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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Does Housing Vintage Matter? Exploring the Historic City Center of Amsterdam*

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Abstract
A home is typically thought of as a bundle of land and structure. Land is supplied inelastically and is non-reproducible. Land values are therefore affected by a number of demand factors. Conceptually, structures are easily produced, and thus are supplied elastically. Under elastic supply, it is reasonable to assume that replacement cost should be equivalent to the value of the structure for new properties. Here, we examine how particular structure characteristics may introduce heterogeneity into these demand and supply relationships. In other words, how do structure vintages influence price dynamics. Older vintages are not easily reproducible leading to the value of an older vintage to potentially diverge from its replacement cost. To test our hypotheses, we employ a nonlinear model in a Bayesian structural time-series approach that explicitly disentangles structure and land values to identify vintage effects separately from physical deterioration and land values. We find large differences in price dynamics between four distinct vintages of Amsterdam old city center apartments. Between 1999 – 2016, new construction had an average return of 1.7%, with a standard deviation of 2.4%. On the other hand, properties build in the 19th century had an average return of 3.6% with a standard deviation of 6.1%, during the same period.

Keywords: land and structure prices, depreciation, new construction, structural time series.
JEL classifications: R21, R31, C11.

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1. Introduction and Background

Homes are typically conceptualized as a bundle of goods comprising a reproducible tangible structure and a non-reproducible plot of land. (See Davis and Heathcote, 2007; Davis and Palumbo, 2008; Bourassa et al., 2011; Chang and Chen, 2011; Francke and Van de Minne, 2017b, among others.) More specifically, housing structures can be easily produced and, thus, should be supplied elastically to the market. Under these assumptions, one would expect that the replacement cost of any existing housing structure to be tightly linked to the cost of building a similar structure which consists of the cost of building materials and wages associated with construction. By contrast, the land, location, and neighborhood amenities associated with an existing home often cannot be easily reproduced. The relatively inelastic supply of land implies that its market value should be largely determined by demand-side factors such as household income, interest rates, or speculative activity. Moreover, substantial differences in residential land values across metropolitan areas may inform pricing dynamics in ways not accounted for by variation in home values.

Extant literature identifies three sources of land supply constraints: regulatory, existing physical development, and topological constraints. Prior to research exploring geospatial aspects of supply constraints, much of the literature focused on the role of development and land use regulations (Glaeser and Gyourko, 2005; Quigley and Raphael, 2005; Mayer and Somerville, 2000). This literature finds that variation in regulation intensity and residents' preferences toward new construction can explain variation in housing prices and construction across metropolitan areas. In addition to regulation and preferences, development may be limited because a city has simply run out of developable land within its boundaries (Hilber and Vermeulen, 2016; Öztürk et al., 2018). Or, the land that is available cannot be built upon due to topological characteristics. In the United States context, Saiz (2010) provides robust evidence for the role of geographic constraints like bodies of water and steep slopes that reduce housing supply in addition to the reduction associated with regulation. Paciorek (2013) highlights the role of supply constraints in increasing housing price volatility. In particular, the elasticity of new housing supply in cities with high levels of regulation decreases as a result of increases in the process time of getting a permit. The cost of supplying new homes is thus pushed upward by the costs associated with the lag as a result of the process time related to getting a permit. Further, geographical constraints are found to induce lower levels of investment on average which limits the ability to increase supply during positive demand shocks.

This paper adds to the literature on housing supply constraints by focusing on the role of non-reproducibility of certain structures. We identify two major factors at play. First, housing built in different time periods contain differential bundles of (unobserved) goods (Wilhelmsson, 2008; Francke and Van de Minne, 2017b). Thus, a property belongs to a specific *vintage* if it was built in an era characterized by a distinct (architectural) style. Second, new supply of old vintages is not (easily) possible. We might expect these constraints to put upward pressure on desirable vintages and induce greater price volatility.[1] While previous literature acknowledges that properties might have a vintage discount or premium, most notably Coulson and McMillen (2008) and Francke and Van de Minne (2017b), our focus is on the differences in the *price dynamics* of properties belonging to separate vintages. To our knowledge, this has not been examined yet within the literature.

Using housing transaction data of over 3,700 sales over 1999 to 2016 within central Amsterdam, we construct vintage-specific house prices indices. The transaction data is supplemented with unit/building specific information on construction quality and maintenance level along with the size of building footprints. In estimating the indices, we rely on the assumption that vintage should only affect structure value and not land value. Further, as location is often correlated with vintage as housing is typically built in tracts, we limit our data to the historic city center of Amsterdam. In doing so, only transactions in neighborhoods that contain a large variation in all vintages are included within the analysis. This variation does not hold for neighborhoods farther out from the city center. Additional benefits of the Amsterdam dataset include strict local zoning restrictions and the relative homogeneity of the houses (size and property type). The former reduces the redevelopment option value of older properties, which is important for some of our model assumptions, and the latter removes noise from the data.

A number of issues arise during estimation. First, there may be a lag between when a new unit is built and when it is sold. In this case, depreciation may impact the structure value. This depreciation is akin to an age effect which is accounted for by controlling for maintenance level. Observing maintenance together with construction quality alleviates concerns regarding the endogenous relationship between the "real estate cycle", construction quality, and renovations. For example, during boom times, contractors may use higher quality materials and households may choose to renovate. While we observe all relevant characteristics in the combined set of data utilized, we are faced with a scarce data problem within some neighborhoods. This issue is addressed by assuming that land and structure prices follow a random walk as deviation from a common trend.

Four different vintages are considered: new construction, properties built between 1960 and 1980, properties built between 1900 and 1945, and properties built in the 19$^{\text{th}}$ century. Results indicate there are large differences in trends across these vintages. When comparing the risk/return profile of the different vintage indices, a clear pattern is found: the older the vintage, the higher the risk/return profile (where risk is measured as the standard deviation of the returns). The average annual (log) return of new construction is 1.7%, with a standard deviation of 2.4% between 1999–2016. By comparison, the oldest vintage (built in 1800-1899) appreciated annually at a rate of 3.6% with a standard deviation of 6.1%. As it is impossible to distinguish between the effect of vintage and functional obsolescence (Wilhelmsson, 2008; Francke and Van de Minne, 2017b), our estimates are likely on the conservative side. An example of functional obsolescence could be an unappealing floor plan or a kitchen without sufficient space to add modern-day appliances. Such characteristics are typically correlated with the construction year. Additionally, and in line with previous literature, we find that land has higher risk and return compared to the different structure returns. For example, the large price decreases during the crisis were largely reflected in land prices, and much less in structure prices.

As a robustness check, the model is re-run on multiple subsets of data. This method is a generalization of the technique discussed in Francke and Van de Minne (2017a). In this methodology, a "true" index is assumed to be found if a similar index to the full sample index is constructed. The results of the robustness check lend strong credibility to our methodology and general findings.

The paper contributes to the price index, housing vintage, and housing supply constraints literature in two ways. First, by proposing and identifying a new mechanism through which housing supply may be constrained. Second, by identifying a true vintage effect in price dynamics within the central city of Amsterdam. In general, our findings are important for mortgage lenders (MFIs) as acknowledging different risk/return relationships for different vintages can allow MFIs to better set interest rates. Further, knowledge of these relationships would allow banks to more accurately determine the value of homes when underwriting. Other actors interested in the value of properties can also benefit from our findings. For example, governments using automatic valuation models for tax or national accounting purposes.

Note that in this paper specific drivers of demand for specific vintages are not investigated. This is beyond the scope of the research presented here, but we acknowledge the potential for interesting future research.

The paper proceeds as follows. Section 2 present the model and Sections 3.1 and 3.2 present a background on Amsterdam housing vintages and a description of the data, respectively. Sections 4.1 and 4.2 provide the results and robustness checks. Finally, Section 5 presents the concluding remarks.

2. Model

2.1. Main model

Our identification strategy allows for the decomposition of house prices into land and structure components. Identification of vintage indices relies on this decomposition given the assumption that the construction vintage should only affect the structure value. The specification builds on work by Francke and Van de Minne (2017b) and is as follows:

$$\ln P_{ivtk} = \ln\big(S_{ivt} + L_{itk}\big) + \epsilon_{ivtk}, \tag{1}$$

$$S_{ivt} = \beta^S_{tv} \times \mathrm{SS}^{\gamma^S}_{ivt} \times \big(1 + \mathrm{cc}_t\big) \times \big(1 + x^S_{ivt}\alpha^S\big), \tag{2}$$

$$L_{ikt} = \beta^L_{kt} \times \mathrm{LS}^{\gamma^L}_{ikt} \times (1 + \phi_t) \times \big(1 + x^L_{ikt}\alpha^L\big). \tag{3}$$

Here i represents an individual property and t the time of sale. Subscript v indicates the vintage of the property and k identifies the submarket. In Equation (1) we assume, similarly to Francke and Van de Minne (2017b), that the value of a property (P) is the sum of the land (L) and structure (S) value. The model is highly non-linear in its parameters. The residuals ϵ are assumed to be t-distributed with estimated degrees of freedom ν, expectation zero and variance σ^2_ϵ.[2] Note that the vintages affect structure values, but not land values, whereas the submarkets only affect land value.

The main assumption of this model is that land and structure values do not interact. This is not always a valid assumption if the land is subject to (redevelopment) option value (Clapp et al., 2012). If there is option value, one needs to introduce a correction in Equation (1), see for example Clapp et al. (2012) and Geltner et al. (2017). However, the Netherlands is subject to heavy zoning restrictions, canceling out most - if not all - option value (Francke and Van de Minne, 2017b). This holds explicitly for the city center of Amsterdam.

We are faced with the issue of scarce data as the analysis is focused on specific neighborhoods within central Amsterdam. This issue becomes more severe when the indices are broken down by submarket and vintage. This is solved by assuming that both structure and land prices (β^S and β^L) follow a random walk:

$$\Delta\beta_{tv}^{S} \sim N\big(0, \sigma_{\beta^S}\big), \tag{4}$$

$$\Delta\beta_{tk}^{L} \sim N\big(0, \sigma_{\beta^L}\big), \tag{5}$$

where the estimated hyperparameters (σ) are separate for the structure and land. These types of structural time series models have been previously used in a (linear) hedonic framework in real estate (Francke and De Vos, 2000; Schwann, 1998).

2.2. Equation for structure value

Equation (2) models the value of the structure. The structure value is a function of its size, SS. The estimated parameter β_{vt}^{S} is interpreted as the price per square meter, per period (t) per vintage (v). Covariates and corresponding parameters specific to the structure value are given by $x_{ivt}^{S}\alpha^{S}$. Finally, we estimate a "scale" parameter, denoted by γ^{S}. For $\gamma^{S} = 1$, the structure value is proportional to the floor size, and for $\gamma^{S} < (>)1$, the structure value is less (more) than proportional to the floor size. The parameter γ^{S} is estimated from the data.

An identification issue arises because an intercept per time period for both land and structure value are required. To overcome this issue, we follow Diewert et al. (2015) and assert that new construction (or $v = 1$) should follow the constant-quality construction costs. New construction is elastically supplied to the market; hence, the value should be similar to the construction costs. The construction costs (cc) are transformed such that cc is zero at $t = 1$, and follows the accumulated percentage change in construction costs over time in Equation (2).

Parameter $\beta_{t=1,v=1}^{S}$ provides the square meter price of houses in period $t = 1$ for new construction, which is estimated from the data. Parameter $\beta_{t,v\neq 1}^{S}$ is the percentage premium of the structure value in vintages other than new construction for every period t. The premiums or discounts are compared to the product of the standard construction costs cc_t and base square meter price $\beta_{t=1,v=1}^{S} SS^{\gamma^{S}}$.

A newly constructed unit may be sold a few years after construction completion which may complicate the interpretation of the coefficients. Thus, it is important to correct the structure value of the newly constructed vintage for any physical deterioration accumulated in the interim period. The effect of physical depreciation over time is typically captured through the use of structure age dummy variables. However, when the goal of the specification is to identify the effect of vintage, the inclusion of age dummy variables creates an identification issue due to multicollinearity of age, vintage, and time (McKenzie, 2006; Coulson and McMillen, 2008). Alternatively, one can "force" age to follow a polynomial (Bokhari and Geltner, 2018a) or log transformation (Harding et al., 2007). Instead, we employ the level of maintenance to control for physical deterioration (Lusht, 2001), which is observed in the data.

Another caveat is that "the real estate cycle" and construction quality might be endogenous. During cycle peaks, contractors may use higher-quality materials and vice versa. This relationship holds across vintages when considering construction associated with maintenance and renovations. Indeed, older properties may receive high (low) quality renovation in booms (busts). This is a well known phenomenon within the maintenance literature (Knight and Sirmans, 1996). To counter this issue, variables representing the quality of the construction are used within the specification. These variables absorb the corresponding discounts and premia in $x_{ivt}^{S}\alpha^{S}$. Note that the dynamics are captured by the *constant quality* construction costs cc_t.[3] This is an added benefit of using (constant quality) construction costs in such a framework.

2.3. Equation for land value

Equation (3) gives the land value equation. Here, β^L_{kt} modeling the price per square meter of land (LS) per period and per submarket (k). γ^L and α^L, represent land specific variables. Both Equation (2) and Equation (3) are substituted into Equation (1).

For land prices, we allow for a common trend (ϕ_t) that affects all properties (hence no subscript k). The motivation for this method relies on the co-movement of granular real estate markets (Geltner et al., 2014; Francke et al., 2017; Geltner and Mei, 1995). This co-movement occurs in land prices as *asset-valuation* risk reflects changes over time in the capital market that cause changes in the opportunity cost of capital. On the other hand, there exist idiosyncratic price movements specific to granular market segments, largely reflecting the space markets. Thus, there should be an allowance for submarkets to deviate from the common land trend, which is indicated by β^L_{kt}.

The common land trend is modeled as an autoregressive time series, see Francke et al. (2017) for more details.[4] Thus, the common land trend ϕ_t is given by:

$$\Delta\phi_t \sim \left(\rho\Delta\phi_{t-1}, \frac{\sigma_\phi}{1-\rho^2}\right). \tag{6}$$

In one of the periods the common trend is required to be zero. As is typical, we fix the first period of common trend $\phi_{t=1} = 0$.[5] Note that the structure value also follows a common trend, namely the construction costs cc_t. The difference being that ϕ_t is estimated from the data and cc_t is an input.

2.4. Estimation

The full model is now given by measurement Equations (1), (2), (3), and state Equations (4), (5) and (6). Full Bayesian inference is applied to derive the posterior marginal distributions for the parameters of interest, mainly the index values for the different vintages. Largely uninformative priors are specified for the parameters: the autoregressive parameter, the variances, covariate parameters, and the degrees of freedom for the t-distribution. The autoregressive parameter of the common trend (ρ) is asummed to be between 0 and 1. In order to derive the marginal distributions of the parameters of interest, Markov Chain Monte Carlo (MCMC) techniques are used within the No-U-Turn-Sampler (NUTS) package developed by Hoffman and Gelman (2014). NUTS is a generalization of the Hamiltonian Monte Carlo (HMC) algorithm. The NUTS algorithm has been used previously in real estate literature by Francke et al. (2017) and Van Dijk et al. (2018). The techniques are implemented within R using the "Rstan" software package (Carpenter et al., 2016).

$2,500$ samples are performed with the first $1,250$ discarded when analyzing the chains during the "warm-up" stage in parallel over 5 chains ($5 \times 2,500 = 10,000$ samples in total). We provide different initial values for each variable in each chain and we do not thin the chains (see Link and Eaton, 2012, for reasons to avoid thinning). Convergence is evaluated based on the $\hat{R}$, the potential scale reduction statistic.[6] The Monte Carlo (MC) error is retained (Koehler et al., 2009) as well as the effective sample size.[7]

3. Data and Descriptives

3.1. Vintages and Submarkets

One of the issues plaguing the literature in the field of vintage versus location, is that real estate tends to be built in tracts. In North America, the urbanization pattern is fairly monocentric, with rings of vintages expanding outward from the central city over time (Geltner et al., 2014; Rolheiser, 2017). Whereas European cities are much older, denser, and smaller but still exhibit patterns of clustered vintages. This clustering adds complexitiy to the task of disentangling location effects from vintage effects. Our strategy to address this complexity is to only look at very granular locations with adequate variation in housing vintage. The historic city center of Amsterdam is therefore of interest to us as it has been well developed since the 17th century. The population during the 17th century was twice as large as it is now, which implies that properties built after the 17th century are replacements of existing structures. Other benefits of focusing on housing in the city of Amsterdam include (1) strict zoning restrictions reducing the redevelopment option value in property values (Clapp et al., 2012; Francke and Van de Minne, 2017b), and (2) the houses are very homogeneous. The city center building stock is over 95% apartments that are similar in size, and exclusively reside in 'building blocks'. See Table 1 for building characteristics.

We distinguish between the following vintages: (A) new construction (everything built after 1999), (B) properties built between 1960 – 1980, (C) properties built between 1900 – 1945, and (D) properties built between 1800 – 1899. This set of vintages was chosen as they are known as distinct vintages with relatively homogeneous architecture within each vintage.

In the 19th century, Amsterdam expanded explosively beyond the original canals, due to the ongoing industrialization. Note that industrialization did happen later compared to, for example, the UK and Belgium. During this modernization and subsequent loss of an "Amsterdam identity", architecture was characterized by looking back at older architectural styles. Multiple older styles (e.g. classicism, Gothic, Baroque, Dutch Renaissance) where mixed into one "neo-eclectic" style. At the end of the 19th century, "rationalism" became more popular. Rationalism dictated that only one style is to be used for specific property types: Public buildings were to be neo-classical, churches neo-Gothic, etc. Most of the housing in Amsterdam during that time was built in the "neo-Renaissance" style. This style prescribed horizontal lines that subdivided the facade in separate pieces. Figure 1a highlights this style where the buildings featured are included within the data analyzed here. During this era, housing was produced quickly and at minimal cost in order to accommodate the explosive growth of the city's population, especially in the second half of the 19th century. See Figure 2 for the population of Amsterdam between 1825 and 2012.

At the turn of 19th century, more modern styles were popularized, partly in reaction to the "traditionalism" of the previous century. Especially the so-called "Amsterdam school" had a big influence. It is sometimes compared to "Jugendstil" or "art-deco", mainly due to similar brick-laying techniques. Homes of this era are valued for their distinct brick architecture. Most studies on housing prices in the Netherlands find the largest premiums for properties built during this era and even for new construction that copied this style (Francke and Van de Minne, 2017b; Buitelaar and Schilder, 2017). Arguably the most expensive neighborhood in Amsterdam, "Zuid" (South), consists of properties only built during the 1920s and 1930s in the Amsterdam school style. Given the high correlation with location and the 1900 – 1945 (C) vintage in this neighborhood, disentangling these two effects is not possible and thus we omit this area from subsequent analysis. See Figure 1b for an example of a property from thus vintage.

(a) 19th century.

(b) 1900–1945.

(c) 1960-1980.

(d) New Construction.

Figure 1: Examples the different vintages in one street, the properties are not necessarily included in the transaction data. The properties are on the Lijnbaansgracht, within 100 meters of each other. Source: own material.

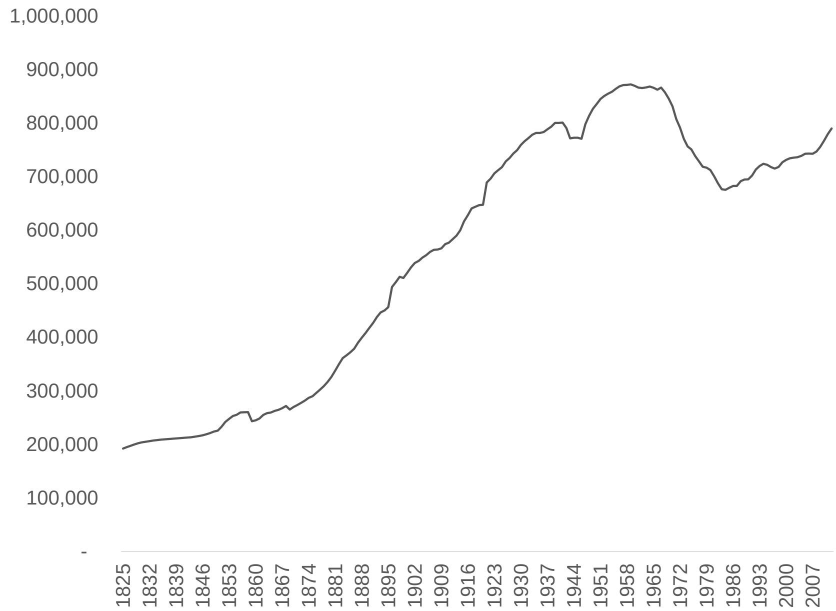


Figure 2: Population growth of Amsterdam, taken from Dröes and Van de Minne (2015).

Compared to the previously mentioned vintages, properties built during 1960 to 1980 do not have a dominant architectural style. Still, it is interesting to compare this vintage to older ones. Further, Francke and Van de Minne (2017b) and Van Dijk and Francke (2018) find that this vintage is associated with the highest price discount for different parts of the Netherlands. This period was also synonymous with a decline in urban population (Figure 2). See Figure 1c for an example of a property of this vintage in the data.

As mentioned, the focus of this study is on the city center of Amsterdam. Some neighborhoods within the city are omitted if there is not enough variations across vintages. Figure 3 provides the geographical distribution of vintages in our sample. Even though most properties are built before 1945 (see Section 3.2 as well), there is a good mix of vintages over the four locations considered. A stylized example of mix of vintages within one neighborhood is given in Figure 1. These four different properties are within 100 meter of each other in one street.

3.2. Data Description

Our sample consists of 3,763 housing transactions in the city center of Amsterdam between 1999 and 2016. These data were provided by the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM). Roughly 70% of all real estate brokers in the Netherlands are affiliated with the NVM and the data contain about 70% – 75% of all housing transactions (Van Dijk and Francke, 2018). Amsterdam is known for having ground leases. However, most of these lease-types remain outside the city center as this system was only implemented in the 19$^{\text{th}}$ century. The few leaseholds in the data have been omitted. Approximately 10% of the observed transactions are for newly constructed houses. The 1960 – 1980 vintage also contributes to approximately 10% of the transactions. The 1900 – 1930 and the 1800 – 1899 vintages each represent 40% of the transactions. Descriptive statistics per vintage are given in Table 1, where variables are subdivided by structure and land components where applicable.

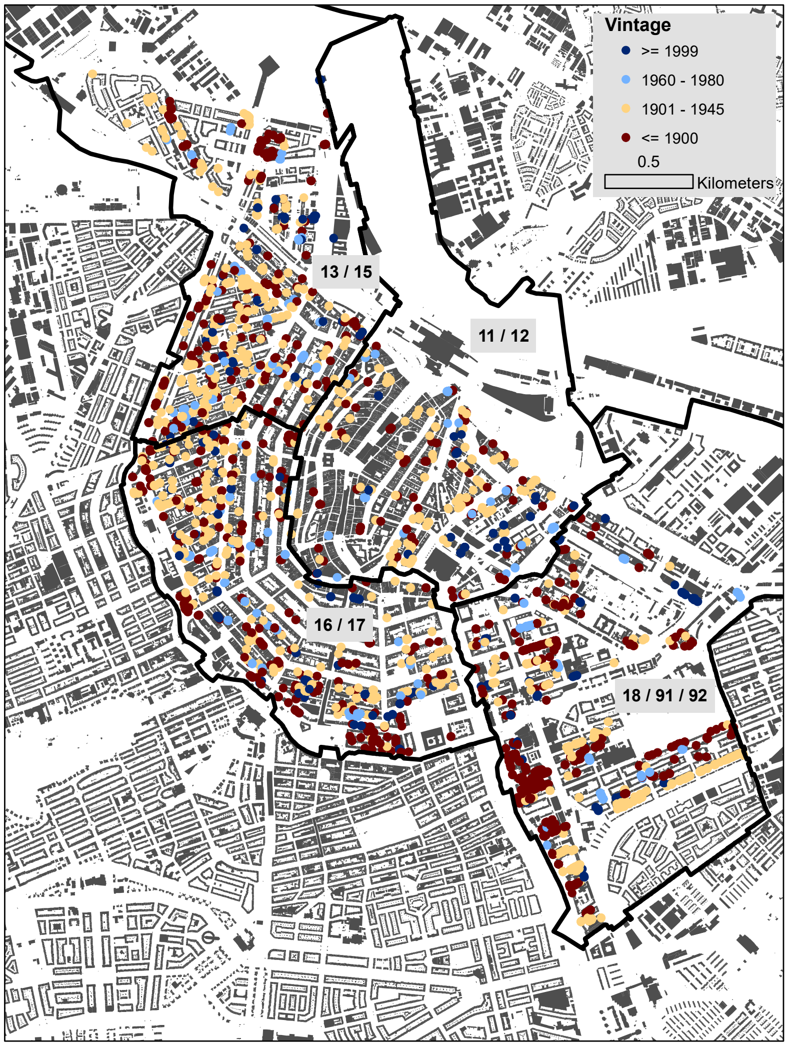


Figure 3: Location of properties. The numbers represent the 4-digit zip-codes.

On average, new construction results in the highest transaction prices. This is unsurprising as properties deteriorate with age (Wilhelmsson, 2008; Coulson and McMillen, 2008; Bokhari and Geltner, 2018b). More surprising is that we observe a reverse order for the older vintages. The 1960-1980 vintage has on average the lowest transaction prices, and the 19th century vintage has the highest transaction prices on average, other than new construction. This is not so much caused by differences in structure sizes (which is minimal), but it can be partly explained by differences in maintenance and quality of construction. Both quality and maintenance are on a categorical scale from 0 (worst) to 2 (best). Quality and maintenance levels are assessed by the brokers associated with the NVM. The brokers are periodically trained in order to maintain professional standards (see Francke and Van de Minne, 2017b, for more information on this topic). Quality and maintenance categories enter the model as dummy variables.[8]

A main difference between the considered vintages is that almost half of the new construction

Table 1: Descriptive Statistics of Our Data per Vintage (means). All variables are dummies, unless indicated otherwise.

	New Construction	**1960-1980**	**1900-1945**	**1800-1899**
Price (x €1,000)	371.13	286.45	305.78	333.90
N. Obs.	345	400	1,656	1,362
Structure Variables				
Structure size (m^2)	83.96	75.16	76.35	84.99
Lift	0.420	0.302	0.063	0.063
Attic	0.000	0.018	0.029	0.021
Maintenance	1.658	1.105	1.226	1.302
Quality	1.383	1.055	1.185	1.198
Land Variables				
Footprint size (m^2)	27.07	24.30	26.30	25.99
Yard	0.203	0.188	0.207	0.217
zip-code 11/12	0.133	0.158	0.121	0.077
zip-code 13/15	0.238	0.265	0.300	0.206
zip-code 16/17	0.423	0.300	0.301	0.247
zip-code 91/92	0.206	0.278	0.278	0.471

and one-third of 1960–1980 properties come with an elevator. In contrast, this is only the case for 5% of the older vintages. On average, an attic is observed in only 2% of the transactions.

Data on the footprint size was retrieved from the Land Registry (Kadaster in Dutch). Subsequently, the footprint for individual properties is computed by multiplying the share of individual structure size to total structure size with the footprint of the total structure. Unsurprisingly, the differences are relatively small. The average footprint per property is approximately 26m^2. A garden is observed in approximately 1 out of 5 transactions, which enters as a dummy variable in the land equation.

Four land price trends are estimated based on: (1) zip-codes 11 and 12, (2) zip-codes 13 and 15, (3) zip-codes 16 and 17 and (4) zip-codes 91 and 92. The location of the zip-codes is provided in Figure 3. The distribution of the vintages over the locations is relatively even. In all cases, the least number of observations per vintage are in the zip-codes 11/12, which is the oldest part of the city and is relatively small.

Finally, a construction cost index is needed that will be representative of the sample considered. Data for the index is provided by "Bouwkostenkompas", which tracks over a 1,000 key figures on construction costs and calculates a construction cost index for different reference categories. The construction cost index of the province in which Amsterdam is situated (North Holland) for apartments that are in buildings with less than 12 stories is used in this study. The construction cost index should capture the price change of new construction, as long as corrections are made for any accumulation in depreciation due to time of sale lag.

4. Results

4.1. Main Findings; Does Vintage Matter?

Figure 4a displays the price indices for the four different vintages. It is immediately clear that the evolution of square meter structure prices varies substantially between 1999 – 2016. Older vintages are valued almost 20% less at the beginning of the sample. At the end of the sample, the constant quality price per square meter is approximately 15% higher for these vintages.

The differences in price dynamics are also visible in Table 2, where the average return and corresponding risk (measured by the standard deviation of the returns) is presented. Older properties enjoy higher price growth, but this growth is accompanied by greater risk. The 1960–1980 vintage exhibits odd dynamics which may be a result of mis-pricing risk for this particular vintage as the return is relatively low but the risk is relatively high.[9] Still, the overall results indicate that older properties are indeed more supply-constrained, i.e. they have a higher risk/return profile (Glaeser et al., 2008; Saiz, 2010). However, there is an important nuance to keep in mind. In constant-quality terms, prices are the highest for the older properties, but older properties are maintained less and have a lower construction quality. Table 2 therefore provides statistics of the estimated structure values per square meter. Here we see that new construction still has the highest structure value on average. For a full distribution of structure values per square meter see Appendix A.1a.

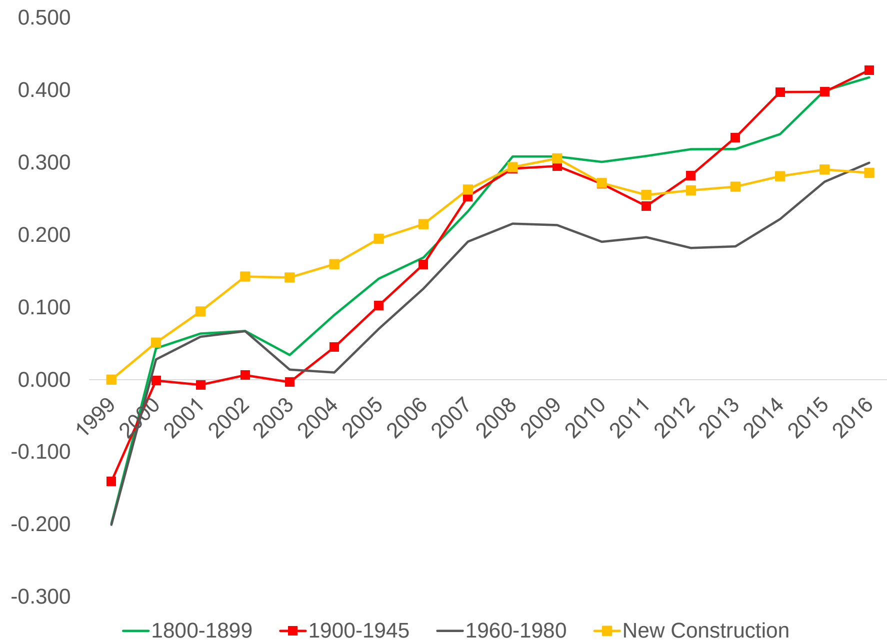
Note that the value of the new construction vintage should closely follow construction costs. The municipality of Amsterdam provides information on the average construction costs per square meter plus a rough range for new construction. The low and high values reported by the municipality are €1,972 and €2,997, with an average of €2,366, for a house of size 90 – 150m^2. Our estimates (€2,578 on average) are slightly higher than the estimates of Amsterdam. However, it should be noted that estimates provided by the municipality are for the complete municipality. It is reasonable to expect that construction within the city center (our sample) is slightly more costly. Further robustness checks can be found in Section 4.2.

It is also important to keep in mind that we do not explicitly separate the vintage effect from functional obsolescence. Indeed, both are highly correlated with construction year (Lusht, 2001; Wilhelmsson, 2008; Francke and Van de Minne, 2017b).

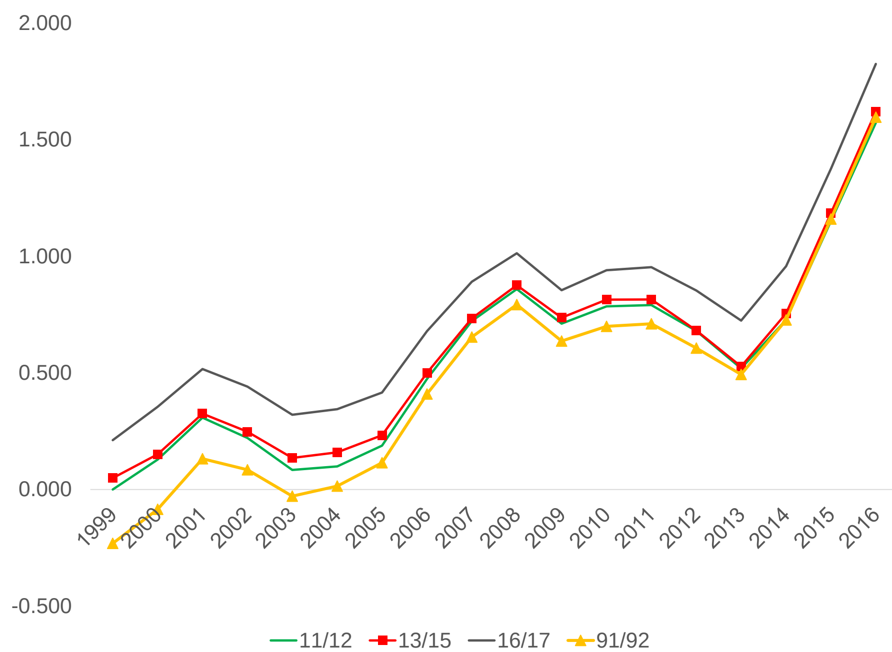
Figure 4b plots the land indices. As expected, the land prices follow each other closely. Interestingly, the land prices appear to converge at the end of the sample with the exception of the area known as "de Jordaan", or zip-codes 16/17, which still appears to have a 20% (constant-quality) premium. In line with theory, we find that the land values are far more volatile than structure values (Davis and Heathcote, 2007; Davis and Palumbo, 2008; Bourassa et al., 2011). A full distribution of predicted land values per square meter footprint is given in Appendix A.1b. The "land leverage" (Bourassa et al., 2011), or the total land value divided by the total property value, is also shown in this figure. The average land leverage is close to 50% in our sample. This number is comparable to the average used by the municipality of Amsterdam for the computation of the ground lease values.

Table 3 provides correlations between the annual returns of the vintage indices. For completeness, the correlation with the land indices is listed as well. Even though we observe only 18 years of data, it is evident that the correlation between the structure values is much larger than the correlation between the structure and land values.

Note that both land prices and structure values display a high run-up in 1999. It is well established that the 1990s were characterized by high house price growth due to the liberalization of the



(a) Vintage Indices.



(b) Land Indices.

Figure 4: Price indices of vintage and land values.

financial markets (Francke et al., 2014). The years 2000 – 2001 are known as a period of slowdown. During the crisis (2008 – 2012), land values declined by approximately 25%.[10] Structure values,

Table 2: Return and price statistics for four structure vintages.

	mean	**sd**	**min**	**max**
vintage returns				
New Construction	0.017	0.024	-0.034	0.051
1960-1980	0.029	0.060	-0.053	0.228
1900-1945	0.033	0.044	-0.031	0.139
1800-1899	0.036	0.061	-0.033	0.242
zip-code returns				
11/12	0.093	0.188	-0.160	0.423
13/15	0.092	0.187	-0.155	0.436
16/17	0.095	0.184	-0.158	0.450
91/92	0.108	0.185	-0.156	0.437
price per m2 structure				
New Construction	€2,578	€501	€1,530	€4,054
1960-1980	€1,949	€474	€1,026	€4,013
1900-1945	€2,111	€589	€872	€4,675
1800-1899	€2,256	€590	€813	€4,346

Table 3: Correlations of the returns of four structure vintages.

	New Construction	**1960-1980**	**1900-1945**	**1800-1899**
vintage: 1960-1980	0.587			
vintage: 1900-1945	0.619	0.754		
vintage: 1800-1899	0.554	0.931	0.746	
zip-code: 11/12	0.115	0.422	0.191	0.317
zip-code: 13/15	0.084	0.376	0.152	0.275
zip-code: 16/17	0.068	0.414	0.187	0.310
zip-code: 91/92	0.144	0.426	0.202	0.316

on the other hand, only declined for new construction and structures built during 1960–1980.

Finally, Table 4 gives the full posteriors of the parameters. Note that most parameters only affect either the structure value or the land value, and not both. This implies the interpretation is slightly different from normal linear hedonic models where the parameters are usually elasticities with respect to the entire property value.

The convergence of the model is adequate as the standard error of the mean (**se_mean**) is low compared to the mean and standard deviation (**sd**) of the posteriors. The effective sample size (**n_eff**) is almost always at least half of the total sample size, and the $\bar{R}$ (**Rhat**) is much lower than the predefined threshold value of 1.1 (Lunn et al., 2013) for all variables.

The root mean square error (RMSE) is 0.148 which is low with respect to values typically found in hedonic modeling literature. The degrees of freedom of the t-distribution is 10. As such, the residuals clearly follow a t-distribution. Note that with $\nu = 2$ ($\nu = +\inf$) the residuals would follow a Cauchy (Gaussian) distribution.

We find a value larger than 1 for the scale parameter on the structure size (γ^S). This is not surprising as there are only few large apartments (i.e. more than 100m^2) in the city center of Amsterdam. These apartments likely house the upper segment/high income households. For apartments of size 60m^2, 80m^2 and 100m^2, the largest proportion of the sample, the structure price per square meter for our reference property is estimated to be: €1,933, €2,218 and €2,467.

The effect of maintenance and construction quality is as expected. A normally maintained (M[1]) structure is valued 7% less compared to well maintained structures (M[2] is the omitted category). Poorly maintained structures have a 22% discount. A structure of "normal" quality (Q[1]) renders a 14% discount, and a cheaply build structure has a discount of more than 20% as compared to the reference category of "luxurious" (Q[2]). A lift increases value by 10%. The attic dummy gives a small negative parameter, note however that the credible interval includes zero (and is not significant in classical econometrics terminology).

For the land variables we find a very small scale parameter (γ^L). This implies that the size of the footprint has no effect on the price of the land and can simply be replaced by location dummy variables in future research. Obviously, a larger footprint can be used to construct larger structures; however, structure size is part of the structure equation. Thus, holding constant the structure size, the footprint size does not matter. This makes intuitive sense as the location gives you all the local amenities, the size of the land does not change that preference. Note that this is also the reason why the coefficient on the reference category for land ($\beta^L_{t=1,k=1}$) is relatively high. Having a yard increases the land value by 12%.

As expected, the variance parameter is higher for the land indices than structure indices (σ_{β^L}, σ_{β^S} respectively), (see Figure 4). The parameter on the autoregressive term in the common trend ϕ_t is 0.72. As expected, this reflects that land prices are be positively autocorrelated on a year-to-year basis.

4.2. Robustness

The main focus of this paper is to examine whether or not the structure values of different vintages evolved differently over the time period considered. Figure 4 clearly indicates that this is the case. Also, as mentioned in Section 4.1, most parameters estimates provide great confidence in the model. However, testing whether or not an index tracks the "true mean" of the market is not straightforward. Most metrics tell us something about the idiosyncratic dispersion between property prices (like noise and credible intervals), which is not of interest here (Guo et al., 2014; Francke et al., 2017). Previous papers have sampled the data without replacement and subsequently re-ran the model. See Francke and Van de Minne (2017a) and Geltner et al. (2017).

In general, if the index does not change erratically between the samples, the true mean is thought to be found. In other words, if the found index is the same, even on different subsets of properties in the data, than that must be the "true" index for that market. Here we generalize this principle. By re-sampling the data and re-estimating the model many times, the error mean and standard deviation of the samples per vintage per year can be calculated.

We re-sample 75% of our newer vintages, and 50% of the two older vintages. Additionally, we stratify per submarket in order to insure that the relative distribution remains the same over vintage and over locations. Thus, we have a unique, but overlapping, subset of properties in each sample. This re-sampling and re-estimation is repeated 100 times. Next the construction cost index is subtracted from the vintages. Note that there is no variation or error in the "new construction" vintage as it uses the construction cost index as input. The mean of the sample and the 1.96 times standard deviation per year can therefore be interpreted as credible intervals, compared to zero (or the new construction). The results for our three vintages are found in Figure 5.

Table 4: Full posteriors of parameters, and convergence statistics.

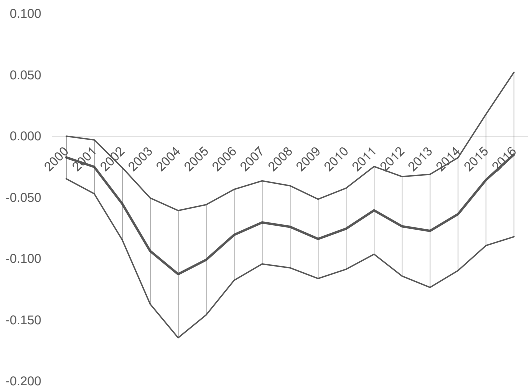
	mean	**se_mean**	**sd**	**lower (2.5%)**	**higher (97.5%)**	**n_eff**	**Rhat**
Measurement Eq.							
σ_ϵ	0.148	0.000	0.003	0.143	0.154	5,000	1.000
ν	10.020	0.022	1.586	7.482	13.689	5,000	1.000
Structure Value							
$\beta^S_{t=1,v=1}$	5.614	0.004	0.215	5.175	6.009	2,831	1.002
γ^S	1.477	0.001	0.043	1.397	1.564	2,851	1.002
M[1]	-0.071	0.000	0.010	-0.092	-0.051	5,000	1.000
M[0]	-0.224	0.000	0.018	-0.260	-0.188	5,000	1.001
Q[1]	-0.136	0.000	0.011	-0.157	-0.115	5,000	1.000
Q[0]	-0.204	0.000	0.022	-0.246	-0.160	5,000	1.000
Lift	0.096	0.000	0.015	0.066	0.126	5,000	1.000
Attic	-0.034	0.000	0.025	-0.082	0.014	5,000	1.000
σ_{β^S}	0.061	0.000	0.019	0.030	0.107	1,970	1.004
Land Value							
$\beta^L_{t=1,k=1}$	10.907	0.002	0.109	10.688	11.117	2,605	1.003
γ^L	0.104	0.000	0.017	0.070	0.138	5,000	1.000
Yard	0.115	0.000	0.017	0.082	0.149	5,000	1.000
σ_{β^L}	0.431	0.002	0.082	0.285	0.602	2,706	1.001
σ_ϕ	0.176	0.002	0.081	0.044	0.349	2,500	1.002
ρ	0.718	0.003	0.133	0.433	0.934	2,612	1.002

The **se_mean** gives the standard error of the mean of the posterior (over sampling), whereas the **sd** is the standard deviation of the posterior. **Lower** gives the 2.50% quantile of the posterior, and **higher** gives the 97.50% quantile of the posterior distribution. The effective sample size is denoted **n_eff** and the $\bar{R}$ is given by **Rhat**.
M is the maintenance and Q is the quality of the structure. Both are on a scale from 0 to 2, with 2 meaning the 'best' category. The left out categories are; Very well maintained (M[2]), luxurious structure (Q[2]), no lift, no attic and no yard.

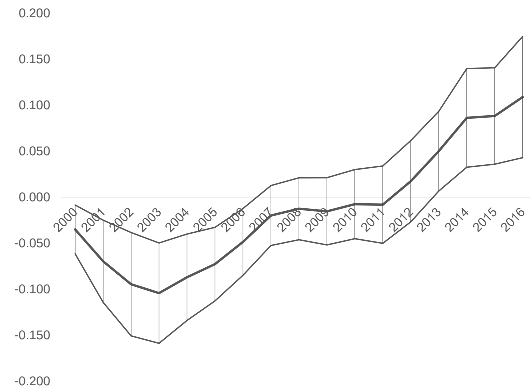
It is evident from Figure 5 that the structure value of the older vintages are significantly different from new construction. The constant-quality price of 1960–1980 vintages is generally lower than the price new construction. One exception is the end of the sample where there is no significant difference. The value of structures built between 1900 and 1945 was higher than the value of new construction only after the crisis (2012), whereas the oldest vintage was already worth more than new construction since 2008 (or just prior before the crisis hit the Netherlands). At the end of the sample, there is no significant difference between the value of the structures built between 1800 – 1899 and 1900 – 1945.

5. Concluding Remarks

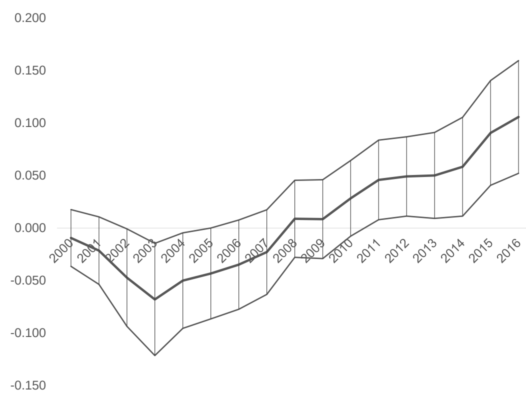
The value of a house is the sum of the value of the land and the value of the structure. It is typically assumed that structures can be reproduced and that land is non-reproducible. This implies that housing structures should be supplied relatively elastically to the market compared to land. The replacement cost of structures should be tightly linked to the costs of building materials and



(a) Vintage: 1960 – 1980.



(b) Vintage: 1900 – 1945.



(c) Vintage: 1800 – 1899.

Figure 5: Mean and 1.96 $\times$ standard errors after 100 samples.

wages in the construction industry. The relatively inelastic supply of land implies that land value is largely determined by demand-side factors (e.g. household income, interest rates, or speculative activity).

We, however, also claim that certain structures are non-reproducible and are in fact supply constrained as well. These supply constraints might induce upward pressure on prices and volatility of desirable structure vintages. Previous literature has recognized that desirable vintages have a price premium over less desirable vintages. We extend this literature by examining the price dynamics across different vintages.

Our model allows for the identification of time varying vintage effects, separate from physical deterioration, and land values. First, we model house prices as a composite of land and structure values. Structure values are affected solely by depreciation, construction quality, and vintage. We correct for deprecation by controlling for the maintenance levels. Correcting for quality alleviates concerns regarding the endogenous relationship between the "real estate cycle" on the one hand

and construction quality and renovations on the other hand. For example, it might be expected that during booms (busts) contractors may use higher (lower) quality materials and households may choose (not) to renovate.

Second, as housing is usually built in tracts, it is difficult to distinguish between land values and vintages. We therefore look at a very granular location that was already fully developed in the 17^{th} century: the old city center of Amsterdam. Thus, newer properties (constructed after the 17^{th} century) are replacements of older existing properties. This results in a unique mix of different vintages in a small geographic area.

Given the small geographical area, we are restricted to a small number of transactions. Therefore, we model the indices in a Bayesian structural time-series approach. More specifically, we assume land and structure prices follow a random walk as deviation from a common trend. The only exogenous input required is a construction index which allows for identification of the model.

We distinguish between 4 distinct vintages: new construction, properties built between 1960 – 1980, properties built between 1900 – 1945, and properties built between 1800 – 1899. Results indicate a large difference in price dynamics between these vintages. Between 1999 – 2016, new construction had an average return of 1.7%, with a corresponding standard deviation of 2.4%. On the other hand, properties built in the 19^{th} century had an average return of 3.6% with a standard deviation of 6.1%, during the same period.

As a robustness check, we re-sample and re-estimate the model 100 times. This provides credible intervals for our results. In general, our results seem to hold no matter which sub-sample is selected, providing confidence regarding the robustness of our results.

We further find that the crisis had little impact on structure values. Most of the price declines were absorbed by the land values. Additionally, we find a strong commonality between the vintage returns. The land and vintage returns are related to a lesser extent.

Our results have practical implications for institutions that are interested in the value of properties and its dynamics. For example, mortgage lenders can price risk more accurately if they make distinctions between vintages. Note that in this paper we only show how to model vintage prices. We do not explain what variables drive the differences in vintage price dynamics. We leave this to future research.

Acknowledgments

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Notes

[1]A positive demand shock for a given vintage will result in a price increase that cannot be dampened by a supply increase given the non-reproducibility (highly inelastic supply) of the structure. A similar shock for new construction will be met by an increase in supply which lowers the equilibrium price. The inability of supply to compensate for demand shocks leads to higher price volatility.

[2]Utilization of a t-distribution in real estate pricing models was introduced by Francke and Van de Minne (2017a).

[3]New construction follows the constant-quality construction costs by assumption.

[4]This autoregressive representation (or "inertia") is inherent to the price formation process in real estate and does not necessarily imply unexploited feasible arbitrage opportunities. More specifically: (1) unique, assets are traded about which participants have incomplete information on the effect of news on the value of any one specific asset; (2) some period of costly search must be incurred by both buyers and sellers, due to the heterogeneity of real estate; (3) trades are decentralized, i.e. market prices are the outcome of pairwise negotiations; and (4) transaction costs are high relative to asset values. (Case and Shiller, 1989; Quan and Quigley, 1991). In this paper we therefore explicitly specify the (log) periodic return in the state equation as an autoregressive (AR) process (Francke et al., 2017).

[5]Alternatively, one can fix one of the (sub)trend $\beta^L_{t=1,k}$ to zero. The value of the ϕ_t then represents the value of the left out category in the base period.

[6]The intuition behind the $\hat{R}$ is that the chains should look alike if the chains do indeed converge. The first step in calculating $\hat{R}$ is the computation of the Gelman-Rubin diagnostic, which calculates both the between-chain variance and the within-chain variance. The $\hat{R}$ is then the fraction between the two variances, see Gelman and Rubin (1992) and Brooks and Gelman (1998) for more details. A value of 1.1 is typically used as an upper limit.

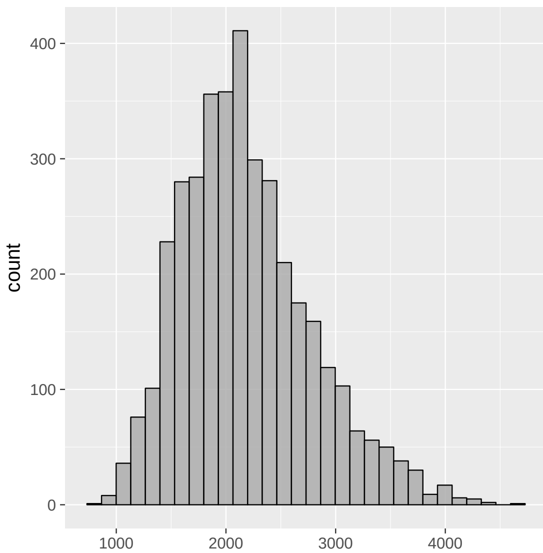
[7]The effective sample size (ESS) is computed as follows: ESS $= \frac{n}{1+2\sum_{k=1}^{\infty}\rho(k)}$, where n is the number of samples and $\rho(k)$ is the correlation at lag k. Each variable provides a different ESS, thus the difference between the effective sample size and the actual sample size gives a measure of how independent the draws are.

[8]There is some discussion in the literature whether or not the brokers fill in a "relative" or an "absolute" level of maintenance (Francke and Van de Minne, 2017b). In other words, is the maintenance of property in vintage B relative to *other* properties in vintage B, or to all vintages. The same question can be asked about the quality of the construction, Q. However, note that in our analysis it does not matter how it is officially defined, as long as our properties are "constant maintained" and "constant construction quality", analysis remains robust.

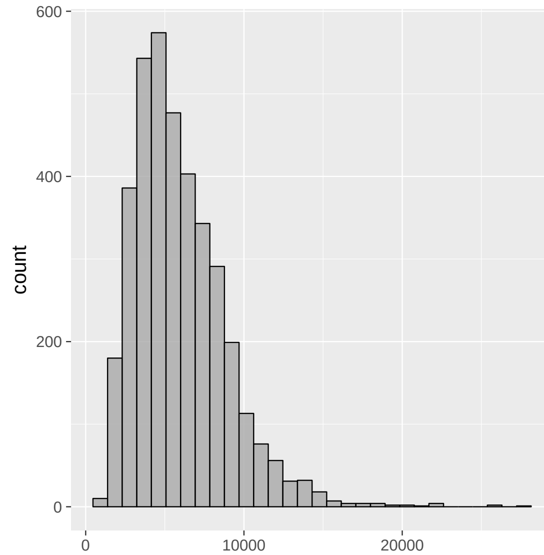
[9]Unfortunately we do not have data on the income side of the properties (imputed rent). Without this data it is impossible to truly test for mis-pricing (Geltner and van de Minne, 2017).

[10]The crisis hit the Netherlands relatively late compared to other countries. This is likely a result of the high Loan-to-Value ratios in the Netherlands. Due to negative equity, decreasing demand resulted in less liquidity and not necessarily lower house prices initially(Genesove and Mayer, 1997; De Wit et al., 2013; Van Dijk and Francke, 2018).

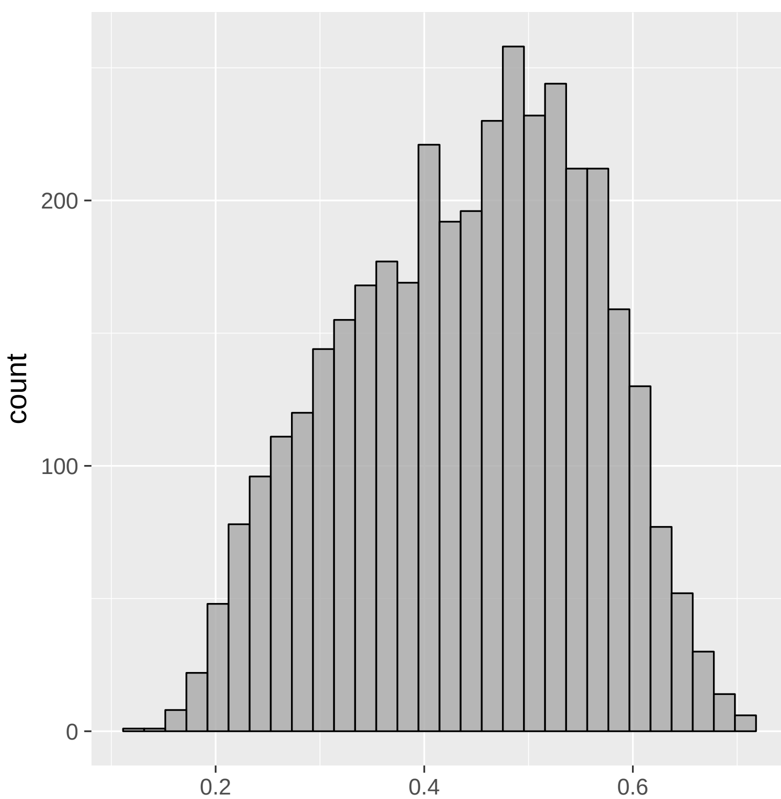
Appendix A. Histograms of the Land and Structure Values



(a) Histogram of structure value per m^2



(b) Histogram of land value per m^2



(c) Histogram of the 'Land Leverage'.

Figure Appendix A.1: Histograms of the square meter prices and the land leverage.

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