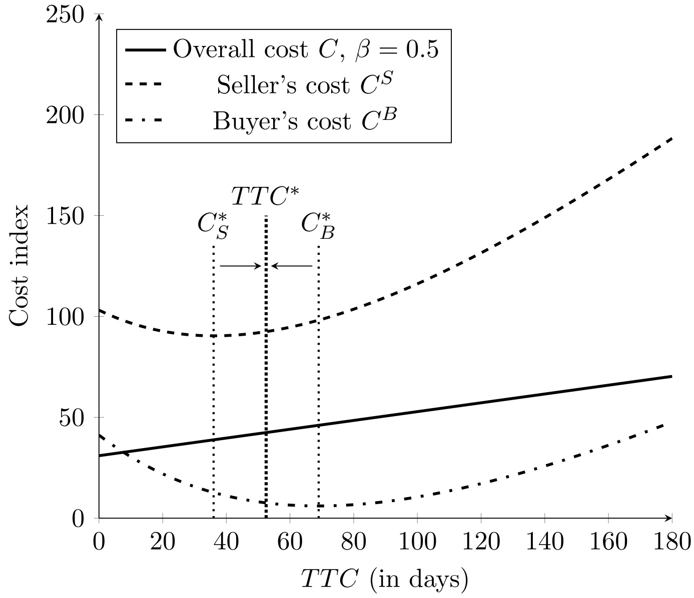


FIGURE C.7 – THE OPTIMAL TTC AND CALIBRATED COST FUNCTION FOR BOTH THE BUYER AND SELLER.

This figure plots the overall, seller, and buyer cost function as stated in Eq. (C.10), (3) and (C.7). Our baseline parameter values are $\lambda = 1/73$, $g = 0.04$, $m = 0.035$, $r = 0.09$. Note that g, m, and r are annual figures and are converted to daily rates. We normalize the cost functions by the same scaling parameter as in the seller's cost function (see Figure 2). We assume symmetric bargaining power between the buyer and seller, $\beta = 0.5$.

compensates the seller. In case of a symmetric bargaining solution ($\beta = 0.5$) the optimal TTC lies somewhere in between that of the optimum for the buyer and that of the seller. A graphical illustration is given in Figure C.7. We take the same baseline parameters as before, $g = 0.04$, $m = 0.35$, $r = 0.09$, $\lambda = 1/73$ for both the seller's costs function and buyer's cost function. So we basically assume that they have similar expectations about the different cost components. According to the figure the seller's optimal cost lies at a TTC of 36 days and the buyer's optimal cost at 69 days. The optimal time-to-close, TTC^*, lies in between at 53 days. Regardless of the optimal TTC, it increases when TTC becomes larger, which is consistent with **Hypothesis 1**.

Appendix C.2. Boom, Busts, and Asymmetric Bargaining Solution

As mentioned, we have empirically evidence that TTC varies across booms and busts. We illustrate the optimal TTC in case of a bust in Figure C.8. During a bust the seller's cost

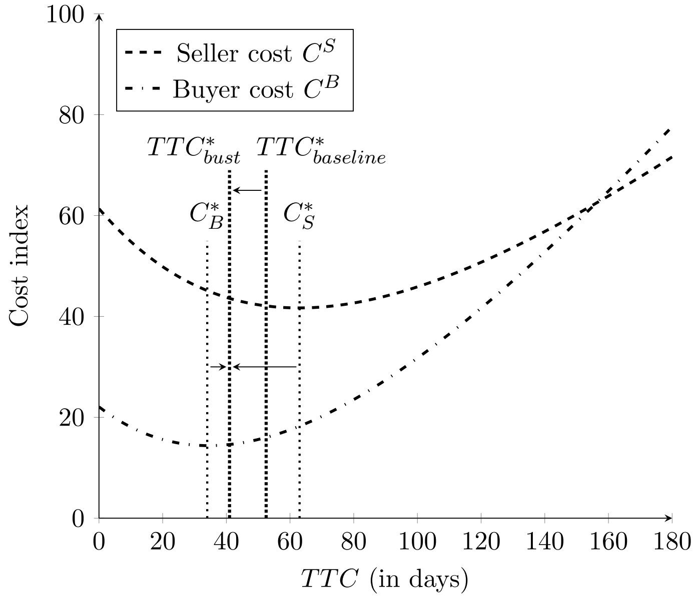


Figure C.8 – The optimal TTC during a bust.

This figure plots the seller's and buyer's cost function during a bust as well as the weighted average optimal TTC assuming a bargaining parameter for the seller of $\beta = 0.25$ and $g = 0.01$, $m = 0.02$, $r = 0.0566$, $\lambda = 1/68$. Note that g, m, and r are annual figures and are converted to daily rates. We normalize the cost functions by the same scaling parameter as in the seller's cost function (see Figure 2).

function *moves to the right* as λ becomes larger and g becomes much smaller, see Eq. (C.9) (see also Figure 2 in the main text). This would imply that purely in a partial equilibrium setting, the optimal TTC would increase from 36 days to 63 days during a bust. This is not consistent with the data. However, the buyer's cost function decreases from 69 to 34 days because of the relatively large decrease in g, see Eq. (C.8). Taking into consideration that the buyer's bargaining power increases and that of the seller decreases (i.e. we set $\beta = 0.25$), the optimal (weighted) TTC *goes down* in a bust, $TTC^*_{bust} < TTC^*_{baseline}$. Conversely, during a boom the optimal TTC is expected to increase. The seller of the property has more bargaining power to negotiate for a larger TTC which provides him with more flexibility to find and buy a new house.

Finally, in Figure C.9 we show the overall cost function during booms and busts. During booms the compensation is towards the seller and an increase in TTC has a stronger effect than in our baseline results. During a bust the level of compensation is negative and, in

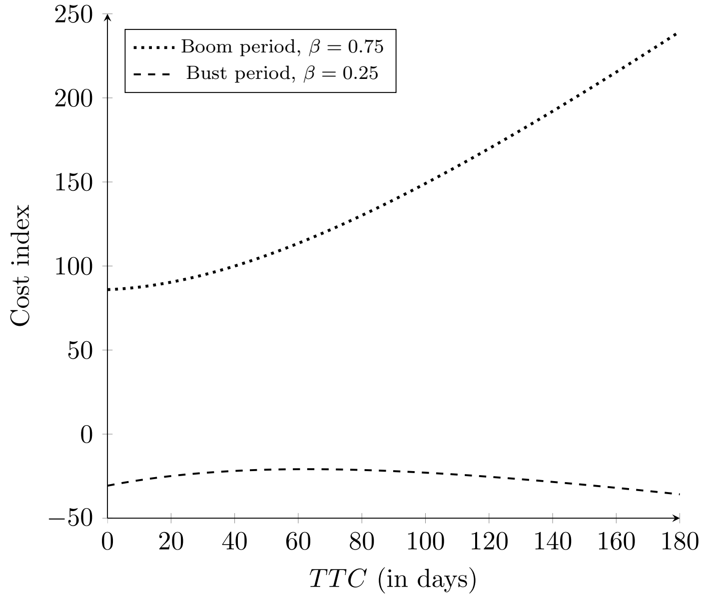


Figure C.9 – Calibrated overall cost function in booms and busts.

This figure plots the overall cost function $C = \beta C^S - (1 - \beta)C^B$ as stated in Eq. (C.10). In case of a boom we assume $\beta = 0.75$ and $\lambda = 1/77$, $g = 0.075$, $m = 0.05$, $r = 0.113$. For the bust period $\lambda = 1/68$, $g = 0.01$, $m = 0.02$, $r = 0.0566$ and $\beta = 0.25$. Note that g, m, and r are annual figures and are converted to daily rates. We normalize C by the same scaling parameter as in the seller's cost function (see Figure 2).

this particular example, relatively flat, suggesting that the sign of the TTC effect during busts might be mainly an empirical question. Yet, overall, these results suggest that during a boom the marginal effect of TTC on prices is expected to be higher than in the baseline or bust period, consistent with **Hypothesis 2**.[19]

[19]In this example, we assume $\beta = 0.75$ in a boom and $\beta = 0.25$ in a bust, but we find very similar results using any β above 0.5 in a boom and below 0.5 during a bust.

Appendix D. Additional Figure and Tables

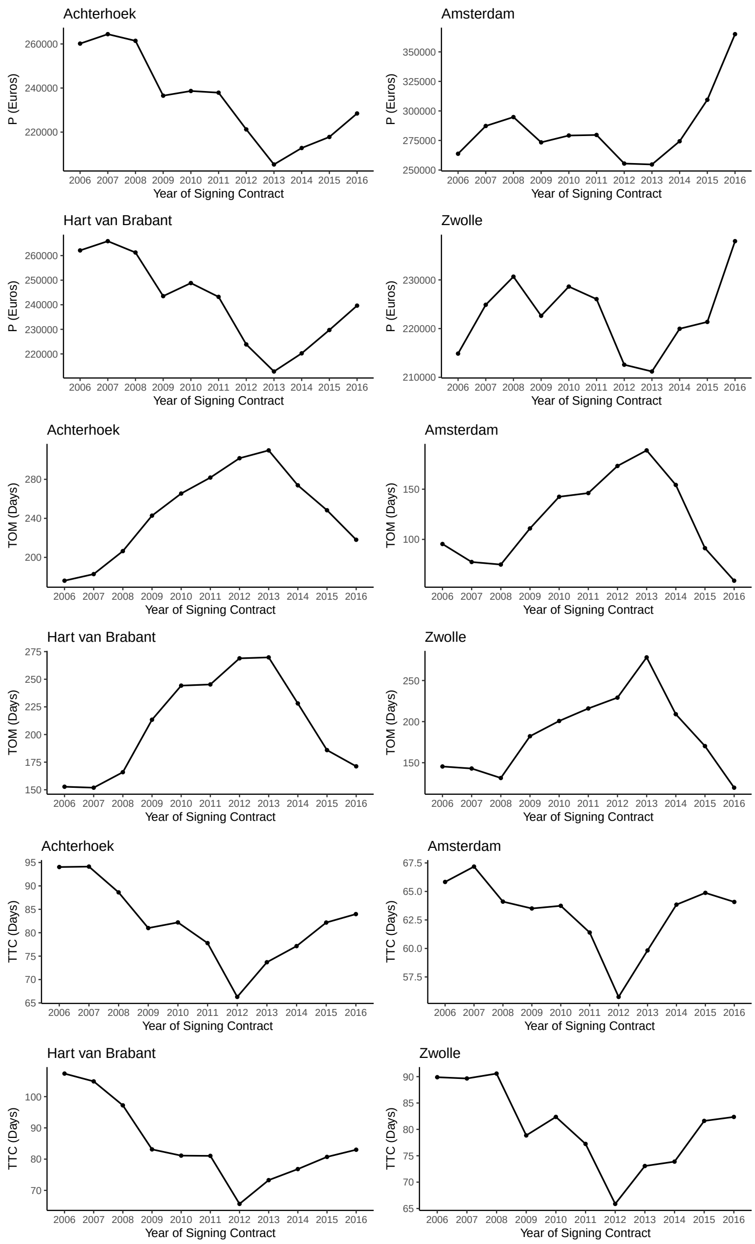


FIGURE D.1 – MEANS OF TRANSACTION PRICES, TOM AND TTC BY REGION.

Table D.1 – First-stage estimation results (SUR)

	Dependent Variable:					
	$\log TOM$	$\log TTC$	$\log P$	$\log TTC$	$\log P$	$\log TOM$
	(1)	(2)	(3)	(4)	(5)	(6)
IV: $\log P_{500m,t_1-90}$			0.3704^{***}	-0.2423^{***}	0.3686^{***}	-0.1288^{***}
			(0.0030)	(0.0125)	(0.0029)	(0.0167)
IV: $\log TOM_{500m,t_1-90}$	0.8398^{***}	-0.0271^{***}			-0.0311^{***}	0.8406^{***}
	(0.0051)	(0.0034)			(0.0009)	(0.0051)
IV: $\log TTC_{500m,t_1-90}$	-0.1092^{***}	0.9848^{***}	0.0002	1.0212^{***}		
	(0.0102)	(0.0080)	(0.0019)	(0.0082)		
Weak IVs F-test	$10{,}292^{***}$	$6{,}988^{***}$	$10{,}858^{***}$	$7{,}169^{***}$	$11{,}664^{***}$	$10{,}272^{***}$
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: $Year_{t_1}$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115,279	115,279	115,279	115,279	115,279	115,279
R^2	0.2951	0.1893	0.8905	0.1916	0.8918	0.2949
Residual Std. Error	1.0499	0.7476	0.1519	0.7465	0.1510	1.0501
F-statistic	168.9^{***}	94.2^{***}	$3{,}282^{***}$	95.6^{***}	$3{,}325^{***}$	168.8^{***}

Note: The spatio-temporal lagged instrumental variables are defined based on a spatial radius of 500 meters and a temporal lag length of 90 days. Columns 1 and 2 relate to the endogenous variables in the price equation, columns 3 and 4 to the ones in the TOM equation, and columns 5 and 6 to the ones in the TTC equation. Their corresponding fitted values are used in the system of equations, Eq. (6). All instrumental variables are highly significant, except for the spatio-temporal lagged TTC in the price model in column 3. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table D.2 – First-stage estimation results for market cycles and regions

	Bust		Boom	
	$\log TOM$	$\log TTC$	$\log TOM$	$\log TTC$
	(1)	(2)	(3)	(4)
IV: $\log TOM_{500m,t_1-90}$	0.9292***	−0.0192***	0.7900***	−0.0292***
	(0.0087)	(0.0057)	(0.0065)	(0.0043)
IV: $\log TTC_{500m,t_1-90}$	−0.0711***	1.0140***	−0.1355***	0.9688***
	(0.0157)	(0.0129)	(0.0137)	(0.0105)
Weak IVs F-test	3,761.15***	2,739.45***	5,980.22***	4,067.83***
Observations	41,456	41,456	73,823	73,823
R^2	0.2429	0.1787	0.2861	0.1922
Residual Std. Error	1.0650	0.7569	1.0400	0.7427
F-statistic	48.03***	32.57***	105.3***	62.5***
	Achterhoek		Amsterdam	
	$\log TOM$	$\log TTC$	$\log TOM$	$\log TTC$
	(5)	(6)	(7)	(8)
IV: $\log TOM_{500m,t_1-90}$	0.9180***	−0.0142***	0.7556***	−0.0376***
	(0.0082)	(0.0046)	(0.0096)	(0.0075)
IV: $\log TTC_{500m,t_1-90}$	−0.0677***	0.9718***	−0.0874***	1.0753***
	(0.0156)	(0.0115)	(0.0199)	(0.0211)
Weak IVs F-test	3,519.47***	3,810.80***	2,888.44***	1,794.01***
Observations	13,703	13,703	62,559	62,559
R^2	0.3958	0.4070	0.2257	0.0896
Residual Std. Error	0.9708	0.5389	1.0303	0.8592
F-statistic	74.77***	78.34***	168.55***	56.91***
	Hart van Brabant		Zwolle	
	$\log TOM$	$\log TTC$	$\log TOM$	$\log TTC$
	(9)	(10)	(11)	(12)
IV: $\log TOM_{500m,t_1-90}$	0.8908***	−0.0265***	0.8597***	−0.0012
	(0.0097)	(0.0053)	(0.0192)	(0.0107)
IV: $\log TTC_{500m,t_1-90}$	−0.1233***	0.9275***	−0.0777**	0.9478***
	(0.0193)	(0.0111)	(0.0388)	(0.0223)
Weak IVs F-test	2,895.42***	2,971.03***	803.71***	774.67***
Observations	28,449	28,449	10,568	10,568
R^2	0.2396	0.2601	0.2212	0.2192
Residual Std. Error	1.0963	0.5958	1.1051	0.6161
F-statistic	82.67***	92.24***	49.74***	49.16***

Note: The spatio-temporal lagged instrumental variables are defined based on a spatial radius of 500 meters and a temporal lag length of 90 days. All specifications include housing characteristics, zip code and year fixed effects. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table D.3 – Alternative spatio-temporal lagged instrumental variables

	1^{st} stage		2^{nd} stage	1^{st} stage		2^{nd} stage
	$\log TOM$ (1)	$\log TTC$ (2)	$\log P$ (3)	$\log TOM$ (4)	$\log TTC$ (5)	$\log P$ (6)
log(Floor area)	0.1228***	0.1848***	0.7703***	0.1745***	0.2320***	0.7744***
	(0.0107)	(0.0086)	(0.0024)	(0.0119)	(0.0093)	(0.0026)
log(Plot area)	−0.0277***	0.0156**	0.1103***	−0.0607***	0.0466***	0.1073***
	(0.0095)	(0.0076)	(0.0026)	(0.0116)	(0.0085)	(0.0027)
Maintenance: Average	0.1196***	0.1598***	0.1171***	0.1544***	0.2085***	0.1206***
	(0.0100)	(0.0074)	(0.0020)	(0.0112)	(0.0079)	(0.0022)
Maintenance: Above average	0.0495***	0.1533***	0.1885***	0.0678***	0.2131***	0.1890***
	(0.0124)	(0.0093)	(0.0023)	(0.0138)	(0.0100)	(0.0025)
Monument: Yes	−0.0210	−0.0049	0.0745***	−0.0443*	−0.0093	0.0735***
	(0.0236)	(0.0211)	(0.0051)	(0.0255)	(0.0227)	(0.0052)
Garden: Yes	−0.0458***	0.0200***	0.0499***	−0.0620***	0.0248***	0.0473***
	(0.0089)	(0.0074)	(0.0017)	(0.0098)	(0.0080)	(0.0018)
P: Garage and no carport	0.0129	−0.0127	−0.0124***	0.0231	−0.0392**	−0.0112**
	(0.0239)	(0.0135)	(0.0048)	(0.0297)	(0.0162)	(0.0051)
P: Garage for more cars	0.0688**	−0.0280*	0.0060	0.1247***	−0.0789***	0.0120*
	(0.0287)	(0.0170)	(0.0067)	(0.0366)	(0.0209)	(0.0070)
P: Carport and no garage	0.0482*	−0.0232	−0.0035	0.0887***	−0.0561***	−0.0002
	(0.0267)	(0.0164)	(0.0054)	(0.0329)	(0.0194)	(0.0057)
P: No parking	−0.0557**	−0.0225	−0.0708***	−0.0856***	−0.0526***	−0.0732***
	(0.0244)	(0.0141)	(0.0049)	(0.0302)	(0.0168)	(0.0052)
P: Parking spot	0.0291	−0.0401**	−0.0214***	0.0429	−0.0629***	−0.0189***
	(0.0276)	(0.0171)	(0.0055)	(0.0337)	(0.0199)	(0.0058)
Attic: Yes	−0.0429***	−0.0061	−0.0173***	−0.0554***	−0.0040	−0.0197***
	(0.0086)	(0.0051)	(0.0015)	(0.0101)	(0.0059)	(0.0016)
IV: $\log TOM_{250m,t_1-120}$	0.8586***	−0.0238***				
	(0.0035)	(0.0024)				
IV: $\log TTC_{250m,t_1-120}$	−0.0923***	0.9958***				
	(0.0062)	(0.0053)				
IV: $\log TOM_{1km,t_1-60}$				0.8441***	−0.0283***	
				(0.0067)	(0.0045)	
IV: $\log TTC_{1km,t_1-60}$				−0.1232***	0.9661***	
				(0.0137)	(0.0099)	
$\log TOM$			−0.0236***			−0.0575***
			(0.0009)			(0.0016)
$\log TTC$			0.0363***			0.0465***
			(0.0017)			(0.0032)
Constant	−0.0287	−1.1060***	9.1440***	−0.2976	−1.2020***	9.2150***
	(0.2367)	(0.2117)	(0.0386)	(0.2559)	(0.2232)	(0.0428)
Durbin-Wu-Hausman χ^2-test			247.4***			711.7***
t-test on endogeneity of $\log TOM$			12.95***			30.94***
t-test on endogeneity of $\log TTC$			16.51***			−13.49***
Weak IVs F-test for $\log TOM$			21,741.7***			6,183.7***
Weak IVs F-test for $\log TTC$			15,485.4***			3,907.9***
Fixed effects: House type	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Construction period	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Zip code	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Year_{t_1}	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115,279	115,279	115,279	115,279	115,279	115,279
R^2	0.3970	0.2837	0.8706	0.2497	0.1486	0.8571

Note: The table contains 2SLS estimation results for different sets of spatio-temporal lagged instrumental variables, using a radius of 250 and 1,000 meters and a temporal lag length of 60 and 120 days. Robust standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.