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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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The relation between supply constraints and house price dynamics in the Netherlands*

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Abstract

We analyze the effect of supply constraints on the dynamics of house prices in the Netherlands. In particular, we look at whether income shocks lead to stronger house price increases in regions characterized with higher supply constraints. We use a panel dataset that contains 316 municipalities over the years 1987-2016. Municipalities are divided in three equally sized groups according to the extent of supply constraints present in each municipality. Our results suggest that income shocks lead to significantly larger increases in house prices in municipalities that are relatively more supply constrained. This holds both in the short- and the long-term. The degree of mean reversion and persistence, however, do not seem to significantly differ between the three groups of municipalities.

Keywords: house prices, income shocks, supply constraints
JEL classifications: G120, R310.

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1. Introduction

After having sharply declined during the Great Financial Crisis, house prices in the Netherlands have been increasing strongly since 2014. There is substantial heterogeneity between regions, however. Nominal house prices in Amsterdam stood in 2018Q1 32% above their pre-crisis peak of 2008Q3, whereas in the more rural province of Friesland they were 8% below their pre-crisis peak. Due to the relevance of house price swings for macroeconomic stability and the existence of spillover effects between regions (Vansteenkiste, 2007; Teye & Ahelegbey, 2017), it is of great importance for policymakers to gain a good understanding of the heterogeneity in house price developments across regions and the drivers of this heterogeneity.

A typical feature of the Dutch housing market is that the price elasticity of housing supply is low, which is partly related to the relatively high population density (Caldera & Johansson, 2013). Moreover, the supply elasticity is generally lower in the major cities compared to the rest of the country (Michielsen et al., 2017). If housing supply inadequately adjusts to changes in housing demand, this might lead to house prices deviating from their equilibrium values for an extended period of time (Capozza, 2002). In the literature, a low supply elasticity is often linked to physical supply constraints related to geography (Saiz, 2010) or a rigid planning system (Hilber & Vermeulen, 2016). For the Netherlands, both sources of supply restrictions are relevant. In various, mostly urban areas, new construction is restricted because a considerable share of land is already developed (physical constraints). In addition, new housing supply is further hampered by a planning system that is fairly restrictive (Rouwendal & Vermeulen, 2007). In this paper, we look at supply constraints as a whole as we are not able to distinguish between physical and regulatory constraints due to lack of data on the rigidity of the planning system. However, physical and regulatory supply constraints are highly correlated in practice (Saiz, 2010).

This paper studies the effect of supply constraints on the dynamics of house prices in the Netherlands. In particular, the hypothesis is that a shock in real household income will have a stronger effect on house prices in municipalities with stronger supply constraints. Based on the methodology developed by Hilber & Vermeulen (2016), we create an index for the extent of supply constraints in a given region (i.e. municipality) by relating the amount of already developed land to total available developable land. Based on this variable, we divide the sample into three equally-sized groups of municipalities: municipalities with low, medium, and high supply constraints, labeled as “least developed”, “medium developed” and “most developed”, respectively. We then study the relation between house prices and income shocks, using a two-step Engle and Granger approach. Our results suggest that income shocks are associated with significantly larger increases in house prices in municipalities that face relatively strong supply constraints.

The rest of the paper is structured as follows. In section 2, we briefly discuss how the existing literature is related to our work. In section 3, we elaborate on our measure of supply constraints. Section 4 first describes the data and the methodology used in the empirical analysis, and then discusses the results. Section 5 concludes.

2. Related literature

Our work is closely related to a large body of literature that discusses the fundamental factors driving house prices (see for instance Capozza et al., 1989, 2002). Empirical studies find that real income, real interest rates and real construction costs consistently prove to be important determinants of long-run house prices (see among others Abraham & Hendershott, 1994). In addition, several studies consider a number of additional variables that appear to also significantly explain the equilibrium house prices such as household wealth, rental prices, population and the housing stock (see, for instance, Kranendonk et al., 2005).

It is often found that regions where housing supply is more restricted due to geographical and/or regulatory constraints exhibit different house price dynamics. These constraints tend to lower the elasticity of housing supply significantly, preventing new housing supply to exert downward pressure on prices (Green et al., 2005). Glaeser et al. (2008) show that areas with stronger supply constraints in the United States, e.g. San Francisco Bay Area, experienced a larger housing boom in the 1982-2007 period. Extending on this research, Huang & Tang (2012) find furthermore that these areas also experienced larger housing busts during the recent global financial crisis. This finding might seem counterintuitive as one might reason that limited construction during a boom phase could also result in a limited downward pressure during a bust period. However, as Huang and Tang argue, during a boom phase the adaptive expectations of those who aspire to buy a house lead to overshooting of prices in the more supply-constrained areas, exacerbating the busts that are due to follow. Heebøll & Anundsen (2016) argue further that besides adaptive expectations, the financial accelerator effect is also more pronounced in more restricted areas. As a result, increasing (decreasing) house prices lead to more (less) optimistic beliefs on future house prices and more (less) collateral to borrow against. Hilber & Vermeulen (2016) find that regulatory constraints induced by the UK planning system, significantly increased house prices and house price volatility in the most constrained areas in the 1974 - 2008 period. Finally, Capozza et al. (2002), the closest work to our paper, analyzes house price dynamics in various US metropolitan areas and find that areas that face stronger supply constraints also experience stronger serial correlation (i.e. persistence in house price growth) and slower mean reversion of prices (i.e. the speed of adjustment to the long-run equilibrium house price).

The goal of this paper is to study the interaction of supply constraints with house price dynamics in the Netherlands. A well-known measure of supply constraints is developed by Saiz (2010), who measures physical supply constraints in the United States by making use of elevation in the landscape. This measure, however, is not suitable for our study as the variation in elevation levels is very low in the Netherlands. Instead, we use the measure developed by Hilber & Vermeulen (2016), i.e. the share of already developed land of total developable land, which is discussed in more detail in Section 3. It is important to note that physical and regulatory supply constraints are highly correlated in practice (Saiz, 2010), and what we observe here as supply constraints is driven by both physical and regulatory constraints.

A few papers have studied the (heterogeneous) price dynamics of the Dutch housing market. Kranendonk et al. (2005) have estimated an error-correction model for the 1980-2003 period and found that house prices tend to adjust to the equilibrium price much more quickly when house prices are below their equilibrium value than when they are above. Galati et al. (2011) study the price dynamics in various Dutch housing markets and conclude that mean reversion is the lowest in the most urbanized areas. This finding seems to be in line with the findings of Capozza et al. (2002), assuming that more urbanized (i.e. more densely populated) areas are also more supply-constrained. However, in a somewhat more recent study Galati & Teppa (2017) come to a different conclusion and find that mean reversion is lowest in both the least and most urbanized segments of the Dutch housing market.

The contribution of our study to this literature is twofold. First, we employ a rich dataset that allows us to study the short- and long-run dynamics of house prices at a more granular level (municipality) than previous work on the Dutch housing market. Second, we add to the existing literature by studying the interaction between income shocks and housing supply constraints.

3. A measure for supply constraints in the Netherlands

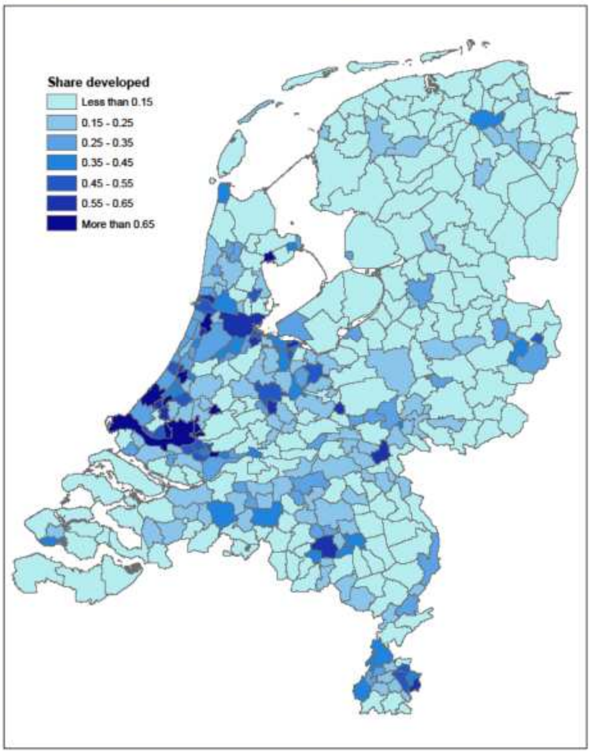
In order to determine the extent of supply constraints, we apply the methodology of Hilber & Vermeulen (2016) to the Netherlands. More specifically, we calculate the ratio of developed land to developable land. We use the Dutch land cover map (*Het Landelijk Grondgebruiksbestand Nederland*, LGN5) as data source. LGN5 is a 25x25m raster file that contains data on 39 different land uses based on satellite images and aerial photos from 2003 and 2004. The database is created and updated by Wageningen University. Although the classification of land uses in the Netherlands is somewhat different compared to that in the United Kingdom, we follow Hilber & Vermeulen (2016) as closely as possible and categorize the classifications into developed land, developable land and non-developable land. The classification between developable and non-developable is sometimes somewhat arbitrary, but new development in the developable category is arguably somewhat easier. Technically all land types, even water in the Netherlands (e.g. *De Flevopolder* was converted from water into land between 1950 and 1968), can be converted into developed land in the (very) long-run. Besides, the main driver behind the measure is the amount of developed land since share of non-developable land is usually rather small.

As developed land we classify the land uses ’urban developed’, ’suburban developed’, ’densely developed in forest’, ’roads and railroads’, and ’rural developed’. In developable land we include ’grass’, ’corn fields’, ’strawberry fields’, ’beet fields’, ’grain fields’, ’other fields’, ’greenhouse’, ’orchard’, ’bulb fields’, ’deciduous woodland’, coniferous woodland’, ’deciduous woodland in developed area’, ’coniferous woodland in developed area’, ’grass in developed area’, ’inland bare ground’, ’heath’, ’medium grassed heath’, ’strongly grassed heath’, ’peat moor’, ’peat moor woodland’, ’swamp’, ’reed vegetation’, ’forest in swamp’, ’peatland’, ’natural reserve’, and ’inland bare ground in natural reserve’. Finally, in non-developable land we include ’salt water’, ’sweet water’, ’saltmarsh’, ’costal bare ground’, ’open dune vegetation’, ’closed dune vegetation’, ’dune heath’, and ’open drift-sand’.

The share of developed land (termed as “share developed” below) is the amount of developed land divided by the total amount of developable land (already developed and potentially developable). As geographical borders, we use the municipal borders according to the municipal definition of 2017. The share developed land is calculated for a total of 388 municipalities and is included in Figure 1. As expected, we clearly observe that large cities like *Amsterdam, Rotterdam, The Hague,* and *Utrecht* are relatively densely developed compared to more rural areas around *Friesland* and

Groningen. The average share developed is 0.21, ranging from 0.03 (*Rozendaal*) to 0.75 (*Leiden*). The value of the four largest cities are relatively high: 0.60 (*Amsterdam*), 0.66 (*Rotterdam*), 0.67 (*The Hague*), and 0.50 (*Utrecht*). Note that this measure captures both regulatory constraints like zoning and physical constraints and should be viewed as a rough measure of the extent of supply constraints for a given municipality.

Figure 1: Measure for supply constraints (share developed land) for 388 municipalities in the Netherlands.



4. Income shocks and supply constraints

We estimate a panel error-correction model to determine the responses of house prices to income shocks. In regions with stronger supply constraints, supply is naturally expected to be less elastic. Therefore, we expect income shocks to have a bigger impact on house prices in these regions. To test for this, we first group the whole sample of municipalities into three groups on the basis of the variable share developed land that we calculated per municipality. We then run our analysis for each of these groups separately, allowing the income-price relationship to be heterogeneous across these three groups.

4.1 Data and methodology

For our dependent variable, we estimate a hedonic annual house price index at the municipality level using individual transaction data from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) between 1987 and 2016. In order to estimate the model for smaller municipalities with fewer transactions, we use the Hierarchical Trend Model of Francke & De Vos (2000) and Francke & Vos (2004). See Annex 7.1 for a more detailed description of the house price index estimation method.

Table 1: Variables and data sources

Variable	Variation	Source
Log real house prices	Municipal, year	NVM
Log real average disposable household income	Municipal, year	CBS
Unemployment rate	Municipal, year	CBS
Log population	Municipal, year	CBS
Log real construction cost index	Year	CBS
Consumer price index (CPI)	Year	CBS
Real mortgage rate	Year	DNB
LTV	Year	DNB
Share developed land	Municipal	LGN05

We are somewhat limited in our selection of explanatory variables as they should ideally exhibit both time- and cross-sectional variation. In line with the literature, we include household income, the unemployment rate, population, construction costs, the mortgage interest rate, and the loan-to-value ratio (LTV) in our analysis (Table 1). House prices, disposable household income, construction costs, and the mortgage rate are deflated by inflation (CPI). The sample period runs from 1987 to 2016. During our sample period several municipalities merged, which we account for by computing the weighted average for a merged municipality (weights based on population). For a more detailed description of this procedure see Burgers (2017). In total, we have complete data for 316 out of the 388 municipalities, determined by the availability of regional disposable household income.

Our main explanatory variable of interest is household income. We expect that an increase in income leads to an increase in house prices as this enables households to afford a more expensive house. We expect the unemployment rate to be negatively related to house prices since it reduces the number of people who can afford a house. Population should be positively related to house prices as the larger the number of people living in a region, the higher the demand for housing will be. Construction costs should be positively related to house prices as this determines the structure value of the house, which in turn is part of total house price. The latter is usually defined as sum of land and structure value (Francke & Van de Minne, 2017). The real mortgage interest rate is expected to have a negative relationship with house prices as debt financing becomes cheaper when interest fall, pushing up house prices.[1] Finally, we include the LTV of first-time buyers as a proxy for credit conditions (we assume that a higher LTV reflects looser credit standards), and expect it to be positively related to house prices. This variable is usually seen as exogenous to house prices, since first-time buyers are assumed to be credit constrained (Francke et al., 2015). For a more detailed description of this variable see Verbruggen et al. (2015). We purposefully do not employ the housing stock as an explanatory variable as it is directly related to the degree of supply constraints, which we account for by the variable share developed land. Including the housing stock would absorb the possibly heterogeneous relationship between household income and house prices.

As mentioned before, the data used to construct the variable share developed land come from the LGN05 data-file and are based on aerial photos taken in 2003 and 2004. Thus, we only have data for one period in time. Nevertheless, we expect that the level of the share developed remains fairly constant over time. We divide our sample into three equally-sized groups (in terms of the number of municipalities) according to the variable share developed land, i.e. municipalities that are the *least*- (value lower than 0.14), *medium*- (value between 0.14-0.25), and the *most* (value higher than 0.25) developed.

We are interested in both the long- and short-run effects of income shocks on house prices. Therefore, our framework should model both the long-run underlying equilibrium relationship and short-run deviations. In the housing market, these are usually modelled in an error-correction (ECM) framework (Francke et al., 2009). Given the fact that we are especially interested in heterogeneous cross-sectional effects, we estimate the model with panel data. In an ECM, the long-run equation estimates the underlying equilibrium relationship in levels. In the short-run, deviations from this long-run equilibrium are modeled. Important components in short-run equation are the speed of adjustment (i.e. the error-correction term, ECT) and the degree of serial correlation.

[1] Between 1987 and 2002, the real mortgage interest rate is the average 5-year mortgage rate for new mortgages between and between 2003 and 2016 the rate is calculated as the average of the average 1 to 5-year rate and average 5 to 10-year rate on new mortgages.

We employ a two-step Engle-Granger approach by first estimating the long-run equilibrium equation (1) and subsequently the short-run error-correction equation (2):

$$h_{it}^{*} = x_{it}\beta_{0,j} + z_t\beta_{1,j} + d_i, \tag{1}$$

$$\Delta h_{it} = \alpha_j \Delta h_{it-1} + \delta_j(h_{it-1} - h_{it-1}^{*}) + \Delta x_{it}\gamma_{0,j} + \Delta z_t \gamma_{1,j} + d_i + \theta_{0,j}\overline{\Delta h_t} + \theta_{1,j}\overline{\Delta h_{t-1}} + \theta_{2,j}\overline{(h_{t-1} - h_{t-1}^{*})} + \theta_{3,j}\overline{\Delta x_t} + \varepsilon_{it}. \tag{2}$$

Here subscript i denotes the municipality for $i \in \{1, N\}$, t the year for $t \in \{1, T\}$, and j the group based on the share developed land for $j \in \{least, medium, most\}$. The dependent variable, h, is log house prices. Further, x is a 1xK row-vector of house price determinants that vary over time and municipality, β_j^0 and γ_j^0 are the Kx1 corresponding long- and short-run coefficient vectors, respectively. Additionally, z is a 1xL row-vector of house price determinants that vary over time only, β_j^1 and γ_j^1 are the Lx1 corresponding long- and short-run coefficient vectors, respectively.

Next, d is a municipal-specific intercept, α is the coefficient on lagged house price changes that represent the degree of serial correlation, and δ measures the speed of adjustment of house prices to long-run values. The *barred* variables include the cross-sectional averages of the variables that vary over the cross-section and time and θ are the respective loadings.[2] Note that all coefficients are allowed to be different across the three share-developed land groups.

We estimate the long-run relation (1) by Dynamic OLS (DOLS) and we report clustered standard errors, which are robust to general heteroscedasticity and autocorrelation patterns within municipalities. The short-run equation (2) is estimated by OLS and we report HAC standard errors clustered at the municipality level. Because we correct for cross-sectional dependence in the short-run equation, we are not able to include the variables that only exhibit time-variation due to perfect multicollinearity (e.g. the mortgage rate and construction costs). However, their effect will be implicitly captured by the cross sectional averages that are included in order to account for cross sectional dependence.

[2] It might be expected that there are spillovers between regions. Therefore, we correct for this possible cross-sectional dependence by including cross-sectional averages of all our explanatory variables (Pesaran, 2006). We assume that this cross-sectional dependence is stationary and should therefore be accounted for in the short-run equation. Intuitively, this implies that these spillovers mainly affect the short-run dynamics of the housing market.

Admittedly, some of our variables might be endogenous to house prices. For our long-run equation this should not be a major issue, as this relationship is simply a long-run relationship between the variables and does not imply causality. Yet, do impose only one co-integrating relationship and do not allow for feedback effects through other variables. However, the literature on panel (V)ECMs is not very well developed in this respect, and there is no standard accepted method is how to approach this problem (like the Johansen approach in a time-series framework). The implications for our findings are that some effects are probably over- or underestimated. For example, in our equations we do not allow for the housing stock to change in response to a demand shock. This implies that the effect of a positive demand shock might be overstated. We are, however, mainly interested in the *differences* between regions with respect to the degree of supply restrictiveness. Assuming that supply is less (more) elastic in more (less) constrained regions, the negligence of these dynamics implies that our estimates of these differences are actually on the conservative side.

4.2 Results

Our empirical analysis consists of two stages. First, we estimate both the long- and short-run relationship for real house prices as given by equations (1) and (2) for the whole sample, without taking into account the role of supply constraints that we proxy by the shared developed land. Second, we estimate these equations separately for each of the three subsamples of municipalities (i.e. “least developed”, “medium developed”, “most developed”), allowing supply constraints to interact with *all* our explanatory variables in an unrestricted manner.

The long-run relation between income and house prices

We begin by estimating the long-run relationship for real house prices at the municipality level for the whole sample, as given by equation (1). Note that all variables except for the mortgage rate, the unemployment rate, and the LTV are in logs, and can thus be interpreted as elasticities. Table 2 presents the estimated coefficients for the main explanatory variables.

As shown in Column 1 of Table 2, all variables have the expected sign. Real house prices are positively related to real income and construction costs, and negatively related to the mortgage rate and the unemployment rate. All coefficients are statistically significant at the 1 percent level, except for the population variable which turned out to be statistically insignificant. The coefficient on our main variable of interest, real income, implies that a 1 percent increase in real income is associated with a 0.7 percent increase in real house prices in the long-run. The size of this coefficient is in line with what is found by the OECD (2004) for the Netherlands (i.e. 0.8) but smaller than the coefficient estimated by Kranendonk et al. (2005) (i.e. 1.4). The coefficient on the real mortgage rate implies that a 1 percent point increase in the mortgage rate is associated with around 3 percent decline in real house prices, whereas the coefficient on the unemployment rate implies that a 1 percent point increase in unemployment is associated with around 3 percent decline in house prices. Furthermore, the coefficient on the LTV implies that a 1 percentage point increase in the LTV is associated with a 3 percent increase in house prices, slightly higher than in Verbruggen et al. (2015)[3]. Finally, real construction costs appear to be strongly and positively related to house prices; a 1 percent increase in construction costs on average increases house prices by 0.9 percent.

Table 2: First stage (long-run) estimates

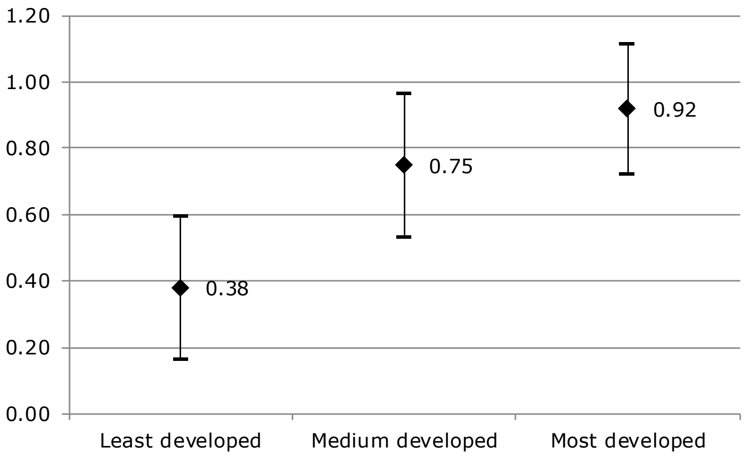
Dependent variable: Log real house price				
	(1)	(2)	(3)	(4)
VARIABLES	Total	Least developed	Medium developed	Most developed
Real average income	0.70***	0.38***	0.75***	0.92***
	(0.06)	(0.11)	(0.11)	(0.10)
Real mortgage rate	-0.03***	-0.03***	-0.03***	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment rate	-0.03***	-0.04***	-0.03***	-0.04***
	(0.00)	(0.01)	(0.00)	(0.01)
Population	0.00	0.24*	-0.14***	0.06
	(0.04)	(0.12)	(0.03)	(0.07)
LTV	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.01)
Real cons. costs	0.89***	0.98***	0.89***	0.71***
	(0.05)	(0.08)	(0.08)	(0.10)
Constant	-2.66***	-4.49***	-1.48***	-3.10***
	(0.47)	(1.20)	(0.43)	(0.93)
Observations	8216	2756	2730	2730
Number of municipalities	316	106	105	105
Adjusted R-squared	0.98	0.98	0.98	0.98
Municipality FE	YES	YES	YES	YES

Heteroskedasticity-and autocorrelation-consistent (HAC) standard errors (in parenthesis) are adjusted for clustering at municipality level; *** p<0.01, ** p<0.05, * p<0.1

Notes: All variables expect for the mortgage rate, unemployment rate and LTV are in logs. Only the coefficients of the main variables are reported here. Sample period is 1987-2016.

[3] This research used a different model (VAR), a different time period and looked at the aggregate housing market. They find that a lowering of the LTV-limit by 10% point ultimately leads to price decrease of 11%. In their study they assume that a 1 percentage point reduction in the LTV-limit leads to a 0.6% lower LTV for first-time buyers. Our results therefore imply a price decrease of 18% if the LTV-limit is lowered by 10% (0,6*10*3%). However, if we restrict our sample to before 2013 (last period in their model) and weigh our municipalities in our regression according to population (to mimic the aggregate regression), our long-term effect is very close to their finding: 15%.

Figure 2: 95% confidence intervals of the estimated coefficients



As a next step, we estimate the long-run price relationship for each of the three subsamples separately, as we are interested in whether income shocks translate into house prices heterogeneously across subsamples that are subject to different supply constraints. The results indicate that in municipalities that are characterized by weak supply constraints ("least developed"), a 1 percent increase in real income leads to a 0.38 percent increase in house prices in the long-run (Table 2, Column 2.) In municipalities that are characterized by medium and strong supply constraints ("medium developed" and "most developed"), a 1 percent increase in real income increases house prices by around 0.75 percent and 0.92 percent, respectively (Table 2, Columns 3-4). Figure 2 shows the 95% confidence intervals of these coefficients. F-tests show that the coefficients of the medium- and most developed groups are statistically significantly higher than the coefficient of the least developed group. While the point estimate for the most developed group is larger than that of the medium developed group, this difference is not statistically significant. In other words, and in line with our hypothesis, the income elasticity of house prices increases with the extent of supply constraints in a given region. Intuitively, this suggests that supply elasticities in supply-constrained areas are relatively low. As a result, a given increase in income leads to a muted supply response and therefore to a relatively strong response in equilibrium house price.

Finally, we take a brief look at the relationship between house prices and a number of other explanatory variables. It could be expected that the change in the mortgage rate affects house prices to a different extent across regions, depending on the extent of supply constraints. Yet, the estimated coefficients for the three subsamples are not significantly different from each other. The same also holds for the unemployment rate and the LTV-ratio. The coefficient on construction costs is significantly higher in the least developed group compared to the most developed group. This finding is plausible since the land component in the total housing price is likely to be higher in the most developed (i.e. most supply restricted) group. Hence, an increase in construction costs will have a larger effect on total housing price in regions where land constitutes a smaller part of the total price and the structure value constitutes a relatively large part. The findings for the population variable are mixed. Whereas the coefficient for the least developed group is positive (as might be expected), it is negative for the medium developed group. The latter is puzzling and we do not have a plausible explanation for it.

The short-run (dynamic) relation between income and house prices

We estimate the short-run relationship for real house prices according to equation (2).[4] As in the first stage, we first run the regression on the whole sample and then separately for each of the three subsamples. Table 3 summarizes the main findings. As given by Column 1, the coefficient on real household income is significant and positive (0.06) but compared to Kranendonk et al. (2005) it is very small (they find it is around 1, however in a different specification). Furthermore the change in unemployment rate and the mortgage rate appears to be statistically insignificant in the short-run. The coefficient of growth in population, the serial correlation term and the error correction term all have the expected signs and are statistically significant.

Next, we estimate the short-run price relationship for each of the three subsamples separately. The results yield statistically significant coefficients for the real income variable only for the medium- and most developed groups. Although the coefficients are small, our hypothesis - that the effect of income on house prices is significantly larger in these groups compared to the least developed group - is confirmed. That the coefficient is small might be related to the fact that the purchase of a house, often the biggest purchase item in a consumer's lifetime, requires some time for orientation, leading to a muted response of house prices in the short-run. For the coefficient on the error correction term, indicating the degree of mean reversion, we do not find any heterogeneity between the three subsamples. The same holds for the other variables.

[4] In annex 7.1 tables A2-A4 we show the results of various panel unit root- and cointegration tests which confirm that our level variables all contain a unit root (except unemployment) and that the residual (ECT) and the first differences are all stationary.

Table 3: Second stage (short run) estimates

Dependent variable: Δlog real house price				
	(1)	(2)	(3)	(4)
VARIABLES	Total	Least developed	Medium developed	Most developed
Δlog real average income	0.06***	0.01	0.09**	0.10***
	(0.02)	(0.02)	(0.03)	(0.03)
(Δlog real house price)t-1	0.38***	0.36***	0.41***	0.35***
	(0.02)	(0.02)	(0.02)	(0.03)
Δ unemployment	0.00	-0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Δ log population	0.12***	0.11**	0.11***	0.12*
	(0.03)	(0.04)	(0.03)	(0.06)
ECT	-0.12***	-0.12***	-0.14***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	8216	2756	2730	2730
Number of municipalities	316	106	105	105
Adjusted R-squared	0.91	0.93	0.92	0.9
Municipality FE	YES	YES	YES	YES

Heteroskedasticity-and autocorrelation-consistent (HAC) standard errors (in parenthesis) are adjusted for clustering at municipality level; *** p<0.01, ** p<0.05, * p<0.1

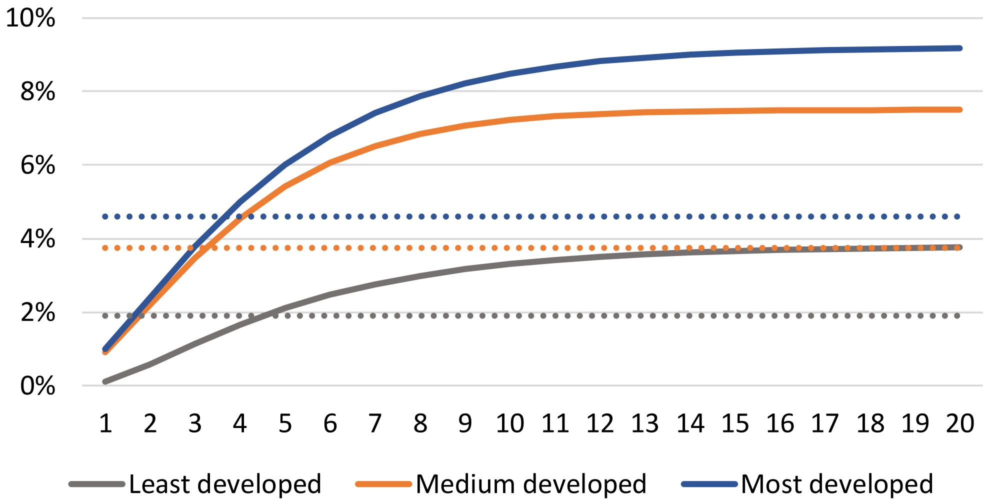
Notes: All variables expect for the unemployment are in logs. Only the coefficients of the main variables are reported here. Sample period is 1988-2016.

As mentioned earlier, the short-run relationship includes the first lag of the dependent variable to account for the degree of serial correlation. If house prices were to adjust to local economic shocks fully in the short-run, the coefficient of this variable would be 0 (Capozza et al, 2002). Yet, the empirical literature has generally found a positive and large coefficient for this variable, hinting at backward-looking price setting behavior by sellers (Van Dijk et al., 2018). As shown by Column 1 of Table 3, the coefficient of the first lag of the dependent variable is positive (0.38) and statistically significant, and in line with earlier findings for the United States. Capozza et al (2002) find a serial correlation coefficient of 0.33 for the United States, based on a panel data set of 62 metro areas from 1979-1995. Similarly, Case and Shiller (1989) find that annual serial correlation ranges from 0.25 to 0.50 across the four cities that they study.[5] When ran per subsample separately, the coefficients of the serial correlation variable appear to be of similar size (see Columns 2-4). Thus, we do not find the degree of serial correlation to be heterogeneous across regions with different supply constraints.

[5] Atlanta, Chicago, Dallas and San Francisco.

Figure 3 includes a 10 percent shock in income at t=1 and depicts the adjustment process of house prices in the least, medium and most developed regions. The Figure clearly indicates a shock in income has a larger effect in the medium and most developed regions, compared to the least developed regions. The time it takes for house prices to make up for half of the shock is more or less equal across the three groups: 4.5 years for the least, 3.5 years for the medium and the most developed regions.[6] Thus, we find no evidence of significant heterogeneity in the degree of mean reversion across regions that are more or less supply restricted.

Figure 3: Responses of house prices to a shock of 10% in disposable income, the dotted lines represent the half of the final shock.



5. Conclusion and future research

We have shown that house price dynamics in the Netherlands differ significantly between the least and most supply constrained municipalities. Our results suggest that positive income shocks are associated with significantly larger house prices increases in municipalities that face stronger supply constraints.[7] The response of house prices to an income shock is found to be rather muted in the short-run, although significantly stronger in municipalities with strong supply constraints. Contrary to findings for the United States by Capozza (2002), we find no difference in the extent of persistence and mean reversion of house prices across municipalities with different supply

[6] These differences are insignificant since the differences between serial correlation coefficients and error-correction terms are insignificant.

[7] We performed various robustness checks and our main result always holds. We, for instance, estimated the specification for different time periods and performed a weighted regression (according to population). Furthermore we estimated a specification where unemployment, which is not I(1), was excluded. We also estimated a specification where population was removed, since the long-run coefficients were puzzling.

constraints. We further find that after an income shock it takes between 3.5-4.5 years for house prices to make up for half of their deviation from the equilibrium house price.

Future research related to our work should explore ways to refine our measure of supply constraints for the Netherlands. As was previously discussed, the ratio of developed land to developable land is an imperfect measure of supply constraints. Not only does it imperfectly capture physical constraints to construction, it also cannot distinguish physical constraints from regulatory constraints. Furthermore, in an ideal setting, such a measure should be exogenous to house prices and vary over time in order to find a causal effect of supply constraints on house prices.

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7. Annex

7.1 House price indices

We estimate annual quality-adjusted (constant quality) house price indices at the municipal level by applying the Hierachical Trend Model (HTM) of Francke & De Vos (2000) and Francke & Vos (2004). The HTM is suitable to construct price indices for thin regions (i.e. regions where little transactions take place). A national (stochastic) house price trend is estimated together with municipal deviations from the national trend. The HTM is defined as:

$$
\begin{aligned}
y_t &= i\mu_t + D_{\upsilon,t}\theta_t + X_t\beta + \varepsilon_t\,, && \varepsilon_t \sim N(0,\sigma_\varepsilon^2 I),\\
\mu_{t+1} &= \mu_t + \kappa_t + \eta_t, && \eta_t \sim N(0,\sigma_\eta^2),\\
\kappa_{t+1} &= \kappa_t + \zeta_t, && \zeta_t \sim N\left(0,\sigma_\zeta^2\right),\\
\theta_{t+1} &= \theta_t + \varpi_t, && \varpi_t \sim N(0,\sigma_\varpi^2).
\end{aligned}
$$

Here, y_t is a vector of log selling prices, μ_t is the national trend and vector θ_t contains the municipal-specific trends. Matrix D is a selection matrix to select the appropriate municipality. Finally, X_t is a vector containing house characteristics with the estimated coefficients β. The estimated coefficients are included in Table A1.

We use individual transaction data from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) to estimate the price indices. The data include the selling price, the date of sale and several housing characteristics. We use a similar set of housing characteristics as in Van Dijk & Francke (2018). A large share of all housing transactions in the Netherlands is included in the data.[8]

In Van Dijk & Francke (2018), the HTM is estimated recursively over 40 smaller COROP-regions such that the municipal indices are estimated as deviation from the COROP-trend instead of the national trend. The caveat is that the level differences between the municipalities are not interpretable this way. We specifically need these level differences for our long-run equation. Therefore, we estimate the HTM in deviations from the national trend instead of the COROP trend.[9]

[8] Van Dijk & Francke report a percentage of 69% and De Wit et al. (2013) a percentage of 55-60%.

[9] The resulting indices, however, are apart from the level differences very comparable. The correlation between the returns is 0.98.

Table A1: Estimates of the coefficients on housing characteristics on the log of transaction price in the Netherlands

	Dep Var: Log Transaction price	
Variable	Beta	t-Stat
Log house size	0.7415	1553.70
Log garden size	-0.0013	13.07
Built before 1905	(Omitted)	
Built 1906–1930	-0.0551	79.04
Built 1931–1944	-0.0544	71.97
Built 1945–1959	-0.0619	79.14
Built 1960–1970	-0.1298	181.55
Built 1971–1980	-0.1117	158.70
Built 1981–1990	-0.0603	83.30
Built 1991–2000	0.0192	25.95
Built after 2000	0.0294	33.34
HT Simple	(Omitted)	
HT Single-family	0.0765	102.68
HT Canal House	0.2947	90.77
HT Mansion	0.2414	276.28
HT Living Farm	0.2298	160.95
HT Bungalow	0.3897	367.57
HT Villa	0.4636	414.54
HT Manor	0.4925	307.08
HT Estate	0.6085	68.65
HT Ground floor ap.	0.0960	91.78
HT Top floor ap.	0.0479	48.42
HT Multiple level ap.	-0.0058	4.82
HT ap. w/porch	0.0541	57.83
HT ap. w/gallery	0.0269	27.69
HT Nursing home	-0.3696	112.49
HT Top and ground floor ap.	0.0695	24.71
Very poor IM	(Omitted)	
Very poor to poor IM	0.0159	2.32
Poor IM	0.0839	24.25
Poor to average IM	0.0856	20.16
Average IM	0.1244	36.19
Average to good IM	0.1420	40.03
Good IM	0.2159	62.76
Good to excellent IM	0.2764	75.88
Excellent IM	0.2862	81.87
Very poor EM	(Omitted)	
Very poor to poor EM	0.0266	3.39
Poor EM	0.0395	10.17
Poor to average EM	0.0653	13.20
Average EM	0.0726	18.93
Average to good EM	0.0945	23.95
Good EM	0.1287	33.51
Good to excellent EM	0.1596	39.21
Excellent EM	0.1595	40.88
Market Conditions	Common Trend (Local Lineair Trend)	
Municipal Trends	Municipal Trends (Random Walk)	
R-sq	0.8672	
RMSE	0.2255	
Observations	2,993,495	

HT = House Type, IM = Internal Maintenance, EM = External Maintenance

7.2 Cointegration tests

In order to validate what unit root test and what model specification is appropriate, we want to test whether our variables that are available at the municipality level are cross-sectionally dependent. The Pesaran (2004) test for cross sectional dependence confirms that log real house prices, log real household income, unemployment, log population, and the residual from the first stage (ECT) are cross sectionally dependent (Table A2).

Table A2: Pesaran (2004) test for cross-sectional dependence

	CD-value	P-value
Log real house price	1206.0	0.000
Log real household income	1167.2	0.000
Unemployment	1121.8	0.000
Log population	540.1	0.000
ECT	194.2	0.000

H0: timeseries in panel are cross-sectionally independent

Next, we perform a normal Dickey Fuller test for the variables that are only available at the country level. For the levels we include a constant and a trend, for the first differences we include only a constant. Table A3 shows that the LTV, log construction costs and the real mortgage interest rate all have a unit root in levels and are all stationary in differences (at a 10% significance level).

Table A3: Dickey Fuller test for unit roots

	Z(t)
LTV	0.77
Log construction costs	0.514
Real mortgage rate	-2.936
Δ LTV	-3.113**
Δ log construction costs	-2.72*
Δ real mortgage rate	-8.362***

Significance levels: *** (1%), **(5%) *(10%). Critical t-values for Dickey Fuller test with trend and constant N>100 -4.343 (1%), -3.584 (5%) and -3.230 (10%). Critical t-values for Dickey Fuller test with constant N>100 -3.730 (1%), 2.992 (5%) and -2.626 (10%).

For the variables that are cross-sectionally dependent, we perform both the Im-Pesaran-Shin (IPS) panel unit root test (2003) and a Fisher type panel unit root test. Both tests take cross sectional dependence into account. We add a trend for the levels and no trend for the first differences. Table A4 shows that both tests confirm that our residual of the first stage (ECT) does not contain a unit root and that one or more of series in the panel are stationary, which is a crucial requirement for finding a cointegrating relationship. Furthermore, both tests show that log real house prices and log population are I(1), since all panels seem to contain a unit root and their first differences are stationary. For log household income, we find somewhat mixed results: the IPS test finds that it might be I (0) and the Fisher test finds that it likely is I(1). In our paper we make the assumption that log household income is indeed I(1). We feel comfortable to do so because we know that panel unit root tests generally lack power and the literature generally recognizes real income to be I(1). We further find that a regression of log household on its lagged value returns a coefficient of 0.97, which is very close to 1 (unit root). For unemployment, both tests conclude that one or more panels are stationary. We do include unemployment in our specification, but excluding unemployment does not alter our main findings.

Table A4: Im-Pesaran-Shin and Fisher panel unit root test

	IPS		*Fisher*	
Variable	z-t-tilde bar	p-value	Z	p-value
Log real house price	0.6008	0.7260	-1.115	0.1324
Log real household income	-97.257	0.0000	45.003	1.000
Unemployment	-307.497	0.0000	-125.592	0.0000
Log population	10.331	0.8492	36.077	0.9998
ECT	-61.703	0.0000	-37.156	0.0001
Δlog real house price	-351.859	0.0000	-361.129	0.0000
Δlog real household income	-528.125	0.0000	-49.226	0.0000
Δunemployment	-602.795	0.0000	-651.864	0.0000

For the IM-Pesaran-Shin test H0: all panels contain unit roots and H1: some panels are stationary. For the Fisher type test H0: all panels contain unit root and H1: at least one panel is stationary. For the Fisher-test Choi (2001) recommends to interpret the Z value in empirical studies with panels with N>100 instead of the other test statistics.

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