

Market conditions, competition and the timing of housing development in the Netherlands

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Abstract

Housing construction is considered to play a crucial role in the economy. Despite the societal and economic importance of housing supply, the determinants of the timing of housing supply have not yet been well understood. We believe that the time period after permits have been issued is particularly suited for economic analyses, since there are less market distortions from regulations after permitting. The literature demonstrates that house price changes, development costs changes and competition play an important role in the timing of housing starts. We therefore aim to answer the research question: How do market conditions and competition influence the timing of housing starts in the Netherlands? We estimate the probability of housing starts to occur after permits are issued by using a hazard model. We find that a one standard deviation increase in house price change leads to a 9.76% increase in the hazard rate, i.e. the probability of development to occur. Furthermore, a one standard deviation increase in development costs increases the hazard rate by 13.57%. In addition, we compare the four major Dutch cities with the rest of the Netherlands. Afterwards, we compare urban and rural municipalities. Competition only affects the timing of housing starts outside the four major cities or, more specifically, in urban municipalities.

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Contents

1	Introduction	3
2	Literature	4
3	Methodology	6
3.1	Hazard model specification	6
3.2	Research design	8
4	Data description	8
4.1	Dataset on housing development	8
4.2	Explanatory variables	10
4.2.1	House price change	10
4.2.2	Development cost change	11
4.2.3	Competition	11
4.2.4	Differences between municipalities	12
5	Empirical results	13
5.1	Base specification	14
5.2	The four major cities and the rest of the Netherlands	15
5.3	Urban and rural municipalities	16
5.4	Robustness checks	17
6	Conclusion	18
	References	19
	Appendix	21

1 Introduction

Prices on the Dutch housing market have shown significant movement in the past decade. After a price peak before the financial crisis in 2008, the prices of owner-occupied homes fell, reaching the lowest point in 2013. Since 2014, house prices have increased strongly (Öztürk, Van Dijk, Van Hoenselaar, & Burgers, 2018) and a reversal seems unlikely (Deelen et al., 2020). Various reasons are mentioned as the cause of rising house prices, such as an increasing demand for owner-occupied houses as a result of low interest rates. At the same time, the development and construction of new houses lags behind, which is often mentioned as one of the main causes of the ever increasing house prices (Michielsen, Groot, & Maarseveen, 2017).

House prices are determined by demand, which is among other things determined by income trends and interest rates, and by the supply of housing. A positive shift in demand implies that more houses are required. However, housing supply is inelastic, predominantly due to geographical factors and regulation (Saiz, 2010). Consequently, a shift in demand results in a relatively large price increase since the supply does not react adequately on the demand shift (Glaeser, Gyourko, & Saks, 2005). This causes the cyclicity of housing markets. If prices rise due to a demand shift, the response of supply is slow and prices overshoot. Afterwards, supply meets demand, prices decline, development stagnates and the cycle starts over (Murphy, 2018).

Housing construction is considered to play a crucial role in the economy (Mayer & Somerville, 2000a). Despite the societal and economic importance of housing supply, the determinants of the timing of housing supply have not yet been well understood (Murphy, 2018). We believe that the time period after permits have been issued is particularly of interest for economic analyses. After all, procedures that cause delays, for example as a result of regulations, take place before permitting (Mayer & Somerville, 2000a) and do not play an important role in this time frame. By focussing on the time frame after a permit to built is issued, we expect that predominantly market conditions are of importance in explaining the timing of housing supply.

The time period between permit issuance and housing starts is examined from a financial perspective (Cunningham, 2006; Bulan, Mayer, & Somerville, 2008). In our study, we take literature from economics and urban and regional sciences as a starting point for our analysis. From our literature review, we will learn that changes in house prices and development costs play an important role in housing supply dynamics (Mayer & Somerville, 2000b). In addition, Bulan et al. (2008) are, as far as we know, the first authors to demonstrate that competition affects the timing of construction. They argue that competition could play an important role in understanding real estate cycles. Therefore, we decided to examine the effects of competition as well.

This leads us to the following research question: How do market conditions and competition influence the timing of housing starts in the Netherlands? We explore an extensive dataset on housing development projects in the Netherlands that is available to us through Kadaster, the Dutch land registry and mapping agency. Carruthers, Hepp, Knaap & Renner (2012) demonstrate

that hazard models hold tremendous potential to accommodate the stochastic character of the built environment. We therefore apply a hazard model in order to examine the effects of house price changes, development cost changes and competition on the duration between permit issuances and housing starts. In addition, we assess whether supply dynamics differ among the four major Dutch cities; Amsterdam, Rotterdam, Utrecht and The Hague, and the rest of the country. Subsequently, we compare urbanized municipalities with rural municipalities.

If we examine the Netherlands as a whole, we find that a one standard deviation increase in house price change leads to a 9.76% increase in the hazard rate, i.e. the probability of development to occur. Furthermore, a one standard deviation increase in development costs increases the hazard rate by 13.57%. If we make a comparison between the four major Dutch cities and the rest of the country, we find a small effect of prices and costs within the cities that is not significant. In all other municipalities, we find effects that are comparable to our base specification. A broader distinction between urbanized and rural areas yields a similar effect of price and cost dynamics in both groups.

We do not find an effect of competition in our regressions on the Netherlands as a whole, nor in either of the four major Dutch cities and in urbanized municipalities. Nonetheless, we find an effect if we run our regression on all other municipalities outside the four major cities or, more specifically, on all rural municipalities. In our estimates, the effect of a one standard deviation increase in competition results in an increase of at least 15.3% in the hazard rate. This indicates that there is a difference in the role of competition between urbanized and rural areas, at least in the Netherlands. Based on several additional regressions, we consider our estimates to be robust.

The paper is structured as follows. We first provide an overview of related literature and discuss its implications for our study. Afterwards, our methodology and research design is discussed. An extensive data description demonstrates the procedures we have followed in order to gain our results. These results are discussed subsequently. Finally, we conclude our research.

2 Literature

In this section we assess literature that relates to our study. First, we will look into the potential of hazard models in a broader urban spatial context. Afterwards, the effects of house prices and development costs on the timing of development are examined. In addition, we discuss some financial studies that relate to our research. Next, we examine differences between housing markets in urbanized areas compared to rural areas. The discussed literature will form the base of our research design.

The application of hazard analysis in urban and regional sciences is somewhat new. Carruthers, Lewis, Knaap & Renner (2010) introduce a spatial hazard model in order to study urban form. The authors explain how hazard analysis could contribute to the study of urban environments in

addition to traditional approaches, such as the Muth-Mills model (Brueckner, 1987). According to Carruthers et al. (2010), hazard models 'hold tremendous potential for the study of urban form because they are probabilistic in nature and therefore, by design, are able to accommodate the stochastic character of the built environment' (p. 70). This stochastic character can, among other things, be explained by market imperfections and land use regulation.

Building on the research by Carruthers et al. (2010), Carruthers et al. (2012) applied a spatial hazard model to evaluate changes in land use through time in the twenty-five highest growth core-based statistical areas (CBSAs) of the United States. Although the topic of their study differs from ours, their analysis demonstrates that hazard models are highly effective in predicting patterns of land-use change.

Housing markets are generally analysed from either the demand side or the supply side of the market. Although the majority of literature has been concerned with demand related issues, more literature on the supply side of the market is emerging. According to DiPasquale (1999), the supply side of housing markets can be modelled based on two approaches. First, there is an investment/asset market approach, in which housing markets are studied based on theories that emerge from finance. Second, one could also model housing markets using an approach based on urban spatial theory. Most research that takes the second approach makes use of aggregated data.

Mayer & Sommerville (2000b) develop an empirical model of housing supply derived from urban growth theory. The authors treat starts of housing development as a function of house prices and costs, in order to estimate the response of housing supply to market changes. Their study demonstrates that housing development is particularly an outcome of changes in house prices and development costs, rather than the price levels.

Literature on the microfoundations of housing supply is scarce. Murphy (2018) estimates the first dynamic microeconomic model of housing supply in which 'economic agents are the owners of parcels of land who decide when and how to develop their parcels' (p. 15). The author demonstrates that parcel owners look to the future about both prices and costs when they decide on the timing of development. This forward looking behaviour results in an incentive for developers to build before price peaks, as they anticipate on increasing development costs. The study demonstrates that variation in house prices and development costs are key to understanding where and when construction occurs.

Research on the duration between permitting and housing starts often takes a real option approach, which originates from finance and can be applied to analyse irreversible investments on tangible assets. According to real option theory, the value of investments decreases as uncertainty increases. Cunningham (2006) argues that land development exercises a real option and tests this prediction based on property transactions in Seattle with a proportional hazard model. He finds that greater uncertainty is associated with a delay in the timing of development and increases land prices.

Furthermore, Bulan et al. (2008) examine a dataset of 1214 condominium developments in Vancouver. The data contains information on the start and completion of construction, combined with data on market uncertainty and volatility. The authors apply a hazard analysis and find that increases in risk lead developers to delay new real estate investment. In addition, the authors examine the effect of nearby competing projects and find that competition diminishes the value of waiting to invest and thus creates incentives to invest earlier. Our research encompasses similarities to this study. However, we aim to approach housing supply on the basis of insights that arise from urban economic literature, rather than from a financial perspective.

Housing market dynamics appear to differ between cities and rural areas. Glaeser & Gyourko (2003) demonstrate that housing prices relate to the construction costs in most US areas, while they are considerably higher than the construction costs in metropolitan areas. In the Netherlands, housing supply adjusts in a different way in urbanized areas compared to rural areas. For example, Michielsen, Groot & Maarseveen (2017) demonstrate that the elasticity of housing supply is generally lower in the major cities compared to the rest of the country. Subsequently, Öztürk et al. & Burgers (2018) demonstrate that housing supply dynamics differ significantly between more and lesser developed municipalities.

3 Methodology

This section provides a detailed outline of our research procedure. We discuss hazard modelling in general and explain our choice for a Weibull specification. Afterwards, we describe our research design.

3.1 Hazard model specification

For our estimation, we apply a data analytic approach called hazard analysis. This is an estimation method in which the dependent variable is the time until an event occurs, i.e. the survival time (Kleinbaum & Klein, 2010). In our case, the event in which we are interested is the start of construction after a permit has been issued. We denote the random variable for survival time as capital T . In addition, a specific value of interest for our random variable T is denoted by a small letter t . From this, we can introduce the survival function, denoted by $S(t)$ and the hazard function, denoted by $h(t)$.

The survival function provides the probability that the survival time T exceeds a specific time t . Thus $S(t) = P(T > t)$. The concept of the hazard function $h(t)$ is somewhat difficult to grasp and defined by Kleinbaum & Klein (2010) as: *"the instantaneous potential per unit time for the event to occur, given that the individual has survived up to time t "*, which is denoted in (1):

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \quad (1)$$

In contrast to the survival function, the hazard rate focuses on failing, or in other words the event to occur. The goal of our analysis is to assess the relationship of explanatory variables on the hazard of development after the issuing of a permit.

There is a variety of hazard models, which can be divided into three main types; non-parametric models, semi-parametric models and parametric models. Non-parametric do not take explanatory variables into account and provide insight in the distribution of the duration data. The main difference between the semi-parametric and parametric models is whether one makes assumptions about the functional form of the distribution, i.e. the baseline hazard. The most well known semi-parametric model is the Cox proportional hazard (PH) model. An advantage of the Cox PH model is that it obtains reasonable good estimates of regression coefficients and hazard ratios of interest, even though the baseline hazard is not specified (Kleinbaum & Klein, 2010).

In addition to semi-parametric models, one could apply a parametric model. The functional form of a parametric model is completely specified, except for the values of the unknown parameters. In addition, estimates from parametric models are typically more consistent with a theoretical survival curve. A parametric model can be estimated if one is comfortable with the underlying assumptions on the distribution. The simplicity and completeness are the main advantages of using a parametric approach (Kleinbaum & Klein, 2010).

We decided to follow Bulan et al. (2008) and apply the parametric Weibull model for our analysis. The Weibull model assumes a monotonically increasing or decreasing shape of the hazard function (Cleves, Gould, Gould, Gutierrez, & Marchenko, 2008). We argue that this model is suited for our objective, assuming that the hazard of development after obtaining a permit typically increases as time goes by. The Weibull model is usually written in terms of the hazard model formula, which is demonstrated in (2):

$$h(t, X) = \lambda wt^{w-1} \quad (2)$$

In which $h(t, X)$ is the hazard rate at time t , given the explanatory/predictor variable(s) $X = (X_1, X_2, \dots, X_i)$. And w is the parameter that estimates the shape of the hazard function. Where:

$$\lambda = \exp\left[\sum_{i=1}^w \beta_i X_i\right] \quad (3)$$

And the baseline hazard function is:

$$h_0(t) = wt^{w-1} \quad (4)$$

Thus, the model estimates how the hazard function deviates from the baseline hazard as a result of our explanatory variables. For robustness, we also examine the alternative distribution of the Cox PH model.

3.2 Research design

Now that we have specified the model, we can introduce our explanatory variables and their expected effect on the hazard rate, which we base on our literature review. First, Mayer & Sommerville (2000b) and Murphy (2018), demonstrate that housing starts are a function of house prices and development costs. More specifically, housing supply is an outcome of changes in prices and costs, rather than the levels of prices and costs. Therefore, we add variables for the monthly change in house prices and the quarterly change in development costs to our regression.¹ We expect that both price and cost increases result in an incentive to invest and therefore, increase the hazard rate.

In addition, Bulan et al. (2008) demonstrate that market volatility and uncertainty affects the timing of development. However, we do not design our study from a finance perspective and therefore, do not explicitly take uncertainty and volatility into account. Nonetheless, it is also demonstrated that competition plays an important role in the timing of development. This variable has not been assessed in other studies and therefore, we add a variable for competition to our regression. We expect that competition increases the hazard rate, similar to Bulan et al. (2008).

Finally, housing supply dynamics in the Netherlands differ between urbanized and rural municipalities. Therefore, we will test if our explanatory variables demonstrate different outcomes in the four major Dutch cities, and in urbanized municipalities as compared to rural municipalities.

4 Data description

In this section we provide an overview of the data that we apply to our research. We start with a discussion of our master dataset on housing development in the Netherlands. Afterwards, we demonstrate how we design our explanatory variables on house price changes, development cost changes and competition. We finalize the data description with a procedure to differentiate between urban and rural municipalities.

4.1 Dataset on housing development

We make use of an extensive dataset that is available to us through Kadaster, the Dutch land registry and mapping agency, from which we obtain observations of residential developments in the Netherlands by separate units. The dataset is complete from 2012 to April 2020, but also contains some observations dating back to 2008. We observe several attributes of the units, such as the developing company, address, parcel number and several dates. We are interested in the

¹For precision, we add the price development in monthly periods. However, we only have data on the development cost changes available in quarterly time periods. Therefore, house price and development cost changes are not measured in the same period of time. A more detailed description of our data availability and the design of our variables can be found in section 4. Data description.

dates at which permits are issued and the dates of housing starts. Since we observe the duration between these events, also known as the survival time, our data is convenient for a hazard analysis. If the survival time is unknown, for example because an observation has not experienced the event (yet), i.e. the development has not started, the observation was censored.

In order to make the data suitable for our analysis, the addresses had to be merged into projects. First, all duplicates were removed by collapsing the data based on a unique identification code for each separate unit. Afterwards, we collapsed the data based on an unique identification number for each apartment building, counting the number of units. This leaves us with information on all apartment projects and the number of units within the building, in addition to the remaining addresses of separate housing units. The housing units were collapsed if the place of residence, the developing company and the date at which the permits was issued are corresponding. As a result, we obtain information on larger housing development projects, including the number of units within the project. Afterwards, we corrected for the fact that some projects are divided over several partially entitled owners.

We aim to make a distinction between individuals who develop a private property and professional developers who are involved in sizeable projects, since we expect that other incentives apply to individuals. Therefore, we decided to follow Bulan et al. (2008), and drop all projects with 4 or less units. In addition, we only take housing units into account that have been sold to private owners, allowing us to focus on the owner occupied market. We decided not to take the rental market into account, since this market also contains social housing. After all, social housing is subsidised, causing other mechanisms to play a role. Furthermore, the Dutch housing market consists predominantly of owner occupied houses (Deelen et al., 2020). Furthermore, some additional data corrections were performed.² This leaves us with 5,554 housing projects in the Netherlands. In order to demonstrate the number of projects in our research period and the number of units in these projects, we provide an overview of our data in figure 1.

²We found one datapoint dating back to the 1993 and one datapoint of which the duration between the issuing of a permit and the start of development was almost 55 years.

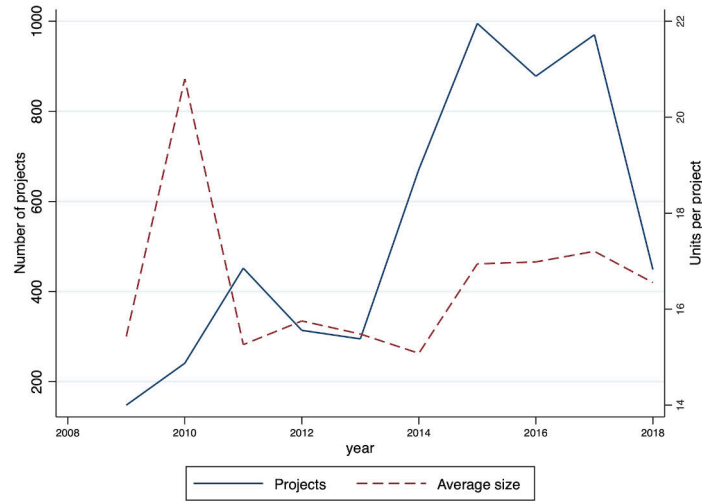


Figure 1: Housing development projects in the Netherlands

4.2 Explanatory variables

4.2.1 House price change

For our house price variable, we made use of a dataset that contains all transactions in the housing market from 2010 to April 2020, which was available through Kadaster. It is important to note that we observe transactions, rather than sales, which is generally administrated two weeks after the moment at which a house is sold. Therefore, the price movements that we observe are slightly delayed compared to the market in which they occur.

We decided to remove a small number of outliers that could distort the results. Following Koster and Rouwendal (2012), we dropped all observations with transaction prices below €25,000 or above €2.5 million and properties smaller than 25m² or larger than 500m² were removed. In addition, it was decided to remove all properties of which the price per square meter exceeded €10,000. We are aware of the fact that this boundary is somewhat arbitrary. However, we had some outliers up to €42,857 per square meter. The number of observations that exceeded a price of €10,000 per square meter was 1317. In total, 8004 out of 1,792,286 observations were removed.

From our literature review, we have learned that changes in house prices are affecting development, rather than the price levels. Therefore, we decided to calculate the monthly price changes, based on the average price per square meter for each municipality. However, a problem with house price data is that there are not enough data points to calculate a reliable monthly average. In order to account for this, we decided to calculate the monthly house price change based on the yearly moving average. Where the yearly moving average (MA) of square meter house price P is calculated from the mean price per square meter p in municipality i in month t :

$$MAP_{i,t} = \frac{p_{i,t} + p_{i,t-1} + p_{i,t-2} \dots p_{i,t-12}}{12} \quad (5)$$

And the relative monthly price change is:

$$Relative\ change\ (MAP_{i,t}) = \frac{MAP_{i,t} - MAP_{i,t-1}}{MAP_{i,t-1}} \quad (6)$$

Afterwards, the monthly house price changes were merged with our master dataset based on the municipality and month at which the permit was issued. This provides us with a proxy for housing market conditions at the moment of permitting.

4.2.2 Development cost change

A similar procedure was followed for the development costs. The data for this variable was available via Statistic Netherlands (CBS). We observe indexed quarterly input prices for housing development at the NUTS-1 region level, which are the northern, eastern, southern and western parts of the Netherlands. There is different data available for owner-occupied houses and rental houses. We decided to take the data on owner-occupied houses into account, according to the type of housing of our interest. Considering that the data was already indexed, we calculated the relative change in development costs C for region r at quarter q as:

$$Relative\ change\ (C_{r,q}) = \frac{C_{r,q} - C_{r,q-1}}{C_{r,q-1}} \quad (7)$$

The NUTS-1 level was manually linked to the municipalities within these regions, and merged with the master dataset subsequently. Similar to the house prices, it provides us with a proxy for construction costs development at the moment of permitting.

4.2.3 Competition

Bulan et al. (2008) measure competition by the number of competing projects within a given distance of each development site. We take a similar, though slightly different approach, since we have country wide data rather than data on one city. Instead of measuring projects within a given distance, we believe that a place of residence is a strong determinant for location choice, especially in a country-wide perspective. Therefore, we argue that competition in the Netherlands predominantly occurs within a place of residence. That is the most specific level of country classification in the Netherlands, which includes cities and villages within municipalities.

In order to construct the variable for competition, we count the total number of new housing units that is permitted within a place of residence after the permitting of project j . Afterwards, we account for the size of a project by dividing the number of competing units for project j over the own units within project j . As a result, we obtain the number of competing new housing

units that will be built in relation to a housing unit of project j . We argue that correcting for the number of housing units in project j adds to the precision of our variable.

Bulan et al. (2008) point out that endogeneity could be a possible complication with this variable. After all, one could expect that a large number of competitors is positively correlated with housing starts, if the number of competitors is larger in an area where demand is unobservably high. However, the authors point out that they ‘expect that the number of potential competitors is more likely related to exogenous factors such as the type of buildings constructed in previous decades as well as pre-existing zoning requirements (p. 247). We decided to follow this insight and perceive competition as driven by exogenous factors. However, since we can not completely exclude endogeneity issues, interpretation of this variable should be done with prudence.

4.2.4 Differences between municipalities

In order to examine differences between municipalities, we follow the procedure by Hilber and Vermeulen (2015) and Özturk et al. (2018) and look into the ratio between developed and developable land within a municipality. The authors focus on the relation between supply constraints and house price dynamics, arguing that municipalities with a higher share of developed land are more physically constrained, which is correlated to regulatory constraints. Özturk et al. (2018) divide the Netherlands into three equally sized municipalities based on the ratio between developed and developable land in the municipality; most developed, medium developed and least developed, which operates as a proxy for the degree of constrainedness. However, in our study we aim to make a distinction between urbanized and rural municipalities. Therefore, we consider the most developed municipalities to be urbanized, and the medium and least developed municipalities as rural.

We obtain data by CBS on the different types of land use per municipality in the Netherlands and calculate the ratio of developed land to undeveloped land. Similar to Özturk et al. (2018), we classify traffic areas, built-up areas, semi-built-up areas and recreation areas as developed land. As developable land, we classify agricultural areas, forests and open natural areas. As non-developable land, we classify inland waterways and open waterways. The share of developed land is the amount of developed land divided by the total amount of developable land (already developed and potentially developable). Municipalities with a value lower than 0.14 are classified as least developed, with value between 0.14-0.25 as medium developed and with a value higher than 0.25 as most developed. In order to provide insight in the magnitudes of our variables and their standard deviations, which is convenient for the interpretation of our results, the summary statistics of our explanatory variables are demonstrated in table 1. ³

³A statistical test on the variance inflation factor (VIF) demonstrates that multicollinearity is not present in our explanatory variables. The test can be found in the appendix A. In addition, the variables should not be time varying in order to get reliable estimates. According to the stvarty test in STATA, our variables are not time varying, which is demonstrated in te appendix B.

	Variation	Obs	Mean	Std. Dev.	Min	Max
House price change %	Municipal, monthly	5,219	.20	1.15	-14.10	6.28
Development costs change %	NUTS-1, quarterly	4,501	.92	1.56	-3.72	4.73
Competition	Units	5,554	25.46	51.00	0	745.8
Duration	Days	4,367	376.38	499.47	0	3787

Table 1: Summary statistics of explanatory variables

5 Empirical results

We start our analysis with a non-parametric estimation, in order to gain a better understanding of our dataset. Figure 3 (left) demonstrates a Kaplan-Meier curve for our observations. The estimation provides further insight in the distribution of the duration between permit issuances and housing starts in our dataset. We estimate our hazard model as described in equation (2). The baseline hazard function, as estimated in equation (4), demonstrates the probability of development to occur as a function of time alone and is assumed to be monotonically increasing over time by the Weibull parameter w i.e. the slope of the baseline hazard, which is also demonstrated in figure 3 (right).

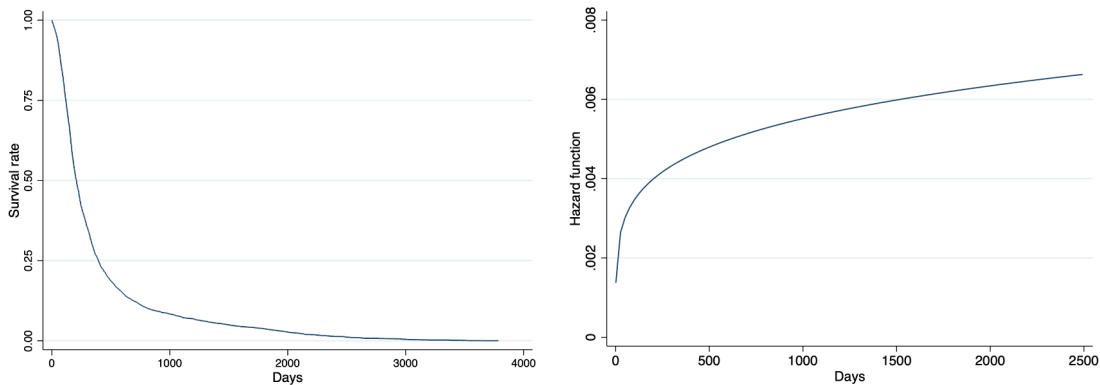


Figure 2: Kaplan-Meier curve (left) and baseline hazard (right)

The explanatory variables affect the probability of development to occur with the multiplication of a factor e^{β} . If β is 0, the coefficient is 1 and the explanatory variable X does not have an effect on the hazard rate. If the coefficient is greater than 1, an increase in the explanatory variable is associated with a positive effect on the baseline hazard and suggests that an increase in the variable increases the probability of development to occur. Similarly, if a coefficient is smaller than 1, an increase in the explanatory variable decreases the probability of development to occur. In addition, the coefficient estimated for variable X is proportional to X and a unit change in

the explanatory variable result in $(e^\beta - 1)$ change in the hazard rate. Our regression results and standard errors are demonstrated in terms of the hazard rate.

We measure competition by counting the permits for future developments that will be built in the place of residence of a project. However, this measure results in a reduction of competition as time moves closer to the end of our dataset. In order to account for this, we follow Bulan et al. (2008) and include all projects in the sample, but run multiple regressions up to earlier points in time. We decided to compare regressions for the entire sample with regressions up to two years before the end of our sample and regressions up to four years before the end of our sample.

5.1 Base specification

In our first specification, we estimate the effects of our explanatory variables on projects in the Netherlands as a whole, which is demonstrated in Table 2. Column (1) displays an estimation for the entire sample. In addition, the effects on our sample up to two years before the end of our dataset are demonstrated in column (2), and up to four years before the end of our dataset in column (3).

	(1)	(2)	(3)
Time horizon	Infinite	-2 years	-4 years
House price change %	1.085*** (0.0169)	1.077*** (0.0181)	1.042* (0.0247)
Development costs change %	1.087*** (0.0115)	1.071*** (0.0122)	1.058*** (0.0150)
Competition	1.000 (0.000462)	1.000 (0.000456)	1.001 (0.000499)
Weibull parameter (w)	1.201*** (0.0147)	1.177*** (0.0157)	1.098*** (0.0207)
Constant	0.00104*** (9.66e-05)	0.00115*** (0.000115)	0.00160*** (0.000214)
Observations	3,573	2,977	1,515

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 2: Regression on the Netherlands

Our first regression (1) demonstrates a relatively strong and significant effect of relative house price change on the hazard rate. If house prices increase by 1% in the month at which a permit is issued, compared to the previous month, it is associated with a 8.5% increase in the hazard rate.

Subsequently, a one standard deviation increase of 1.15 in house price change increases the hazard rate by 9.76%. We find similar, yet slightly less strong effects, in our second and third regression. In addition, we lose significance in the third regression, which is only significant at the 10% level.

The effect of changes in the development costs is similar to the effect of house price change. If the development costs increase by 1% in the quarter at which a permit is issued, compared to the previous quarter, it is associated with a 8.7% increase in the hazard rate. In addition, a one standard deviation increase in the development costs of 1.56 increases the hazard rate by 13.57%. This demonstrates that changes in development costs have a stronger effect on the hazard rate than changes in housing prices.

In addition, the first two regressions suggest that there is no effect of competition on the hazard rate in our base specification. In the third regression, a unit increase in competition is associated with a 0.1% increase in the hazard rate. Nonetheless, none of the estimations on competition are significant. Finally, we can interpret the Weibull parameter as the form of our baseline hazard, as specified in the methodology.

5.2 The four major cities and the rest of the Netherlands

We now examine the differences between municipalities of the four major cities in the Netherlands; Amsterdam, The Hague, Rotterdam and Utrecht, and compare the results with the rest of the Netherlands. In table 3 regressions within the four most urbanized municipalities (1), (3), (5) and outside (2), (4), (6) are alternated for the three different time horizons.

Several differences between the two groups stand out. Within the four cities, the effect of house price change becomes slightly negative, albeit not significant. However, outside of the four cities, the magnitude of the effect increases from 8.5% to 9.8%, significant at the 1% level. Similar to our previous regressions, this effect decreases as the end of our sample shortens and remains significant.

The effect of development cost change is again greater than effect of house price change. Although the sign of the coefficients remains the same as in our previous setting, we lose significance within the four most urbanized municipalities. For the rest of our sample, the effect of a one percent increase in development costs on the hazard rate is now 11.0%, compared to 8.7% in our base specification. The magnitude decreases as the length of our sample becomes shorter. The effect remains significant at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cities	Outside	Cities	Outside	Cities	Outside
Time horizon	Infinite		-2 years		-4 years	
House price change %	0.970 (0.120)	1.098*** (0.0173)	0.988 (0.126)	1.090*** (0.0185)	0.723 (0.189)	1.055** (0.0255)
Development costs change %	1.015 (0.0388)	1.110*** (0.0125)	1.003 (0.0397)	1.093*** (0.0133)	1.071 (0.0609)	1.078*** (0.0167)
Competition	0.998* (0.000978)	1.003*** (0.000700)	0.999 (0.000980)	1.004*** (0.000693)	0.999 (0.00112)	1.005*** (0.000785)
Weibull parameter (w)	1.198*** (0.0595)	1.212*** (0.0152)	1.212*** (0.0627)	1.187*** (0.0164)	1.133* (0.0799)	1.111*** (0.0217)
Constant	0.000990*** (0.000393)	0.000929*** (9.04e-05)	0.000870*** (0.000366)	0.00103*** (0.000108)	0.00126*** (0.000684)	0.00139*** (0.000198)
Observations	238	3,335	213	2,764	112	1,403

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 3: Regression on the four major Dutch cities and the rest of the country

The effect of competition now becomes completely different for the two groups. Within the four cities, we find a negative effect of -0.2% on the hazard analysis per unit increase in competition in regression (1), which is significant at the 10% level but becomes smaller and loses significance if we decrease the sample length. For the rest of the Netherlands, we find a positive effect of 0.3%, 0.4% and 0.5% for the three sample lengths respectively, which are all significant at the 1% level. Considering that the standard deviation of our competition variable is 51.00, the influence of competition appears to be substantial outside of the four big cities.

5.3 Urban and rural municipalities

For further analysis, we compare urbanized to rural municipalities. In order to examine this, we apply our regression to an alternative segmentation of the Netherlands. Following Öztürk et al. (2018), we divide the Dutch municipalities into three equally sized groups in terms of the number of municipalities; municipalities with a low (less than 14%), medium (14%-25%), and high (25% and higher) shares of developed land. We consider the municipalities with a high share of developed land as urbanized and the rest as rural. In table 4 regressions for urban municipalities (1), (3), (5) and rural municipalities (2), (4), (6) are alternated for the three different time horizons.

	(1)	(2)	(3)	(4)	(5)	(6)
	Urban	Rural	Urban	Rural	Urban	Rural
Time horizon	Infinite		-2 years		-4 years	
House price change %	1.093*** (0.0269)	1.083*** (0.0217)	1.082*** (0.0290)	1.076*** (0.0231)	1.026 (0.0457)	1.047 (0.0295)
Development costs change %	1.089*** (0.0150)	1.090*** (0.0185)	1.077*** (0.0159)	1.068*** (0.0198)	1.072*** (0.0194)	1.047* (0.0253)
Competition	0.999 (0.000522)	1.004*** (0.00135)	1.000 (0.000518)	1.004*** (0.00135)	1.000 (0.000568)	1.005*** (0.00152)
Weibull parameter (w)	1.222*** (0.0199)	1.177*** (0.0217)	1.196*** (0.0212)	1.156*** (0.0235)	1.135*** (0.0281)	1.058* (0.0306)
Constant	0.000906*** (0.000115)	0.00118*** (0.000162)	0.00102*** (0.000138)	0.00128*** (0.000191)	0.00126*** (0.000231)	0.00201*** (0.000399)
Observations	2,033	1,540	1,709	1,268	878	637

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Table 4: Regression on urban and rural municipalities

Again, we find positive effects of house price change on the hazard rate, both in urban and rural areas. The findings are comparable to our earlier estimates in terms of magnitude and are significant at the 1% level for the entire sample, except for the shortest time horizon in regressions (5) and (6). Similarly, we find effects of development costs that correspond to our previous regressions in terms of magnitude and significance, albeit regression (6) is only significant at the 10% level. A difference with our estimates under 5.2 is that the effects of house price change and development cost change are now also significant for the urban areas, which was not the case for our regression on the four big cities. This suggests that house price and development cost dynamics do not play an important role within the four big cities.

When we examine the effect of competition, the estimates are analogous to our regression under 5.2. We find no effect of competition in urbanized municipalities. The effects in rural areas of the Netherlands ranges from 0.4% to 0.5% and is significant at the 1% level for all sample lengths.

5.4 Robustness checks

We did several checks for robustness in order to test the persistence of our findings. First, we estimated our regressions using a Cox PH model, instead of the Weibull model. The Cox PH model is a semi-parametric model and allows for more flexibility in the baseline hazard. Thus,

where we assumed the baseline hazard to be monotonically increasing or decreasing over time, the baseline hazard is not specified in the Cox PH model. The regressions are demonstrated in the appendix under C.1.

The estimations using the Cox PH model yield similar results for our three specifications in terms of the sign and significance. The magnitude of our estimations on the effect of changes in the house prices and development costs become slightly smaller. In addition, the effect of competition is similar. We find no effect in our base specification, within the four major Dutch cities and in urban municipalities. In our other regressions, the effect ranges from 0.3% to 0.5% per unit increase of competition.

Furthermore, we estimated both the Weibull model and the Cox PH model with a shared frailty component, a method to introduce unobservable group heterogeneity into the hazard function. We decided to adjust for year specific effects. The results with a frailty component for both the Weibull and the Cox PH model are similar to the outcomes that are reported in our empirical results for all specifications. The magnitude of the effects of house price and development cost change increases, whilst the effect of competitions slightly decreases but still persists. In addition, we also added year dummies to our model instead of frailty and found similar results. Based on these additional estimations, we consider our results to be robust.

6 Conclusion

The results of our study support earlier findings on the effects of house price and development cost dynamics on housing supply. If we examine the Netherlands as a whole, we find that a one standard deviation increase in house price change leads to a 9.76% increase in the hazard rate of development to occur. Furthermore, a one standard deviation increase in development costs increases the hazard rate by 13.57%. Subsequently, a decline in house prices and development costs would decrease the likelihood of construction to occur. The fact that development costs changes have a greater effect on the hazard rate than house prices changes suggests that development costs are a stronger determinant in the timing of construction than house prices. This endorses the findings by Murphy (2018), who demonstrates pro-cyclical behaviour of developers as they anticipate on increasing future costs, causing construction to occur before price peaks.

If we make a comparison between the four major Dutch cities and the rest of the country, we find a small effect of prices and costs within the cities that is not significant. This suggests that costs and prices play a less important role here. However, we cannot provide a conclusive statement on this since the small effects are not significant. In all other municipalities, we find effects that are comparable to our base specification. If we make a broader distinction between urbanized and rural areas, price and cost dynamics appear to play a similar role in both groups.

Our competition variable yields results that partially support the findings of Bulan et al.

(2008). The authors find that competition diminishes the value to postpone construction and thus indirectly increases the hazard rate of construction to occur. However, in the regressions where we find an effect of competition, this effect is direct. Furthermore, the study by Bulan et al. (2008) is based on a dataset with condominium developments in the city of Vancouver, which is a relatively large city. In our study, we do not find an effect of competition in either the four major Dutch cities nor in urbanized municipalities.

Nonetheless, we do find an effect if we run our regression on all other municipalities outside the four major cities or, more specifically, on all rural municipalities. In our estimates, the effect of a one standard deviation increase in competition results in an increase of at least 15.3% in the hazard rate. This indicates that there is a difference in the role of competition between urbanized and rural areas, at least in the Netherlands.

For all our regressions, we find similar estimates in terms of sign, magnitude and significance if we apply an alternative model, if we correct for yearly fixed effects using a frailty specification and if we include year dummies. Therefore, we consider our regression results to be robust.

This study contributes to the understanding of housing supply dynamics in real estate cycles. Our findings confirm that the timing of housing development is affected by house prices and construction costs. More specifically, increasing costs appear to play a more important role than rising house prices. However, our dataset contains predominantly observation in an expanding phase of the real estate cycle. Although we also observe declining prices and costs in our data, it would be interesting to examine the time period between permitting and housing starts during an economic downturn. Finally, we find evidence that competition plays a role in the timing of housing supply. From a policy perspective, the mechanism of competition could be useful to counteract housing shortages in general, or when shortages result from declining investments during a recession. Therefore, a better understanding of competition in housing supply dynamics is desired.

References

- Brueckner, J. K. (1987). The structure of urban equilibria: A unified treatment of the Muth-Mills model. *Handbook of Regional and Urban Economics*, 2(20), 821–845.
- Bulan, L., Mayer, C. J., & Somerville, C. T. (2008). *Irreversible investment, real options, and competition: Evidence from real estate development* (Tech. Rep.). Journal of Urban Economics.
- Carruthers, J. I., Hepp, S., Knaap, G.-J., & Renner, R. N. (2012). The American way of land use: a spatial hazard analysis of changes through time. *International Regional Science Review*, 35(3), 267–302.

- Carruthers, J. I., Lewis, S., Knaap, G.-J., & Renner, R. N. (2010). Coming undone: A spatial hazard analysis of urban form in American metropolitan areas. *Papers in Regional Science*, 89(1), 65–88.
- Cleves, M., Gould, W., Gould, W. W., Gutierrez, R., & Marchenko, Y. (2008). *An Introduction to Survival Analysis Using Stata*. Stata Press.
- Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: Evidence for real options in Seattle. *Journal of Urban Economics*, 59(1), 1–31.
- Deelen, A., van der Wiel, K., Olsen, J., van der Drif, R., Zhang, L., & Vogt, B. (2020). Beweging op de woningmarkt: prijzen en volumes. *CPB Notitie*.
- DiPasquale, D. (1999). Why don't we know more about housing supply? *The Journal of Real Estate Finance and Economics*, 18(1), 9–23.
- Glaeser, E. L., & Gyourko, J. (2003). The Impact of Building Restrictions on Housing Affordability. *Economic Policy Review*, 9(2).
- Glaeser, E. L., Gyourko, J., & Saks, R. E. (2005). Why have housing prices gone up? *American Economic Review*, 95(2), 329–333.
- Hilber, C., & Vermeulen, W. (2015). The impact of supply constraints on house prices in England. *The Economic Journal*, 126(591), 358–405.
- Kleinbaum, D. G., & Klein, M. (2010). *Survival Analysis: A Self-Learning Text* (Vol. 3). Springer.
- Koster, H. R., & Rouwendal, J. (2012). The impact of mixed land use on residential property values. *Journal of Regional Science*, 52(5), 733–761.
- Mayer, C. J., & Somerville, C. T. (2000a). Land use regulation and new construction. *Regional Science and Urban Economics*, 30(6), 639–662.
- Mayer, C. J., & Somerville, C. T. (2000b). Residential construction: Using the urban growth model to estimate housing supply. *Journal of Urban Economics*, 48(1), 85–109.
- Michielsen, T., Groot, S., & Maarseveen, R. (2017). Prijselasticiteit van het woningaanbod. *CPB Notitie*.
- Murphy, A. (2018). A Dynamic Model of Housing Supply. *American Economic Journal: Economic Policy*, 10(4), 243–67.
- Öztürk, B., Van Dijk, D., Van Hoenselaar, F., & Burgers, S. (2018). The relation between supply constraints and house price dynamics in the Netherlands. *DNB Working Paper*.
- Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3), 1253–1296.

Appendix

Variance inflation factor (VIF) test for multicollinearity

Table 5 demonstrates a correlation matrix of our explanatory variables, of which we can see that the correlation is generally low. In table 6 we find the variance inflation factors of the variables. The rule of thumb is that there is a multicollinearity problem if the VIF exceeds 4, which does not apply to any of our variables.

	% House price change	% Development costs change	Competition
House price change %	1.000		
Development costs change %	0.2530	1.000	
Competition	0.0722	0.0034	1.0000

Table 5: Correlation matrix of explanatory variables

	VIF	1/VIF
House price change %	1.17	0.855239
Development costs change %	1.14	0.878465
Competition	1.10	0.0034
% Mean VIF	1.12	0.293255

Table 6: Variance inflation factors of explanatory variables

Test for time varying variables

We tested for time varying variables using the stvary test in STATA after a Cox PH regression. The outcomes demonstrate that our variables are not time varying and thus, we did not have to apply a correction.

	Constant	Varying	Never missing	Always missing	Sometimes missing
House price change %	4140	0	4140	213	0
Development costs change %	3612	0	3612	741	0
Competition	4353	0	4353	0	0

Robustness checks

Regressions in Cox PH model

Base specification

	Reg. (1)	Reg. (2)	Reg. (3)
Time horizon	Infinite	-2 years	-4 years
House price change %	1.063*** (0.0164)	1.058*** (0.0176)	1.040* (0.0244)
Development costs change %	1.059*** (0.0113)	1.047*** (0.0121)	1.038*** (0.0148)
Competition	1.000 (0.000462)	1.000 (0.000456)	1.001 (0.000501)
Observations	3,573	2,977	1,515

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

The four major cities and the rest of the Netherlands

	Reg. (1)	Reg. (2)	Reg. (3)	Reg.(4)	Reg. (5)	Reg. (6)
	Cities	Outside	Cities	Outside	Cities	Outside
Time horizon	Infinite		-2 years		-4 years	
House price change %	0.919 (0.112)	1.076*** (0.0168)	0.933 (0.118)	1.071*** (0.0181)	0.756 (0.198)	1.053** (0.0252)
Development costs change %	0.997 (0.0380)	1.078*** (0.0123)	0.983 (0.0389)	1.066*** (0.0132)	1.031 (0.0582)	1.058*** (0.0164)
Competition	0.998* (0.000963)	1.003*** (0.000709)	0.999 (0.000963)	1.004*** (0.000705)	0.999 (0.00111)	1.005*** (0.000807)
Observations	238	3,335	213	2,764	112	1,403

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Urban and rural municipalities

	Reg. (1)	Reg. (2)	Reg. (3)	Reg.(4)	Reg. (5)	Reg. (6)
	Urban	Rural	Urban	Rural	Urban	Rural
Time horizon	Infinite		-2 years		-4 years	
House price change %	1.073*** (0.0261)	1.063*** (0.0212)	1.066** (0.0283)	1.057*** (0.0226)	1.037 (0.0459)	1.043 (0.0291)
Development costs change %	1.061*** (0.0149)	1.063*** (0.0184)	1.052*** (0.0158)	1.044** (0.0197)	1.048*** (0.0192)	1.031 (0.0251)
Competition	0.999 (0.000518)	1.004*** (0.00139)	1.000 (0.000515)	1.005*** (0.00138)	1.000 (0.000566)	1.005*** (0.00157)
Observations	2,033	1,540	1,709	1,268	878	637

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Frailty and dummies

Normal vs. frailty on entire dataset for the three specifications

	Reg. (1)	Reg. (2)	Reg. (3)	Reg.(4)	Reg. (5)	Reg. (6)
	Base		Outside cities		Rural	
House price change %	1.085*** (0.0169)	1.137*** (0.0181)	1.098*** (0.0173)	1.140*** (0.0182)	1.083*** (0.0217)	1.109*** (0.0224)
Development costs change %	1.087*** (0.0115)	1.152*** (0.0129)	1.110*** (0.0125)	1.173*** (0.0138)	1.090*** (0.0185)	1.158*** (0.0209)
Competition	1.000 (0.000462)	0.999*** (0.000488)	1.003*** (0.000700)	1.002*** (0.000734)	1.004*** (0.00135)	1.003** (0.00145)
Weibull parameter (w)	1.201*** (0.0147)	1.242*** (0.0149)	1.212*** (0.0152)	1.250*** (0.0154)	1.177*** (0.0217)	1.220*** (0.0222)
lntheta		0.104*** (0.0540)		0.0939*** (0.0497)		0.112*** (0.0606)
Constant	0.00104*** (9.66e-05)	0.000824*** (0.000119)	0.000929*** (9.04e-05)	0.000741*** (0.000106)	0.00118*** (0.000162)	0.000926*** (0.000167)
Observations	3,573	3,573	3,335	3,335	1,540	1,540
Number of groups		9		9		9

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Frailty in Cox PH model on entire dataset for the three specifications

	Reg. (1)	Reg. (2)	Reg. (3)
	Base	Outside cities	Rural
House price change %	1.108*** (0.0178)	1.111*** (0.0180)	1.084*** (0.0222)
Development costs change %	1.116*** (0.0130)	1.132*** (0.0140)	1.124*** (0.0210)
Competition	0.999** (0.000487)	1.002*** (0.000741)	1.003** (0.00147)
Observations	3,573	3,335	1,540
Number of groups	9	9	9

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Dummies in Weibull model on entire dataset for the three specifications

	Reg. (1)	Reg. (2)	Reg. (3)
	Base	Outside cities	Rural
House price change %	1.139*** (0.0183)	1.142*** (0.0185)	1.110*** (0.0227)
Development costs change %	1.156*** (0.0131)	1.176*** (0.0141)	1.165*** (0.0213)
Competition	0.999*** (0.000489)	1.002*** (0.000736)	1.003** (0.00146)
2007	-	-	-
2008	-	-	-
2009	-	-	-
2010	-	-	-
2011	-	-	-
2012	0.837 (0.279)	0.859 (0.287)	0.854 (0.339)
2013	1.313 (0.262)	1.304 (0.261)	0.663 (0.193)
2014	2.485*** (0.402)	2.401*** (0.391)	2.175*** (0.521)
2015	2.258*** (0.344)	2.322*** (0.354)	1.830*** (0.415)
2016	1.583*** (0.232)	1.572*** (0.231)	1.251 (0.274)
2017	1.381** (0.201)	1.451** (0.212)	1.147 (0.250)
2018	1.261 (0.183)	1.344** (0.196)	1.054 (0.229)
2019	0.979 (0.142)	1.025 (0.149)	0.804 (0.174)
2020	-	-	-
Weibull parameter (w)	1.245*** (0.0154)	1.253*** (0.0160)	1.226*** (0.0228)
Constant	0.000549*** (9.56e-05)	0.000486*** (8.62e-05)	0.000740*** (0.000189)
Observations	3,573	3,335	1,540

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Dummies in Cox PH model on entire dataset for the three specifications

	Reg. (1)	Reg. (2)	Reg. (3)
	Base	Outside cities	Rural
House price change %	1.111*** (0.0179)	1.114*** (0.0181)	1.087*** (0.0223)
Development costs change %	1.121*** (0.0131)	1.138*** (0.0141)	1.134*** (0.0215)
Competition	0.999** (0.000489)	1.002*** (0.000744)	1.003** (0.00148)
2007	-	-	-
2008	-	-	-
2009	-	-	-
2010	-	-	-
2011	-	-	-
2012	1.052 (0.353)	1.071 (0.360)	1.034 (0.441)
2013	1.386 (0.277)	1.356 (0.273)	0.862 (0.252)
2014	2.065*** (0.335)	1.965*** (0.322)	2.130*** (0.511)
2015	1.967*** (0.300)	2.001*** (0.307)	1.824*** (0.415)
2016	1.445** (0.213)	1.414** (0.209)	1.299 (0.285)
2017	1.294* (0.189)	1.347** (0.197)	1.224 (0.267)
2018	1.213 (0.176)	1.276* (0.186)	1.176 (0.255)
2019	0.964 (0.140)	1.001 (0.146)	0.909 (0.197)
2020	-	-	-
Observations	3,573	3,335	1,540

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses