Spatial, Transport and Environmental Economics
Track: Real Estate Economics and Finance

Housing Demand in a Work-From-Home Economy

Master's Thesis

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Abstract

This thesis is analyzing changes in the Dutch housing market that occurred after the outbreak of COVID-19. Specifically, it studies the willingness to pay for an additional room since the increase of working from home.

For the research two datasets are used and eventually merged, one of them containing housing transactions in three provinces of the Netherlands between 2010 and 2022, and the other indicating the share of highly educated inhabitants per region. Hedonic pricing model is applied in the analysis. Besides looking at general trends, the model is applied to two data subsets, created according to education levels per area.

The results show that in 2021, when a large share of the population worked from home, the willingness to pay for an extra room in a house increased sharply, relative to the previous years. Furthermore, the increase was larger in regions with more highly educated people. The year after that shows a decrease in the marginal value attributed to an additional room, however, it is still high, compared to the years before COVID-19.

The outcomes of this study indicate that an increase in working from home is associated with a higher value for an additional room in a house. However, research over a longer post-COVID-19 period should be conducted to evaluate whether the effect is significant in the long run.

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1. Introduction

The Dutch government has set a goal to build 900,000 houses until 2030 to fight the current housing shortage (Rijksoverheid.Nl, n.d.). In many municipalities there are regulations for types of houses that must be built, for example, the share of social housing as well as the ratio of purchase and rent. However, discussions also arise over the size of housing units. Because of the ageing society and increasing number of single-person households (CBS, 2024; CBS, 2021), smaller units may be higher in demand, meaning that this should also be taken in consideration in new construction. On the other hand, since COVID-19 a trend of working from home (WFH) has developed, requiring space for the working function in the houses. This may result in higher demand for extra space in case this trend continues.

There is enough evidence that WFH will remain a significant aspect in the modern working culture. Since the outbreak of COVID-19 working from home has gained significant popularity. It is known to provide multiple benefits, like increased job satisfaction, improvement of work-life balance and higher productivity (Aksoy et al., 2022; Behrens, Kichko & Thisse, 2021; Bloom, Han & Liang, 2023). Employers are forced to adjust to this new way of working to attract and keep talent, since especially the professionals from younger generations appreciate flexibility (Pajević, 2021). Dingel and Neiman (2020) estimated that currently 37% of the jobs can be realized remotely, however, with the advancement of technology this number could get even higher in the future. In 2022 39.2% of the working population in the Netherlands were sometimes working from home, while 12.7% indicate to be working from home most of the time (CBS, 2024). According to CBS (2024), the number of people that sometimes work from home has been increasing.

This change in the working culture has affected cities as well as real estate markets. An increase in WFH is resulting in diminishing agglomeration effects; properties in central locations may be losing their value while suburbs are expanding (Ramani & Bloom, 2022). Also preferences for certain types and characteristics of housing are changing (Malik, Kim & Cultice, 2023), therefore this thesis aims to assess some of the effects on residential real estate caused by the increased popularity of remote working.

The main goal of the thesis is to explore how the Dutch housing market has been affected by the increase of working from home since the pandemic of COVID-19. The objective is to specifically addresss the willingness to pay (WTP) for an additional room, since it can potentially be used as a home office. The impact of location is also considered. As highly skilled jobs are more often done remotely (Dingel & Neiman, 2020), the demand for an extra room may be higher in regions with higher education levels.

Therefore, the main research question is to explore how the increase of working from home affects the demand for housing in the Netherlands. Specifically, do houses with an extra room have a higher value since the increase of WFH rates? Furthermore, how do these effects vary among areas with different education levels? And finally, are there other significant trends emerging due to teleworking and what are possible implications for the Dutch housing market on the long run?

To answer the research question of the thesis, a dataset containing housing transactions in three provinces of the Netherlands is used and applied in a hedonic pricing model to study the changes in willingness to pay for an additional room in the house. Data on education levels is incorporated to examine the differences between regions with varying levels of education.

Quite some attention in scientific literature has been paid to commercial real estate, especially retail, while not much research has been done on housing. Furthermore, there is limited research conducted in Europe about this topic in general for all types of real estate. WFH is a trend that has a high potential in the future (Barrero, Bloom & Davis, 2021), making this a relevant research question to address the shifts in residential real estate market as well as the typology of housing that may be more demanded in the future.

The thesis is structured as follows. After introduction in chapter 1, recent scientific literature is reviewed in chapter 2. Then, the data used for the research is described in chapter 3, followed by the method explanation in chapter 4. Chapter 5 contains the obtained results and interpretation, and finally the conclusions are presented in chapter 6.

2. Literature Review

The COVID-19 pandemic has been impactful on the lifestyle and working culture. Remote work and its impact on real estate and cities is a topic that has been often discussed in scientific literature during the past few years. However, the pandemic is a relatively recent phenomenon, so there are still numerous gaps in research to be filled, especially related to long term implications.

In this section current scientific literature is reviewed by first delving into the future potential of working from home (WFH) to establish the relevance of the topic and future perspectives, and then analyzing the impacts of WFH on cities and residential real estate.

2.1. The future potential of WFH

There is a lot of evidence that working from home (WFH) may remain important in the future working culture. Some of the main reasons for that are reduced costs and commuting time, as well as increased productivity (Barrero et al., 2021). During the pandemic the WFH rates spiked up, and after COVID-19 they have stabilized at higher levels than before the outbreak of the virus, signaling that this may become a part of the standard way of working in the long run. According to Kmetz, Mondragon and Wieland (2022), the share of work done from home in the US increased sharply with COVID-19, rising from roughly 5% in the pre-pandemic period to 60% in the spring of 2020. By august 2022 around 30% of work was still being done remotely (Kmetz et al., 2022). If we look at the current data of the Netherlands, 52% of the working population worked sometimes or mostly from home in 2023, and in total almost 20% of all the working hours were worked from home (CBS, 2024). According to the data of 2022 that includes all countries of the European Union, the Netherlands is the leader in the percentage of people who at least sometimes work from home (CBS, 2024), making this an interesting location for conducting research on this topic.

Some researchers have attempted to make predictions about the rates of teleworking in the future. Dingel and Neiman (2020) defined the borders of possibilities in the labour market for remote work. They looked at different jobs in the United States to conclude that 37% have the potential to be fully performed on distance. Meanwhile, Behrens et al. (2021) tried to estimate the optimal amount of remote work for the highest productivity levels. The productivity graph takes an inverted U shape, and the authors found that the highest performance can be achieved if the WFH rates are between 20% and 40%. This does, however, depend on several aspects, like the skill level of the workers and technologies, since higly skilled workers and more developed technologies result in higher benefits from remote work. (Behrens et al., 2021)

Aksoy et al. (2022) conducted a survey that involved employees and managers in 27 countries to find out about their expectations and preferences for remote work. It was concluded that managers prefer to work on average 0.7 days per week from home, while the employees stated a preference of 1.7 days. This shows that there are different opinions and preferences among different job positions, however, the general opinion is that at least some share of the working time should be spent at home.

The trends around WFH are still evolving and the future is somewhat uncertain. According to the CBS, between years 2021 and 2023 the number of Dutch people who sometimes worked from home increased while the number of people that worked from home most of the time decreased (CBS, 2024). The share of the working population that at least sometimes works from home dropped by 2%, falling from 54% in 2021 to 52% in 2023 (CBS, 2024). This data shows that the WFH rates are still slightly changing, however, the share of remote workers in the Netherlands is substantial, so there is enough reason for looking further into the implications of teleworking.

In summary, while remote working most probably has a future, it is not certain yet to which extent it will be sustained in the long run. The observed WFH rates are still changing, and the preferences for remote work between managers and employees vary. However, because of the multiple benefits that teleworking brings there is a positive perspective for it in the future, and that aligns with most of the current expectations.

2.2. Impact on cities

The Coronavirus and the new way of working have certainly left a mark on the cities. The greatest impact has been experienced during the lockdown, however, some of the consequences may remain for longer. The study of Ramani and Bloom (2022) looks at a phenomenon named donut effect, which is explained as a shift of economic activity from city centers to suburbs, affecting businesses as well as real estate. The authors observed that this effect has had the most impact on the largest cities. The donut effect has been very influential for firms, since the reduced density in central business districts (CBDs) has an impact on the agglomeration effects that the businesses benefit from. Rosenthal, Strange and Urrego (2022) studied the valuation of proximity to city centers and observed that this value dropped after the outbreak of COVID-19. This effect was more pronounced in the cities that rely on public transport than in car-based cities.

Also other characteristics affect the city's sensitivity to WFH. The data in the article of Kmetz et al. (2022) reveals that there is a difference between cities with different dominating types of jobs. For example, cities with a lot of employment in technology will experience higher rates of remote work, while areas with more pronounced retail sector may be less affected by the changes (Kmetz et al., 2022). The data from CBS (CBS, 2024) also shows that the WFH rate varies considerably between different occupations. Creative and technology-related jobs have the highest WFH rates while service-oriented jobs are rarely being done remotely. This is in line with Dingel and Neimen (2020), who observed heterogeneity among cities because higher WFH rates are associated with higher levels of education.

Another aspect is that cities with lower housing prices and higher availability of housing stock may attract more remote workers, since the residential space has become more important because of the additional function of working from home, making offices less important(Kmetz et al., 2022). Furthermore, the data from American cities shows that a better climate of an area is another determining factor for remote workers to choose their housing location (Kmetz et al., 2022). According to Delventhal, Kwon and Parkhomenko (2022) the amenities of a neighborhood also play an important role, since areas with better amenities are expected to experience larger growth than other neighborhoods. Therefore, the impact of WFH is location-sensitive, and aspects like housing availability, prices, types of jobs and climate play an important role.

Delventhal et al. (2022) created a model to investigate how a city structure changes if remote working remains permanent. The study takes place in the metropolitan area of Los Angeles, United States, and the results predict welfare gains for teleworkers as well as on-site workers. The group that works from home benefits the most because of the reduction of commuting, as well as the possibility to move to cheaper neighborhoods. Meanwhile the other group benefits from reduced congestion and more affordable real estate because of the fall of house prices on average.

Stanton and Tiwari (2021) stress that household mobility plays a crucial role in order to achieve those welfare gains. While office costs could be saved by letting more people work from home, these savings may not pay out, because the housing prices are rising if people have to use their homes for the working function. Therefore, the savings from remote work may have been overstated, unless the workers have the possibility to move to low cost areas, however, this may not always be realistic because of household immobility and limited supply.

The study of Delventhal et al. (2022) suggests a similar structure as the donut effect that was proposed by Ramani and Bloom (2022). They expect the housing demand to decline in the city centers, since people prefer to move to cheaper neighbourhoods if there is possibility to work remotely. Furthermore, the office prices in CBDs are also expected to fall because of the reduction of required workspace. According to Delventhal et al. (2022) this will result in lower real estate prices. While the prices may increase in the suburbs, the real estate prices on average are expected to go down, resulting in the previously mentioned welfare gain.

The key takeaway is that location plays a crucial role in assessing the effects of teleworking on cities and real estate. This is partly due to the differences in WFH rates, since some cities facilitate more jobs that can be done remotely than others. Furthermore, remote and more affordable locations experience higher real estate demand than before the pandemic, and climate as well as neighbourhood amenities have become more important aspects for choosing location.

2.3. Impact on residential real estate

The effects of remote work are certainly reflected in residential real estate. As concluded in the previous section, the demand for different types of real estate has shifted, affecting city structures and real estate prices.

According to Modragon and Wieland (2022), the housing prices in the United States had increased by 23,8% between December 2019 and November 2021. They studied the impact of WFH on this significant price growth and show that a 1% increase in the levels of WFH leads to a 1,47% increase in house prices. The findings state that more than a half of the price increase in this time period is explained by WFH. The authors also point out that the reasons for this price growth are rather fundamental and not explained by a market bubble, migration or lower interest rates, emphasizing the importance of WFH since it may have a large impact on the housing prices also in the future.

The increase of WFH is positively correlated with the housing prices, while the correlation with commercial real estate rents is very little or even negative (Mondragon & Wieland, 2022). The study of Mondragon and Wieland (2022) found that the increase of the local inflation is very little affected by the exposure to remote work if housing inflation is not considered. In other words, the share of expenditures on housing are increasing with more exposure to WFH. The number of granted building permits also improved with the increase of remote work, so the authors state that the shortage of housing is not the reason for the boost of prices. Mondragon and Wieland (2022) emphasize that policy makers should keep the trend of remote working in mind, since it has a large impact on the development of house prices either way, by increasing and decreasing the prices if WFH levels rise of decline.

Kmetz, Mondragon and Wieland (2022) also show that, according to IPUMS/Census Bureau and Zillow, core-based statistical areas (CBSAs) that had higher WFH levels before the pandemic experienced a higher house price increase after the outbreak of COVID-19, while before the pandemic the housing prices were growing at the same rate in all areas, independent of the shares of remote work. This again implies that teleworking has had an impact on housing prices, affecting areas with higher remote work rates the most. However, the measure of telework rates has been relevant only since the pandemic, as before there was no difference.

How inflation and housing affordability are affected by teleworking is what Howard, Liebersohn and Ozimek (2023) have been investigating in their study. Both short-run and long-run effects were considered and compared. These effects are not the same, since housing supply on the short-run is inelastic. The authors expect an increase in housing prices because of the increased demand, however, they also mention that the effect may be smaller on the long run because of a higher supply elasticity. Howard, Liebersohn and Ozimek (2023) created a simple US housing market model to explore the effects of remote work on the house prices. While in the short-run the market experienced a significant price increase, the model implies that in the long-run the rents will decrease, possibly even ending up lower than before the outbreak of COVID-19.

To conclude, most research shows that WFH is accountable for an increase in housing prices. The expenditure share on housing has increased, resulting in higher property prices, and areas with higher shares of remote workers have experienced the sharpest increase. Remote work is an important factor in real estate markets an therefore should be observed closely in the future.

2.4. Housing preferences

While the housing market has been affected by WFH resulting in an increase in prices, also the demand for specific housing characteristics has changed. The paper of Stanton and Tiwari (2021) compares housing preferences of households that work from home and those that do not. The authors conclude that in the period before COVID-19 households with remote workers were spending a 7% higher share of their expenditures on housing than households of on-site workers. This is mainly explained by the consumption of larger housing units with extra rooms. Furthermore, the price per room is also higher in the houses of remote-working households. However, this study is based on a model using data from households in the U.S. between 2013 and 2017, leaving a research gap for empirical analysis on this topic when more recent data is available, especially after the outbreak of COVID-19.

Also Robbennolt et al. (2023) created a model to study how the housing choices are affected by an individual's preference to work from home. It is concluded that attitude and lifestyle have a significant impact, and so does the preference to work from home. Neighbourhood amenities are more important for individuals that prefer remote working, while commuting distances for this group tend to be longer on average. This is in line with Delventhal et al. (2022), who stated that hedonic pricing functions shift because neighbourhood amenities and certain housing characteristics become more important while the relevance of workplace location disappears. This is due to the reduced importance of commuting in case of WFH.

Malik et al. (2023) used hedonic pricing approach to examine the desirability of green amenities in the cities of the U.S. The results of this study imply that the changes in working and commuting due to COVID-19 have resulted into a reversed trend. While in the years before the pandemic the hedonic price of private green space was decreasing, this trend was reversed and in the post-COVID years it started to increase. However, the authors also show that while this change of trend was clearly observed after the outbreak of the pandemic, the marginal willingness to pay for green space has no correlation with the exposure to WFH in the specific area. According to Malik et al. (2023) the marginal willingness to pay (MWTP) for public green space adjacency has not been affected.

Also other studies (Ramani & Bloom, 2022) agree that the preference for private green spaces may increase, being favoured over public spaces. This again results in higher value for individual property characteristics.

Overall, it can be observed that there have been changes in the desirability of house attributes since COVID-19, and these changes may be implied by the increase of remote work, since households with remote workers show different preferences than others. Also expenditure share on housing in these households is higher, showing a higher willingness to pay for extra comfort at home.

3. Data

3.1 Dataset

For this study, housing transaction data from NVM (*De Koninklijke Nederlandse Coöperatieve Vereniging van Makelaars en Taxateurs)* is used. Three provinces are chosen for this research to cover most of the central areas of the Netherlands, that are Noord-Holland, Zuid-Holland and Utrecht. As concluded in the literature review, the largest cities tend to be the most sensitive to changes, so the provinces that are chosen also include some of the largest cities in the Netherlands. Also diversity is important in order to cover larger cities in central areas as well as more remote places. Therefore, the chosen dataset includes the provinces that provide this diversity, since four largest cities of the country are included (Wikipedia, n.d.), as well as remote and less-densely populated cities and towns, mostly in the northern parts of Noord-Holland.

The transactions in the dataset are covering the time period between 2010 and 2022 (included), adding up to 861,004 observations in total after data cleaning. The dataset covers a sufficient amount of time to make distinction between the trends that took place before the outbreak of the pandemic and the trends that have arisen after the shock. As concluded from the literature, because of the recency of the trend of WFH there is not much data about the consequences of teleworking, which makes it complicated to estimate the effects that will remain in the long run. This paper is using relatively recent data, aiming to provide a more precise outlook on the future scenarios.

The dataset contains a variety of variables, however, not all of them will be applied in the research. For the hedonic regression models the following variables are used. The dependent variable is the transaction price, which is the sales price expressed in euros. The number of rooms is the main variable of interest. Size is used as a control variable and expressed in square meters. A dummy variable that indicates whether a house has a garden is also included, as well as categorical dummy variables for housing type (apartment, detached etc.) and construction year, indicating the time period in which the building was constructed. There are also variables that indicate the score of inside and outside maintenance levels. The previously mentioned are used as control variables, however, the dataset also contains time variables like day, month and year of the transaction. These will be used to control for time-specific fixed effects (FE), as well as divide the dataset into periods before and after COVID-19. Variables indicating the 6-digit zip code and identity of a property are used for fixed effects as well, and the division into COROP regions is applied to make distinction between different education levels.

To compare housing transactions between regions with different education levels, CBS data about highly educated inhabitants is used (CBS, n.d.). A new variable is added to the dataset that indicates the percentage of inhabitants that have obtained at least a bachelor's degree, both academic or professional, also named as WO and HBO in the Dutch education system. This indicator is collected on COROP region[1] level, so a percentage of highly educated inhabitants is assigned to each of the 14 regions in the dataset. The regions with their corresponding education levels are summarized in Table 01. A map with the division of regions can be found in Figure 1A in the Appendix.

COROP region	Highly educated
Groot-Amsterdam	46.1%
Utrecht	43.3%
Agglomeratie Haarlem	43.0%
Het Gooi en Vechtstreek	40.2%
Agglomeratie Leiden en Bollenstreek	39.9%
Agglomeratie 's-Gravenhage	39.2%
Delft en Westland	36.5%
Oost-Zuid-Holland	34.3%
Groot-Rijnmond	33.9%
Alkmaar en omgeving	32.9%
IJmond	32.8%
Zaanstreek	30.1%
Zuidoost-Zuid-Holland	29.8%
Kop van Noord-Holland	28.7%

Table 01: COROP regions and percentages of highly educated inhabitants, from high to low, according to CBS (n.d.)

[1] COROP regions consist of one or more adjacent municipalities within the same province. The Netherlands is divided into 40 COROP regions, which correspond to the European NUTS-3 level. (*COROP Region | CBS*, n.d.)

3.2 Data cleaning

The original dataset of NVM is cleaned before using the data for the research of this thesis. Firstly, a minimum and maximum transaction price is set to 50,000 and 5,000,000, respectively. The transactions outside of this range are dropped, since they are considered outliers and may therefore not represent the housing market well. Also, the range of the house size is set between 25 m^2 and 1000 m^2 to exclude very small or large units from the dataset, since smaller floor areas are not common for housing function, and very large units like palaces would also not represent the mainstream housing market. For the same reason a maximum of 15 rooms is set, so properties with a larger number of rooms are excluded from the dataset. A new variable is created that contains the house prices per square meter. This is done by dividing the transaction price by the number of square meters. Observations that fall outside of the range between 500 euro/m^2 and 30,000 euro/m^2 are dropped.

After data cleaning the dataset consists of 861,004 observations. This is 99.76% of the original dataset, which contained 863,069 observations. Therefore the share of the dropped observations is very small, and the selection is not expected to affect the results.

3.3 Descriptive statistics

First, the data is explored and evaluated by means of descriptive statistics. The information about the main variables used in the regression is summarized in Table 02.

	Price	Size	Rooms
Mean	347,109.5	111.58	4.33
Standard deviation	257,146.3	49.93	1.54
Minimum	50,000	25	1
Maximum	5,000,000	1,000	15

Table 02: Descriptive statistics of variables price, size and rooms

From the frequency plot obtained for the variable “price” it can be observed that the prices are not normally distributed. There is positive skewness, as the distribution is shifted to the left and has a long tail on the right side. A new variable is created that captures the natural logarithm of the price. For further regressions in the thesis this variable will be used, since the distribution of the logarithm of price is closer to normal distribution. For the comparison of the distribution of these variables see the figures below (Figure 1a and Figure 1b).

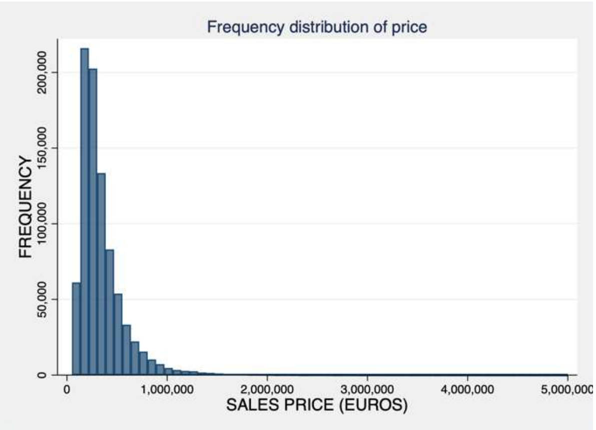


Figure 1a: Frequency distribution of price

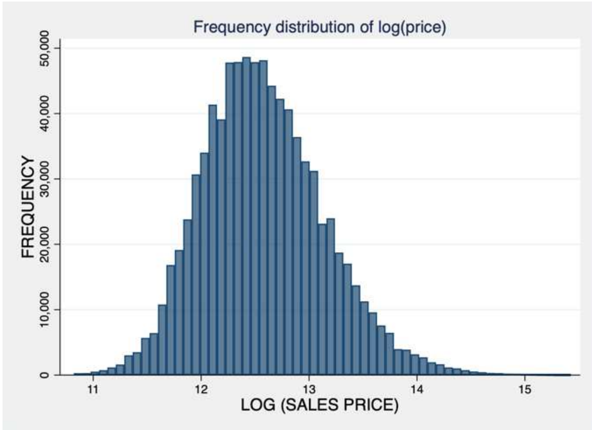


Figure 1b: Frequency distribution of log(price)

The value of a natural logarithm is also applied to another variable that will eventually be used in the regression, namely, the size of the house. Therefore, also this variable should be normally distributed. It can be seen in the Figure 2a that the distribution of the size variable is skewed. Therefore, another variable is created as the natural logarithm of size, and its distribution is closer to normal distribution, what can be seen in Figure 2b.

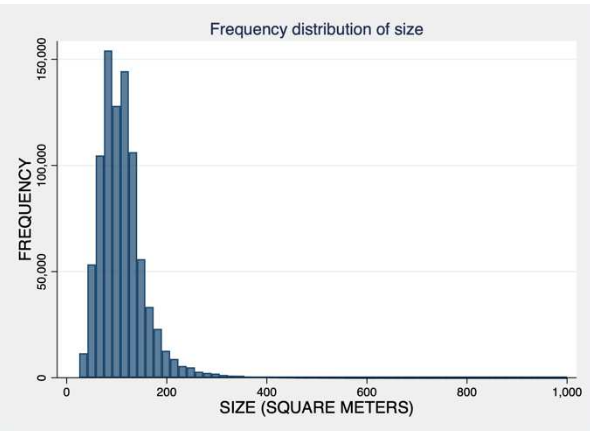


Figure 2a: Frequency distribution of size

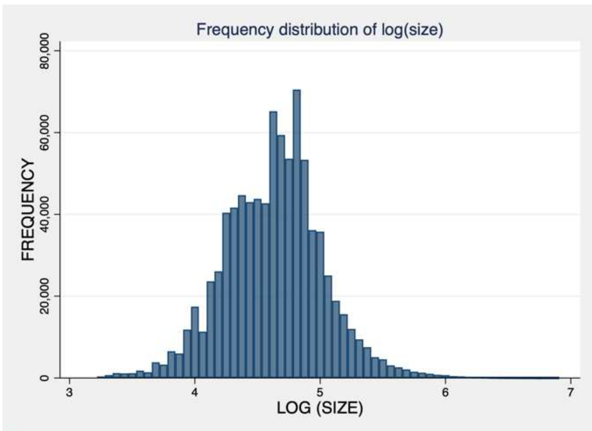


Figure 2b: Frequency distribution of log(size)

Since the main research question concerns the changes in willingness to pay for an additional room in the house, this variable will also be included in the regression and its distribution is shown in Figure 3. Most of the houses in the dataset have three to five rooms, the most common number of rooms being five.

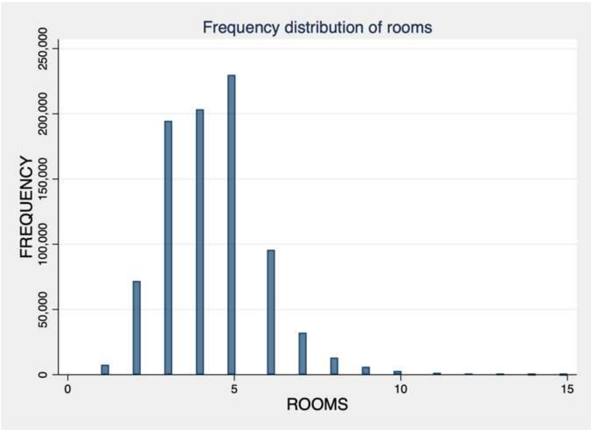


Figure 3: Frequency distribution of the number of rooms

3.4 Exploring the data

To get a better impression about the data, several additional plots are created. In Figure 4 it can be seen that between 2013 and 2022 the housing prices per square meter have increased. While until 2020 the increase was gradual, after 2020 there was a sharp increase in the average transaction prices, creating a jump in the trend line, which resembles a treatment effect after the beginning of the COVID-19 pandemic.

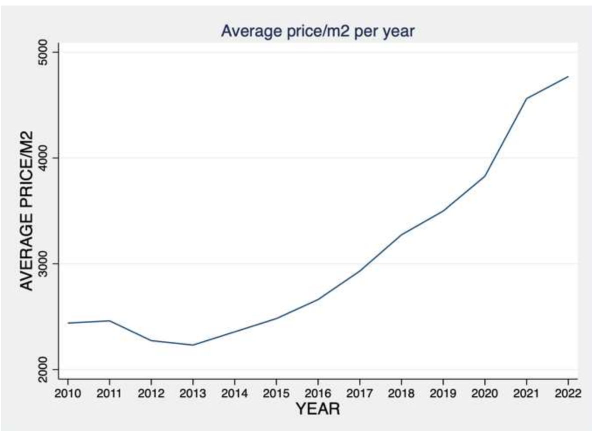
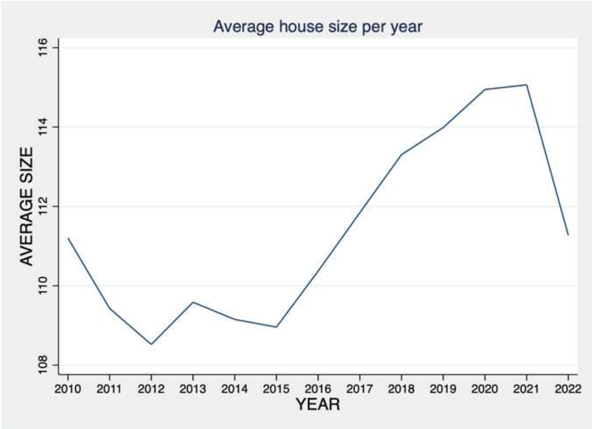


Figure 4: The changes of average housing transaction prices per m^2 in time

Then, the average housing size per year is captured in Figure 5. Contrary to expectations that the required space might increase, the average transacted house size stabilized in 2021 and decreased sharply in 2022. The average house that was sold in 2021 was 115.06 m^2 large, and in 2022 it decreased to 111.27 m^2. A similar trend can be observed in the number of rooms. After a gradual increase until 2020, when the average number of rooms in a transacted house reached 4.45, this number decreased to 4.36 in 2022, what is graphically shown in Figure 6.



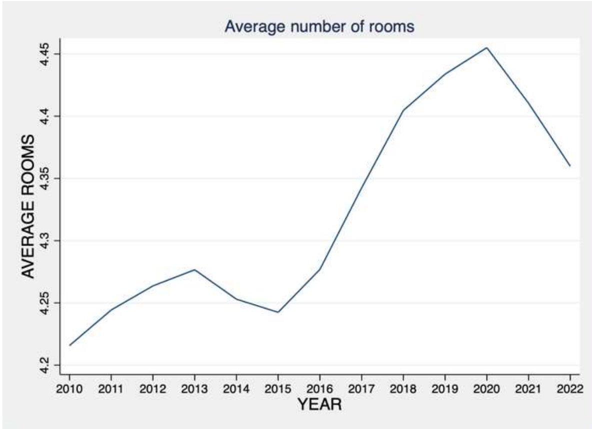


Figure 5: Average house sizes per year *Figure 6: Average number of rooms per year*

From exploring the data, it can be observed that there has been a shift in the residential real estate market after 2020, and it has affected the demand and housing prices. The price per square meter experienced a sharp increase, which might be an indication of a tight housing market. While the average house size was increasing for transactions between 2012 and 2021, in 2022 on average smaller housing units were sold. Also, the number of rooms decreased in the last years. This is counterintuitive, since with the increased WFH rates an increase in the required space and number rooms was expected. This is not likely to be a housing supply effect, since it cannot change in the short run, thus it indicates that people may occupy smaller homes because of an increase in prices. It can possibly be explained by the increase in mortgage rates in 2021 and 2022 (Statista, n.d.). In times of high mortgage interest rates, the buyers can borrow less and therefore consume smaller and more affordable housing units. From the current observations there is a negative relation between WFH rates and the number of rooms and space consumed, however, the changes in willingness to pay (WTP) for an additional room, while other aspects are excluded, is studied in the following chapters.

4. Methods

Since the main research question is to find out whether teleworking has affected housing preferences, a hedonic pricing model is constructed and the changes in time are observed. While the dataset contains various house characteristics, for a better model fit and unbiasedness also fixed effects are included. This chapter explains the build-up of the regression model of this research.

The hypothesis is that since the outbreak of coronavirus there might be more demand for an additional room in the house, as people are working from home and a possibility to set up a home office may be desirable. To assess the changes in willingness to pay for an additional room, a hedonic pricing model is set up, where the dependent variable is price, and the variable of interest is the number of rooms. Other independent control variables that describe the house quality and characteristics are also included, like size, house type, construction year, presence of a garden and maintenance scores. Housing type and construction year are categorical dummy variables, and one category per variable must be left out and assumed as a reference category to avoid perfect multicollinearity. As it can be seen in the chapter of descriptive statistics, the price and size variables are not normally distributed, so variables with the value of natural logarithm are used for prices as well as size. This leads to the following hedonic regression:

$$log(price)_{it} = \alpha + \beta_1 rooms_{it} + \beta_2 \log(size)_{it} + \beta_3 garden_{it} + \beta_4 maintoutside_{it} + \beta_5 maintinside_{it} + \boldsymbol{X}_{it}\boldsymbol{\gamma} + \varepsilon_{it}$$

The index "i" refers to the entity and "t" to the time of transaction; α is the constant and β denotes coefficients for the variable of interest (rooms) and other housing characteristics, like the presence of a garden and maintenance levels. X is a vector of control variables (house type and construction year), and γ is a vector of coefficients for these variables. Finally, ε represents the error term.

To control for unobserved heterogeneity and mitigate omitted variable bias, fixed effects must be included in the model. Time-invariant unobserved factors, like wealth level in the neighborhood, could have positive correlation with other explanatory variables as well as the prices. For example, it may be true that houses in wealthier neighbourhoods have on average larger floor space and more rooms, and the transaction prices in these neighbourhoods are on average also higher. Also time-specific unobserved factors that are constant among the entities and affect the dependent variable (price) should be controlled for. Therefore, both time-invariant and time-specific fixed effects are included in the model.

To find the best fit for fixed effects, a number of options are considered. An overview with the results can be found in Table 1 in the next chapter. Year and month FE are included to control for aspects like economic cycles and trends, which can be seasonal as well as annual. To control for unobserved effects within the same year within the same zip code area, a new variable is generated that assigns a different identifier for each unique combination of the 6-digit zip code and year. Because the dataset contains repeated sales, it is possible to control for house fixed effects. House fixed effects address omitted variable bias and account for unobserved factors that are invariant in time.

When house fixed effects are included, several independent variables are omitted because of collinearity with the fixed effects. Those variables are related to house characteristics that normally do not change over time, like the type of housing (apartment, terraced etc.) and the construction year. Therefore, for further model specification these variables will not be included in the regression as control variables, as long as the model is controlled for house fixed effects.

Besides including FE in the regression, interaction terms are also included to assess the main research question, i.e. compare the willingness to pay for an extra room in times of higher WFH rates. March 2020 is the moment that marks the beginning of the pandemic in the Netherlands, bringing immediate increase in WFH rates (Rijksoverheid.Nl, n.d.). According to Rijksoverheid (n.d.), the last COVID-19 prevention measures where relaxed in March 2022. From then on, the post-COVID-19 period started and working from home was recommended, but not mandatory. Therefore, years 2020, 2021 and 2022 are important to assess the impact of WFH on the prices.

Including interaction terms will show how the effect of one variable on the price changes depending on the level of another variable. In this case, an interaction term between rooms and year variables is chosen to show how the effect of the number of rooms is changing depending on the year of transaction, which is the main area of interest in the research. Also the control variables are interacted with years. This leads to the main regression:

$$\log(price)_{it} = \alpha + \beta_{1t} rooms_{it} * year_{it} + \beta_{2t} \log(size)_{it} * year_{it} + \beta_{3t} garden_{it} * year_{it} + \beta_{4t} maintoutside_{it} * year_{it} + \beta_{5t} maintinside_{it} * year_{it} + \mu_t + \eta_t + \sigma_i + \varepsilon_{it}$$

The notation is the same as in the previous regression. In addition, year fixed effects are added as μ_t; month fixed effects are represented by η_t and house fixed effects by σ_i.

As concluded from the literature, cities with higher education levels tend to be more sensitive to changes in WFH rates. Since the research question entails the exploration of these differences, a percentage of highly educated inhabitants is assigned per COROP region. Figure 2A in the Appendix depicts regions from the dataset with the corresponding share of highly educated inhabitants, according to the CBS data from 2021 (CBS, n.d.). The dataset is split into two subsets, dividing it into regions that have on average at least 40% highly educated inhabitants and regions with less than 40% highly educated inhabitants, leaving 4 regions in the first subset and 10 regions in the other one. The choice of 40% is made based on the number of observations in the regions, so that the division creates two approximately equal groups. Then, the main regression is repeated for both subsets. The results of the regressions are summarized and interpreted in the following chapter.

5. Results and Interpretation

Table 1 shows the baseline model and its build-up with different fixed effects. In column 1 no fixed effects are included. Column 2 shows regression results where time-specific fixed effects, namely year and month, are added. In column 3 the model is also controlled for variation within the same zip code within the same year. Column 4 contains property fixed effects instead, and in column 5 the results are shown where all of the previously mentioned fixed effects are included.

Table 1: Hedonic regression with fixed effects

VARIABLES	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
rooms	0.0159***	0.00867***	0.00380***	0.00443***	0.00538*
	(0.000489)	(0.000379)	(0.000313)	(0.000764)	(0.00323)
log(size)	0.837***	0.842***	0.710***	0.342***	0.227***
	(0.00194)	(0.00150)	(0.00137)	(0.00916)	(0.0352)
garden	-0.0462***	-0.0546***	0.00839***	0.00390***	0.000556
	(0.00103)	(0.000801)	(0.000654)	(0.00137)	(0.00444)
maintenance out	0.245***	0.379***	0.0446***	-0.00778	-0.0973***
	(0.00606)	(0.00470)	(0.00345)	(0.00568)	(0.0191)
maintenance in	0.377***	0.360***	0.355***	0.426***	0.307***
	(0.00486)	(0.00377)	(0.00268)	(0.00425)	(0.0150)
Constant	8.712***	8.200***	8.989***	10.58***	11.14***
	(0.0164)	(0.0128)	(0.0123)	(0.0413)	(0.154)
Observations	861,004	861,004	457,182	195,441	17,874
R-squared	0.529	0.717	0.974	0.978	0.995
control variables	yes	yes	yes		
year FE		yes	yes	yes	yes
month FE		yes	yes	yes	yes
house FE				yes	yes
pc6Xyear FE			yes		yes

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

The model in column 5 provides the best model fit, however, a considerable number of singleton observations are dropped. Since the research question concerns differences between pre- and post-COVID-19 trends, the data is split into two periods to control the convenience of the remaining data. Furthermore, a comparison is made between regions with higher and lower education levels, so there should be a sufficient number of observations in each group for objective results. However, as it is shown in Table 1A in the Appendix, after including the fixed effects from specification 5, the number of observations after COVID-19 is very low, leaving only 60 observations in higher educated regions after the outbreak of the pandemic, and 86 observations in the remaining regions. Considering that the dataset after cleaning contained 861,004 observations and is covering three large provinces of the Netherlands, the number of remaining observations is very low and can therefore not represent the overall dataset. Therefore, the obtained coefficients may not be generalizable. For this reason, the model specification from column 4 is chosen, which includes year, month and property fixed effects. By choosing this specification, the model fit is still relatively high (R-squared value is 0.978) and time-specific as well as detailed time-invariant fixed effects are included, while the number of remaining observations is sufficient to analyze the subsets of the data, see Table 2A in the Appendix.

Table 2 shows the regression results of the hedonic pricing model when year, month and property fixed effects are included, as well as interaction terms between the independent variables and years. Interaction coefficients for all control variables can be found in the Appendix (Table 3A), while Table 2 shows the interaction with the main variable of interest – number of rooms.

Column 1 shows the full hedonic pricing model for all transactions between 2010 and 2022. The interaction terms between “rooms” and “year” show how the willingness to pay for an additional room changes throughout the years. Column 2 contains the data subset with COROP regions that have at least 40% highly educated inhabitants, while the subset in column 3 represents areas where this indicator is under 40%. Also here the year, month and house fixed effects are included.

For a better overview of the differences in coefficients, the data from Table 2 is depicted in the following figures. Figure 7 shows the interaction between variables “rooms” and “year” for all observations (column 1). Figure 8 contains results from the data subsets (columns 2 and 3). These results are depicted in the same graph to provide insight on the differences between areas with higher and lower average education levels.

Table 2: Hedonic regression with FE and interaction terms

VARIABLES	(1) all observations	(2) >=40% highly educated	(3) <40% highly educated
2010 X rooms	5.27e-06	0.000481	-0.00212
	(0.00175)	(0.00245)	(0.00238)
2011 X rooms	0.00354*	0.00492*	0.00242
	(0.00183)	(0.00255)	(0.00250)
2012 X rooms	-0.000949	-0.000764	-0.000436
	(0.00186)	(0.00264)	(0.00250)
2013 X rooms	0.00402**	-0.00131	0.0101***
	(0.00194)	(0.00266)	(0.00268)
2014 X rooms	0.0100***	0.0124***	0.00622***
	(0.00166)	(0.00229)	(0.00228)
2015 X rooms	0.0112***	0.0130***	0.00770***
	(0.00148)	(0.00203)	(0.00205)
2016 X rooms	0.00910***	0.00844***	0.00620***
	(0.00141)	(0.00196)	(0.00193)
2017 X rooms	0.00601***	0.00660***	0.00206
	(0.00140)	(0.00200)	(0.00188)
2018 X rooms	-0.000147	0.000645	-0.00306
	(0.00146)	(0.00204)	(0.00198)
2019 X rooms	-0.00206	-0.00335	-0.00319
	(0.00144)	(0.00204)	(0.00195)
2020 X rooms	-0.000193	0.00150	-0.00302
	(0.00136)	(0.00191)	(0.00185)
2021 X rooms	0.0146***	0.0181***	0.0106***
	(0.00147)	(0.00206)	(0.00201)
2022 X rooms	0.00929***	0.0102***	0.00809***
	(0.00151)	(0.00210)	(0.00208)
Constant	10.46***	10.30***	10.67***
	(0.0396)	(0.0557)	(0.0537)
Observations	195,441	93,482	101,959
R-squared	0.980	0.981	0.979
house FE	yes	yes	yes
year FE	yes	yes	yes
month FE	yes	yes	yes
control variables X year	yes	yes	yes

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

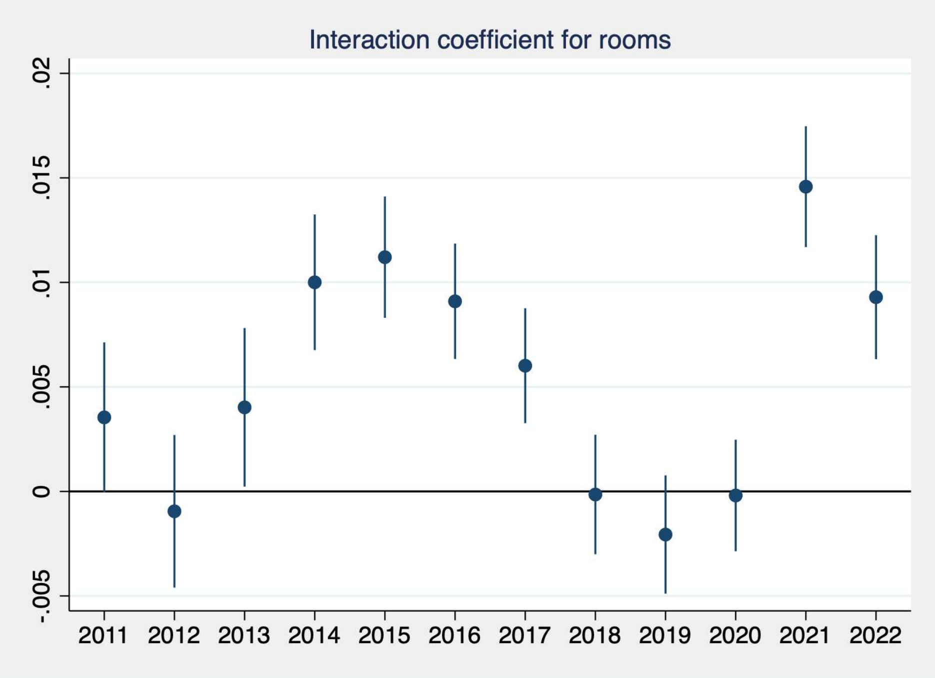


Figure 7: Results of the main regression for "rooms" (Table 2, column 1)

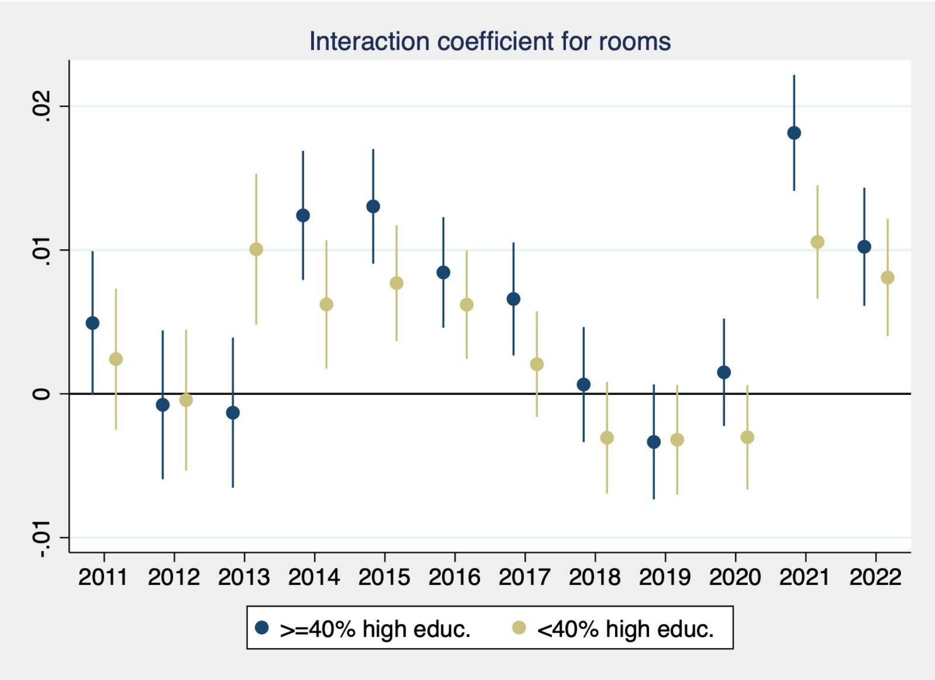


Figure 8: Results of the main regression for "rooms" (Table 2, columns 2 and 3)

The results in Figure 7 show the changes in the willingness to pay (WTP) for rooms throughout the years 2011 to 2022 in all regions on average. The WTP for an additional room has been fluctuating, and in some years the results are not statistically significant at a 90% confidence level. This means that in a number of years the marginal value of an additional room was not significantly different from zero and therefore had a very small or no impact on the house price.

However, in 2021 there was a considerable spike in the results. The coefficient increased from -0.000193 in 2020 to 0.0146 in 2021. This can be interpreted as follows. In 2020 an additional room in a house, all else being equal, on average resulted in a 0.0193% (0.000193*100%) decrease in the house price. In 2021 this was an increase of 1.46%. The coefficient in 2021 is statistically significant, unlike for 2020, when it was not significantly different from zero.

Economic significance can be assessed by looking the following example. A house that has an additional room would be 77.2 euros cheaper than an identical house without the room if the selling price was 400,000 euros in 2020. This is obviously not economically significant, since it is a very small share of the total price. In 2021 an additional room would result in an increase of 5,840 euros, which in some cases could be considered economically significant.

Overall, the increase of the marginal value of a room in 2021 is remarkable because of the trends in the previous years, as the coefficient has even been negative in 2012, 2018, 2019 and 2020. This means that an additional room in a house on average decreased the value of a house, all other aspects held constant. This makes sense, since more luxurious properties often have larger rooms, and people may be willing to pay more for spacious rooms, so a house with the same floor area but smaller number of rooms may at times on average be more expensive. However, during the pandemic (in 2021) the WTP for an additional room was significantly positive and increased sharply in comparison with the previous years. It dropped again in 2022, but still remained relatively high, contributing to a 0.929% increase in the transaction price per extra room.

After running the regression on all regions, subsets have been made by splitting the data into higher and lower educated COROP regions, and the outcomes of the coefficient for rooms are presented in Figure 8. In general, until 2021 both groups follow a similar trend, however, in most of the years an additional room is valued higher in regions with higher education levels. This is no different in 2021, when buyers in regions with more highly educated inhabitants valued an extra room in a house higher, but in this year the marginal willingness to pay increased sharply for both groups. While this increase can be observed in both groups, the higher educated areas showed a steeper rise, which is aligned with the expectations. As concluded in the literature review, higher education levels are also associated with higher WFH rates, and this conclusion is in line with the results that show increased value for an additional room in areas with more highly educated people. In 2022 the coefficients dropped, however, the marginal value of an additional room remained relatively high.

While an additional room in a house in 2021 resulted in a 1.81% price increase in regions with at least 40% highly educated inhabitants, in 2022 it dropped to 1.02%. In other regions it was 1.06% and 0.809%, respectively. The results show that the WTP for an additional room increased during the pandemic years, when WFH rates were high. Nevertheless, the long-term trends should be observed in the coming years to estimate the lasting effects of WFH.

To assure robustness of the results, the outcomes should not be sensitive to the assumptions made and data subsets used. For this reason, the regression is repeated for the full dataset as well as two subsets separately. The results are compared and interpreted in the previous paragraphs. The choice of fixed effects is discussed in chapter 4.

Since the dataset consists of a large number of observations, it was possible to include detailed fixed effects (on a property level) and still have a sufficient number of observations. Therefore, the obtained results are controlled for unobserved aspects and the omitted variable bias is mitigated. To also control for time-specific fixed effects, month and year FE are added. Finally, variables that show collinearity with FE are omitted from the model. This ensures robust and reliable regression results.

6. Summary and Conclusions

The main research question of this thesis was to explore how increased rates of working from home (WFH) have affected the Dutch housing market. More specifically, the goal was to find out whether WFH is associated with an increased demand for an additional room in a house. To answer the research questions, a hedonic pricing model was used. The regression was controlled for detailed time-invariant fixed effects on the house level as well as time-specific fixed effects, i.e. year and month. Interaction terms between years and the main variable of interest (rooms) as well as control variables were included. Housing transaction dataset from NVM was used in combination with data from CBS that contains education levels per COROP region, and the results were reviewed for the full dataset as well as two subsets, split according to the education levels. One of the subset contains COROP regions where at least 40% of the inhabitants have a bachelor's (or higher) degree. The other subset contains regions where less than 40% of the population are highly educated. The results are thereafter compared to arrive at conclusions and answer the research questions.

The obtained results are in line with the expectations based on the literature review. It is clearly visible that the pandemic with its implications has had an impact on the Dutch housing market, furthermore, this impact varies between regions with different education levels.

To arrive at the conclusion, the willingness to pay (WTP) was analyzed for an additional room in a house. The marginal value that the buyers attribute to an additional room has been fluctuating, sometimes even being statistically insignificant or negative. However, in 2021 it spiked, reaching the highest level in the time period between 2010 and 2022. By looking separately at the two data subsets, it is concluded that both groups were affected by COVID-19 and working from home. While there is an increase in the marginal WTP for a room in 2021 in both groups, the increase is somewhat larger in the regions with relatively more highly educated inhabitants, where an additional room increased the house value by 1.81% in 2021. In other regions an additional room contributed to a 1.06% increase on average. While the impact of the extra room dropped in 2022, it still remained significant, implying that research in the following years may be necessary to estimate the long term effects.

To sum up, the results obtained are aligned with the expectations from the analyzed literature. Willingness to pay for an additional room in a house increased during the pandemic. Furthermore, regions in the Netherlands with larger shares of highly educated inhabitants proved to be somewhat more sensitive to the changes induced by COVID-19, since the marginal value attributed to an extra room increased more in these regions. Working from home has become a part of the Dutch working culture, and it has an impact on the housing market. An additional room in a house is highly valued since the popularization of the new working culture. All in all, there is a notable impact on the housing market, but the future of WFH is not certain and the related trends in the housing market should still be observed in the coming years.

For further research and more detailed results, all twelve provinces could be studied, since the dataset used in this thesis covers three provinces of the Netherlands. Also, the data with education levels is applied on COROP region level. This could be further examined by choosing smaller spatial units, like municipalities or even neighborhoods. Furthermore, besides education levels, a division of areas by occupation type could also deliver useful insights. The evolution of housing preferences should be studied for several more years after the pandemic to assess the extent to which the consequences of WFH are relevant in the long run.

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Appendix

Figure 1A: COROP regions in the Netherlands (*COROP - Wikipedia*, n.d.)

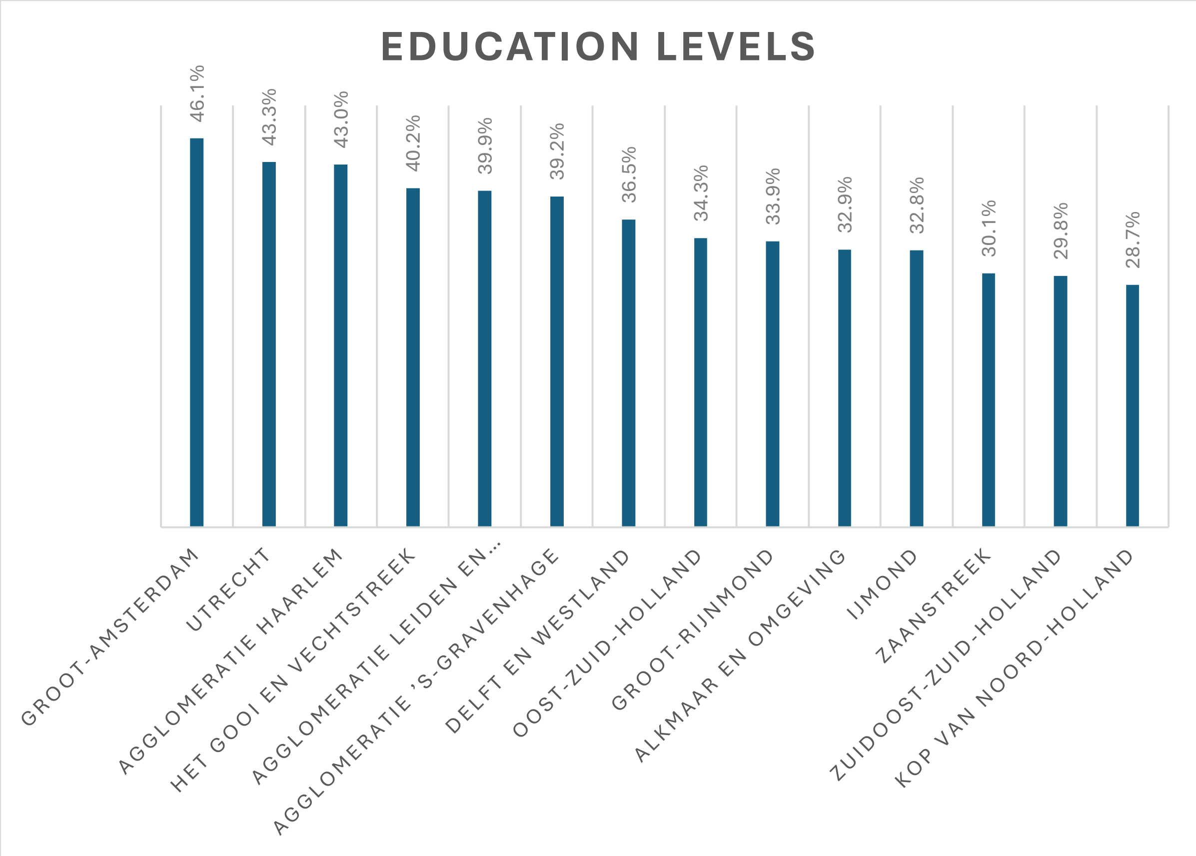

Figure 2A: Percentages of highly educated inhabitants (at least a bachelor's degree) per COROP region (*Waar Wonen de Meeste Hoogopgeleiden? | CBS*, n.d.)

Table 1A: Hedonic regression before and after COVID[2]

VARIABLES	(1) all observations before	(2) all observations after	(3) high educ. before	(4) high educ. after	(5) low educ. before	(6) low educ. after
rooms	0.00409	-0.0486	-0.00217	0.0424	0.0103	0.0266
	(0.00479)	(0.0327)	(0.00626)		(0.00746)	(0.0487)
log(size)	0.254***	0.836	0.221***	3.398	0.316***	0.296
	(0.0479)	(1.140)	(0.0623)		(0.0752)	(1.224)
garden	-0.00326	0.0331	-0.00177	0.0958	-0.00586	-0.136
	(0.00659)	(0.0485)	(0.00854)		(0.0104)	(0.0876)
maintenance out	-0.0803***	0.0351	-0.0959***	0.0752	-0.0655	0.503
	(0.0263)	(0.253)	(0.0341)		(0.0412)	(0.444)
maintenance in	0.282***	0.252*	0.304***	0.831	0.264***	0.232
	(0.0210)	(0.129)	(0.0280)		(0.0321)	(0.369)
Constant	10.89***	8.916*	11.15***	-2.507	10.50***	10.77
	(0.208)	(4.908)	(0.270)		(0.329)	(5.385)
Observations	7,752	154	4,023	60	3,729	86
R-squared	0.995	0.995	0.995	0.996	0.993	0.999
house FE	yes	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes	yes
month FE	yes	yes	yes	yes	yes	yes
pc6Xyear	yes	yes	yes	yes	yes	yes

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

Table 2A: Hedonic regression before and after COVID

VARIABLES	(1) all observations before	(2) all observations after	(3) high educ. before	(4) high educ. after	(5) low educ. before	(6) low educ. after
rooms	0.00722***	0.00695**	0.00734***	0.00907*	0.00418***	0.00420
	(0.00109)	(0.00348)	(0.00155)	(0.00539)	(0.00145)	(0.00460)
log(size)	0.334***	0.388***	0.395***	0.390***	0.259***	0.390***
	(0.0122)	(0.0734)	(0.0175)	(0.109)	(0.0162)	(0.101)
garden	0.00144	-0.0158**	-0.000762	-0.0174	0.00421*	-0.0144
	(0.00188)	(0.00716)	(0.00266)	(0.0110)	(0.00253)	(0.00946)
maintenance out	-0.0201***	0.00772	-0.0215*	0.0130	-0.00858	0.000208
	(0.00752)	(0.0283)	(0.0111)	(0.0459)	(0.00971)	(0.0361)
maintenance in	0.441***	0.470***	0.380***	0.474***	0.486***	0.470***
	(0.00552)	(0.0207)	(0.00854)	(0.0343)	(0.00687)	(0.0258)
Constant	10.47***	10.71***	10.37***	10.81***	10.67***	10.62***
	(0.0549)	(0.334)	(0.0779)	(0.493)	(0.0735)	(0.462)
Observations	109,164	4,915	51,847	2,225	57,317	2,690
R-squared	0.974	0.985	0.974	0.985	0.973	0.985
house FE	yes	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes	yes
month FE	yes	yes	yes	yes	yes	yes

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

[2] The reference date for the start of COVID-19 is assumed 13 March 2020, since that marks the starting date of COVID-19 measures in the Netherlands, according to CBS (n.d.).

Table 3A: Hedonic regression with FE and interaction terms

VARIABLES	(1) all observations	(2) >=40% highly educated	(3) <40% highly educated
2010 x rooms	5.27e-06	0.000481	-0.00212
	(0.00175)	(0.00245)	(0.00238)
2011 x rooms	0.00354*	0.00492*	0.00242
	(0.00183)	(0.00255)	(0.00250)
2012 x rooms	-0.000949	-0.000764	-0.000436
	(0.00186)	(0.00264)	(0.00250)
2013 x rooms	0.00402**	-0.00131	0.0101***
	(0.00194)	(0.00266)	(0.00268)
2014 x rooms	0.0100***	0.0124***	0.00622***
	(0.00166)	(0.00229)	(0.00228)
2015 x rooms	0.0112***	0.0130***	0.00770***
	(0.00148)	(0.00203)	(0.00205)
2016 x rooms	0.00910***	0.00844***	0.00620***
	(0.00141)	(0.00196)	(0.00193)
2017 x rooms	0.00601***	0.00660***	0.00206
	(0.00140)	(0.00200)	(0.00188)
2018 x rooms	-0.000147	0.000645	-0.00306
	(0.00146)	(0.00204)	(0.00198)
2019 x rooms	-0.00206	-0.00335	-0.00319
	(0.00144)	(0.00204)	(0.00195)
2020 x rooms	-0.000193	0.00150	-0.00302
	(0.00136)	(0.00191)	(0.00185)
2021 x rooms	0.0146***	0.0181***	0.0106***
	(0.00147)	(0.00206)	(0.00201)
2022 x rooms	0.00929***	0.0102***	0.00809***
	(0.00151)	(0.00210)	(0.00208)
2010 x log(size)	0.431***	0.518***	0.326***
	(0.0106)	(0.0147)	(0.0145)
2011 x log(size)	0.443***	0.526***	0.325***
	(0.0108)	(0.0150)	(0.0148)
2012 x log(size)	0.450***	0.539***	0.328***
	(0.0109)	(0.0152)	(0.0149)
2013 x log(size)	0.455***	0.567***	0.302***
	(0.0111)	(0.0155)	(0.0153)
2014 x log(size)	0.441***	0.515***	0.347***
	(0.0104)	(0.0146)	(0.0144)
2015 x log(size)	0.425***	0.491***	0.362***
	(0.0100)	(0.0140)	(0.0139)
2016 x log(size)	0.414***	0.469***	0.385***
	(0.00986)	(0.0138)	(0.0135)
2017 x log(size)	0.390***	0.430***	0.367***
	(0.00986)	(0.0139)	(0.0134)
2018 x log(size)	0.344***	0.397***	0.302***
	(0.00998)	(0.0140)	(0.0136)
2019 x log(size)	0.309***	0.373***	0.252***
	(0.00997)	(0.0141)	(0.0135)
2020 x log(size)	0.286***	0.356***	0.210***
	(0.00979)	(0.0138)	(0.0133)
2021 x log(size)	0.250***	0.326***	0.158***
	(0.0101)	(0.0141)	(0.0137)
2022 x log(size)	0.284***	0.371***	0.183***
	(0.0101)	(0.0142)	(0.0137)
2010 x garden	0.0534***	0.0451***	0.0575***

	(0.00315)	(0.00446)	(0.00428)
2011 x garden	0.0504***	0.0423***	0.0490***
	(0.00341)	(0.00469)	(0.00474)
2012 x garden	0.0382***	0.0227***	0.0456***
	(0.00354)	(0.00497)	(0.00483)
2013 x garden	0.0336***	0.0224***	0.0370***
	(0.00377)	(0.00523)	(0.00520)
2014 x garden	0.0135***	-0.00468	0.0296***
	(0.00319)	(0.00434)	(0.00449)
2015 x garden	-0.00852***	-0.0299***	0.0162***
	(0.00280)	(0.00384)	(0.00392)
2016 x garden	-0.0153***	-0.0312***	0.00585
	(0.00266)	(0.00370)	(0.00366)
2017 x garden	-0.0221***	-0.0250***	-0.0113***
	(0.00271)	(0.00382)	(0.00367)
2018 x garden	-0.0214***	-0.0149***	-0.0211***
	(0.00286)	(0.00405)	(0.00387)
2019 x garden	-0.0141***	-0.00348	-0.0212***
	(0.00285)	(0.00404)	(0.00384)
2020 x garden	-0.00367	0.0141***	-0.0218***
	(0.00270)	(0.00372)	(0.00375)
2021 x garden	0.000133	0.0199***	-0.0210***
	(0.00294)	(0.00405)	(0.00408)
2022 x garden	0.0112***	0.0265***	-0.00809*
	(0.00301)	(0.00417)	(0.00415)
2010 x maintenance outside	0.0469***	0.0699***	0.0641***
	(0.0176)	(0.0257)	(0.0233)
2011 x maintenance outside	0.0123	0.00548	0.0683***
	(0.0184)	(0.0267)	(0.0243)
2012 x maintenance outside	0.0225	0.0619**	0.0318
	(0.0183)	(0.0263)	(0.0244)
2013 x maintenance outside	0.0300	0.0691**	0.0237
	(0.0191)	(0.0279)	(0.0252)
2014 x maintenance outside	-0.0241	0.00557	-0.0211
	(0.0174)	(0.0244)	(0.0237)
2015 x maintenance outside	0.0133	0.00891	0.0133
	(0.0162)	(0.0231)	(0.0218)
2016 x maintenance outside	0.000765	0.00312	-0.0356*
	(0.0155)	(0.0226)	(0.0205)
2017 x maintenance outside	0.0150	-0.0148	-0.00934
	(0.0162)	(0.0244)	(0.0208)
2018 x maintenance outside	0.0260	0.0105	0.0115
	(0.0172)	(0.0258)	(0.0223)
2019 x maintenance outside	-0.0251	-0.0352	-0.0223
	(0.0189)	(0.0284)	(0.0243)
2020 x maintenance outside	-0.0408**	-0.0432	-0.0167
	(0.0197)	(0.0290)	(0.0257)
2021 x maintenance outside	-0.0570**	0.0123	-0.0941***
	(0.0225)	(0.0320)	(0.0303)
2022 x maintenance outside	-0.0674***	-0.0722**	-0.0331
	(0.0232)	(0.0338)	(0.0307)
2010 x maintenance inside	0.345***	0.309***	0.384***
	(0.0132)	(0.0199)	(0.0169)
2011 x maintenance inside	0.385***	0.369***	0.402***
	(0.0138)	(0.0205)	(0.0179)
2012 x maintenance inside	0.406***	0.339***	0.464***
	(0.0142)	(0.0205)	(0.0189)

2013 x maintenance inside	0.439***	0.395***	0.479***
	(0.0144)	(0.0213)	(0.0188)
2014 x maintenance inside	0.481***	0.417***	0.533***
	(0.0134)	(0.0191)	(0.0180)
2015 x maintenance inside	0.482***	0.436***	0.516***
	(0.0126)	(0.0184)	(0.0166)
2016 x maintenance inside	0.467***	0.408***	0.516***
	(0.0122)	(0.0184)	(0.0157)
2017 x maintenance inside	0.449***	0.383***	0.501***
	(0.0128)	(0.0194)	(0.0164)
2018 x maintenance inside	0.433***	0.364***	0.470***
	(0.0138)	(0.0215)	(0.0173)
2019 x maintenance inside	0.446***	0.408***	0.459***
	(0.0156)	(0.0235)	(0.0198)
2020 x maintenance inside	0.367***	0.335***	0.379***
	(0.0168)	(0.0251)	(0.0215)
2021 x maintenance inside	0.329***	0.248***	0.393***
	(0.0192)	(0.0274)	(0.0256)
2022 x maintenance inside	0.312***	0.312***	0.307***
	(0.0202)	(0.0301)	(0.0261)
Constant	10.46***	10.30***	10.67***
	(0.0396)	(0.0557)	(0.0537)
Observations	195,441	93,482	101,959
R-squared	0.980	0.981	0.979
house FE	yes	yes	yes
year FE	yes	yes	yes
month FE	yes	yes	yes

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