Master thesis

MSc Economic Geography

Regional effects of the electricity power grid capacity on housing prices in the Netherlands: a comparative housing prices analysis in the Netherlands.

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Abstract

The interaction between electricity services and housing price formations is a topic that has been extensively researched, especially in recent years as electricity consumption and production rose. However, literature has failed to successfully address the influence of the newly arisen problems on the electricity grid on transaction prices. A database of transaction data was created for the Netherlands for 2023 containing building specific and neighbourhood specific characteristics. Using this data, this study has examined the relationship between the electricity grid and housing prices are by estimating linear and multi-level regression models. The results of this paper reveal that areas experiencing higher levels of grid congestion, face decreases in housing prices. More importantly, in urban areas the negative influence of limited electricity grid capacity tends to be more severe when compared to rural areas. This study contributes to a broader understanding of how changes in the electricity supply influence housing prices in the Netherlands. It provides valuable insights for policymakers and stakeholders involved in urban developments and energy management. The conclusions of this study underscore the importance of further research on this relationship.

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1. Introduction

Due to the impact of fossil fuels on the environment, 197 nations, including the Netherlands, have pledged to prevent global warming from exceeding the critical two degrees Celsius by signing the Paris Agreement in 2015 (UNFCCC, 2015). As emissions have risen, and are still rising (Ritche et al., 2020). To reach this globally accepted goal, the European Union has adopted the Climate Law, which obligates all European nations to be climate neutral in 2050, by significantly reducing greenhouse gas emissions, focusing on exploiting renewable energy sources, and improving energy efficiency (European Union, 2021). In the Dutch Climate Plan for 2021-2030, specific incentives, subsidies, and laws are listed to encourage businesses and individuals to invest in green energy alternatives contributing to the set climate goals (Ministerie van Economische Zaken en Klimaat, 2020).

Most notable in solar and wind energy in which investments multiplied by a factor of 13 for wind energy and 3 for solar energy respectively between 2011 and 2022 (CBS*b*, 2024). As a result, the Netherlands has recorded massive reductions in the amount of CO_2 equivalents emitted, dropping from 214,5 billion in 2019 to 175,8 billion in 2023, in which the electricity industry recorded the greatest drop in emissions with approximately 43% (CBS*a*, 2024). At the same time, gas-powered systems such as stoves and central heating are replaced by electric counterparts, as well as the electrification of transportation modes such as cars. Electricity consumption and production thus rose drastically over the past decade. In addition, electricity creation is increasingly geographically dispersed as central points of electricity creation, such as power plants, are replaced by big solar- and wind parks. Moreover, individuals and small companies have increasing amounts of solar panels lying on their roofs. In 2023 the amount of solar panels owned by individuals and small companies rose by a quarter compared to 2022, resulting in a doubling of the amount of consumers that requested a heavier electricity connection (Bremmer & van Zoelen, 2023).

The electricity grid, being the infrastructure transmitting electricity between consumption and production sources, is not built for the increased volume and the decentralised system of electricity generation. Consequently, electricity demands exceed the electricity grid capacity, referred to as net congestion.

1.1 Research gap and question

Net congestion problems are quite recent, yet very important as they may assert negative effects. This is underscored by Jetten (2024), former Dutch Minister of Climate and Energy, warning the cabinet that 1.5 million households and small firms may experience externalities caused by the crammed electricity grid in the coming years up to 2030, consisting of flickering lights, not good working equipment and risks of power losses. Some areas in the Netherlands, however, already experience the consequences of the crammed electricity grid. For instance, in the province of Utrecht, 90% of housing and commercial projects face possible delays as they cannot acquire a heavy electricity connection. In some neighbourhoods charging stations for cars are reduced in speed during electricity usage peak hours (RTL Nieuws, 2024). Moreover, solar panel users nowadays are forced to pay for delivering energy back to the net, while in some areas the energy providers turn off individual solar panels to prevent power outages, reducing the benefits of owning solar panels (Wijkman, 2024; van de Pol, 2024).

To prevent this from happening, annual investments of 8 billion Euros in the electricity grid are projected, however, the boundaries of the networks are expected to be reached in 2026, three years before the expansion of the electricity network is realised (Stedin, 2023). Interestingly, the expansion of electricity grid capacity, accommodating the energy transition, may experience resistance as is the case in Amsterdam. Plans for building 2600 new small powerhouses and 29 electricity stations (van

Zoelen, 2024), led to neighbourhood protests preventing construction, as inhabitants fear health complications and reduced street attractivity (Bianchi, 2021).

A lot of recent research has been done on the influence of different factors on housing prices. On national levels, low supply rates and high building constraints may increase housing prices (Caldera & Johansson, 2013; Saiz, 2010). More specifically, housing prices vary geographically because of differences in the existing housing stock (Wijburg et al., 2018; Musterd et al., 2016). Consisting of variations in energy efficiency (Taruttis & Weber, 2022), the proximity of amenities (Glaeser et al., 2001; Li & Brown, 1980; among others) or the presence of externalities (Cordera et al., 2019; De Vor & De Groot, 2011). Locational factors such as neighbourhood characteristics may also influence housing price dynamics (Mirkatouli et al., 2018; Musterd et al., 2016; Hiller & Lerbs, 2016).

More recently, researchers have implemented electricity infrastructure into housing price literature. In the US, the expansion of charging stations for electric vehicles has resulted in higher housing values for houses in proximity (Liang et al., 2023). Taruttis & Weber (2022) find that in Germany houses with high energy efficiency are valued higher than those that do not, putting more emphasis on the implementation of sustainable energy infrastructure. Wesz et al (2023) incorporate adequate electricity supply and facilities in their urban Quality of Life framework. Worsening of urban services, such as electricity externalities could lead to lower perceived quality of life values, reducing the attractivity of certain urban areas, influencing housing values. The negative experiences of the addition of small powerhouses and electricity stations contribute to this argument (Wesz et al., 2023).

Literature lacks studies conducted on electricity grid capacity and housing prices, probably because of the recentness of the problems. The only known research addressing this topic is that of Marope & Phiri (2024) who conclude that in South Africa, load-shedding, deliberately shutting down electric power in particular areas or regions to prevent widespread power failures, could lead to decreased property values. Urban Quality of Life studies, and studies on electricity infrastructure support this. On the contrary, however, building constraints, such as waiting times and less construction, could cause rising housing prices (Caldera & Johansson, 2013; Saiz, 2010). Raising questions about the relationship between the electricity grid and housing prices, as current literature has failed to answer this question.

Addressing this knowledge gap, this paper aims to contribute to the existing literature on electricity infrastructures and housing prices. It explores the relationship between the availability of electricity grid capacity and housing prices, and the direction of this relationship. Specifically, it seeks to answer the following research question:

To what extent does electricity grid capacity influence housing prices in the Netherlands, and is spatial heterogeneity observable within this relationship?

To determine whether electricity grid capacity and housing prices are related and whether this relation is geographically different, this study proposes two different regression models. One being a linear regression model and the other a multi-level regression model, accounting for the spatial differences within this relationship. The research will consist of a comparative analysis between rural and urban areas. The analyses will be based on a self-constructed dataset, consisting of Dutch transaction data over the year 2023, will be used. This transaction data is advanced by adding building-specific and location-specific variables to each transaction.

1.2 Contributions and paper structure

The results of this paper could contribute to the literature on segregation dynamics. If housing prices are affected by electricity grid capacity, the geographical distribution of affluent and poorer areas may change. Residential location choice is dependent on the structure of the housing market (Hedman et al., 2011), and individuals and households tend to sort themselves geographically based on socioeconomic characteristics (Musterd et al., 2016). Monitoring positive or negative impacts on geographically diverse housing price dynamics could help governments implement new policies preventing segregation based on electricity grid capacity. The outcomes of this study might prove valuable for real estate companies, developers, electricity distribution companies and agencies, as the potential risks of investing in residential real estate are better understood in relation to net congestion problems. Lastly, the results of this paper could benefit other European countries with similar housing markets, who may experience net congestion problems at later stages of the energy transition.

The remainder of this paper is organised as follows. Section 2 reviews previous research on housing price formation, specifically for liberalised housing markets. Section 3 outlines the quantitative and statistical approach of the analysis of this research, followed by Section 4, which presents the results of the analyses. Section 5 presents the discussions followed by a conclusions in Section 7.

2. Literature

First research conducted on price formation dates back to the end of the 19th century, when one of the most influential books in economy laid the basis for a lot of modern economic concepts. The book 'Principle of Economic' describes how supply and demand will reach an equilibrium, creating the price of a product or service. Elaborating on the elasticity between supply and demand, and how demand is affected by changes in the supply (Marshall, 1890). Pioneers in investigating housing price formation are among others Tiebout (1956), who stated that people have different personal valuations of services and prices and are willing to move from community to maximise their utilities. Baumol (1972), was the first to implement hedonic price models into housing price research to explore correlations between living characteristics and housing values. This literature section contains, firstly, how personal valuations of services and prices are formed by governmental policies and global trends and how they influence housing prices, focussing on the Dutch housing market. Secondly, a wide range of characteristics influencing housing prices are reviewed, among the recently gained importance of adequate electric infrastructure.

2.1 The (Dutch) Housing Market

The Dutch housing market was well known for its large share of social housing, which originated from housing corporations set up by the government to rebuild the housing stock after the Second World War. Around 1990 half of the Dutch housing market consisted of regulated housing. This changed following new ideologies concerning social housing, shifting from being an accommodation for the lower and middle classes to a last resort and short-term temporary solution for the most vulnerable households (Robinson, 2013; Fitzpatrick & Pawson, 2014). At the same time, homeownership was heavily advertised and promoted by the government as it should make citizens more responsible for their dwelling and surroundings, more independent and wealthier (Hochstenbach, 2022). To realise these ideologies subsidies for housing corporations were stopped, forcing them to be self-sufficient. Moreover, citizens received tax discounts on mortgages making homeownership more attractive. This liberalisation of the housing market paved the way for financialization processes on the housing market.

Since the rise of telecommunications and information technologies, the mobility and liquidity of capital have increased drastically, resulting in more and greater foreign investments, defined as globalisation (Sassen, 2004). Globalisation processes are fuelled by the weakening of the national as a spatial unit due to privatisation and deregulation, making regions increasingly active on global markets, resulting in more global and national competition (Smith, 2002). It has sparked the entry of real estate investment trusts (REITs) into the housing market, who are looking to buy or develop large amounts of real estate to generate stable cash flows via rental income (Wijburg et al., 2018). The implementation of the law ‘doorstroming huurmarkt’, enabled more privatised renting by allowing short-term contracts, making buy-to-let investments increasingly attractive as rent can be adjusted to market prices more frequently, increasing possible returns. It has contributed to changing perceptions towards homeownership where it is considered more as an investment as opposed to a place to live (Hochstenbach, 2019), deepening the process of housing as an income-producing financial asset (Wijburg et al., 2018). Ryan-Collins & Murray (2023) underscore this by stating that in Australia: *“returns to owning housing … dominate economic incomes and the prospect of capturing these rents now dominate investments decisions, public investment and subsidies.”* (p. 23).

It has resulted in a reduction of owner-occupied houses and an increase of private renting houses (CBSc, 2024; Hochstenbach & Ronald, 2020). Table 1 shows the annual change of owner-occupied, regulated rents, and privatised rents in the Netherlands. Over the past 11 years, from 2012 to 2023, the amount of privatised rent dwellings rose with 39,3% while regulated rents via corporations only rose with 2,6%.

Table 1: Annual change of housing stock in the Netherland between 2012 and 2023 split by property *Source: CBSc, 2024*

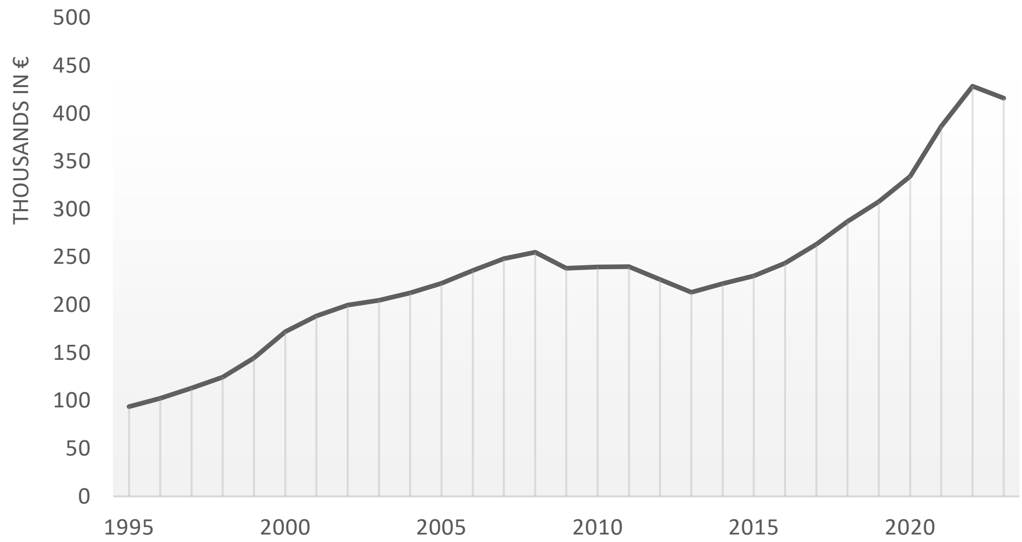
Type of dwelling:	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2012-2023
Owner-occupied	4263	3138	2482	4066	1801	4230	7090	885	914	3941	7437	40247
	1,8%	*1,3%*	*1,0%*	*1,6%*	*0,7%*	*1,7%*	*2,7%*	*0,3%*	*0,3%*	*1,5%*	*2,7%*	*16,8%*
Rent: Total	1453	3126	3051	3194	1738	2498	9346	8071	4700	7271	11841	56289
	0,4%	*0,8%*	*0,8%*	*0,8%*	*0,5%*	*0,7%*	*2,4%*	*2,0%*	*1,2%*	*1,8%*	*2,9%*	*15,2%*
Rent: Corporations	-1583	-832	5017	-4789	-2724	1872	3222	-1901	1608	1854	4719	6463
	-0,7%	*-0,3%*	*2,1%*	*-1,9%*	*-1,1%*	*0,8%*	*1,3%*	*-0,8%*	*0,7%*	*0,8%*	*1,9%*	*2,6%*
Rent: Other	3036	3958	-1966	7983	4462	626	6124	9972	3092	5417	7122	49826
	2,4%	*3,1%*	*-1,5%*	*6,1%*	*3,2%*	*0,4%*	*4,2%*	*6,6%*	*1,9%*	*3,3%*	*4,2%*	*39,3%*

Classic capitalist theories suggest that market mechanisms are sufficient and always reach an equilibrium in which supply always meets demand. However, for the housing market it seems not to be the case as companies and individuals owning multiple homes aim to extract as much potential value from former de- or not fully-commodified houses by transforming them to more luxurious standards, maximising rents (Wijburg et al., 2018).

Less regulations have thus resulted in rising housing prices in the Netherlands. On the contrary, however, lot of research show that more regulations seem to be related to rising housing prices as well. The speed of which supply and demand close in on each other, the so called speed of propagation, is determined by the efficiency of institutional frameworks (Adams & Füss, 2010). This varies between countries as each nation has different laws and regulations, taxes and administrative processes (Catte et al., 2004). In countries and metropolitan areas that are land-constrained, more regulations are prevalent because the scarcity of land makes land use more important, slowing down the supply of housing, resulting in higher housing prices (Saiz, 2010). On the contrary, Hilber & Vermeulen (2016) argue that areas with a lot of constraints and limited developable land make housing prices more sensitive to economic changes. The recent nitrogen emission crisis also acts as a constraint slowing down the supply of new housing projects (Caldera & Johansson, 2013).

Moreover, antigrowth land policies are kept in place because a lot of people and governments benefit from rising housing prices. High and rising housing prices are deemed so important because of the new role of real estate within global financial markets and the macroeconomic stimuli it can create (Bosma et al., 2018). It has resulted in opposition to city growth as individuals and institutions want the value of their asset to cost more (Ortalo-Magne & Prat, 2014). The consequence of these trends are extremely significant rising housing prices increasing from €93.750 in 1995 to €416.153 in 2023 (CBSd, 2024). This is underscored in recent research which shows that three out of the five most expensive cities in Europe based on rent are from the Netherlands: Amsterdam, Rotterdam and The Hague (Baaz, 2024).

Graph 1: Average price paid for a house in the Netherlands between 1995 and 2023



2.2 Neighbourhood characteristics

Although regulations, or the absence of regulations, are important in shaping the housing stock and market, buyers' preferences are ultimately the most important factor in determining housing prices, as they create demand for certain housing types or locations. Housing preferences are mostly referred to as residential location choice and mainly consist of four different classifications; built environment, socioeconomic environment, points of interest and accessibility. These four classifications ultimately contain location-specific and building-specific attributes, while accessibility combines both (Schirmer et al., 2014). In residential location choice models it is important to acknowledge the differentiation of households based on household lifestyle and lifecycles. Walker and Li (2007) find different housing preferences for urban density, retail and service density by categorising three distinct types of households. Preferences thus vary depending on household type resulting in a variation of preferences based on the demographics of a country or region. For example, young families may prioritise a big house closely located in a dense area where services are located close by, while older families prefer smaller houses in lower-density areas (Walker & Li, 2007). In this regard, housing prices are formed by societal housing preferences such as marital status, size of the household, age, education level and household income (Bujang et al., 2010).

In the past decades the number of single-person households has been gradually increasing in many developed countries such as the U.S., Australia and Western European countries (Deka, 2014; De Vaus & Qu, 2015). More recently, research has shown that in Finland, 1% rise of young single households, meaning younger than 34 years, increased apartment prices by 0,51% (Tyvimaa & Kamruzzaman, 2019). In addition, Kohler and van der Merwe (2015) conclude that the reduction of household size is an instrumental factor in the long-term trends of the housing market, as it results in new demand for dwellings. It also claims that singles prefer to live in urban, city areas, where apartment prices are higher than in suburbs. The apartment market will thus continue to experience an upsurge if the current trend of declining household size continues, especially for young single households. Age thus matters in the price forming of real estate. Some argue that the growing share of elderly people and possible declining populations will result in lower demand for housing and thus lower housing prices in the coming decades (Takáts, 2012). Hiller and Lerbs (2016) state that ageing populations may cause declines of housing prices for single homes and condominiums while real rents may rise, mostly taking place in cities.

On the other hand, multiple scholars suggest that ageing populations do not influence real housing prices as much. The elderly only influence the housing market when they are close to life expectancy, and not when entering retirement at an average of 65 years old, making it unlikely that house prices will drop significantly (Heo, 2022). Comparable results are found in the research by Eichholtz & Lindenthal (2014), who conclude that housing consumption keeps growing until a household reaches the age between 60 and 65. Moreover, housing consumption and willingness to pay for a dwelling do not decrease to values lower than the age group of 40 to 54 years. It shows that demand does not decline when populations grow older. Instead, because new generations have more human capital, measured in education level and health, housing demand will rise even though populations shrink.

Yet, to avoid shrinking populations cities are attracting immigrants for work, stimulating the economy. Wang et al. (2017) show that in China inter-regional immigration and the level of urbanisation drive up housing prices on the city level. It underscores that highly-educated migrants assert a bigger influence on housing prices as they are more likely to obtain well-paid jobs and are more willing to settle down in urban areas.

High education levels are almost always related to high age levels. This is proven for the housing market as well, as in the Netherlands the amount of homeowners aged older than 60 is rising, while the amount of young adults owning a house is decreasing, making it harder for younger generations to obtain capital (Hochstenbach & Arundel, 2021), driving spatial segregation simultaneously along age and wealth, as discussed earlier (Sabater & Finney, 2023). This polarisation could also be a cause for people moving to or from certain areas.

This also determines housing prices as households tend to move to neighbourhoods meeting their socioeconomic standards. The larger the difference between one household to the median of the particular neighbourhood, the higher the probability that a household will move (Musterd et al., 2016, p. 242). In other words, affluent areas attract wealthier households while impoverished areas attract poorer households. There is, however, a big difference between those two groups moving to match one's socioeconomic status. Richer households can move to better areas out of a position of luxury and preference, while poorer households are more than often forced to move.

2.3 Amenities

As mentioned, global, national and regional trends, policies and regulations can influence housing prices massively by altering residential preferences. In the 1960s and '70s, the Dutch government promoted rural life as cities were poor and declining and car usage became normalised (Dieleman & Musterd, 1991). This trend turned around in the decades thereafter as cities rose in popularity, partly driven by urban renewal and city policies (Musterd & Ostendorf, 2008) trying to compete on a global scale with other metropolitan areas (Smith, 2002). This changing perspective of city life is described by Glaeser et al (2001) who introduced the term 'consumer city'. People want to live in cities because of the vibrancy of city life, the large amount of amenities, the aesthetics of the built environment, the quality of public services, liveability and quick and easy accessibility of jobs (Glaeser et al., 2001). He supports his claim by proving that urban rents rose quicker than urban wages meaning that the demand for living in cities exceeds incomes. Furthermore, cities with more amenities have grown faster than cities with low amounts of amenities. The influence of the presence or absence of certain facilities, amenities and externalities on housing prices has been widely researched.

Quality of Life (QoL) theories have examined factors that contribute to one's well-being in general (Felce & Perry, 1995). More recently, this has been put in the urban context. Wesz et al (2023) provide a wide range of Urban QoL dimensions and subsequent indicators, based on an extensive literature review. They argue that areas that score high on all urban quality of life indicators could receive rising housing prices as they rise in attractiveness. Important to mention is the division between objective and subjective dimensions of urban QoL. The subjective dimensions describe individuals' perceptions of the built environment and their satisfaction with facilities or amenities. This subjective dimension of QoL characteristics is acknowledged in recent studies that have shown that buildings need to be considered as choice alternatives, analysing how previous residential location and building characteristics influence location choice (Habib & Miller, 2009).

According to Li and Brown (1980), the price of a house is the sum of the value of its attributes split into five different categories; (1) structural and site characteristics; (2) neighbourhood characteristics; (3) local public services and costs; (4) macro-accessibility to CBD; (5) micro-neighbourhood characteristics such as aesthetics, pollution levels, and proximity to non-residential activity. Bigger houses with large amounts of rooms and sleeping rooms and great outer space areas such as gardens or balconies report higher prices. Moreover, housing prices seem to decline when the dwelling gets older but rise in value when it becomes a landmark or historical building (Li & Brown, 1980). This could be because of lower energy efficiency rates for older buildings. Dutch real estate agents agency, the NVM, has shown that in 2023 buildings rose significantly in value when their energy label was increased, noting a rise of 7,3% when the energy label was upgraded from D to A (Brainbay, 2023).

Accessibility from and to one's home is also considered to be of major influence on housing prices as long commuting times are experienced negatively. Real estate closely located to such transportation modes are proven to be of higher value than property that is not. Especially rail systems offer great housing premiums; tramlines in small urban areas or centres (Chwiałkowski & Zydroń, 2022; Eftymiou & Antoniou, 2013), light rail in metropolitan areas (Hess & Almeida, 2007; Xu et al., 2016; Sharma & Newman, 2018; Mulley et al., 2018), and commuter trains on national level, where places in the periphery benefit more (Dubé et al., 2013; Chen & Haynes, 2015). On the other hand, some find negative effects of rail proximity, specifically for rail tracks as they cause noise pollution (Paliska & Drobne, 2020). Mostly, however, the externality effects do not outweigh the positive effects of rail proximity (Seo et al., 2014). Moreover, research has shown that Transit-Oriented Development, developing areas around public transit nodes to be pedestrian-friendly, could further increase real estate prices surrounding those nodes (Xu et al., 2016; Duncan, 2011).

The same evaluation between positive and negative effects takes place when assessing highway accessibility. Proximity to the highway and its on and off ramps created rising housing prices in the Netherlands, even before construction was completed (Levkovich et al., 2016). On the contrary, others find that accessibility benefits do not outweigh externalities such as noise pollution, increased traffic on collector roads and health risks. Resulting in housing discounts for dwellings adjacent to the highways (Allen et al., 2015). Therefore, the positive effects of general accessibility seem to be more significant for shorter commuting times with public transportation when compared to private transportation options (De Palma et al., 2007). The severity of benefits and disadvantages are thus dependent on geographical location, which is also argued by Paliska & Drobne (2020) who state that in rural areas, the negative effects of motorways are less pronounced, while the positive effects of accessibility are stronger and extend over wider vicinity.

High accessibility in general is mostly referred to as low commuting times to a variety of points of interest. When not available, network-based or Euclidean distances are used. One of the oldest facilities researched in this regard is the proximity of jobs. The accessibility from one's home to their job is important in their residential location choice, as the least possible commuting time is preferred. Following this preference, houses with high accessibility to jobs report higher values than houses where fewer jobs are in proximity (Kim & Jin, 2019; Ding et al., 2010). Furthermore, excessive job creation could lead to the entrance of other companies and spark local economies boosting areas fostering regional prosperity, and uplifting housing prices (Feldman, 2014). However, as is the case with transportation modes, job sites causing externalities, negatively affect housing prices. The presence of industrial sites that produce health risks for surrounding inhabitants by contaminating ground and air and creating noise pollution, causes houses in the proximity to be of less value, exceeding the benefits of accessible jobs (Cordera et al., 2019; De Vor & De Groot, 2011).

Supporting the consumer city theory of Glaeser (2001), everyday use amenities, such as shops, supermarkets and schools, are of equal importance in determining housing price determinants. Proximity of good performing public schools results in higher property values in Paris (Fack & Grenet, 2010). The same results are found in China where the presence and quality of educational facilities, from kindergartens to high schools and colleges, positively influence housing prices (Wen et al., 2014; Mirkatouli et al., 2018). Moreover, Beckers & Boschman (2019) find that in the Netherlands universities might put more pressure on inner-city neighbourhoods that offer a high degree of urban vibe as this is preferred among (especially international) students.

Other everyday facilities are supermarkets and retail, in which new retail developments increase housing prices by 1,5% when located within 500 meters (Kurvinen & Wiley, 2019). Other research is more critical, stating that this correlation only applies to big high-end and high-leisure shopping malls that are not located in core city areas. Small-scale, and mid to low-end and -leisure shopping malls exert either no or negative impact on housing prices (Zhang et al., 2020).

Moreover, sports facilities also influence housing prices. The presence of sports facilities in the US has a positive but distance-decaying effect on surrounding residential housing values (Propheter, 2023; Feng & Humphreys, 2018). In the US, however, most research is done on professional sporting facilities. However, public sports and leisure facilities also increase the average housing price significantly (Lee, 2010). Sporting facilities contribute to one's quality of life as it enables people to exercise, improving both their physical and mental health. As mentioned earlier, other factors of quality of life include amenities for leisure like cinemas, restaurants, theatres or events. Lan et al (2018) conclude that high accessibility of commercial and leisure facilities improves housing prices although the effect is smaller when compared to medical and educational facilities.

Lastly, but in recent years deemed increasingly important, green spaces and facilities. Urban green spaces are apparent in a diverse scala in the built environment. Large and small city parks, green walkways, trees among roads, or accessibility to forests or lakes. A lot of research has been done on all of these green amenities in which almost proximity of all green infrastructure yields housing price premiums. Large green infrastructure such as big lakes or forests tends to have the most influence on housing prices, which also may be because of scenic views from houses or apartments over the green spaces in question (Liang et al., 2018). The same results are found by Czembrowski & Kronenberg (2016), stating that small forests and the percentage of green space within a radius of 500 meters contribute to higher apartment values. Moreover, high accessibility to city and community parks results in higher housing prices (Wu et al., 2017), as does the number of trees in neighbourhoods (Saphores & Li, 2012).

2.4 New externality

Since climate problems arose, countries across the globe have invested in sustainable energy creation, trying to limit the negative effects of climate change. It has resulted in a great influx of both electricity consumption and creation, putting pressure on the electricity grid in various locations, one of which is the electricity network in the Netherlands. It has increased the risks of power outages or other negative effects such as reduced speed for electric charging stations (RTL Nieuws, 2024), reduced benefits for solar panel owners (Wijkman, 2024; van de Pol, 2024) or the creation of numerous small powerhouses, electricity stations or batteries (van Zoelen, 2024). The Quality of Life scheme, depicted by Wesz et al (2023), lists the availability of electricity and the consistency of electricity supply as an indicator of urban services. The absence of adequate electricity supply may thus be viewed as an externality as it could be seen as a decline in the attractiveness of certain areas.

No sufficient electricity supply could lead to dissatisfaction among inhabitants, especially in the light of increased sustainability awareness among citizens. Research has shown that the presence of charging stations for electric vehicles increases housing prices (Liang et al., 2023). The most important values for public charging of electric vehicles are (in order): queuing time, charging time, price, energy source and surrounding amenities (Brückmann & Bernauer, 2023), further amplifying the importance of adequate electric vehicle charging stations. Moreover, Plenter et al (2018) find that people are willing to pay more for faster charging stations, especially in urban areas. Less availability and reduction in speed and thus queuing time could be seen as an externality for people owning electric vehicles. In addition, the premium that is paid for houses with solar panels might decline because electricity operators stated that during peak times, they will have the option to shut down solar panels. In this case, individuals are not able to generate electricity, not for themselves nor for delivering back. Since a lot of houses have solar panels, which cost a lot of money and contribute to the value of a house, also by energy label, houses located in areas that experience net congestion may be less attractive in comparison to houses that do not experience such problems, causing relatively lower housing prices.

Lastly, the addition of powerhouses and electricity stations could cause disturbances in neighbourhoods as inhabitants dislike decreasing neighbourhood aesthetics. Moreover, inhabitants fear health complications. This has sparked protests in Amsterdam, trying to prevent construction from happening (Bianchi, 2021). As of yet, the only known research that has found evidence of the effects of electricity supply on housing prices is that of Marope & Phiri (2024) who show that in South Africa load-shedding, deliberately shutting down electric power in particular areas or regions to prevent widespread power failures, could lead to decreased property values. In this way, bad electricity supply conditions may result in altering residential location choices, as residents may prefer areas where no net congestion problems are present.

3. Methodology

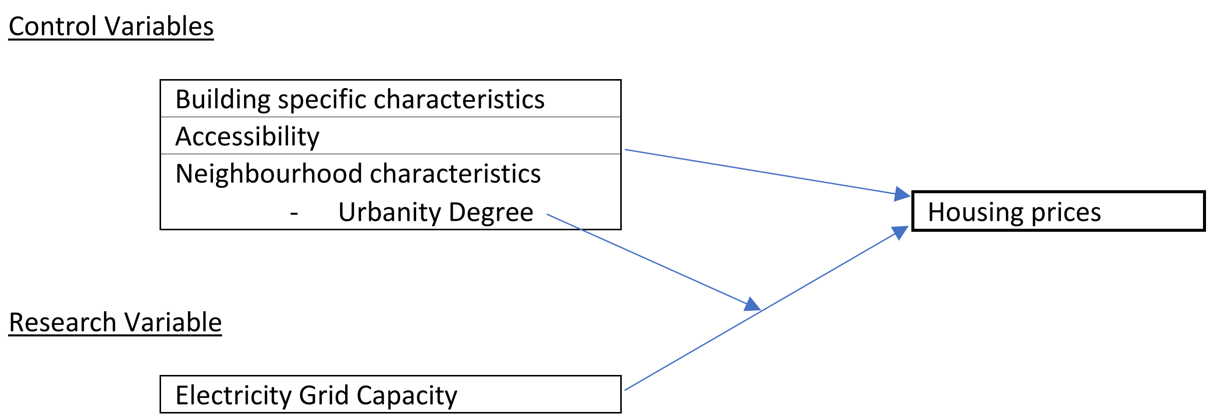
3.1 Regression models

To investigate whether electricity grid capacity, with its recent net congestion problems, influences housing prices in the Netherlands, I propose quantitative research trying to answer the following research question:

To what extent does electricity grid capacity influence housing prices in the Netherlands, and is spatial heterogeneity observable within this relationship?

The succeeding paragraphs have explored the relationship between several determinants and housing prices. Following the presented studies and knowledge gap in the literature section, the next determinants are considered; (1) Electricity Grid Capacity, (2) Building Specifications, (3) Accessibility, (4) Neighbourhood Characteristics (see Table 2 for an overview of all the variables within these groups). Subsequently, all the variables within the determinant groups are expected to influence housing prices. In total three distinctive relationships are expected to be observed. The influence of the key determinant, the electricity grid capacity, on housing prices is tested. Therefore, a relationship between the two variables is assumed. The proven relationships of the control variables in the literature section justify the forecasted relationships. Lastly, the geographical differences of observed proven determinants on housing prices, make it likely that this geographical difference is also experienced within electricity grid capacity dynamics. Therefore, the third expected relationship is between urbanity degree and the amount of influence the electricity grid capacity asserts on housing prices. This leads to the following conceptual model, summarising the three relationships:

Figure 1: Conceptual Model



Following the residential location choice model, in which individuals are less likely to pay for houses in regions experiencing negative surrounding effects (Schirmer et al., 2014), I expect to find a negative relationship between electricity grid capacity and housing prices. Less demand for houses in certain areas may result in lower housing values. Therefore, the below hypothesis is considered:

(1) Houses located in regions with low or no electricity grid capacity are of lower value when compared to houses that are located in areas where there is capacity available on the electricity grid.

Considering the proven geographical differences in housing price determinants, I assume that the urbanity degree influences the relationship between the electricity grid capacity and housing prices. As rural houses have greater potential for investments in green energy infrastructures I expect greater influence of electricity grid capacity in those areas. Following this expectation, the next hypothesis is formulated:

(2) Houses located in rural areas experience greater influence of the electricity grid capacity on their value when compared to houses that are located in urban areas.

Experiencing greater influence means that housing prices will vary more between rural areas that report either availability or no availability on the electricity grid capacity than urban areas with varying electricity grid capacity. To test the two hypotheses, answering the research question, quantitative research will be conducted consisting of different regression models and approaches. As is shown in other scholarly research, a Linear Regression mordel is not accurate for data with geographical clusters (Mulley et al., 2018). Instead, a Multi-Level Regression approach would suit better as it acknowledges variables on different hierarchical levels. In this case, the neighbourhood characteristics variables would be level two variables and the individual variables, level one.

In the analyses, both linear and multi-level regression models will be tested. By doing so, the potential added value of the multi-level regressions is observable. Both regression approaches are split into urban and rural models, making comparison between the two geographical areas possible. After interpreting and comparing the models both hypotheses are either confirmed or rejected, whereafter the research question can be adequately answered.

The analyses are done on a database which has been put together manually listing all transactions for houses in the Netherlands in 2023. The data was obtained by using the NVM database, which was accessed through the CRM Realworks website. It contains individual transaction data; transaction price, transaction date, location, square meters of living area, parcel and garden, energy label and dwelling types. This individual data was then complemented with neighbourhood and locational data. The variables are split into four groups following the aforementioned determined determinants; (1) electricity grid capacity for consumption, (2) building-specific characteristics, (3) accessibility and accessibility to facilities and (4) neighbourhood characteristics. In Table 2 below, these four groups of variables are split by dimensions and indicators. The indicators are the variables used in this research. Each of the used variables is justified by previous research who have found significant impact of such a variable on housing prices.

Table 2: Specifications of determinants with theoretical justification and data source.

Determinants	Dimensions	Indicators	Previous research	Source
Electricity Grid Capacity (EGC)	Consumption	Available Capacity	Marope & Phiri (2024)	NetbeheerNL
Building specific characteristics	Building	Building year	Li & Brown (1980)	CRM Realworks
		Living	Li & Brown (1980)	CRM Realworks
		Housing type		CRM Realworks
		# Rooms	Li & Brown (1980)	CRM Realworks
		# Sleeping rooms	Li & Brown (1980)	CRM Realworks
		Energy label	Brainbay (2023); Taruttis & Weber (2022)	CRM Realworks
	Surroundings	Building bound outside area/ garden	Li & Brown (1980)	CRM Realworks
		Storage		CRM Realworks
Accessibility and accessibility to facilities	Accessibility	Bus stations and stops	Hess & Almeida (2007); Xu et al (2016); Eftymiou & Antoniou (2013)	OpenStreetMap
		Train stations	Chen & Haynes (2015); Dubé et al (2013); Eftymiou & Antoniou (2013)	OpenStreetMap
	Accessibility/ externality	Within or outside 500 metres of highways	Paliska & Drobne (2020); Levkovich et al (2016); Allen et al (2015)	OpenStreetMap
	Sports	Sporting locations	Propheter (2023); Feng & Humphreys (2018)	SavillsMaps
	Education	Primary school	Fack & Grenet (2010); Mirkatouli et al (2018)	OpenStreetMap
		Secondary school	Wen et al (2014); Mirkatouli et al (2018)	OpenStreetMap
	Shops	Small and large supermarkets	Kurvinen & Wiley (2019); Zhang et al (2020)	OpenStreetMap
	Healthcare	Hospital	Wesz et al (2023); Li et al (2019); Ding et al (2010)	OpenStreetMap
		General Practitioner	Wesz et al (2023)	OpenStreetMap
	Green Spaces	Parks and green spaces	Wu et al., 2017	SavillsMaps
		Forests	Czembrowski & Kronenberg (2016); Liang et al (2018)	SavillsMaps
	Electricity	EV charging stations	Liang et al (2023)	OpenStreetMap
Neighbourhood characteristics	Demographics	Age ratio	Hiller & Lerbs (2016); Takáts (2012)	CBS (2023)
		Education ratio	Bujang et al (2010); Musterd et al (2016); Wang et al (2017)	CBS (2022)
		Household income ratio	Bujang et al (2010); Musterd et al (2016)	CBS (2022)
	Housing stock	Average amount of persons per household	Bujang et al (2010); Kohler & van der Merwe (2015)	CBS (2023)
		Percentage owner-occupied houses	Gyourko & Molloy (2015);	CBS (2023)
		Percentage single person houses	Tyvimaa & Kamruzzaman (2019); Deka (2014)	CBS (2023)
		Density of addresses/ Degree of urbanity	Glaeser (2001); Walker & Li (2007); Lan et al (2018); Wang et al (2017)	CBS (2023)
	Surroundings	Amount of water in hectares	Liang et al (2018)	CBS (2023)

3.2 Data collection and modification

The first variable is the main determinant and research variable in the research, the electricity grid capacity for using electricity. The data for the amount of congestion is provided by NetbeheerNL, an organisation which collects data from all different electricity providers in the Netherlands. Since the rise of congestion problems, they publish a publicly available map and its underlying dataset of congested areas, approximately each six months. The dataset contains information about the severity of congestion on postal code level. The availability of electricity for consumption is given as an ordinal variable categorised as follows: (1) Capacity available, (2) Limited available capacity, (3) Congested, (4) No capacity available. For congested areas long queuing times for new connections on the electricity grid are apparent, waiting for congestion management research. Figure 1 below shows the geographical differences for the congestion on the electricity grid, as provided by NetbeheerNL. Colours range from grey (1) to red (4), moreover, in arched areas, congestion management is already in place, or not possible further limiting electricity usage.

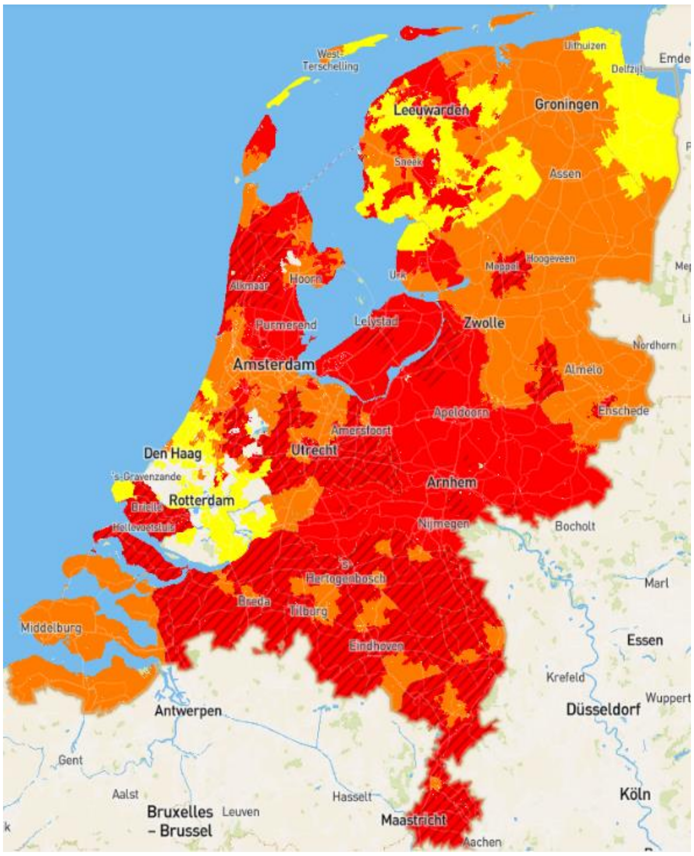


Figure 1, Source: NetbeheerNL.
https://capaciteitskaart.netbeheernederland.nl/

The map indicates that most congested areas are located outside of the Randstad. Especially in the provinces of Noord-Brabant and Limburg net congestion problems are prevalent. Although most congested areas are rural or suburban regions surrounding cities, some urban areas experience net congestion problems as well, for instance, Utrecht, Alkmaar and Maastricht. As mentioned above, to control for the impact of limited electricity grid capacity on transaction prices various sets of variables are introduced.

The first control variables describe dwelling characteristics. The variables are included in the NVM transactions dataset acquired via CRM Realworks. For the analyses, these variables did not need to be modified. Variables describing area sizes, like *living, garden* and *storage* are given in amount of square metres. The *rooms* and *sleeping rooms* variables are listed as numeric, as for *building year*. The variable *housing type* is categorised as follows: (1) terraced house, (2) corner house, (3) semi-detached house, (4) detached house. *Energy Label* ranges from the lowest energy label G (1) to the highest energy label A+++++ (13). Higher scores on these variables thus indicate better housing types and greater energy efficiency respectively.

The second set of control variables further describes individual transaction characteristics. These variables contain accessibility measures to different points of interest by calculating Euclidean distances from each transaction to multiple different points of interest. This is done by using software program GIS. Location data of these points of interest are obtained via the publicly available data source OpenStreetMap, who allocate facilities to specific addresses. The variables *sporting locations, forests* and *parks and green spaces* are acquired via the data portal SavillsMaps, which is data gathered and managed by Savills. Those variables are given as polygons. The highway variable does not contain Euclidean distance measures. Instead, a buffer analysis is used. Houses located within 500 meters of a highway are valued as one, and houses that are not as zero.

Lastly, the third set of variables are neighbourhood characteristics. Centraal Bureau voor Statistiek (CBS), a Dutch organisation which independently collects and presents data on varying societal subjects, annually publishes a dataset called Kerncijfers Wijken en Buurten. In this dataset, aggregated data is listed for each municipality, region and neighbourhood. Neighbourhood data is then joined to individual transaction data based on its geographical location by using spatial join via GIS. The variables describing the housing stock and surroundings of the neighbourhood are not modified. For the ratios specifying the demographics of each neighbourhood modifications were needed. The *age ratio* is calculated by dividing the number of people aged over 65 by the number of people aged under 65. The *education ratio* is calculated by dividing the amount of highly educated citizens, all who successfully finished a bachelor's degree, by the amount of low-educated citizens, those who finished practical education maximum. The variable *household income ratio* is computed by dividing the percentage of households with high income, those who belong to the national top 20% household earnings, by the percentage of households with low income, those who report incomes that belong to the national bottom 40% of households earnings. Higher ratios thus indicate a greater share of older, higher educated and wealthier citizens as opposed to younger, low-educated and poorer citizens for each neighbourhood respectively.

As previously mentioned transaction data was acquired via the CRM Realworks website. This website grants access to the transaction database of the NVM. However, it has constraints in downloading large portions of transaction data. Therefore, the database was manually constructed by downloading and combining numerous smaller portions of transactions. After combining all the smaller portions of transaction data, the dataset contained a total of 196.036 dwellings. Due to the manual downloading and combining of the data the dataset contained numerous inconsistencies. Transactions were deleted from the database when the address could not be geocoded in GIS. This is mostly caused by insufficient data in the provided database, lacking street names and house numbers. Most newly built projects were referred to with building numbers, lacking an address at all. More transactions were deleted when no neighbourhood or accessibility characteristics were allocated after the calculations done by GIS. Houses located in the municipality of Voorne aan Zee were deleted as the *household income ratio* and *education ratio* could not be allocated due to the merger of three municipalities, changing neighbourhood boundaries and names. In addition, due to how the data was collected, a lot of duplicates were found and subsequently deleted. Eventually, the transaction database contains a total of 169.218 transactions.

Table 3: Descriptive statistics of all the variables split by urbanity and electricity grid availability

1 = Capacity Available, 2 = Limited Capacity, 3 = Congested, 4 = No Capacity

	Rural				Urban				Total		
	1	2	3	4	1	2	3	4	Rural	Urban	All
Housing specifications											
Transaction price	483073	418620	453092	459276	416641	405050	477861	405866	456090	428962	442113
Building Year	2004	1972	1977	1980	1969	1966	1960	1969	1978	1966	1972
Living	122.7	129.4	130	130.3	103.6	107.6	104.3	106.3	129.6	105.6	117.2
Garden	7.4	16.69	15.76	16.91	5.21	6.10	6.66	7.78	15.86	6.89	11.24
Storage	3,5	6.34	7.33	8.21	6.82	7.50	6.85	6.95	7.47	6.99	7.22
Rooms	4.4	4.87	4.91	4.94	4.07	4.18	4.14	4.29	4.89	4.20	4.53
Sleeping Rooms	3.1	3.47	3.44	3.39	2.82	2.97	2.86	2.96	3.39	2.92	3.14
House Type	2.5	3.77	3.54	3.53	1.84	1.85	2.10	2.12	3.47	2.05	2.92
Label	4.2	6.73	6.59	6.45	6.88	7.31	7.29	7.01	6.35	7.13	6.75
Accessibility and accessibility to facilities											
Highway proximity	0.12	0.10	0.10	0.09	0.13	0.15	0.09	0.09	0.09	0.10	0.10
DistTrain	4778	4476.1	5272.8	4511.2	1897.8	1366.8	1702.8	1938.1	4755.2	1769.1	3216.7
DistBus	426.4	324.5	374.6	342.5	226.9	226.1	211	202.8	356.8	211.7	282
DistSeScho	2438	2609.1	2874.2	2642.6	842.15	817.49	737	863	2694.5	814.8	1726
DistPrScho	683.2	653.6	612.6	579.7	339.5	352.53	365	365.3	602.5	360.4	477.8
DistSuper	828.6	931.5	855.8	763.5	333.5	348.97	344.5	361.2	808.4	351.1	572.8
DistEVchrg	1314.4	2133.2	1874.7	1773.7	312.4	454.3	559.1	623.6	1797.7	543	1151.2
DistHosp	9223.4	9223.4	9223.4	9223.4	4543.9	6728	9223.4	9133.9	9223.4	8377.8	9223.4
DistGP	1773.5	2220.5	2113	2205.3	715	958.4	822.7	1027.4	2147.7	920	1515.1
DistParkGr	671.7	546.4	507.7	560.7	292.1	226.8	263.6	236	551.8	249	395.8
DistFrst	1101.3	890.1	821.6	732.2	1455.2	1253.1	1189.4	1154.9	797.5	1213.6	1011.9
Neighbourhood characteristics											
Ageratio	0.22	0.30	0.31	0.30	0.23	0.25	0.25	0.26	0.30	0.25	0.27
Educationratio	1.58	1.37	1.54	1.4434	2.21	1.78	2.19	2.03	1.48	2.05	1.76
Incomeratio	2.21	1.18	1.25	1.16	0.78	0.77	0.84	0.61	1.26	0.72	0.99
Average household size	2.5	2.3	2.3	2.3	2.1	2.1	1.9	2.0	2.3	2.0	2.2
P one family homes	85.3	83.6	85.0	83.8	37.9	42.7	45.8	54.6	84.3	48.2	65.7
P owner-occupied dwellings	75.8	70.6	72.4	71.7	52.1	52.4	50.2	51.7	72.1	51.4	61.4
Address density	740.4	754	775.1	817.2	3813	3164.5	3552.5	2783	794.3	3191.5	2029.4
Amount of water	10.8	14.9	8.7	10.5	6.2	4.3	1.9	2.5	10.3	3.0	6.6

Table 3 presents average values for each of the variables split by urbanity and degree of electricity availability. The average transaction price of a dwelling in 2023 in the Netherlands, as per this dataset, records €442.113. The table provides for some presumed differences between rural and urban houses. Houses located in rural areas are newer, contain more rooms and have greater living, garden and storage areas when compared to urban houses. This may have contributed to higher average transaction prices for rural areas. However, when the transaction price per m² was calculated, urban areas noted a price premium of approximately €550 per m² when compared to rural areas. A probable cause is the density of addresses and facilities in urban areas, where all distances to facilities were notably shorter than in rural areas, excluding the distance to forests.

Remarkably, the descriptive statistics indicate that in rural areas with available electricity grid capacity, the average building year is considerably higher than in other areas. This could indicate that the location of new housing projects is dependent on the geographical differentiation of the electricity grid. Another notable finding is that for both urban and rural areas the household income ratio is the lowest in areas where no capacity is available, amplifying the need for research on the impact of the electricity grid on residential patterns.

Houses located in rural areas encounter greater net congestion values (2,33) when compared to houses in urban areas (2,05). Table 4 depicts the relationships between electricity grid capacity and address density per square kilometre. It shows that on average areas with electricity grid congestion are less dense than areas where no grid congestion occurs. However, as can be seen in Table 3, this relationship is inversed for rural areas where rising densities are observed as congestion levels rise. It thus seems that dense rural areas and thinly populated urban areas most prominently experience net congestion.

Table 4: Descriptive statistics of density and transaction price split by congestion

Electricity Grid Capacity	Address density	Transaction price
Capacity available *N = 15285*	2621	442423
Limited capacity *N = 20298*	2431	409178
Congested *N = 51222*	2224	466017
No capacity *N = 82413*	1700	435309
Total *N = 169218*	2029	442112

As can be seen in the descriptive statistics, transaction prices lack the patterns observed in address density. To explore the relationship between the electricity grid capacity and transaction price bivariate correlations were measured. As for the whole database no significant correlations were found (0,352). After splitting the database based on urbanity, rural areas remained insignificant while for urban areas a small significant negative correlation was found (-0,013), indicating that higher congestion values result in lower transaction prices for rural dwellings. The correlation measures suggest that urbanity influences the relationship between electricity grid capacity and transaction prices, justifying the split approach. Correlation calculations are, however, very simplistic and fail to include other factors that may influence transaction prices. To incorporate other factors of influence on housing prices, as the previously introduced determinants on housing prices, multiple regression models are estimated.

4. Results

4.1 Linear regression models

The linear regression models presented below show a significant influence of a variety of variables in the models. By adding the control variables separately, the impact of these variables on the correlation between transaction prices and electricity grid capacity is observed. By doing so, the R^2 values can be compared as well. For all three linear regression models, the R^2 value increases when adding control variables to the model, indicating that a larger share of the variance in the dependent variable can be explained by the independent variables. Thus, the addition of the control variables increases the accuracy of all models in determining the influence of the variables on transaction prices.

The models show a significant negative relationship between transaction prices and the electricity grid. This means that the model suggests that if the available electricity grid capacity decreases, the transaction price is reduced by €5.790,85 for the database as a whole. After splitting the model based on urbanity, results indicate urban areas are being affected more by decreasing electricity capacity when compared to rural areas. For each decline in available electricity capacity, the transaction price of a dwelling in urban areas decreases €7415,44 while in rural areas it decreases €3352,48 respectively.

The control variables in the linear regression models yielded some expected and surprising results. Most remarkable is the negative relation between transaction prices and energy labels, for both the urban and rural context. Opposite of what was expected, houses with lower energy labels were sold for higher prices when compared to energy-efficient dwellings. Another interesting result is the influence of the building year on housing transactions. Where in urban areas the relation is negative, for each newer building year the transaction price decreases by €301,73, in rural areas a very small positive relationship is found, with housing prices increasing by €43,51 for each newer building year. Other house specification variables show expected results; the size of living and garden areas and the number of rooms and sleeping rooms result in higher transaction prices, as well as better housing types. Storage space however negatively affects transaction prices. The distance to various amenities has varying results on transaction prices. Surprisingly, for both urban and rural contexts the greater distance to public transportation results in higher transaction prices. Greater distance to primary schools also yields transaction price premiums. The influence of these variables on transaction prices are higher in urban regions when compared to rural regions. Greater distances to EV charging stations, hospitals, parks or green spaces and forests all decrease transaction prices meaning that when closely located to these points of interest, housing transactions rise. Results are comparable between the urban and rural context, where in urban areas distances to green spaces and forests assert greater impacts. The neighbourhood characteristics showed expected results as higher average education, income and age ratios result in higher transaction prices, as well as density of addresses and amount of water for each neighbourhood. Notably, however, the percentage of owner-occupied dwellings and one-family households yielded negative relationships with transaction prices.

Table 5: Linear Regression Models

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-15461,9***	-14769,3***	-5790,852***
Building specific characteristics				
	Building Year	-501,1***	-477,611***	-82,574***
	Living area	670,9***	646,284***	518,430***
	Garden area	321,8***	377,365***	437,067***
	Storage area	-937,9***	-922,679***	-868,554***
	Amount of rooms	40.428,1***	39505,547***	34902,841***
	Amount of sleeping rooms	21385,5***	16507,019***	10177,474***
	Housing Type	30143,1***	40665,199***	42217,673***
	Energy Label	-12.752,3***	-12439,475***	-8005,924***
Accessibility and accessibility to facilities				
	Highway		252,287	1540,046
	Train		-1,036***	1,370***
	Bus		22,507***	7,338***
	Primary school		-8,269***	8,785***
	Secondary school		11,786***	-2,832***
	Supermarket		4,800***	-,127
	EV charging station		-16,162***	-6,703***
	Hospital		-3,990***	-2,865***
	General Practitioner		-4,478***	,461
	Park or green space		-7,911***	-3,695***
	Forest		-1,042	-8,694***
Neighbourhood characteristics				
	Age			95150,646***
	Education			43402,473***
	Income			6443,634***
	Household size			134809,515***
	One family dwellings			-1715,009***
	Owner-occupied dwellings			-310,775***
	Amount of addresses			19,593***
	Amount of water			338,013***
R^2		0,308	0,370	0,491
N		116610	116610	105434

Significance levels *** < 0,001 ** < 0,01 * < 0,1

Table 6: Linear Regression Models, split by urbanity: URBAN

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-23538,487***	-15349,179***	-7415,442***
Building specific characteristics				
	Building Year	-1113,888***	-1035,781***	-301,734***
	Living area	704,436***	689,476***	535,755***
	Garden area	-369,770***	-339,179***	241,345***
	Storage area	-1539,099***	-1515,202***	-1437,223***
	Amount of rooms	47629,125***	48330,064***	35807,606***
	Amount of sleeping rooms	21683,479***	17912,877***	12161,971***
	Housing Type	37684,013***	39632,956***	43359,989***
	Energy Label	-16277,793***	-15445,683***	-9243,896***
Accessibility and accessibility to facilities				
	Highway		588,673	-3544,721
	Train		-,640	3,463***
	Bus		53,108***	29,246***
	Primary school		8,209	18,405***
	Secondary school		53,108***	-4,907***
	Supermarket		19,964***	10,293**
	EV charging station		-28,949***	-5,984***
	Hospital		-4,366***	-2,411***
	General Practitioner		-7,982***	1,525*
	Park or green space		-21,858***	-10,232*
	Forest		4,580**	-17,308***
Neighbourhood characteristics				
	Age			58677,662***
	Education			40146,214***
	Income			3511,253***
	Household size			176065,308***
	One family dwellings			-1812,946***
	Owner-occupied dwellings			-247,915***
	Amount of addresses			25,812***
	Amount of water			479,355***
R^2		0,321	0,358	0,533
N		45770	45770	41179

Significance levels *** < 0,001 ** < 0,01 * < 0,1

Table 7: Linear Regression Models, split by urbanity: RURAL

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-4228,717 ***	-10491,857***	-3352,480***
Building specific characteristics				
	Building Year	349,740***	159,739***	43,510*
	Living area	704,633***	676,138***	548,108***
	Garden area	431,708***	445,996***	457,045***
	Storage area	-877,102***	-840,590***	-735,273***
	Amount of rooms	37240,818***	35351,284***	34522,464***
	Amount of sleeping rooms	15717,122***	13458,051***	7685,584***
	Housing Type	36632,755***	43060,314***	41621,812***
	Energy Label	-9932,487***	-9515,071***	-7100,007***
Accessibility and accessibility to facilities				
	Highway		4186,048	3387,384
	Train		-,742***	1,023***
	Bus		16,588***	6,095**
	Primary school		11,307***	7,796***
	Secondary school		-7,156***	-2,605***
	Supermarket		4,103***	,273
	EV charging station		-13,665***	-6,404***
	Hospital		-3,686***	-2,908***
	General Practitioner		-3,003***	,395
	Park or green space		-8,063***	-2,308*
	Forest		-7,602***	-3,396***
Neighbourhood characteristics				
	Age			89686,011***
	Education			48149,357***
	Income			7463,978***
	Household size			102985,987***
	One family dwellings			-1962,267***
	Owner-occupied dwellings			-327,854***
	Amount of addresses			15,243***
	Amount of water			326,334***
R^2		0,341	0,400	0,479
N		70840	70840	64254

Significance levels *** < 0,001 ** < 0,01 * < 0,1

4.2 Multi-Level regression models

Although the linear regression models report significant results, findings are probably not reliable as the models do not consider the spatial clustering of the variables. Therefore, a multi-level regression analysis is proposed to account for spatial heterogeneity, and the hierarchical structure of the data. The models estimate variation at multiple data levels, allowing for more accurate results. For this analysis, data is grouped based on neighbourhood boundaries as determined by the CBS. It is on the same scale level as the neighbourhood characteristics variables. Preliminary tests showed significance for grouping the data on the neighbourhood scale level for both the urban, rural and total multi-level regression models. The models calculate both a random intercept and a random slope for the electricity grid capacity. This is done to capture the hierarchical structure of the data more accurately. The random intercept predicts the variation of the average transaction price between the different neighbourhoods. It acknowledges that for each neighbourhood the average transaction price might be influenced by unmeasured contextual factors. By implementing a random slope for the electricity grid capacity the model takes into account that the influence of the electricity grid capacity on transaction prices may vary between neighbourhoods, determining the strength and direction of the relationship between the two. By including both effects, the model better reflects the complexities and the heterogeneity of real-world data, increasing the interpretability of the findings (Snijders & Bosker, 2011).

The results of the multi-level regressions show greater R^2 values, meaning that the models better predict the influence of the determinants on transaction prices. The marginal pseudo R^2 indicates the percentage of the transaction price that is explained by the fixed effects. The conditional pseudo R^2 indicates how much the transaction price is explained by the fixed and random effects. The hierarchical distribution of the variables and the adaptation of both random slope and intercept have thus resulted in higher explanatory power of the models.

The multi-level regression model reports a greater significant negative influence of the electricity grid capacity on transaction prices as compared to the linear regression model, increasing approximately €3.500 to €9.274,39. More importantly, geographical differences between rural and urban areas are substantially bigger within the hierarchal regression models. The coefficient for rural areas is comparable to the linear regression, increasing by €500 to €3.819,34. For urban areas, however, the negative impact of the electricity grid capacity on transaction prices has increased drastically, where each rise in the electricity grid capacity variable leads to a reduction of €16.908,43 in transaction prices. Moreover, the multi-level regression model for rural areas shows lower significance when compared to the urban one. To observed effects of electricity grid capacity are thus less representative in rural areas.

In general, the differences between rural and urban areas yield more expected differences within the multi-level regression models. In rural areas, newer buildings are sold for higher prices, while in urban areas no significant influence was found. This is probably because cities accommodate older buildings with historical values mostly located within inner cities, often being more expensive than newer buildings (Li & Brown, 1980). Remarkably, the negative effect of higher energy labels on housing prices is still apparent in the multi-level regression analyses, which is in contrast to the findings of the NVM (Brainbay, 2023). A possible explanation could be that bigger or older buildings have not been renovated yet because of higher costs for renovations, therefore lacking sustainability measurements. The dummy for highway proximity also shows geographical differences. For urban areas, the effect is small (€4.762,44) and less significant when compared to rural areas, where transaction prices drop by €11.385,85 when located within 500 metres from a highway. It is a plausible finding as urban areas are more dense and thus inherently closer to driveways. Moreover, it is assumable that people in rural areas have a greater preference towards living in quiet surroundings, and are therefore willing to pay higher premiums for houses not in proximity of highways when compared to people in urban areas.

These findings are consistent with the results of Walker & Li (2007), stating that residential location choice preferences vary between urban densities. Similar results are found for the distance to the closest EV charging station. While being insignificant for rural areas, houses in urban areas are sold for slightly more for each metre closer to such charging station. Houses located in both rural and urban areas increase in value when closely located to hospitals, general practitioners, parks or public green spaces and forests. The influence of parks, green spaces and forests is bigger in urban areas, most notable for parks and green spaces, €20,16 versus €5,13 respectively. Remarkably, short distances to public transportation nodes, schools and supermarkets did not result in lower housing prices. Instead, no significant or significant increases in transaction prices are found for the variables in the urban context. It suggests that in the urban setting, these amenities may be experienced as an externality, for example, because of noise pollution. In rural areas opposite relationships are found for train stations and secondary schools. Lastly, geographical differences are found for the influence of the amount of addresses on transaction prices. Whereas in rural areas transaction prices drop when density increases, in urban areas transaction prices rise for each extra address per km^2. Both results further reinforce the arguments made by Walker & Li (2007).

Table 8: Multi-Level Regression Models

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-7790,930***	-9858,651***	-9274,389***
Building specific characteristics				
	Building Year	183,233***	159,563***	191,337***
	Living area	511,849***	508,565***	445,035***
	Garden area	463,121***	421,622***	433,203***
	Storage area	-694,295***	-681,553***	-680,448***
	Amount of rooms	43406,643***	43201,090***	41147,141***
	Amount of sleeping rooms	-216,729	454,948	-437,521
	Housing Type	49649,184***	48525,677***	47361,632***
	Energy Label	-9337,150***	-9102,571***	-8313,165***
Accessibility and accessibility to facilities				
	Highway		-10265,419***	-9001,910***
	Train		-3,987***	-1,953***
	Bus		29,553***	21,344***
	Primary school		13,498***	9,577***
	Secondary school		-7,257***	-7,495***
	Supermarket		16,152***	7,833***
	EV charging station		-,013	-,135
	Hospital		-5,204***	-3,909***
	General Practitioner		-5,225***	-5,124***
	Park or green space		-3,647*	-6,391***
	Forest		-10,922***	-9,545***
Neighbourhood characteristics				
	Age			62005,718***
	Education			25362,843***
	Income			6050,576***
	Household size			56930,443***
	One family dwellings			-610,773***
	Owner-occupied dwellings			-95,043**
	Amount of addresses			3,778**
	Amount of water			287,038***
R^2	Marginal	0,238	0,280	0,417
	Conditional	0,742	0,728	0,657

Significance levels *** < 0,001 ** < 0,01 * < 0,1

Table 9: Multi-Level Regression Models, split by urbanity: URBAN

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-21049,261***	-18409,542***	-16908,434***
Building specific characteristics				
	Building Year	-50,912*	-77,209**	36,952
	Living area	524,251***	521,659***	463,809***
	Garden area	390,235***	405,559***	429,315***
	Storage area	-1212,948***	-1209,459***	-1182,052***
	Amount of rooms	42538,465***	42456,414***	39836,270***
	Amount of sleeping rooms	3367,506**	3240,270**	2997,533**
	Housing Type	49689,784***	48800,215***	49028,390***
	Energy Label	-10474,664***	-10385,972***	-9400,308***
Accessibility and accessibility to facilities				
	Highway		-8097,618*	-4762,440*
	Train		-7,063***	-1,071
	Bus		23,775***	19,395***
	Primary school		27,863***	18,529***
	Secondary school		,535	2,053
	Supermarket		41,704***	30,989***
	EV charging station		-3,003	-4,700*
	Hospital		-7,670***	-3,775***
	General Practitioner		-2,159*	-4,353*
	Park or green space		-18,308***	-20,158***
	Forest		-3,389	-8,601***
Neighbourhood characteristics				
	Age			54414,252***
	Education			24613,349***
	Income			6413,995***
	Household size			47044,115***
	One family dwellings			-484,018***
	Owner-occupied dwellings			-164,606*
	Amount of addresses			143,050*
	Amount of water			7,829
R^2	Marginal	0,151	0,207	0,424
	Conditional	0,788	0,793	0,653

Significance levels *** < 0,001 ** < 0,01 * < 0,1

Table 10: Multi-Level Regression Models, split by urbanity: RURAL

		Model 1	Model 2	Model 3
Electricity Grid Capacity				
	Available Capacity	-1634,122	-5812,296*	-3819,237*
Building specific characteristics				
	Building Year	325,076***	299,186***	287,454***
	Living area	537,896***	534,594***	462,496***
	Garden area	469,080***	430,113***	432,736***
	Storage area	-581,839***	-570,759***	-550,698***
	Amount of rooms	42882,612***	42554,588***	41117,787***
	Amount of sleeping rooms	-2490,908**	-1516,261**	-2585,471**
	Housing Type	48830,934***	47642,338***	46215,081***
	Energy Label	-8233,920***	-7949,010***	-7477,728***
Accessibility and accessibility to facilities				
	Highway		-11385,836***	-11385,845***
	Train		-2,209***	-1,211*
	Bus		30,091***	22,271***
	Primary school		13,230***	8,211***
	Secondary school		-8,943***	-8,540***
	Supermarket		11,420***	3,652*
	EV charging station		-1,000	,492
	Hospital		-4,127***	-3,585***
	General Practitioner		-5,529***	-4,728***
	Park or green space		-1,465	-5,130**
	Forest		-11,005***	-7,294***
Neighbourhood characteristics				
	Age			59976,230***
	Education			25232,405***
	Income			5021,796***
	Household size			62134,865***
	One family dwellings			-887,665***
	Owner-occupied dwellings			27,203
	Amount of addresses			-11,258**
	Amount of water			296,567***
R^2	Marginal	0,307	0,356	0,415
	Conditional	0,675	0,664	0,657

Significance levels *** < 0,001 ** < 0,01 * < 0,1

5. Discussions

5.1 Interpretations

The presented analyses of the linear and multi-level regression models provide comprehensive insights into the little-known relationship between electricity grid capacity and housing transaction prices. Specifically, this research has tried to answer the following research question:

To what extent does electricity grid capacity influence housing prices in the Netherlands, and is spatial heterogeneity observable within this relationship?

To answer this question two hypotheses were proposed and subsequently tested. One explores the relationship between electricity grid capacity and transaction prices and the other explores possible geographical differences within this relationship. Following the results as shown above, the first hypothesis is confirmed:

Houses located in regions with low or no electricity grid capacity are of lower value when compared to houses that are located in areas where there is capacity available on the electricity grid.

More specifically, I found in both regression models significant evidence for a negative relationship between electricity grid capacity and transaction prices. The multi-level regression model was more successful in explaining the variances of transaction prices from the determinants, making the results of this regression more accurate and reliable. It reported an even greater negative influence of electricity grid capacity on transaction prices when compared to the linear regression model. Estimates of the model suggest that for each rise in congestion levels, housing transaction prices dropped by €9.274,39.

After successfully testing the first hypothesis, both the linear and multi-level regression models were split into urban and rural analyses, testing the possibility of geographical differences apparent in the relationship found in the previous analysis. The linear regression models indicate that transaction prices in urban areas decrease by €7.415,44 with each decline in available electricity capacity, compared to a decrease of €3.352,48 in rural areas. Like in the previously conducted analyses, the multi-level regression analyses reported greater explanatory power of the determinants on electricity grid capacity, making the models more accurate. The models also yielded greater differences. Especially, urban areas, showing a reduction of €16.908,43 for each rise in the electricity grid capacity variable. For rural areas, the reduction in housing prices is much smaller at €3.819,34. Additionally, the significance level of electricity grid capacity in the rural multi-level regression has declined, making the observed effects less representative, further increasing the geographical differences. Thus, a stronger impact of electricity grid capacity on housing prices in urban areas rather than rural areas is observed, rejecting the second hypothesis:

Houses located in rural areas experience greater influence of the electricity grid capacity on their value when compared to houses that are located in urban areas.

The findings of this study are in line with the recent study of Marope & Phiri (2024), concluding that lacks of electricity supply could lead to lower housing prices. Interestingly, however, houses in the Netherlands did not suffer from frequent power outages as a consequence of electricity grid congestion. Instead, negative side effects of low electricity grid capacity, such as reduced EV charging speeds (RTL Nieuws, 2024), lower benefits for solar panel owners (Wijkman, 2024; van de Pol, 2024) and fear of the addition of numerous small powerhouses, electricity stations or batteries (van Zoelen, 2024), may have negatively influenced housing prices. Electricity amenities and externalities assert influence on one's perceived urban Quality of Life (Wesz et al., 2023). Benefits or disadvantages thus may influence the opinion of specific neighbourhoods, altering residential location choices (Schirmer et al., 2014), which in turn might affect housing prices as demand changes. Although geographical differences in the relationship between electricity grid capacity and transaction prices are found, they do not behave as expected. Few to no literature supports any claims of a certain direction of this relationship. However, I assumed houses in rural areas to suffer more from grid congestion due to their higher probability of owning solar panels or other green electricity infrastructures, which would be less beneficial. On the contrary, I provide evidence that urban areas exhibit greater losses in housing values for declining electricity grid capacity. An explanation might be the findings of Plenter et al (2018) who state that people are willing to pay more for faster charging stations, especially in urban areas. This is also consistent with the findings of this study in which shorter distances to EV charging stations resulted in higher transaction prices, for urban areas only. Moreover, it is assumable that people in urban areas on average own more electric cars due to shorter commuting distances and greater availability of charging stations. Therefore, more people would be negatively affected by decreased access to EV charging stations as a consequence of net congestion. In addition, the construction of improvements to the electricity grid infrastructure, such as powerhouses or electricity stations and batteries, affects more people when built in densely populated areas as compared to rural areas, where empty plots of land might be used.

5.2 Limitations and further research

Although the findings of this study are significant, the adopted study framework has some limitations. Firstly, the data gathering process. Unfortunately, I could not access the NVM transaction database as a whole. Instead, the data gathering was a manual process of downloading and combining transactions based on postal codes, making the database increasingly error-prone, with greater data inaccuracies and subsequently data losses. Moreover, neighbourhood income and education data was obtained from 2022 while all other variables originate from 2023. In the analyses both variables showed significant results, however, greater accuracies within the models can be expected when coherent datasets are used. Secondly, the computing of variables could be more extensive. Because of time constraints and lacking computing power, Euclidean distances to the points of interest are calculated while commuting times or network-based distances are proven to be more accurate measurements. In addition, generalisation which occurs by computing ratios for the education, age and income variables for the neighbourhood characteristics has made the analyses somewhat simplistic. Lastly, and most importantly, this research has failed to implement electric infrastructure which is allocated the individual houses and dependent on electricity supply. Individually owned solar panels or EV charging stations could interact greatly with electricity grid capacity problems and would therefore be crucial to further explore housing price dynamics.

Future research on the influence of electricity grid capacity on housing prices is much needed as little to no research has been done on this topic. As the consumption and production of electricity continue to rise due to environmental concerns, the pressure on the already congested electricity grid is not expected to drop, possibly increasing its influence on housing prices even more. Although not statistically proven, I find that the most congested areas for both rural and urban areas are the poorest when compared within their own geographical context. This underscores the importance of researching the consequences of electricity grid capacity on housing prices as variation in housing prices is caused by differences in the existing housing stock, where richer households can afford to move to a location of choice where leaving poorer households cannot (Mirkatouli et al., 2018; Musterd et al., 2016). Net congestion problems could cause electricity grid segregation, where only poorer households experience electricity externalities. Furthermore, the analytical models could be enhanced by adopting a Geographically Weighted Regression (GWR). Although Paliska & Drobne (2022) argue that multi-level regression models are not far off spatial models, in other studies GWR has yielded more accurate results (Mulley et al., 2018; Efthymiou & Antoniou, 2013). Research on how congestion problems are perceived within the urban Quality of Life theories, and how it relates to residential location choices, could further contribute to a better understanding of the relationship between the electricity grid and housing price dynamics. Lastly, research on the relation between electricity grid capacity and commercial transactions could further explore real estate dynamics in general and developments concerning net congestion.

To address net congestion problems local and national governments should invest in innovative projects, by adapting niche management strategies. When done successfully, new technologies may arise that could help relieve the current stress on the electricity grid. Importantly, investments should be equally granted across different regions, mitigating geographical differences.

6. Conclusions

Amenities and externalities are key determinants of housing prices. Growing electricity consumption and production have created tension on the electricity grid capacity in a way that inhabitants experience negative effects of net congestion. In this study, I have explored the relationship between electricity grid capacity and housing transactions, and the geographical differences within this relationship using transaction data from the Netherlands for 2023. The dataset was manually constructed by gathering data from the CRM Realworks website and allocating distances to points of interest and neighbourhood characteristics to each transaction. To adequately research the effect of the electricity grid capacity on housing prices both linear and multi-level regression models were estimated.

The results of the paper suggest that housing prices are negatively affected by rising net congestion problems. After splitting the database based on urbanity, geographical differences became apparent. Specifically, urban areas are affected significantly more by the negative effects of electricity grid capacity when compared to rural areas. These results contribute to the very sparse existing literature on ECG and housing price dynamics. But are consistent with similar research on the impact of electricity externalities on housing prices (Marope & Phiri, 2024). More research is needed however to further explore the relationship between the electricity grid capacity and housing prices, creating a deeper understanding of housing price dynamics with regard to energy transition movements.

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