Short-Term Rentals and Housing Prices

A Mixed Methods Study in Non-Urban Regions of Portugal

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Abstract

The global proliferation of short-term rentals (STRs), particularly through platforms such as Airbnb, has had a significant impact on the housing market. Current research focuses primarily on urban areas and shows a positive correlation between short-term rentals and rising home values. Especially in inelastic markets, where STR growth is absorbed by price increases and not by an expansion of housing capacity, this correlation leads to problems such as gentrification, summarized under the phenomenon of *Airbnbfication*.

Focusing on the case of Portugal, this study fills a research gap by examining the relationship between STRs and non-urban residential real estate markets. It uses a comprehensive dataset covering 11 years in 115 mainland Portuguese cities and advanced regression techniques, including the synthetic difference-in-differences method. The results suggest that an increase in the density of STRs is associated with an increase in house prices. However, there is evidence of a complex relationship, reflecting an inelastic housing market, where the relationship varies with the density of STRs.

With these findings, this study makes an important contribution to current research by refining the understanding of the impact of STRs on house prices in non-urban areas and providing evidence that the phenomenon of *Airbnbfication* extends to non-urban regions. It encourages policy makers in Portugal and beyond to consider the broader impact of STRs on urban and non-urban housing markets. In doing so, the findings can support the identification of proactive and effective regulatory policies that balance the growth of STRs with the welfare of residents.

Short-Term Rentals and Housing Prices - A Mixed Methods Study in Non-Urban Regions of Portugal

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Keywords: Short-Term Rentals, Housing Market, Airbnbfication, Portugal, SDID

Resumo

A proliferação global de estabelecimentos de alojamento temporário para turistas - estabelecimentos de alojmento local (ALs) - potenciada por plataformas como a Airbnb, tem tido um impacto significativo no mercado imobiliário. A investigação atual centra-se principalmente nas zonas urbanas e mostra uma correlação positiva entre os AL e o aumento do valor das casas, o que conduz a problemas como a gentrificação, resumida no fenómeno da *Airbnbfication*.

Este estudo preenche uma lacuna de investigação ao examinar a relação entre os ALs e os imobiliários residenciais não urbanos em Portugal. Utiliza um conjunto de dados abrangente que cobre 11 anos em 115 cidades de Portugal continental e técnicas de regressão avançadas, incluindo o método de diferença em diferenças sintéticas. Os resultados sugerem que um aumento da densidade de ALs está associado a um aumento dos preços da habitação. No entanto, existe evidência de uma relação complexa, refletindo um mercado imobiliário inelástico, em que a relação varia com a densidade de ALs.

Com estas conclusões, este estudo dá um contributo para a investigação atual, ao aperfeiçoar a compreensão do impacto dos ALs nos preços da habitação e ao fornecer provas de que o fenómeno da *Airbnbfication* se estende a regiões não urbanas. Incentiva os decisores políticos em Portugal e no estrangeiro a considerar o impacto mais alargado dos AL nos mercados imobiliários urbanos e não urbanos. Ao fazê-lo, os resultados podem apoiar a identificação de políticas reguladoras proactivas e eficazes que equilibrem o crescimento das ALs com o bem-estar dos residentes.

Alojamento Local e Preços da Habitação - Um Estudo de Métodos Mistos em Regiões Não Urbanas de Portugal

Marie Schwertner

Palavras-chave: Alojamento Local, Mercado Habitacional, Airbnbfication, Portugal, SDID

Table of Contents

List of Figures

List of Tables

List of Abbreviations

STR	-	Short-Term Rental
AL	-	Alojamento Local
OLS	-	Ordinary Least Squares
TWFE	-	Two Way Fixed Effects
SCM	-	Synthetic Control Method
DID	-	Difference-in-Differences
SDID	-	Synthetic Difference-in-Differences
IV	-	Instrumental Variable
STRD	-	Short-Term Rental Density
MHP	-	Median Housing Price
MHP_Log	-	Median Housing Price (Log-transformed)
UR	-	Unemployment Rate
CD	-	Company Density

1. Introduction & The Case Portugal

In 2019, the tourism sector accounted for more than 10% of global GDP (Genovese et al., 2023). Within this scope, short-term rentals (STRs) have become a key driver. Over the past decade, STRs have grown steadily worldwide, with a compound annual growth rate of nearly 20% (Diffenderfer, 2023). Driven by rising daily rates and growing demand, European STR revenues increased by about 46% year-on-year in May 2023, and by as much as 96% compared to 2019 (AirDNA, 2023).

The rise and institutionalization of STRs is driven by sharing economy platform models, particularly Airbnb (Hoffman & Heisler, 2020). By 2022, Airbnb had 6.6 million active listings facilitated by more than 4 million hosts worldwide, resulting in a cumulative 1.4 billion guest arrivals since its founding in 2008 (Airbnb, n.d.). By sharing underutilized space, these platforms have transformed profit-driven business-to-consumer rental models into more efficient and sustainable consumer-to-consumer ecosystems (Diffenderfer, 2023; Hossain, 2020). For consumers, they provide a variety of low-cost accommodations (Barron et al., 2021), with trust and reputation systems ensuring both quality and accountability (Bao & Shah, 2020; Zou, 2019). For landlords, STRs are a way to maximize the value of their properties by utilizing vacant space to its most profitable potential, i.e., short-term tenants (Koster et al., 2021). Thereby, STRs not only benefit landlords and tenants, but also strengthen local economies by stimulating job creation, increasing tourist spending (Bao & Shah, 2020), and improving neighborhood quality through outside investment (Sheppard & Udell, 2016).

Despite their positive aspects, STRs pose significant economic, socio-cultural and environmental challenges. Termed *Overtourism*, *Tourism Phobia* (Veríssimo et al., 2020), and *Airbnbfication* (Mermet, 2022), the growth of tourist accommodation has been linked to racial discrimination and gentrification (Todd et al., 2022), tax evasion (Bao & Shah, 2020), and increased noise and crime rates (Sheppard & Udell, 2016). Mostly, STRs have a significant impact on real estate markets as they are increasingly displacing long-term rentals (Hoffman & Heisler, 2020) with large investors such as the Blackstone Group converting existing multifamily properties into STR units (Diffenderfer, 2023). As a result, STRs have a significant impact on residents' affordable housing concerns (Zou, 2019). In this context, Portugal is a particularly relevant case, as the country is experiencing a dichotomy between an ever-growing tourism industry and a rapidly worsening housing affordability crisis.

Between 2010 and 2019, the country registered a significant increase of over 90% in tourist arrivals and overnight stays (Statista, 2023a). After a tourism downturn during the COVID-19 pandemic, Portugal demonstrated resilience, registering nearly 47 million international guest nights in 2022, figures comparable to pre-pandemic levels (Luz, 2023; Santos & Oliveira Moreira, 2021). The first quarter of 2023 broke all previous records, attracting more than 2.8 million international travelers despite pressing global economic concerns (Reuters, 2023). Contributing nearly 15% to the country's GDP in 2023, the tourism sector's growth is expected to outpace the overall economy, averaging 3.4% per year over the next decade (WTTC, 2022).

Despite the tourism boom, however, Portugal faces a housing affordability crisis (Rua et al., 2023), a problem that affects metropolitan areas as well as nonmetropolitan areas worldwide (Wachsmuth & Weisler, 2018). To illustrate, EU housing prices increased by 37 % between 2010 and 2021 (Eurostat, n.d.). However, Portugal's figures are well above this average: in 2022, real estate prices exceeded the 2010 level by 61% and continued to grow even during the COVID-19 pandemic (Delmendo, 2023). The combination of low incomes and rising rents makes Lisbon the third least viable city to live in in the world (M. Pereira & Nunes, 2023). Notably, the monthly minimum wage in Portugal is €760 (Demony et al., 2023), with more than half of the workforce having earned less than €1,000 per month in 2022 (Rua et al., 2023). In contrast, the average rent for a one-bedroom apartment in Lisbon stands at around €1,350 (M. Pereira & Nunes, 2023).

This situation is partly the result of misplaced government incentives introduced in response to the financial crisis (Demony et al., 2023). In particular, the Golden Visa program, introduced in 2012, fueled real estate speculation and house price inflation (Rua et al., 2023) by offering residence rights and potential citizenship to non-EU citizens in exchange for investment in Portugal. Between 2014 and 2022, approximately 27,400 golden visas were issued, attracting €7.2 billion in foreign investment by 2023, of which more than 80% related to real estate. (Global Citizen Solutions, 2022) In response, legislative changes to the Golden Visa program are currently underway, one of which is the exclusion of real estate as an eligible investment project (Global Citizen Solutions, 2021). Another governmental driver is the Alojamento Local, or short AL program, which covers local accommodation in Portugal. The program, introduced in 2008, serves as a legal framework for STR accommodation. Its main purpose is to enable property owners to legally offer their properties for short-term vacations, even if they do not meet conventional criteria for tourism accommodations.

(Directorate of Tourism Supply Development, 2016) Although approved in 2008, it was not until Legislative Decree No. 128/2014 (Diário da República, n.d.-c) that the program received a clear definition and legal categorization, making ALs a legitimate and regulated segment within the tourism industry (A. Pereira & Vaz, 2021). Thus, after registering online through the National Local Lodging Register, property owners can offer their houses, guesthouses, apartments, and rooms for short-term stays (Directorate of Tourism Supply Development, 2016).

ALs are seen as a key catalyst for the rise in STRs in Portugal, evidenced by a 3,000% growth between 2010 and 2020 (A. Pereira & Vaz, 2021). This increase has had both positive and negative consequences. On the one hand, property owners have been able to generate additional income, stimulating a general investment and urban revitalization momentum (Almeida et al., 2022). On the other hand, rapid STR expansion has contributed to exacerbating the country's housing crisis (Pereira & Vaz, 2021) through increased pressure on rental prices, social displacement, and gentrification (Almeida et al., 2022).

These dynamics can be significantly influenced by local regulations (Horn & Merante, 2017). Consequently, it is incumbent upon policymakers to take proactive measures to effectively address the challenges that STRs pose to housing affordability (Bao & Shah, 2020). Existing literature identifies three main regulatory approaches: laissez-faire, outright prohibition, and permitting with spatial, qualitative, or quantitative restrictions (Hübscher & Kallert, 2023). A majority of cities have taken proactive measures to address the impact of STRs on the housing market. For example, Los Angeles, amid a housing crisis, was one of the first cities to regulate STRs (Lee, 2016). Following this trend, many European cities have implemented or are planning to implement regulations, including London and Berlin with full restrictions and Barcelona with a combination of restrictions and partial bans (Hübscher & Kallert, 2023).

In line with the Barcelona approach, the Portuguese government has implemented several prohibitive and regulatory measures in recent years, including the introduction of Decree-Law No. 62/2018 in 2018 (Diário da República, n.d.-a). This law strengthened the regulatory control of local authorities over AL facilities, with the ability to restrict them partially or fully (Almeida et al., 2020). Subsequently, the registration of new ALs was banned in certain areas of Lisbon (Peralta et al., 2020), leading to an 8% drop in property prices in the affected neighborhoods (Gonçalves et al., 2022). Decree-Law No. 68/2019 (Diário da República, n.d.-b) introduced the Affordable Rent Scheme, providing tax incentives for long-term rentals to support a balanced housing sector (Mendes, 2022). Further regulation of the AL program is expected in 2023. New measures could include further bans on AL licenses in densely populated municipalities and tax breaks for landlords who convert ALs properties to long-term rentals. (The Portugal News, 2023)

However, despite existing approaches, effective regulation of STRs remains complicated. First, there is a notable lack of actionable data, complicating evidence-based decision making (Zou, 2019). Additionally, the multifaceted nature of the STR landscape, driven by platforms such as Airbnb, combined with inconsistent enforcement capabilities, makes it difficult to assess the impact of regulations pre- and post-implementation (Robertson et al., 2023). For example, some researchers argue that these regulations would have little impact on the long-term housing market as only a small number of properties would be converted back from short-term to long-term rentals (Gauß et al., 2022). Thus, understanding the nuanced relationship between STRs and housing market dynamics in different settings is crucial for developing effective regulations and promoting housing affordability.

While most current research supports the notion that house prices increase with the number of STRs, the results are mostly limited to urban areas and are based on web-scraped data, either using self-developed scrapers or data from third-party scrapers such as Inside Airbnb (Zou, 2019). This methodological approach leaves a conspicuous gap in understanding, particularly with respect to non-urban areas. Yet, research in these regions is becoming increasingly important as pandemic-related shifts in work and travel preferences have stimulated tourist interest in non-urban areas (Colomb & Gallent, 2022). Also, it is essential to determine the socio-economic impacts of the interaction between STRs and housing prices - are they always positive, strengthening the local economy, or do they shift to the negative, potentially displacing and disadvantaging the local population?

In this context, the goal of this study is to examine the impact of STRs on housing prices in under-researched non-urban areas. The intent is to support future regulatory efforts with empirical evidence. The central research question driving this study is:

> *"How does the proliferation of STRs in Portugal's non-urban areas affect housing prices? And, how does this relationship change with different STR densities?"*

The structure of this thesis is as follows. Chapter 2 outlines the hypothesis development and theoretical foundations, highlighting current research trends. In chapter 3, data sources and datasets used are reviewed along with a description of the variables employed. Section 4 focuses on the methodology, model building and regression analysis. The empirical results are then presented, analyzed, and interpreted in Chapter 5. Finally, section 6 discusses implications, limitations, and possible directions for future research.

2. Literature Overview & Hypothesis Development

There is a broad field of research on price determinants and developments in the real estate market. In this regard, traditional economic hedonic models (Palmquist, 1984) primarily examine traditional supply and demand factors as key determinants of real estate prices (Chow & Niu, 2015). Here, the focus lies on macroeconomic forces (Harris, 1989; Zhang et al., 2012), property characteristics (Wittowsky et al., 2020), demographic trends (Gong & Yao, 2022) and even psychological factors (Case & Shiller, 2003). However, an emerging line of research focuses on the impact of non-traditional factors, particularly tourism. In this context, STRs hold a critical importance as they operate in both the tourism sector and the residential real estate landscape.

2.1. Directional Analysis

Some researchers have suggested that STRs cause negative side effects that lower real estate prices, a relationship referred to as the *Externality Effect* (Koster et al., 2021; Sheppard & Udell, 2016). For example, an increase in STRs can lead to an increase in crime rates, noise pollution, or traffic congestion, making neighborhoods less attractive and causing residents to move away. The subsequent decrease in demand for real estate leads to a decline in property values (Sheppard & Udell, 2016). Aside from a study by Biagi et al. (2015) using a latent class model that shows mixed results, including a decrease in property values associated with STRs in some cities, there is little empirical evidence for the *Externality Effect*. Conversely, most recent research suggests that STRs are positively correlated with increasing house prices.

Barron et al. (2020) conduct a study in the United States from 2012 to 2016. The researchers evaluate Airbnb listings across the United States using a self-developed web scraper and employ Ordinary Least Square (OLS) and Fixed Effects (FE) regressions with an Instrumental Variable (IV) approach to analyze the impact of Airbnb listings on housing prices. The results show that a 1% growth in Airbnb listings leads to a 0.026% to 0.037% increase in house prices, depending on the owner-occupancy rate. The study also points to a reallocation effect, in which a proliferation of STRs is offset by a displacement of housing units from the long-term rental market.

Sheppard and Udell (2016) use hedonic FE and Difference-In-Differences (DiD) regression to analyze the impact of Airbnb listings on residential property prices in New York City from 2003 to 2015. Incorporating web-scraped Airbnb data from third-party provider InsideAirbnb, the results show that a doubling of Airbnb listings is correlated with an increase in home values of between 6 and 31 %, depending on the model used.

Garcia-López et al. (2020) assess the impact of Airbnb on the housing market in Barcelona between 2007 and 2017. Using official cadastral data and land and property records, they apply FE regression with IVs and event studies. They show that Airbnb activity increases rents in each neighborhood by an average of 1.9 % and a maximum of 7 %.

While there is general agreement that STRs have a positive impact on housing prices, this consensus cannot be generalized because the impact of STRs on housing prices can vary by region (Quattrone et al., 2016). However, the geographic coverage of existing research has been narrow (Bao & Shah, 2020), focusing on urban, touristic areas, particularly in the United States (Franco & Santos, 2021). This leaves a gap in understanding the impact of STR in less urbanized areas in Europe. Yet, this very context is becoming increasingly important given the growing demand for STRs in non-urban areas, driven by flexible working practices and new tourism trends (Gurran & Redmond, 2021). Portugal is a particularly relevant case, as the country with few urban centers is currently experiencing a tourism boom, especially in rural regions (Instituto Nacional de Estatística, 2023).

However, the already limited research in the Portuguese region focuses mainly on Lisbon and Porto. For example, Cunha & Lobão (2021) examine the impact of STRs on house prices in Lisbon and Porto from January 2011 to December 2019, using official data from the Portuguese Institute of Tourism and Statistics along with a DiD approach. They show that a one percentage point increase in the STR share is associated with an increase in house prices of about 16% in Porto and about 27.5% in Lisbon.

Similar to the present study, Franco and Santos (2021) also examine the impact of STRs on house prices in non-urban areas of Portugal. Using web-scraped Airbnb data, the researchers examine data for more than 44,000 Airbnb listings in 137 municipalities between 2011 and 2016. Via DiD regression and IV approach, they find that a 1% increase in Airbnb share is associated with an average 3.7% increase in house prices, whereby the exact impact depends on the tourist specificity of each community.

In order for Portuguese policymakers to formulate and implement effective and balanced regulations, more in-depth research is needed. Building on this, the objective of this paper is to provide further evidence to better understand the impact of the growing STR sector on housing affordability in non-urban regions of Portugal, with the first hypothesis being:

Hypothesis 1: *A higher density of STRs in non-urban areas in Portugal will be positively associated with higher housing prices.*

2.2. Effect-Based Exploration

The prevailing consensus on a positive correlation between STRs and housing prices has led to more nuanced studies of the underlying relationships and the resulting sociocultural effects. These studies have focused on specific implications, such as the *Efficient Use* and *Rental Housing Supply Effect* (Koster et al., 2021; Sheppard & Udell, 2016).

The *Efficient Use Effect* states that residential property owners can maximize their income by efficiently using underutilized space (Koster et al., 2021). This additional income not only allows owners to maintain their property longer and more economically by decreasing ownership costs (Sheppard & Udell, 2016). It is also factored into housing values (Barron et al., 2021), as the inherent value of a property is derived from its future rental potential (Cunha & Lobão, 2021). Given that an enhanced rental revenue increases the capitalization rate, a prominent indicator for the potential return of real estate investments (Chen, 2023), overall investment momentum is fueled (Sheppard & Udell, 2016). Looking at the region as a whole, spillover effects can occur, as an increase in tourist arrivals supported by STRs, for example, leads to greater local consumption and thus an economic boost, which in turn enhances the quality of the region and thus property values (Sheppard & Udell, 2016).

However, the potential economic benefits to residents and communities are often not realized. Rather, a growing number of commercial landlords are acquiring residential properties, converting them from long-term to short-term rental markets (Bao & Shah, 2020). In doing so, they are renting out multiple entire properties (Dogru et al., 2020) - 64 % of Airbnb hosts in the United States have two or more listings, with about 70 % being entire homes (Lane & Woodworth, 2016). In fact, even large real estate investors such as UDR Inc. and the Blackstone Group have embraced STRs as a new asset class (Diffenderfer, 2023). In inelastic markets, this trend is particularly problematic because an increase in STRs is not offset by new housing development, but rather corresponds to a decrease in housing units (Cunha & Lobão, 2021).

Described by the *Rental Housing Supply* effect (Koster et al., 2021), this change in housing availability leads to a negative supply shock. The supply curve shifts to the left and the shock is absorbed by price rather than quantity adjustments (Cunha & Lobão, 2021). Long-term tenants absorb this price premium, which particularly threatens low-income minorities (Zou, 2019). The resulting effects are often grouped under the phenomenon of *Airbnbfication* (Mermet, 2022), which can be defined as: "the form of gentrification characterized by the permanent or temporary conversion of residential housing into STRs accompanying the development of STR platforms in such a way that it displaces existing users due to the arrival of more affluent groups" (Mermet, 2022). Wachsmuth & Weisler (2018) discuss how these dynamics places local property owners in a tension between profiting from STRs and coping with the resulting pressure on housing affordability. Nieuwland & van Melik (2020) go further, describing the situation as a vicious cycle in which the need for local residents to let properties on a short-term basis to offset rising rents leads to even higher rents, further accelerating the letting need.

In the context of Portugal, such effects would be particularly severe, as the country is already experiencing a dichotomy between rising STR numbers, driven by government initiatives such as the AL program, and an accelerating housing crisis for the local population. Assuming an inelastic market, higher levels of STR density - i.e., a higher number of STRs relative to the population - would not lead to relatively higher housing prices, but to accelerated price pressures that place local populations in distressed positions.

The second hypothesis is therefore:

Hypothesis 2: *The impact of STRs on housing prices will vary with different levels of density.*

2.3. Current Paradigms in Research Design

Identifying patterns, relationships, and drivers among a variety of individual effects in the relationship between STRs and house prices over different time periods and regions requires the integration of comprehensive data sources and methodological approaches.

However, as shown above, studies on the impact of STRs on housing markets rely primarily on data from Airbnb listings, typically obtained through self-conducted web scraping or web scraped data provided by third-party vendors such as *AirDNA* (Barron et al., 2021; Wachsmuth & Weisler, 2018). This approach has implications for the generalizability and explanatory power of the respective analyses, as the overall reliability of such datasets is limited, particularly due to the lack of investigation of their validity (Alsudais, 2021; Prentice & Pawlicz, 2023).

Regarding methodological design, many researchers investigating the relationship between STRs and house prices have relied on Rosen's (1974) hedonic pricing method for real estate (Cunha & Lobão, 2021). This approach employs actual transaction prices to assess how different factors, such as property size and neighborhood characteristics, affect property values (Hargrave, 2021). Building on this, researchers use mixed methods for deeper analysis, as recommended by Sheppard & Udell (2016), for example, through a series of linear models that include FE and DiD procedures. Both techniques can control for common endogeneity biases, with FE regression known to control for omitted variable bias (Nygård & Thoresen, 2023), while DiD models are commonly used for causal inference (Bertrand et al., 2004). To strengthen the robustness of causal inference (Becker, 2016), research designs are increasingly being augmented with instrumental variables (Barron et al., 2021; Franco & Santos, 2021).

While current research already employs a wide range of methods that account for various endogeneity errors, the present work exploits the potential of using improved versions of existing methods as well as advanced computational techniques to process large and heterogeneous datasets even more accurately and efficiently. In particular, a possible incomplete picture due to the aforementioned low data diversity is addressed by compiling a comprehensive dataset from different sources of Portuguese government institutions, as discussed in more detail below.

3. Data Collection

The next section presents the dataset compiled. By explaining the specific characteristics of the data set, clarifying the definition of variables, and identifying potential biases, this detailed data presentation serves as a thorough foundation for the subsequent analyses.

3.1. Panel Data

Panel or longitudinal data consist of observations that have a cross-sectional and a time-series dimension. This enables the processing of a large number of observations with many degrees of freedom, as well as the coverage of inter- and intra-individual effects (Hsiao, 2007). Such a comprehensive and rigorous approach is essential to the present analysis, given the variety of factors that can affect real estate prices. The panel data set extends over four variables: The dependent variable Median Housing Price (MHP), the independent variable Short-Term Rental Density (STRD), and the control variables Unemployment Rate (UR) and Company Density (CD).

As discussed in chapter 1, house prices are influenced by a multitude of factors (Jacobsen & Naug, 2005). While this study aims to provide an in-depth analysis, the inclusion of a comprehensive set of covariates over 11 years at the regional level is limited by both data availability and the scope of the study. Therefore, two robust covariates measuring the unemployment rate and company density were used. These factors are key indicators of household disposable income and thus have a direct impact on house prices (Özmen et al., 2019). In this study, both variables are assumed to have a lagged effect on economic indicators, which led to the inclusion of a one-year lag in the model. Including these lags provides a more nuanced understanding of the intertemporal relationships while ensuring the robustness and accuracy of the results.

Portugal is administratively divided into districts, municipalities and parishes. The municipal level was chosen to structure the cross-sectional dimension of the dataset, balancing the breadth and granularity of the data. Out of the 308 municipalities in the country, municipalities in the autonomous regions of the Azores and Madeira were not included, due to their individual economic, legal and social dynamics, which may differ from the characteristics of mainland Portugal. Following the OECD definition of functional urban areas (OECD, 2019), an additional 10 municipalities classified as urban were excluded. These are listed in Appendix 1. Accordingly, 278 municipalities were initially considered for further analysis.

The analysis is conducted over an 11-year period, from 2012 to 2022 for the dependent and independent variables, and from 2011 to 2021 for the lagged control variables. Including earlier years would have required the exclusion of many cities from the analysis due to the lack of consistent data for years prior to 2011. Therefore, it was decided to use a broader cross-sectional dimension rather than a deeper time-series dimension. This 11-year period covers the significant growth period of STRs and 10 periods of change, allowing for a thorough examination of the relationship under study. In addition, data from this most recent decade benefits from advances in digitization and data collection, ensuring greater reliability and consistency.

Missing data points were handled using Complete Case Analysis, which provides more robust results and is easier to implement than Available Case Analysis (Pigott, 2001). In case of missing data points for any of the four variables, a listwise deletion was performed, i.e., the entire municipality was excluded from the dataset for all years. The final dataset contained 5,060 data points, spanning 4 variables and 1,265 observations in 115 cities in mainland Portugal. An overview of the cities included and excluded can be found in Appendix 1.

3.2. Variable Description

3.2.1. Dependent Variable: Median Housing Price (MHP)

The dependent variable - median housing price per square meter for each year and each municipality – was obtained through Pordata. Pordata is a publicly available Portuguese database provided by a private non-profit foundation that provides comprehensive socioeconomic data for Portugal (Pordata, 2023e).

The specific variable used in this study is the median value of bank technical valuations of houses, expressed in EUR per square meter. The variable was collected by the National Statistics Institute (INE), the official statistical agency in Portugal. It is collected annually as part of a statistical survey of bank valuations by the leading credit institutions in the Portuguese mortgage market. (Pordata, 2023d) Pordata's commitment to data integrity and its comprehensive information base, sourced from established institutions such as INE, underscore the suitability of the variable for this empirical analysis and ensure the validity and depth of the results.

Pordata defines housing as the place where people live, characterized by being distinguishable and independent, and allowing residents to live separately and have access without passing by other accommodations (Pordata, 2023d). In this research, this definition is expanded to include the characteristics of residential property, which is defined as "property zoned specifically for living or dwelling for individuals or households; it may include standalone single-family dwellings to large, multi-unit apartment buildings" (Chen, 2022).

The unadjusted dependent variable is right skewed, as shown in the histogram in Appendix 2. Such skewness can lead to heteroskedasticity and non-normally distributed errors, creating biased estimates. To mitigate these effects, the dependent variable was log transformed. Logarithmization mitigates skewness by compressing the scale of variation and creating a more symmetric distribution that better fits the assumptions of linear regression and other modeling techniques. (Feng et al., 2014)

3.2.2. Independent Variable: Short-Term Rental Density (STRD)

The independent variable STRD is a ratio between the cumulative number of STRs and the population size for each year and municipality, which is a similar approach to that of Horn & Merante (2017). The ratio provides a consistent measure, especially when compared to growth rates, which can be significantly affected by the base effect. If the baseline is exceptionally low, the subsequent growth rate may appear disproportionately high, and vice versa. (Kenton, 2021) The risk of overestimating growth rates would have been particularly strong in this study as the total number of STRs is zero for most cities in the early years of the analysis.

The cumulative number of STRs for each municipality and year was obtained from a dataset listing all ALs in Portugal, derived from travelBI Open Data – an open access data platform maintained by Turismo de Portugal, the tourism authority of Portugal (Turismo de Portugal, 2023). As of August 4, 2023, this dataset contained 114,435 registrations with a total user capacity of 659,174. It thus stands out from previous studies due to its comprehensive coverage and high validity, given its public sector origination.

The cumulative number of STRs was calculated using user capacity rather than the actual number of listings, as this is believed to better reflect actual occupancy and the potential impact of STRs on the housing market, particularly in terms of potential displacement of long-term tenants. When assigning the listings to the respective years, a distinction was made between the registration date and the official opening date. If the official opening date preceded the registration date, the registration date was used, and vice versa. In this way, only operating ALs complying with the guidelines of Legislative Decree No. 128/2014 were considered (Diário da República, n.d.-c). It was assumed that once an AL is opened, it does not leave the STR market anymore.

The data was manually verified and cleaned. In accordance with the provisions of Legislative Decree No. 128/2014 (Diário da República, n.d.-c), lodging establishments with more than 9 rooms or a capacity of more than 30 people were removed from the dataset. In addition, entrepreneurial establishments, such as hostels and hostels, were excluded from the analysis under the assumption that they compete more directly with hotels than with residential properties. The cleaned dataset included 74,549 listings with a total user capacity of 403,810.

The cumulative user capacity per year and city was then divided by the corresponding resident population. The latter was obtained from Pordata and is based on an annual estimate by INE (Pordata, 2023c).

3.2.3. Control Variable: Unemployment Rate (UR)

The control variable UR was obtained from Pordata. It is collected annually by the Portuguese Institute for Employment and Vocational Training and measures the number of registrations at employment and vocational training centers in Portugal. (Pordata, 2023b) UR is thus an indicator of the level of disposable income in a municipality, which affects housing demand and hence MHP.

3.2.4. Control Variable: Company Density (CD)

The control variable CD, defined as the average number of companies excluding financial institutions per square kilometer, was also collected through Pordata and is reported annually by INE (Pordata, 2023a). CD serves as an indicator of economic activity and employment opportunities in a region, which affects disposable income and, in turn, real estate demand and prices.

3.3. Descriptive Statistics

The descriptive statistics section of this paper provides a comprehensive overview of the data set, detailing the distributional characteristics of each variable. By examining the trends, minima, and maxima, an understanding of the underlying patterns and influencing factors is generated, which serves as the basis for the subsequent analysis.

3.3.1. Sample Distribution

As shown in Table 1, with about 32 %, most of the sample cities are located in the regions Centro and North. The Lisbon metropolitan region and the Alentejo region each account for about 14 % of the municipalities, while the Algarve region has the lowest share with 7 %. This distribution reflects regional characteristics: while the Algarve and Alentejo regions are dominated by rural tourism and agriculture (Turismo de Portugal, 2013b, 2013c), the northern regions have a higher population density and stronger economic activity (OECD, 2022).

Table 1: Regional Sample Distribution

Region	Sample Municipalities	
	Absolute	%
Alentejo	16	13.91
Algarve	8	6.96
Centro	37	32.17
North	37	32.17
Lisbon Metropolitan Region	17	14.78
Total	115	100.00

As shown in Table 2, about 83.5% of the municipalities have less than 90,000 inhabitants. Only four municipalities, or about 3.5% of the total sample, have a population greater than 180,000 inhabitants, confirming the exclusion of urban areas in this study.

Table 2: Population Sample Distribution

Number of Inhabitants	Sample Municipalities	
	Absolute	%
(1) ≤ 90,000	96	83.48
(2) > 90,000, ≤ 180,000	15	13.04
(3) > 180,000, ≤ 275,000	2	1.74
(4) > 275,000	2	1.74
Total	115	100.00

3.3.2. Regression Variables

Table 3 provides detailed descriptive statistics for all regression variables. While the sample period for the independent and dependent variables ranges from 2012 to 2022, the lagged control variables cover the period from 2021 to 2021.

The standard deviation for STRD and CD is high when compared to their means, indicating considerable variability and potential outliers in these metrics. Outliers distort statistical estimates such as sample means and standard deviations, leading to inaccuracies (Kwak & Kim, 2017). However, careful consideration must be given to whether outliers are due to, for example, errors in data collection or trends that deviate from the mean (Wada, 2020). To ensure that no unusually high or low values outside the average data distribution were included, manual sorting and scatter plots were used. Since all data was obtained from official Portuguese authorities, the basic quality of the data is assured, so that marginal, non-anomalous deviations can be considered as real differences that require further analysis.

Overfitting or even eliminating these cases through techniques such as winsorization or trimming (Wilcox, 2005) would remove important variations and compromise the quality of the analysis (Jones, 2019).

Table 3: Descriptive Statistics of Study Variables

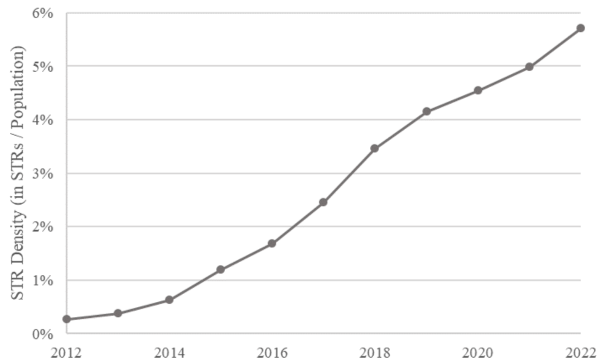
		(1) N	(2) mean	(3) sd	(4) min	(5) max
STRD	(STRs / population)	1,265	0.03	0.08	0.00	0.85
MHP	(€ / sqm)	1,265	852.31	309.26	483.00	2,738.00
UR	(%)	1,265	7.02	2.70	2.30	18.50
CD	(companies / population)	1,265	57.92	110.09	1.60	776.50

3.3.2.1. Independent Variable: Short-Term Rental Density (STRD)

The average sample ratio of STRs to population is 0.027, meaning that there are approximately 27 STR accommodations per 1,000 residents. Entroncamento and Albufeira, exhibit sample extremes. Entroncamento has a relatively low density, with about one STR per 5,500 inhabitants, which can be explained by the fact that Entroncamento is not a traditional tourist center but an important railway junction (Câmara Municipal do Entroncamento, n.d.). In contrast, Albufeira in the Algarve counts around 440 STRs per 1,000 inhabitants, reflecting the city's robust tourism industry as one most visited destinations in the Algarve (Turismo de Portugal, 2013a). These differences highlight the varying degrees to which cities in Portugal accommodate and are affected by STRs.

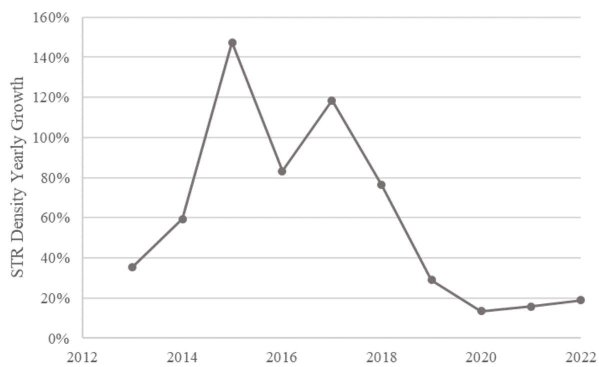
Referring to Figure 1, STRD shows a constant annual growth over the entire ten-year period. In 2012, the average ratio of STRs to population was 0.0027. In 2022, this ratio has increased twenty-fold to 0.057, meaning that there are approximately 57 STRs for every 1,000 residents. This continuous increase could be attributed to several factors, such as the growing popularity of Portugal as a tourist destination, changing travel behavior that favors more flexible accommodations, or advances in platforms that facilitate STR operations. However, this upward trend also reflects the inevitability of changing socioeconomic dynamics for the residential population.

Figure 1: Overall Development of STRD



The growth trend is further illustrated by an average year on year (YoY) growth of 60 % as shown in Figure 2. A notable peak in this upward trend is observed in 2014, when the periodic growth rate reaches 147%. This peak can be associated to the introduction of Decree-Law No. 128/2014, as pointed out by Franco and Santos (2021). By simplifying regulatory challenges, the law legitimized STR operations (Portugal, 2014), which likely catalyzed the rapid expansion of the market during this period. Since 2017, there have been signs of a slowdown in the annual growth rate, with the lowest growth rate observed in 2019 at around 13.5%. This slowdown is likely due to the regulations the Portuguese government has started to implement to stop the proliferation of STRs, as discussed in chapter 1. In addition, the outbreak of the COVID-19 pandemic has caused caution among both tourists and potential real estate investors (Santos & Oliveira Moreira, 2021), probably causing a slowdown in the expansion of the STR market.

Figure 2: YoY Growth of STRD



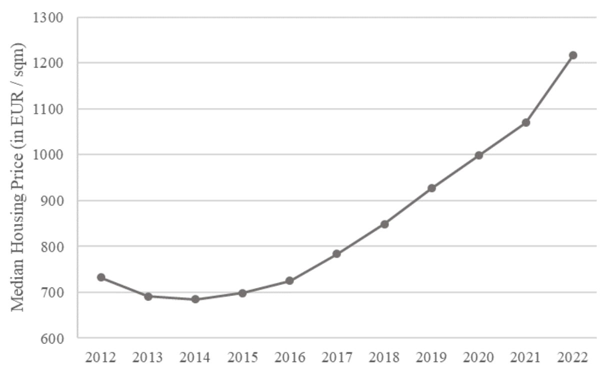
3.3.2.2. Median Housing Price (MHP)

The following description focuses on the original MHP variable rather than its log-transformed counterpart (MHP_Log). While log transformations stabilize the variances and bring the data closer to the normal distribution (Metcalf & Casey, 2016), they also complicate interpretation (Alba, 1987). Therefore, describing the non-log variables ensures a more intuitive and direct interpretation of the inherent data trends and characteristics.

The analysis of MHP over the sample shows an average median price of around €814 per sqm, with differences between the sample cities. The lowest MHP of €556 per sqm was registered in Nelas. Cascais, on the other hand, known for its proximity to the coast and Lisbon (Turismo de Portugal, 2013d), has the highest value at €1,712 per sqm. Assuming that in Cascais there is a discrepancy between disposable income and the cost of living for the local population, a further increase in house prices due to the proliferation of STRs may lead to greater financial pressure than in comparatively more affordable cities. However, to the extent that basic income in Cascais is above average per se, residents may be better able to compensate for higher costs. In any case, the range of MHP illustrates the importance of taking geographical conditions into account when analyzing the relationship between STRs and house prices.

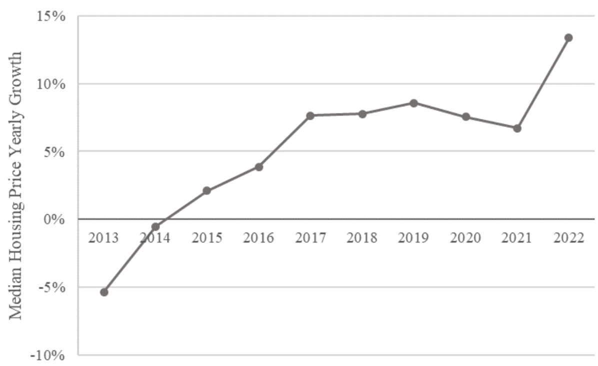
Looking at price trends across the sample, as shown in figure three, an overall increase of 66 % from an MHP of €732 per sqm in 2012 to €1,217 per sqm in 2022 is observed. The trend is not uniform though. In 2013 and 2014, MHPs decreased, potentially due to low investment activity and tight credit conditions in the context of the global financial crisis. As a result, unemployment in Portugal rose to 17.7 % in 2013 (Statista, 2023b), with youth unemployment reaching 40 % (Statista, 2023c).

Figure 3: Overall Development of MHP



However, as shown in Figure 4, an average annual MHP growth of around 7% is observed after 2014, illustrating Portugal's economic recovery. In fact, in 2022, the country recorded the strongest annual increase in MHP over the sample period, at 13%.

Figure 4: YoY Growth of MHP

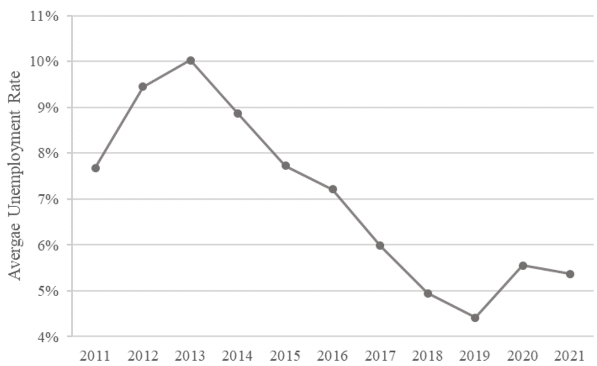


In summary, STRD and MHP show a consistently positive trend over the ten-year period, with regional differences. However, the two variables differ in their response to external shocks. While the independent variable peaked in 2014 in response to the legalization of ALs, the dependent variable experienced a decline over similar time periods, likely related to the global economic downturn.

3.3.2.3. Unemployment Rate (UR)

As shown in Figure 5, the control variable UR also reflects the shocks observed in the dependent and independent variables, with a peak after the Euro Crisis in 2012 and a further increase during the COVID-19 pandemic. However, there has been a general decline over the years, with an overall decrease of around 3%, which is similar to the European average (Statista, 2023d).

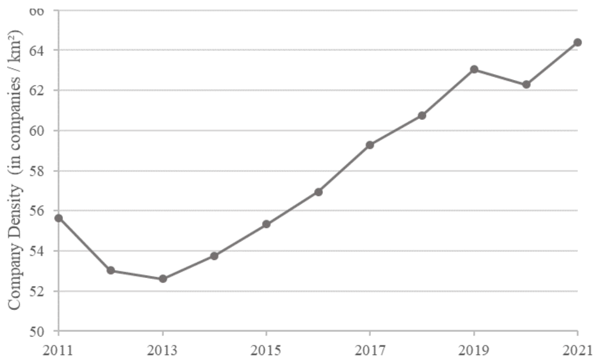
Figure 5: Overall Development of UR



3.3.2.4. *Company Density (CD)*

Figure 6 shows that the control variable CD shows similar trends to the other variables, with a decrease in 2012 coinciding with the financial crisis and another decline in 2019 coinciding with the COVID-19 pandemic. Overall, however, the average CD in the country increased by about 16% between 2011 and 2021, underscoring Portugal's economic recovery.

Figure 6: Overall Development of CD



4. Model Building

In order to investigate the relationship between STRs and the Portuguese housing market, this study used a cross-methodological approach. The design was embedded in a four-stage analysis, guided by a synthesis of the research approaches presented in section 2.3, while incorporating advanced methodological improvements.

It should be noted that the following conceptual description as well as the listed (regression) equations are intended to improve both the understanding of the underlying logic of the models as well as the interpretability of the resulting data. However, the steps displayed and the calculations themselves were all performed automatically by means of the respective Stata commands. The decision to use Stata was influenced by the software's commitment to continuous development and its user-driven innovations, as highlighted by Baum (2005). One of these innovations is the SDID command developed by Clarke et al. (2023), which was used in this study and is discussed in detail in Chapter 4.3.

4.1. Ordinary Least Square Regression (OLS)

To provide an initial understanding of the possible relationship between STRD and MHP, OLS regressions were run without and with controls. OLS attempts to minimize the squared differences between the predicted values from the regression equation and the observed data points. By identifying a linear relationship in the data set, the method estimates the coefficients of the predictor variables. (Burton, 2021)

The OLS Regression without controls, following called model O1, can be described as follows:

(1) $MHP\_Log_{it} = \beta_0 + \beta_1(STRD_{it}) + e_{it}$

Where:

- MHP_Log_{it} is the dependent variable
- $STRD_{it}$ is the independent variable
- β_0 is the intercept
- β_1 is the coefficient capturing the effect of a one-unit increase in *STRD* on *MHP_Log*, holding other factors constant
- e_{it} is the error term for municipality *i* in year *t*, capturing any unexplained variation

The OLS regression with control variables, hereafter referred to as model O2, is formulated as follows:

(2) $MHP\_Log_{it} = \beta_0 + \beta_1(STRD_{it}) + \beta_2(CD_{it-1}) + \beta_3(UR_{it-1}) + e_{it}$

Where:

- CD_{it-1} is the lagged control variable Company Density
- β_2 is the coefficient capturing the effect of a one-unit increase in *CD* on *MHP_Log*, holding other factors constant
- UR_{it-1} is a lagged control variable Unemployment Rate
- β_3 is the coefficient capturing the effect of a one-unit increase in *UR* on *MHP_Log*, holding other factors constant

4.2. Two Way Fixed Effect Regression (TWFE)

Because the relationship between STRD and MHP was assumed to be driven by time-invariant local characteristics, such as geographic location or cultural amenities, and time-fixed effects, such as national economic performance, global financial trends, or nationwide policy changes, a TWFE regression was run. Unlike OLS, which can be affected by unobserved heterogeneity, TWFE models control for unobserved, time-invariant heterogeneity and common time shocks. In essence, they are a robust approach to analyzing variation both within units and across time periods. By controlling for omitted variables and mitigating unobserved confounders, it reduces bias, improves model fit as evidenced by higher R-squared values, and allows for improved causal inference. (Hill et al., 2020)

The TWFE regression, which will be referred to as model T, is described as follows:

(3) $MHP_{it} = \beta_0 + \beta_1(STRD_{it}) + \beta_2(CD_{it-1}) + \beta_3(UR_{it-1}) + \alpha_i + \gamma_t + e_{it}$

Where:

- α_i is the unit-specific fixed effect for municipality i, capturing all unobserved, time-invariant characteristics
- γ_t is the time-specific fixed effect for year *t*, capturing all unobserved, time-specific effects that affect all municipalities

4.3. Synthetic Diff-in-Diff Regression (SDID)

A TWFE regression, while controlling for both time and community effects, may not account for all unobserved heterogeneities (Hill et al., 2020). In particular, time-varying and municipality-specific unobservable factors that are also correlated with STRD could influence MHP_Log, posing challenges for valid causal inference. To increase the robustness of the analysis and mitigate this heterogeneity, an SDID approach was used. SDID provides a more sophisticated control for potential unobservable confounders that could bias the observed relationship between STRD and MHP_Log. The SDID method represents a notable advancement in statistical analysis, combining the strengths of Difference in Differences (DiD) methods and Synthetic Control Methods (SCM), as introduced by Arkhangelsky et al. (2021).

The DiD technique works by estimating the difference in mean pre- and post-treatment outcomes between a treated group and a control group. While controlling for time-constant unobserved heterogeneity, this method relies heavily on the assumption of parallel trends between the treated and untreated groups, which may limit its applicability. (Callaway & Sant'Anna, 2021)

SCM relaxes the parallel trend assumption (Xu, 2017). This approach designed to study a single treated unit (Ben-Michael et al., 2021) creates a synthetic control group by pooling untreated units to closely mimic the treated unit during the pre-intervention period.

Subsequent post-treatment outcomes then measure the impact of the treatment. (Ben-Michael et al., 2021)

SDID, first proposed by Arkhangelsky et al. (2021), builds on SCM by creating synthetic control groups with optimal time and unit weights, while DiD is applied to determine the average treatment effect, short ATT. Uniquely, SDID accounts for differential trends between multiple treatment and control units (Clarke et al., 2023) while providing reliable estimates without relying on the parallel trend assumption (Arkhangelsky et al., 2021). Building on Arkhangelsky et al. (2021) findings, Clarke et al. introduced the SDID command for Stata, which forms the basis for the SDID procedure conducted in this study. The procedure allows for a variety of estimation techniques, including bootstrap, jackknife, placebo, and no-inference. This study used the bootstrap method. While computationally intensive, its results provide unparalleled robustness. (Clarke et al., 2023).

The SDID module includes three treatment guidelines. First, once a unit is treated, it must be continuously exposed to the treatment. Second, pure control units must be present. Third, units must have a pretreatment period. (Clarke et al., 2023). Adherence to this principle required the removal of six cities from the dataset. In this study, "treated" was defined as the presence of an STR density above the population mean. Treatment was captured by a binary variable W_{it}, taking the value 1 for above-average STRD and 0 for the opposite. Thereby, a nuanced approach was developed to categorize communities into treated and non-treated units using an above-average criterion divided into nine thresholds. These thresholds were successively increased by 5%, starting at 55% and ending at 95%. For any given threshold, a municipality i in year t was designated as a control unit if its STRD was below that specific threshold. For instance, at the 55% threshold, all municipalities i in year t with an STR density below the median STRD across the population were designated as controls. Conversely, municipalities equal to or above this 55% threshold were classified as treated. Of all units (N_{total}), a number of control units ($N_{control}$) showed consistently below-average STR densities for each threshold. Applying a staggered adoption design (Clarke et al., 2023), the remaining units ($N_{treated}$) were treated at specific time points (a), captured by the row vector A. This methodology was repeated for each threshold, resulting in nine separate applications of the SDID method. This systematic approach allowed for a granular examination of how varying STR densities affect housing prices.

The ATT was derived using the Stata module provided by Clarke et al. (2023), which builds on the work of Arkhangelsky et al. (2021). To compute the ATT, the command performs the following three steps (Clarke et al., 2023):

First, unit weights ($\widehat{\omega}_{\alpha,i}^{sdid}$) are retrieved to harmonize pre-treatment outcomes of non-treated units with treated ones and time-focused weights ($\hat{\lambda}_{\alpha,t}^{sdid}$) to balance in pre- and post-exposure periods.

Second, the ATT for each distinct adoption sample ($\hat{\tau}_{\alpha}^{sdid}$) via the SDID estimator is calculated, using:

$$(4)\ (\hat{\tau}_{\alpha}^{sdid}, \widehat{\mu_{\alpha}},, \widehat{\alpha_{\alpha}}, \widehat{\beta_{\alpha}}) = \arg min\{\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \alpha_i - \beta_t - X_{it}\gamma - W_{it}\tau)^2\ \widehat{\omega}_{\alpha,i}^{sdid}\ \hat{\lambda}_{\alpha,t}^{sdid}\}$$

With:

- $\widehat{\mu_{\alpha}}$ being the estimated general mean or constant for the adoption interval
- $\widehat{\alpha_{\alpha}}$ being the estimated unit-specific effects for the adoption interval
- $\widehat{\beta_{\alpha}}$ being the estimated time-specific effects for the adoption interval
- Y_{it} being the observed outcome for unit *i* at time *t*
- μ being the general mean or constant term representing average across all units and times.
- α_i being unit-specific fixed effects, capturing inherent differences among units that don't change over time
- β_t being time fixed effects, capturing temporal trends or changes common to all units
- $W_{it}\tau$ being the treatment effect for municipality *i* in year *t*
- $X_{it}\gamma$ being the coefficient and matrix of covariates for municipality *i* in year *t*

Third, the comprehensive ATT is derived by calculating the weighted average of the ATTs calculated in the previous step using:

$$(5)\ \widehat{ATT} = \sum_{for\ a\epsilon A}\frac{T_{post}^{a}}{T_{post}} \times \hat{\tau}_{a}^{sdid}$$

With:

- T_{post} being the total number of post-treatment periods observed in treated units

4.4. Robustness-Check

The following section discusses potential complexities and confounders that may cause endogeneity and thus affect study results, as well as the countermeasures taken to ensure the accuracy and robustness of the findings.

4.4.1. Selection Bias

Selection bias is a concern when collected data doesn't adequately represent the underlying population of interest. This type of bias can occur when the sampling method or other factors result in nonrandom selection, potentially distorting and weakening the generalizability of outcomes. (Heckman, 1990)

In this analysis, there may be selection bias due to the exclusion of certain cities, with the remaining subset of 115 municipalities in the sample potentially not being representative in the broader scope. The analysis design itself, primarily due to the data-intensive requirements of the SDID method, restricted the ability to mitigate such a risk through methods such as stratified random sampling (Bethlehem, 2010). However, the overall risk of selection bias is considered low, as the dataset covers almost half of all available municipalities in Portugal in different regions, thus representing a wide range of cases. Moreover, the chosen analytical methods, including the use of the SDID, address inherent shortcomings of selection bias, such as omitted variable bias.

4.4.2. Omitted Variables

Omitted variable bias arises when a regression model excludes a significant third variable that is correlated with the independent and dependent variable, thus potentially leading to endogeneity, i.e. the explanatory variable being correlated with the error term (Hill et al., 2020; Wilms et al., 2021).

Due to the large number of factors affecting house prices and the inconsistency of previous research, this study carries a risk of omitted variable bias. While the selected covariates capture important economic and structural aspects, they represent only a subset, mainly due to the limited availability of data over several years and cities in Portugal. However, the dual approach of this research, using TWFE and SDID methods, controls for omitted variable bias, as validated by Nygård & Thoresen (2023) and McEwan (2010), respectively.

4.4.3. Multicollinearity

Multicollinearity occurs when predictors are highly correlated with each other. This makes it difficult to separate individual effects on the dependent variable and leads to inflated variances in the estimators, reducing the overall precision and explanatory power of the model (Burton, 2021).

To minimize the ever-present risk of multicollinearity, a correlation matrix was applied following the recommendation of Alin (2010). As shown in Appendix 3, there are no correlations between the predictors that are considered critical, i.e., correlations greater than 0.8 (Burton, 2021). Furthermore, the SDID module itself controls for multicollinearity (Clarke et al., 2023), meaning that the overall risk of multicollinearity is low.

4.4.4. Reversed Causality

Reversed causality, a driver of endogeneity, occurs when the presumed causal relationship between variables is reversed (Leszczensky & Wolbring, 2022). Rising MHP would thus increase STRD, which is rather counterintuitive.

While lagged explanatory variables are frequently used to claim causality, they often lead to inaccurate findings. Rather, the overall study design is critical for causal inference. (Bellemare et al., 2015) Therefore, TWFE and SDID methods are applied, which control for the main sources of endogeneity, namely omitted variables, measurement error, and concurrent causality (Zaefarian et al., 2017).

5. Empirical Findings & Analysis

This section presents and discusses the regression results to assess the underlying research question:

> *"How does the proliferation of STRs in Portugal's non-urban areas affect housing prices? And, how does this relationship change with different STR densities?"*

Abstract 5.1 focuses on the evaluation of the first hypothesis, considering the results of all three models employed. Paragraph 5.2 discusses hypothesis two, focusing on the SDID regression results. Subsequently, section 5.3 analyses the impact of the control variables. Finally, chapter 4.4 assesses the robustness and reliability of the overall findings.

5.1. Hypothesis One

An objective of this research is to investigate whether short-term rentals affect housing prices in non-urban areas in Portugal.

Table 4: Results from OLS and TWFE Regressions

	(1) O1	(2) O2	(3) T
STRD	0.810***	0.829***	0.149***
	(0.049)	(0.045)	(0.018)
UR	-	-0.014***	0.001
		(0.001)	(0.001)
CD	-	0.001***	0.002***
		(0.000)	(0.000)
Constant	2.887***	2.958***	2.758***
	(0.003)	(0.007)	(0.009)
Observations	1,265	1,265	1,265
Number of Municipalities	115	115	115
R-squared	0.241	0.506	0.908
F-Stat	269.9	298.4	859
Municipality FE	-	-	YES
Year FE	-	-	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown in Table 4, the direct relationship measured in model O1 without control variables shows that an unit increase in STRD leads to a 0.81% increase in MHP_Log, which is significant at the 1% level. This means that the prevalence of STRs has a positive and statistically significant impact on the dependent variable, not controlling for other influencing factors.

As the models are refined, the coefficient decreases but remains significant at the 1% level. When control variables are included in model O2, the coefficient on STRD decreases moderately to 0.83. When controlling for time and unit fixed effects in model T, the coefficient further reduces to 0.15, suggesting that some of the initial variance associated with STRD is explained by unobserved time or municipal characteristics. Such characteristics could include regional historical significance, local regulations, macroeconomic changes, or global events such as the COVID-19 pandemic.

Building on the results of the previous analyses, the SDID study extends the understanding of the relationship between STRs and house prices. While the S60 to S85 models did not produce significant results, setting the threshold to 55% yielded an ATT of about -0.01, significant at the 10% level, as presented in Table 5[1]. Thus, for regions with a high STRD compared to less dense regions, a 1% decrease in MHP_Log is implied. Discussing the results from S55 further in the next section, S90 and S95 showed positive robust results with an ATT of 0.02 at the 5% significance level and an ATT of 0.04 at the 1% significance level, respectively. Since all models except S55 found a positive correlation, with S55 showing the lowest level of significance, the conclusion is a rejection of the first null hypothesis in favor of the first alternative hypothesis, implying an overall positive correlation between STRs and house prices in non-urban areas. Nevertheless, the results of the S55 model highlight the need to disaggregate the impact of STRs across density levels to ensure a more comprehensive understanding of their impact on house price dynamics - leading to the second hypothesis.

5.2. Hypothesis Two

The second hypothesis examines whether the impact of short-term rentals on house prices is contingent on individual levels of STR density.

Table 5: Significant Results from SDID Regressions

	(1) S55	(2) S90	(3) S95
$W_{55\,it}$	-0.014* (0.008)	-	-
$W_{90\,it}$	-	0.0214** (0.009)	-
$W_{95\,it}$	-	-	0.048*** (0.009)
Observations	1,265	1,265	1,265
Number of Municipalities	115	115	115
Municipality FE	YES	YES	YES
Year FE	YES	YES	YES

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

[1] For clarity, only the significant results from the SDID regressions are presented in Table 5. Non-significant results for thresholds S60 - S85 can be found in Appendix 4.

As shown in Table 5, S55 resulted in a negative ATT, which is inconsistent with previous results. One possible explanation could be that neighborhoods experience a transitional phase at a moderate STR concentration. Following the *Externality Effect* (Koster et al., 2021), communities in such a phase might experience preliminary negative changes in local dynamics, such as noise pollution, traffic congestion, or safety concerns causing long-time residents to relocate. Eventual changes might be even more pronounced in non-urban areas than in urban areas, the latter being affected by externalities anyway. This initial churn could lead to a decrease in housing demand that is not offset by the increase in STRs, putting downward pressure on housing prices. Buonanno et al. (2013) support this idea, emphasizing that perceptions of neighborhood safety directly affect property values.

However, as described above, the ATT becomes positive as STR density increases. Looking at the potential upside, neighborhoods with high STRD may have established themselves as tourism centers, benefiting from infrastructure development, tourist spending, and thus a strong local economy reflected in high housing prices (Sheppard & Udell, 2016). Consistent with this, Colomb & Gallent (2022) describe STRs as boosting local economies and contributing to community revitalization in rural areas. Consistent with the *Efficient Use Effect* (Koster et al., 2021), the growing influx of tourists may also increasingly motivate property owners to convert their properties into STRs, generating additional income that translates into rising housing values. This assumes an elastic housing market where land is available for new construction, so that the proliferation of STRs does not necessarily displace long-term housing. Contrary to this assumption, the strong rise in the ATT from 0.02 to 0.04 when the threshold is increased by only 5%, i.e., from 90% to 95%, indicates an inelastic market. Given the *Rental Housing Supply Effect* (Koster et al., 2021), the proliferation of STRs would then lead to a shortage rather than an expansion of housing supply and hence to price premiums. This dynamic puts the local population in a complex dichotomy of growing tourism and limited housing supply. As such, DiNatale et al. (2018) find evidence that smaller communities often do not have the necessary resources or infrastructure to accommodate an increase in STRs. The strong increase in ATT might also be a sign of aggressive external investment behavior, with investors willing to pay a premium in inelastic, high STRD markets in anticipation of even higher yields. A notion also supported by Adamiak (2018) - thus, the sharing idea behind STRs would decrease in major tourist destinations while commercialization increases. Cocola-Gant & Gago (2021) build on this. Analyzing Lisbon's

STR market, they find no evidence of a sharing economy, but of professionalization, displacing residents with tourists, a process they call "buy-to-let gentrification".

In summary, the second null hypothesis can be rejected in favor of the second alternative hypothesis, i.e., the impact of STRs on house prices varies by density level. Thus, a significant increase in ATT is found with a comparatively small increase in STRD at high densities. This suggests an inelastic housing market, potentially reducing housing affordability and increasing gentrification processes for the residential population. However, the drivers of these uneven effects, their socio-economic impacts on the residential population, and the role of investor dynamics cannot be conclusively assessed.

5.3. Controls

Although business density serves as an important economic and infrastructural factor (Kröhnert, 2012) that can influence both supply and demand dynamics in the housing market, the coefficients in the O2 and T models show a significant but small effect of increasing CD on MHP_Log. A possible reason for this finding could be the prevailing income dynamics in Portugal. Given the overall low wage level in the country, residents may have low disposable income even in areas with high business concentration, resulting in no substantial upward pressure on real estate prices.

Looking at the relationship between the UR and MHP_Log, model O2 shows a significant negative coefficient: for each unit increase in UR, MHP_Log decreases by 0.01%. This trend is consistent with the findings of Abelson et al. (2005) and Jacobsen & Naug (2005), which suggest that rising unemployment generally decreases house prices as lower income affects housing affordability and debt capacity. In the T model, however, the effect is no longer significant. A rationale could be that TWFE regressions, control for unobserved heterogeneities across communities and time, such as those induced by governmental stimulus programs. The economic adjustment program negotiated between Portugal and European institutions in 2011 is one such example. It may have stabilized housing prices by strengthening bank liquidity while changing labor dynamics by promoting more flexible labor models. (European Commission, Directorate-General for Economic and Financial Affairs, 2011; Portugal, 2015)

5.4. Model Robustness

In assessing model quality, the sequential increase in R-squared from 0.24 to approximately 0.91, as shown in Table 4, combined with the consistently significant F-statistic, illustrates the explanatory capacity of the O1, O2, and T models, which improves with the inclusion of controls and fixed effects.

Crucially, throughout the O1, O2 and T models, the relationships between variables consistently show significance and direction. Most of the results maintain a 1% confidence level, reinforcing the robustness of the model. While the results for models S60 - S85 are not significant, those for models S55, S90, and S95 achieve significance at the 10%, 5%, and 1% levels, respectively.

The results underscore the validity of the methods currently prevailing in the study of the relationship between STRs and housing prices. They are also consistent with Sheppard & Udell's (2016) recommendation for the implementation of a multi-method strategy.

6. Advancements, Limitations & Outlook

6.1. Advancements

This work represents a significant advance in understanding the nuanced relationship between STRs and house prices. Its distinctiveness lies in three main areas: geographic focus, data sourcing, and methodological advances.

Previous research has focused on large metropolitan areas in the United States and Europe, such as New York (Sheppard & Udell, 2016) and Barcelona (Garcia-López et al., 2020). This study uniquely focuses on Portugal's non-urban regions, which responds to the rising demand for STRs in these underexamined areas, reflecting the shifting paradigms of remote work and rural leisure (Colomb & Gallent, 2022).

Most prior research has analyzed web-scraped data from platforms such as *Airbnb* (Sheppard & Udell, 2016; Horn & Merante, 2017). The present methodology departs from that, drawing on a wide range of information from Portuguese administrative and statistical agencies. This ensures granularity and precision while avoiding potential inaccuracies associated with web scraped datasets (Zou, 2019).

Traditional methods rely heavily on the hedonic pricing model (Rosen, 1974) and regression strategies such as OLS, FE, and DiD (Cunha & Lobão, 2021; Sheppard & Udell, 2016). By combining OLS, TWFE, and SDID, the chosen research approach not only extends the analytical paradigm, but also adds innovative analytical robustness through the use of Clarke et al.'s (2023) SDID Stata module.

In examining the results, while no definitive judgment can be made about the ultimate consequences of STR proliferation on the local residential population, the analysis shows that the presence of STRs in non-urban areas is positively correlated with house prices, the effects being stronger at higher STR densities. These results not only support existing evidence of a positive relationship between STRD and house prices, but also extend previous findings by suggesting that the phenomenon of *Airbnbfication* is transferable to non-urban areas.

6.2. Limitations

The results of this study are subject to certain limitations in terms of data collection, data processing, choice of methodology and scope.

First, reliance on bank-financed housing data introduces potential biases as banks typically use conservative property valuations that may not fully capture the nuances of actual market trends (Dyer, 2018). Also, bank data does not reflect the full market, as it excludes, for example, pure equity financed properties. Second, using STR data from official national statistics could misrepresent the overall STR landscape as some landlords may not have officially registered their STR properties with the Portuguese authorities, leaving them unaccounted for in the analysis. The use of a panel dataset across multiple cities and time periods, as well as the requirements of the SDID process, also created a risk of misrepresentation. Due to missing data points, it was necessary to exclude certain cities. This exclusion may have inadvertently missed important trends or patterns.

Regarding the methodological limitations of the study, although the SDID method allows for the construction of a robust control group, it limits the size of the treatment group, especially at high thresholds. Thus, although the research gains rigor from the extensive controls, it may affect the depth of analysis and generalizability of the findings. In addition, the use of Clarke et al.'s (2023) SDID Stata module adds another layer of complexity. As a relatively new solution, it is not widely understood or used in the academic community. Verification of usability in different situations, as well as possible improvements and refinements to the module, are still pending. Therefore, the results obtained should be interpreted with some caution until further studies confirm the robustness of the module.

Third, while the research methodology used in this work addresses critical concerns of endogeneity, such as omitted variable bias or measurement error (Zaefarian et al., 2017), it cannot comprehensively control for reverse causality. Here, IVs can serve as an important proxy by providing exogenous variation (Becker, 2016). This research conceptualized to use community-level AL regulations for different years as potentially powerful IVs unaffected by the endogenous relationship. However, it was not possible to obtain sufficiently detailed data from the relevant Portuguese administrative authorities. This lack of data access limits methodological robustness.

Finally, the generalizability of the study's findings is limited by its narrow focus. Concentrating on non-urban conditions in Portugal limits the applicability of the results to, for example, urban centers or other countries. In addition, annual data collection may miss trends and peaks throughout the year that are particularly relevant to the seasonally fluctuating tourism and STR markets. Similarly, focusing on housing prices as the dependent variable may not capture potential socio-cultural impacts. As a result, while this study provides guidance, it does not provide a holistic understanding of the broader impacts that STRs may have on other geographic contexts, intra-annual trends, and socio-economic dynamics for local residents.

6.3. Outlook

The results of this study raise a number of implications and opportunities for further research. In particular, the outlier in the form of a negative ATT at an STR density of 50% highlights the complex nature of the relationship between STRs and house prices and underscores the urgency of additional research.

In terms of data depth and diversity, the reliance on bank-financed housing data, the elimination of cities due to missing data points, and the limited scope of covariates underscore the importance of diversifying and expanding data sources in subsequent studies. For example, combining web scraping and official datasets can improve data availability and validity, which is critical for a fair representation of the STR market.

When investigating methodological gaps, the use of advanced machine learning and geospatial analysis techniques offers significant potential for analyzing increasingly granular and large STR datasets. These techniques can extract complex patterns from the data to provide a more comprehensive understanding. In addition, emphasis should be placed on examining valid IVs that are exogenous to the relationship between STRs and house prices to assure causality.

Broadening the scope of the research remains essential. While this work has filled a gap in the study of non-urban Portuguese areas, future efforts could include a mix of urban and non-urban regions or even more granular studies of purely rural areas. In addition, it is recommended to adopt a greater temporal focus, such as a monthly disaggregation, to account for nuanced seasonal variations.

In terms of open perspectives, it is important to explore socio-cultural dimensions, i.e. the spillover effects of STR diffusion on local communities, whether they lead to prosperity or are catalysts for hardship. Here, qualitative methods such as interviews can be an effective tool to link quantitative results to individual experiences. From a policy perspective, it is critical that policymakers create frameworks that strike a harmonious balance among the myriad actors involved in the STR market. This requires empirical studies that thoroughly test different regulatory approaches to create a functioning STR ecosystem while keeping the welfare of local communities in mind.

7. Conclusion

The rapid proliferation of STRs, driven by platforms like Airbnb, has changed the landscape of global tourism. By offering consumers diverse and affordable accommodations, STRs enable landlords to generate additional revenue streams from their properties. However, the rise of STRs also brings challenges, as the example of Portugal shows. While they have been an important driver for the country's tourism industry, especially during the post-pandemic recovery period, they may also have contributed to the housing affordability crisis. Government initiatives such as the AL or Golden Visa programs have exacerbated this problem by encouraging a sharp increase in foreign real estate investment.

Accordingly, there has been a shift in current research. While traditional approaches have focused on broader economic determinants, a stream of current research emphasizes the role of STRs as a link between the tourism industry and the residential real estate market. While some researchers postulate a potential devaluation of property due to the nuisance associated with STRs, most current studies - particularly those focused on urban areas - find a positive correlation between STRs and increased property values. The resulting negative consequences, such as gentrification, subsumed under the term *Airbnbfication*, thrive primarily in inelastic markets where the growth of STRs leads to price pressures rather than an expansion of housing capacity. A major gap in this area is the lack of research on non-urban areas. Most studies focus on Western metropolitan areas and base their conclusions on Airbnb data, limiting the scope and generalizability of their findings.

To address this research gap, a robust panel dataset based on Portuguese administrative data was developed, covering 11 years and 115 cities in mainland Portugal. Through a comprehensive multi-method approach using advanced regression techniques, including SDID procedures, the relationship between STRs and house prices in the less urbanized regions of Portugal was analyzed.

Although the study does not allow a definitive assessment of whether the prevalence of short-term rentals has predominantly positive or negative socio-economic effects, the empirical results provide important indications. Consistent with previous research in urban areas, the results suggest an overall positive correlation between short-term rentals and house prices in non-urban regions of Portugal. Specifically, variations in the density of short-term rentals can cause a change in house prices of between 0.15% and 0.81%, depending on the model applied. However, this relationship is complex and suggests that the impact shifts depending on the level of density. Thus, there is evidence that the non-urban housing market is inelastic. While there are negative outliers when short-term rental densities are comparatively low, high densities correlate with comparatively high house prices and increasing price premiums. Thus, the proliferation of short-term rentals is associated with price increases rather than dispersion in housing supply, fueling housing unaffordability and the effects of *Airbnbfication* on local populations. This underscores the urgent need for regulatory strategies that balance the promotion of short-term rentals with the protection of residents' interests.

With the results presented, this study provides methodological and contextual advances for current research. By employing a multi-method approach incorporating the SDID procedure via the newly developed Stata module by Clarke et al. (2023), a solid foundation has been laid for the extended and optimized application of such an approach incorporating new methodology in similar research contexts. In addition, the work confirms existing findings in the academic discourse on the positive impact of STRs on house prices, while refining them with respect to the specifics of STR density and extending them to non-urban regions. It is expected that these results will provide incentives for policy makers in Portugal to extend the debate on the impact of STRs on the housing crisis to rural areas, in order to proactively adopt mitigating regulatory measures.

This study has limitations. In particular, it does not control for reversed causality and does not conclusively examine the sociocultural impact of STRs. Therefore, multifaceted approaches need to be developed that incorporate multiple data sources, use advanced computational methods, and cover a broader geographic and temporal spectrum. This will not only enrich scientific understanding, but also pave the way for holistic policy-making that ensures the sustainable coexistence of tourism and residential housing.

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Appendices

Appendix 1: List of Municipalities - Included vs. Excluded

Municipalities excluded, due to		Municipalities included
Missing Data Points	OCED Definition	
(1)	(2)	(3)
Aguiar da Beira	Aveiro	Abrantes
Alandroal	Braga	Águeda
Alcácer do Sal	Coimbra	Albergaria-A-Velha
Alcanena	Faro	Albufeira
Alcoutim	Guimarães	Alcobaça
Alfândega da Fé	Lisboa	Alcochete
Alijó	Porto	Alenquer
Aljezur	Póvoa de Varzim	Almada
Aljustrel	Viana do Castelo	Almeirim
Almeida	Viseu	Amadora
Almodôvar		Amarante
Alpiarça		Anadia
Alter do Chão		Arcos de Valdevez
Alvaiázere		Arouca
Alvito		Arruda dos Vinhos
Amares		Azambuja
Ansião		Barcelos
Arganil		Barreiro
Armamar		Beja
Arraiolos		Benavente
Arronches		Bragança
Avis		Caldas da Rainha
Baião		Caminha
Barrancos		Cantanhede
Batalha		Cartaxo
Belmonte		Cascais
Bombarral		Castelo Branco

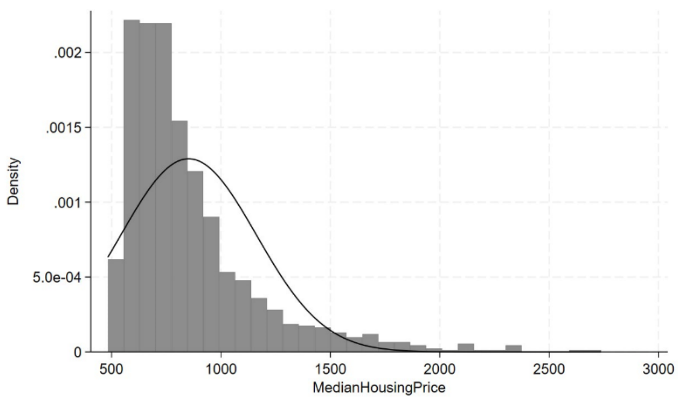
Borba	Chaves
Boticas	Condeixa-A-Nova
Cabeceiras de Basto	Coruche
Cadaval	Covilhã
Campo Maior	Elvas
Carrazeda de Ansiães	Entroncamento
Carregal do Sal	Espinho
Castanheira de Pêra	Esposende
Castelo de Paiva	Estarreja
Castelo de Vide	Évora
Castro Daire	Fafe
Castro Marim	Felgueiras
Castro Verde	Figueira da Foz
Celorico da Beira	Fundão
Celorico de Basto	Gondomar
Chamusca	Grândola
Cinfães	Guarda
Constância	Ílhavo
Crato	Lagos
Cuba	Lamego
Estremoz	Leiria
Ferreira do Alentejo	Loulé
Ferreira do Zêzere	Loures
Figueira de Castelo Rodrigo	Lourinhã
Figueiró dos Vinhos	Lousã
Fornos de Algodres	Lousada
Freixo de Espada À Cinta	Macedo de Cavaleiros
Fronteira	Mafra
Gavião	Maia
Góis	Marco de Canaveses
Golegã	Marinha Grande
Gouveia	Matosinhos
Idanha-A-Nova	Mealhada
Lagoa	Mirandela

Mação	Moita
Mangualde	Montemor-O-Velho
Manteigas	Montijo
Marvão	Nazaré
Mêda	Nelas
Melgaço	Óbidos
Mértola	Odemira
Mesão Frio	Odivelas
Mira	Oeiras
Miranda do Corvo	Olhão
Miranda do Douro	Oliveira de Azeméis
Mogadouro	Oliveira do Bairro
Moimenta da Beira	Ourém
Monção	Ovar
Monchique	Paços de Ferreira
Mondim de Basto	Palmela
Monforte	Paredes
Montalegre	Penafiel
Montemor-O-Novo	Peniche
Mora	Pombal
Mortágua	Ponte de Lima
Moura	Portalegre
Mourão	Portimão
Murça	Porto de Mós
Murtosa	Póvoa de Lanhoso
Nisa	Rio Maior
Oleiros	Salvaterra de Magos
Oliveira de Frades	Santa Maria da Feira
Oliveira do Hospital	Santarém
Ourique	Santiago do Cacém
Pampilhosa da Serra	Santo Tirso
Paredes de Coura	São João da Madeira
Pedrógão Grande	Seixal
Penacova	Sesimbra

Penalva do Castelo	Setúbal
Penamacor	Silves
Penedono	Sines
Penela	Sintra
Peso da Régua	Tavira
Pinhel	Tomar
Ponte da Barca	Tondela
Ponte de Sor	Torres Novas
Portel	Torres Vedras
Proença-A-Nova	Trofa
Redondo	Vale de Cambra
Reguengos de Monsaraz	Valongo
Resende	Vila do Conde
Ribeira de Pena	Vila Franca de Xira
Sabrosa	Vila Nova de Famalicão
Sabugal	Vila Nova de Gaia
Santa Comba Dão	Vila Real
Santa Marta de Penaguião	Vila Real de Santo António
São Brás de Alportel	Vila Verde
São João da Pesqueira	Vizela
São Pedro do Sul	
Sardoal	
Sátão	
Seia	
Sernancelhe	
Serpa	
Sertã	
Sever do Vouga	
Sobral de Monte Agraço	
Soure	
Sousel	
Tábua	
Tabuaço	
Tarouca	

Terras de Bouro
Torre de Moncorvo
Trancoso
Vagos
Valença
Valpaços
Vendas Novas
Viana do Alentejo
Vidigueira
Vieira do Minho
Vila de Rei
Vila do Bispo
Vila Flor
Vila Nova da Barquinha
Vila Nova de Cerveira
Vila Nova de Foz Côa
Vila Nova de Paiva
Vila Nova de Poiares
Vila Pouca de Aguiar
Vila Velha de Ródão
Vila Viçosa
Vimioso
Vinhais
Vouzela

Appendix 2: Non-Log-Transformed Distribution of MHP



Appendix 3: Pairwise Correlation Matrix

Variables	MHP_LOG	STRD	UR	CD
MHP_LOG	1.00			
STRD	0.49***	1.00		
UR	-0.32***	-0.07**	1.00	
CD	0.38***	-0.08***	0.03	1.00

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

Appendix 4: Non-Significant Results from SDID Regressions

	(2) S60	(3) S65	(4) S70	(5) S75	(6) S80	(7) S85
$W_{60\ it}$	-0.008 (0.008)					
$W_{65\ it}$		-0.009 (0.008)				
$W_{70\ it}$			0.002 (0.008)			
$W_{75\ it}$				0.003 (0.009)		
$W_{80\ it}$					0.004 (0.01)	
$W_{85\ it}$						0.012 (0.014)
Observations	1,265	1,265	1,265	1,265	1,265	1,265
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

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