Defining a Housing Market Area using a spatial autocorrelation approach

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List of Tables

List of Figures

List of Equations

List of Appendices

i. ABSTRACT

The delineation of Housing Market Areas (HMAs) is central to effective urban planning, housing policy formulation, and the broader pursuit of sustainable, inclusive cities. This study addresses the ongoing challenge of defining scalable and replicable housing market boundaries, a task complicated by dynamic socioeconomic, demographic, and technological change. Focusing on Greater Manchester, UK, the research leverages advanced spatial statistical methods and big data analytics to empirically identify and analyse HMAs, moving beyond traditional administrative boundaries and outdated census-driven definitions.

Grounded in the United Nations Sustainable Development Goal 11, which aims to ensure inclusive, safe, resilient, and sustainable human settlements, this investigation integrates diverse data sources: house prices, rental values, price-to-rent ratios, and migration and commuting flow statistics. These datasets, drawn from official agencies and contemporary online platforms, are analysed at fine spatial resolutions, including Middle Layer Super Output Areas (MSOAs), postcode districts, and borough levels across Greater Manchester. The focus on semi-detached two-bedroom houses ensures a representative and policy-relevant lens.

The methodology employs exploratory spatial data analysis, including global and local spatial autocorrelation (Moran's I and LISA), to detect clustering, dispersion, and spatial outliers in housing outcomes. This approach uncovers complex patterns of housing demand, supply, and affordability-patterns that conventional models based on commuting or migration alone often fail to capture, especially in a post-COVID-19 era marked by high levels of remote working and evolving household mobility. The research demonstrates that, in contemporary contexts, housing-related indicators (notably house prices and rents) should serve as the principal basis for HMA delineation, with migration and commuting patterns providing supplementary insights.

Key findings reveal significant spatial dependence in housing outcomes: high house prices and rents cluster in urban cores such as Manchester, Trafford, and Stockport, while outer boroughs exhibit greater heterogeneity and affordability. The price-to-rent ratio emerges as a robust metric for distinguishing owner-occupied from rental-dominated areas, equipping policymakers with actionable intelligence for targeted interventions. The study also highlights the limitations of legacy methods- particularly their temporal lag and inability to reflect fluid, market -driven boundaries.

Ultimately, this research advances a data-driven, adaptive framework for defining HMAs, advocating for the ongoing integration of emerging technologies (such as machine learning and IoT data) and spatial-temporal modelling. This paradigm shift is essential to ensure that housing market boundaries remain relevant amid rapid urban, economic, and technological transformation. The findings provide practical tools for planners and policymakers striving to create equitable, resilient, and future-ready housing markets.

Keywords: Autocorrelation, Dependence, Heterogeneity, Housing, Rents.

1. INTRODUCTION

1.1. WHY THE HOUSING MARKET MATTERS.

The housing market is a central topic in urban development; it is an important area of research that touches the fundamental human necessity: everyone, regardless of race, age, or gender, must have a place to live. Over centuries, individuals and Households have made residential decisions based on factors that maximize their satisfaction (Colin Jones, 2009); (Coombes & Statistics, 2015). Population changes, both natural (births and deaths) and artificial (migration, including in-migration and out-migration), raise ongoing concerns about housing demand and supply over time and space.

Despite extensive studies, research, and policy interventions, creating scalable and replicable housing market boundaries remains a challenge. Understanding the dynamics of the United Kingdom's housing market, particularly in Greater Manchester, a metropolitan county in the Northwest, can inform the formulation of relevant housing policies and help forecast the future housing demand and supply to achieve a better housing balance in the area.

This study is grounded in the 11th United Nations Sustainable Development Goal, which aims to ensure that human settlements are safe, resilient, and inclusive. (United Nations, 2015); (Radovic, 2019) Two of the top targets under this goal focus on providing adequate, safe, and affordable housing, as well as accessible transport systems, by 2030 (Radovic, 2019). In this context, intelligent urban planning and spatial analytics are essential for demarcating functional boundaries rather than relying only on default administrative boundaries. Understanding the economic mechanisms and spatial patterns underlying housing markets is crucial for uncovering hidden trends and developing more accurate, reliable, and sustainable housing forecasts.

Over several decades, scholars, practitioners, and policymakers have attempted to define and delineate the housing market by drawing on social, economic, environmental, and structural factors. Early work by (Alonso, 1964; Kain, 1962; Muth, 1969), focused on modelling labour market areas using commuting patterns and producing Travel to Work Areas (TTWAs). These TTWAs were later used as a proxy for housing market areas (Hincks, 2006; Hincks, 2010), based on the assumption of a "perfect" environment in which house prices are inversely related to distance from the city centre (Access-space model) (Alonso, 1964)

Later contributions by (Jones, 2002; Macclennan, 1992) and (Brown, 2008) defined housing market areas that contributed to migration statistics modelling and contiguous settlements. In their work, an HMA is a relatively fixed area with a certain level of self-containment, where in- and out-migration is of minor significance. This raises important questions that require further research and empirical testing. In particular, it is crucial to ensure that house prices, rents, neighbourhood characteristics, and accessibility factors are fully considered when defining and delineating housing market areas.

1.2. THE SCOPE OF THE RESEARCH

This research focuses on the empirical identification and analysis of housing market areas (HMAs) using spatial statistical methods. It examines spatial patterns in house prices and rental values to determine the extent of the housing market.

Even though there are other dimensions to housing market studies, such as Colin Jones (2009), who applied household search and migration trends to define self-contained housing market areas, specifically defining them as areas where there is a balance between demand and supply of housing amenities. Moreover, (Vargas, 2009; Wong, 2010) discovered inadequacies in relying not only on migration patterns but also on commuting patterns and thus applied a combined approach with upper and lower tiers of commuting thresholds and migration thresholds, respectively.

The recent rise of Internet of Things (IoT), big data, and artificial intelligence (AI) has created new opportunities to analyse and evaluate the housing market dynamics at finer spatial and temporal scales. (Hirano, et al., 20). These developments have accelerated the adoption of advanced spatial data analytics to uncover complex relationships between house prices and rental data across time and space.

In this research, big data are used at the spatial scale of the Middle Layer Super Output Areas (MSOAs), postcode districts, and borough levels across the Greater Manchester boroughs. These data were extracted, cleaned, sorted, transformed, and integrated with online datasets to test for spatial relationships.

House price data are drawn from Her Majesty's Land Registry (HMLR), and rental data from the Valuation Office Agency (VOA). Migration and commuting flow statistics are exported from the National Census 2001, 2011, and 2021 Censuses, with 2001 serving as a baseline. These official sources were supplemented with online data sets on house prices and rental data by postcode district from Greater Manchester, as the core case study was retrieved from the Home.co.uk website.

The house types purposefully sampled for analysis were semi-detached houses with two bedrooms, which were among the most desirable. Commuting and migration in the 2011 Census were more accurate than those of the 2021 census because of the mobility factor. Since the 2021 census was conducted during the inter-regional and international remedy for global pandemic of Covid-19(Lockdown) whereby level of commuting and migration was of low value. This led us to the next chapter.

Although the question that reckons in minds of policymakers, researchers and administrative authorities is, what is the best possible, plausible, reliable and replicable definition of housing market area? Noting that function of house demand and supply crosses beyond the gates of local administrative authority. Despite the time lag between the first nationwide delineation of functional boundaries for Housing and market areas defined in 2010, using the 2001 census (Wong, 2010). There has been an imminent change in population, house prices, rental prices, commuting flow, and migration flow on both temporal and spatial scales.

Hence, this research aims to utilise the potential of up-to-date house prices data, rental statistics, commuting and migration flow data to bridge the gap created in housing market research.

1.3. THE STRUCTURE OF THE RESEARCH PAPER.

The research paper flow is organised in such a way that it starts by pinning important information on the background and foreground of housing market evolution over time and space, as exemplified in Chapter One (1). It then continues to explore the theoretical nuggets from the existing body of knowledge that has been depicted in the preceding Chapter Two (2). The theoretical analysis and evaluation necessary for formulating intelligent guesses (hypotheses) on the housing market were derived. From global studies, including European and Australian research, a theoretical understanding of methods, assumptions, and practicability in defining housing market areas. It is in the second chapter where the examination of the advantages and disadvantages of each method was discussed and concluded with a summary of the review.

Chapter Three (3) initiated the primary aim of the research as well as the specific objectives of the research. The objectives will be verified and supported by UK official statistics (secondary data) from the Office of National Statistics (ONS), His Majesty's Land Registry (HMLR), and the Valuation Office Agency (VOA). The reason for selecting Great Manchester is explained further in this Chapter, which is the third most populous county in England, preceded by London and Birmingham. This led to the empirical study chapter Four (4).

It is in Chapter Four (4), where the detailed analysis stage took place. Data has been rigorously analysed, programmed, and modelled using open-source software programs, packages, and functions. These programs included Microsoft Excel, the Python programming language, and GIS analysis packages for summarizing and visualizing spatial data. The experimentation and testing of hypotheses was done using spatial statistics to clearly delineate housing markets through analysing hotspots, cold spots, strength, and intensity of the relationships.

The outcomes of the analysis were evaluated and scored against the purposes of the research to form the ground truth in the body of knowledge in the preceding Chapter Five (5), and proposed further areas for continual mining of wisdom and insights in the subject matter of housing market have been displayed in the conclusion and recommendation chapter six (6).

Conclusively, the housing market area is an important research theme necessitating theoretical exploration.

2. THEORETICAL FRAMEWORK OF HOUSING MARKET AREAS.

2.1 INTRODUCTION TO THEORIES

The concept of the Housing Market Area (HMA) has been the subject matter of extensive research and debate for many years, particularly from a policy perspective. HMAs delineate boundaries that differ from conventional administrative lines and are essential for comprehending housing dynamics, market behaviours, and effective policy formulation. Scholars such as (Wong, 2010)and (Doan, 2022), have contributed significantly to this field, highlighting the importance of HMAs in informing real-world housing policy decisions.

The boundaries of HMAs have evolved to reflect market realities and shifting policy objectives. Such changes are crucial to ensure that HMAs continue to capture the dynamic nature of housing markets, including affordability and demographic shifts. From a vendor's perspective, HMAs are defined as geographical areas where houses are actively bought and sold (Forster, 1996). If an area lacks market activity, meaning no houses are sold or rented, it does not qualify as a housing market area. (Pieda, 2004) Further characterized HMAs as self-contained areas exhibiting an equilibrium between housing demand and supply. This means that within these boundaries, residents can buy or rent homes because there is sufficient, affordable, and desirable housing stock. Additionally, this ensures that occupants have access to a variety of housing options that meet their needs and preferences.

(Coombes, 2002) extended this analysis by examining the commuting behaviours of households, particularly those of working-age individuals, based on journey-to-work interaction patterns across counties in England and Wales. Earlier, (Coombes, 1985), mapped the local labour market areas by identifying regions where labour demand and supply are balanced- specifically, areas that offer enough jobs to match the skills of the resident working population. In such regions, the number and types of available jobs align with the qualifications and needs of the local workforce. This concept is further illustrated by (Alonso, 1964), findings from 1960s, which showed that households weighed the trade-off between journey-to-work (travel costs) and residential costs (house prices). As a result, people were often willing to move to more affordable areas, even if those locations were farther from their workplaces to minimise housing costs and/or enhance personal satisfaction.

(Jones, 2002), clarified the HMAs as the geographical area where there is a high degree of internal migration, and the in-out migration is only of negligible impact. This definition highlights the significance of internal migration patterns in delineating HMAs and highlights the relative stability of population movements within these regions. Though in any process of migration, there is a prior house search and evaluation mechanism, hence (Vargas, 2009) marked the HMAs as the area characterized with a high level of house market search patterns. Housing markets play a critical role in shaping residential mobility, economic development, and social well-being across various countries and are not unique to the United Kingdom, but are also observed in other European countries, including Sweden (Tyrcha, 2020) , along with the Australian continent (Dodson, 2021)

2.2 DIFFERENT METHODS AND ASSUMPTIONS USED TO DERIVE THE HOUSING AND MARKET AREAS(HMAs)

This subsection deepens its focus by exploring theoretical methodologies used by previous researchers, practitioners, and governments to demarcate housing market areas.

2.2.1 USING COMMUTING PATTERNS (TRAVEL TO WORK AREAS-TTWAs).

The earliest attempts to estimate labour and housing market area originated with urban housing and planning scholars such as (Kain, 1962; Alonso, 1964; Muth, 1969), who used commuting flow data as a foundational proxy for delineating Housing and Labour Market Areas. These studies modelled household residential choice by weighing the opportunity cost between transportation expenses and housing costs- a concept that drew further support from(Schimidt, 1956) research, which found that over 40 percent of surveyed travellers commuted for work, while the remaining individuals travelled for purposes such as recreation, shopping, and other activities.

The commuting flow theory posits that individuals seek to balance the opportunity cost of affordable housing prices with the travel-to-work costs associated with residing in less expensive areas (Diaz, 2003) , assuming all other market conditions remain constant (ceteris paribus). This relationship is illustrated in Equation 1 below,

Equation 1: Formula for depicting TTWAs as per *(Alonso, 1964)*

$$TTWA_s \propto Longest\ distance\ travelled\ to\ work\ within\ the\ area\ \frac{1}{\infty}\ \ House\ prices$$

This implied that the shorter the distance travelled, the higher the house price paid; while the longer the distance travelled to work, the lower the house prices paid, as the Travel to Work Areas (TTWAs) were directly proportional to distance travelled by the long-distance traveller, while inversely related to house prices surrounding the area. Most households frequently contemplate the opportunity cost of house prices relative to transport costs when making decisions about housing, which in some cases may cause a certain increase in the distance travelled between a household's home, work, or other destinations around (Brown, 2008).

The official release of Travel to Work Areas (TTWAs) by the Office for National Statistics (ONS), based on commuting flow data from the 1971 Census, marked a significant advance in delineating functional labour and housing market areas. The methodology developed by (Coombes, 1985), enabled the identification of local labour market areas by evaluating both the demand side (working population) and the supply side (nature and number of jobs), thereby revealing regional unemployment levels. Building on this, researchers such as (Manuel, 2003) and (Coombes, 2002) further advanced TTWA's research in the United Kingdom under the auspices of the Office of National Statistics (ONS). This approach was officially adopted as the methodology for deriving housing market areas in regions such as the North West England region (Hincks, 2010).

The commuting pattern evaluation method (Colin Wymer, 2010) was assessed using three key technocratic criteria: Contiguousness, similarity and robustness of the methods used. The optimal estimates were required to meet all three- ensuring contiguous zones, similar area sizes and methodological robustness. However, the resulting Housing Market Areas (HMAs) displayed significant variation in area size, and some Travel to Work Areas (TTWAs) encompassed multiple TTWAs (Stephen Hinks, 2010). Sensitivity analyses showed that commuting pattern-based definitions did not always pass these tests, prompting the use of additional theoretical criteria (Colin Wymer, 2010). These limitations led researchers such as (Jones, 2002) to seek greater authenticity in defining housing market areas by also verifying levels of household migration and degree of housing search patterns.

2.2.2 HOUSING MARKET AREA DERIVED FROM MIGRATION PATTERN.

A second major method used for delineating housing market areas involves migration statistics, particularly the analysis of trends and patterns (Jones, 2002) . Inter-regional migration is central to the functioning of both regional housing and labour markets, as illustrated by (Murphy, 2005) in the case studies for Wales and England. The approach of using spatial arbitrage and migration patterns to define and allocate spatial boundaries in housing markets has historical roots in the 1980s. During this period, scholars increasingly recognised the importance of spatial dynamics in economic activity- including both labour and housing markets- for effective policy design and planning.

The core principle underlying this method is migration self-containment (Scottish, 1993; Jones, 2002). An area is classified as a Housing Market Area (HMA) if it achieves at least 50 per cent internal migration and no more than 5 per cent external migration (Jones, 2002). This methodology has been successfully applied beyond the United Kingdom cities, including Melbourne, Australia (Dodson, 2021), where key factors influencing migration of housing utility prices were identified. In Sweden, analysts have used migration patterns- particularly tenure-specific integration clusters- to reveal subtle changes within the housing market (Tyrcha, 2020). Like England, Sweden's housing market comprises diverse tenure types, including owner-occupied housing, social housing, and private rentals. These tenure-specific clusters delineate distinct market segments, each characterised by unique features, affordability profiles, and policy implications.

More recently (Doan, 2022) advanced this methodology by analysing spatial migration interactions within Greater Manchester's housing market using a geographical information system (GIS). This study provided in-depth insights into the multifaceted dynamics of migration and their implications for the regional housing market. (Doan, 2022) The findings offer valuable guidance for addressing housing challenges and fostering sustainable urban development in Greater Manchester. Importantly, identifying hotspots and cold spots in migration patterns, as well as evaluating the elasticity of mobility factors, is essential for refining current housing supply strategies and forecasting future demand. Migration frequently marks the culmination of an ongoing housing search, whether households seek to rent or purchase homes in new locations. (Macclennan, 1992)

2.2.3 USING HOUSING MARKET SEARCH

Housing market search represents the demand-side perspective, where households seek specific house types in preferred neighbourhoods with the intention of renting or purchasing. This process is widely recognised as initial step in migration (Forster, 1996; Brown, 2008). Since the early 1970s, housing search activity has become increasingly prominent, as individuals and families evaluate information about public and private amenities for reasons such as proximity, accessibility, neighbourhood, social factors, service infrastructure, environmental quality(including density and green space), safety, and municipal influences- all of which shape housing search behaviour (Kintrea, 1986). Over the past two decades, sampled household search data have served as a valuable proxy for delineating housing market areas. Researchers such as (Dunning, 2016) and (Alasdair, 2015) have analysed the intensity and direction of housing searches to identify cluster of areas with similar search patterns. More recently, (Doan, 2023) revealed hidden patterns by analysing the relationship between housing search activity and realised sales, specifically through clustering areas with high house search volume versus those with high sales activity.

Historically, most of analyses of housing search patterns have focused on the purchase dimension, likely because buying a home is typically a stable, long-term commitment, whereas the rental sector is more volatile and subject to medium-term decision making. As a result, there is a growing need to incorporate rental search patterns, particularly by leveraging the vast quantities of big data generated by major online property platforms.

Moreover, relying solely on search patterns has proven insufficient, as these approaches focus exclusively on the demand side and do not account for the intensity or volume of completed transactions- supply side (Macclennan, 1992; Brown, 2008). Therefore, this study aims to explore the combined dimensions of housing search and migration as an integrated process for delineating housing market boundaries, following (Doan, 2023) approach.

Thus, the Travel to work areas (TTWAs) have been criticized because of instability and sensitive nature (Coombes & Statistics, 2015), the boundaries have been constantly reviewed over time due to increase in long distance commuting which increase boundaries and conversely led to decrease the number of TTWAs. It has been depicted since the 1971 Census when the journey to work statistics were published, there were 388 TTWAs; they were reduced to 332 TTWAs in 1984 based on the 1981 census (Coombes, 1985). According to the ONS, there have been constant decrease in the number of TTWAs to 308, 243 and 228TTWAs for the 1991 census, 2001 census, and 2011 census respectively. This change has not been at a specific uniform rate but at an irregular rate as depicted in table1 below, (Coombes & Statistics, 2015). The TTWAs based on 2021 were of low value (gathered during Covid-19 lockdown), hence were not used. This is shown in the Table 1 below,

Table 1: Changes in number of TTWAs across Census years

ONS Census	TTWAs	% Change
1971	380	
1981	322	-15.3%
1991	308	-4.3%
2001	243	-21.1%
2011	228	-6.2%

Source: ONS Census 1971, 1981, 1991,2001 and 2011.

2.3. STRENGTHS AND LIMITATIONS OF METHODS TO DELINEATE HOUSING MARKET AREA.

Migration has been demonstrated as an efficient estimator for delineating sub-regional housing market areas by aligning local demand and supply (Jones, 2002); (Jones, et al., 2010). This approach is applicable for defining a local housing market area only when a minimum level of self-containment is achieved, and migration from neighbouring areas remains negligible. Migration itself results from ongoing house searches driven by spatial and structural preferences as well as the changing neighbourhood dynamics and household lifestyles. However, a key limitation is the timeliness of migration data, which often relies on census statistics with a ten-year lag.

Additionally, migration rates vary significantly among different housing tenures: owner-occupied, socially rented, and private rented households. The highest rate of migration was typically observed among private rented (Colin Wymer, 2010)

Despite extensive research on the definition of the housing market areas, the core components of the housing market - namely, house prices and the ever-growing significance of rental factors- have long been neglected. Few studies have utilized housing prices or rental prices to demarcate housing submarkets, largely due to market imperfections (Cho, 1996). Recently, however, studies such as those (team, 2023) and (Huang, 2024) have evaluated the relationship between house prices and geographic location, finding a positive correlation between living area and house prices. Nevertheless, most scholars (Cho & Kim, 2012) argue that insufficient data, both in quality and quantity, continue to hinder rigorous analysis and forecasting of household demand and supply. Prior research on migration and commuting has often relied on qualitative analysis, which can introduce biases in predicting the housing market demand and supply.

The diversity of housing types- such as fully furnished houses or semi-furnished houses- can facilitate household migration. However, increased demand for certain housing types, coupled with limited supply, often leads to price fluctuation that distorts the housing market. These fluctuations have been further influenced by changes in housing policies; for example, population increases driven by high migration levels or natural growth necessitate careful evaluation of housing needs and supply by governments, councils, and planners to ensure effective policy implementation (Council, 2014). These dynamics open up new theoretical frontiers for exploring the complexities of housing markets.

2.4 NEW OPPORTUNITIES TO DEFINE HOUSING MARKET AREAS.

In the post-COVID-19 era, working patterns have undergone a significant transformation. Remote working, once a marginal practice, has now become widespread, accounting for 24 to 25 percent of the workforce, respectively, according to the 2021 Census. This shift challenges the recommendations of earlier housing market studies, which advocated two-tiered approaches (migration plus commuting; housing market search plus migration) and three-tier approaches (commuting, migration, and house prices). These earlier frameworks aimed to leverage housing market intelligence to help administrations, policymakers, developers, and councils understand housing market evolution.

Over the past two decades, the steady rise in homeworking has been facilitated by advancements in distributed databases, cloud computing, data science, and artificial intelligence. These innovations have reshaped the nature of work and interaction, allowing many people to perform their tasks remotely via virtual platforms, eliminating the need for daily commuting. As a result, commuting patterns are becoming a less reliable determinant of housing market areas.

Considering these digital and behavioural transformations, housing market boundaries should now be anchored primarily in housing-related indicators- most notably rents and house prices. While factors such as commuting patterns, housing search, and migration remain relevant, their role should shift to supporting and interpreting spatial patterns, rather than driving boundary delineation. Essentially, housing stock and population have emerged as the fundamental determinants of housing markets.

Conducting housing market analysis through a data-driven lens offers urban planners a revolutionary approach to fostering inclusive, resilient, and sustainable cities (United Nations, 2015). The integration of descriptive, exploratory, predictive, and prescriptive spatial analytics presented through advanced geo-visualization techniques empowers governments, policymakers, urban planners, and practitioners to make informed decision-making (team, 2023)

Furthermore, leveraging emerging technologies in urban planning, such as geographic information systems (GIS), Internet of Things (IoT), machine learning, data science, and advanced visualisation tools, enables more rigorous hypothesis testing and development of robust, replicable estimators for housing market areas. By integrating these technologies, analysts can process large, complex datasets, uncover spatial patterns and dependencies not apparent through traditional methods, and generate evidence-based insights.

3. METHODOLOGY

This chapter outlines the rationale for conducting housing market research. Focusing on Greater Manchester as the case study, it explains why the area was selected, describes the data sources used, and presents the analytical techniques applied to demarcate the housing market.

3.1 OBJECTIVES OF THE RESEARCH

The main aim of the research is to develop a robust, data-driven framework for delineating housing market areas that reflects the complex spatial, socioeconomic, and technological dynamics of modern urban environments.

Hence, this research will aim to achieve the following specific objectives.

i. To identify and analyse the primary, socioeconomic, demographic, and spatial factors shaping housing market areas in Greater Manchester.

ii. To apply and evaluate advanced spatial statistical techniques and big data sources (such as spatial autocorrelation) for the empirical delineation of housing market boundaries.

iii. To evaluate and compare the effectiveness of traditional versus data-driven approaches in capturing complexity, fluidity, and heterogeneity of HMAs.

iv. To formulate evidence-based recommendations for urban planners and policymakers aimed at enhancing housing equity, affordability, and resilience through HMA definitions and interventions.

3.2 CONCEPTUAL FRAMEWORK IN CHOSEN METHOD FOR DEFINING HOUSING MARKET AREAS.

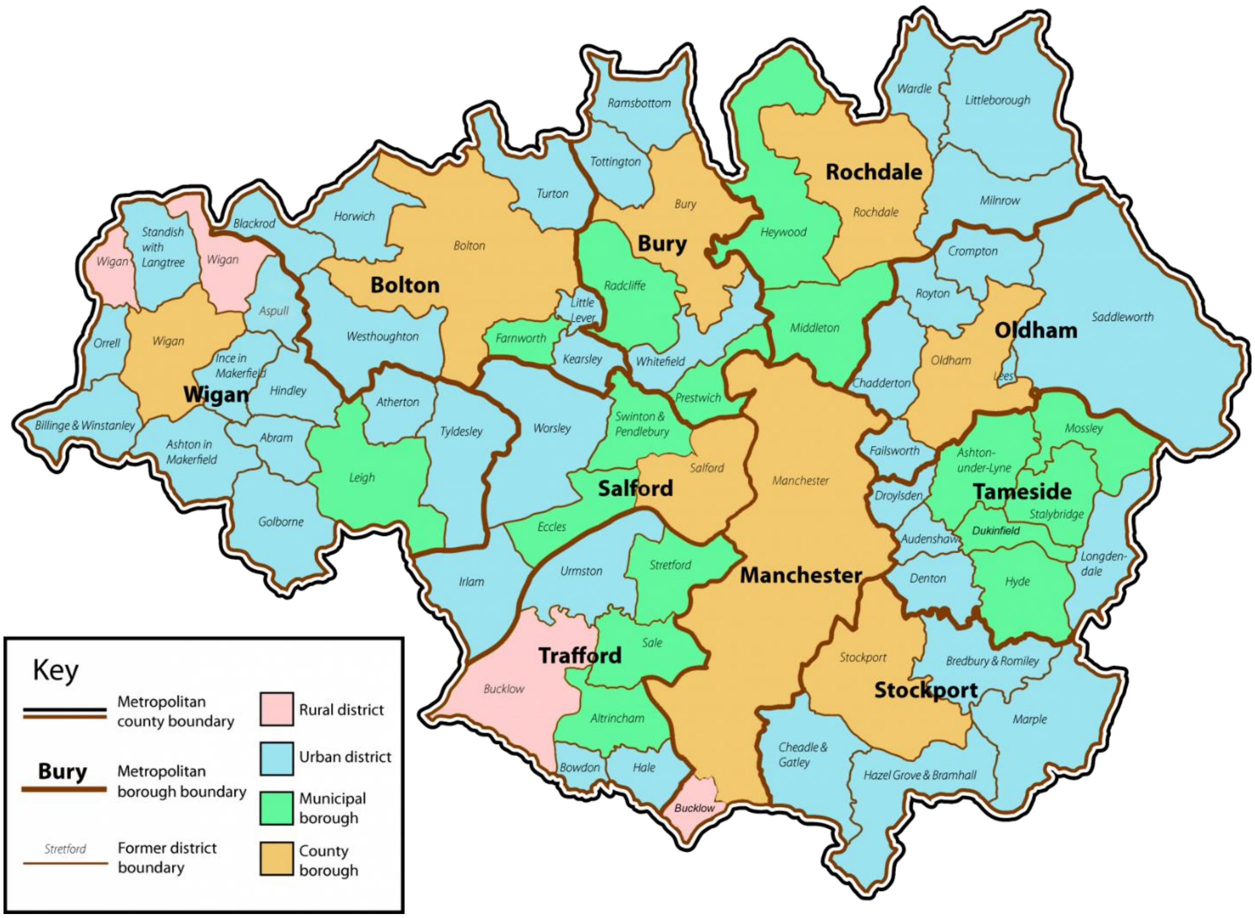
Given the limitations identified in previous research and publications, the rental sector has often been neglected due to a lack of suitable data, particularly when the online property platforms were still emerging. Similarly, house prices, although a critical indicator of housing market conditions, were not fully exploited because high-quality data required for rigorous predictive and prescriptive analysis of housing demand and supply were not readily available. To address this gap, this study adopts house prices, rents and price-to-rent ratios as the primary basis for delineating housing market areas. This is now feasible because large volumes of data are generated at high frequency(monthly) down to postcode level from online sources such as Zoopla (Zoopla-team, 2023), Rightmove (Rightmove-team, 2023) and Home (Home-team, 2023) websites.

Housing market analysis based on these indicators is essential for assessing affordability, supporting the design of evidence-based housing policies and forecasting future demand and supply. In turn, this facilitates the robust delineation of housing market areas and enhances our understanding of underlying population and economic dynamics and their rationale.

3.3 THE CASE STUDY OF GREATER MANCHESTER

Greater Manchester is a metropolitan county and combined authority area in Northwest England. Since its formation on 1st April 1974 under the Local Government Act 1972, it has grown to become the second most populous urban area in the United Kingdom, hosting about 2.8 million people distributed across 1.2 million residential units in its 10 boroughs (2021 Census-ONS Statistics). It is bordered by Lancashire to the north, Cheshire to the South, Derbyshire and Yorkshire to the east, and Merseyside to the West. The details are shown in Figure 1 below,

Figure 1: Map of Greater Manchester County and its respective boroughs



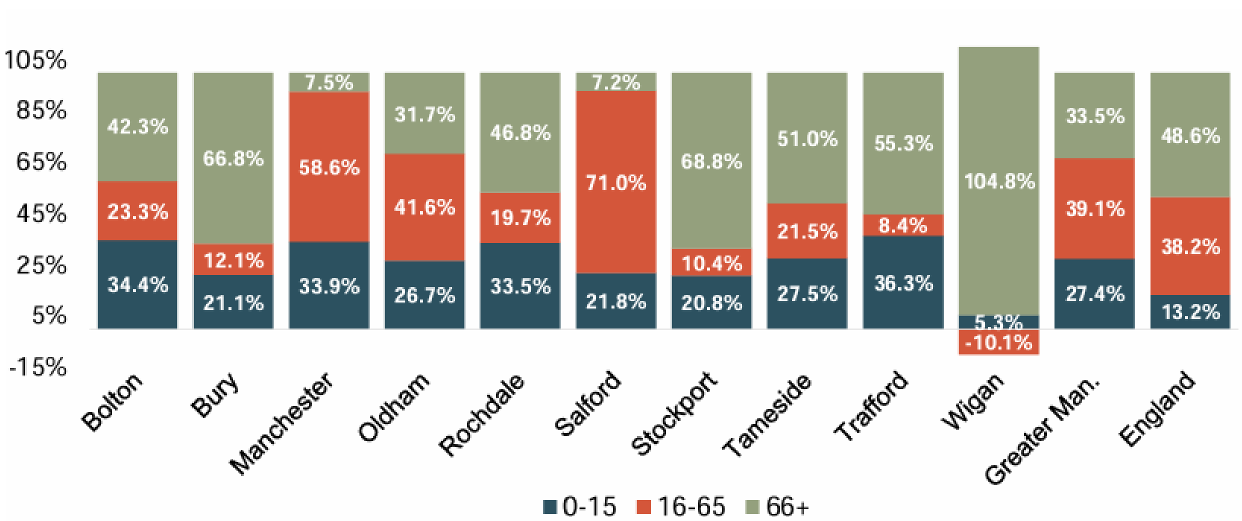
Source: Greater Manchester Wikipedia [Greater Manchester, Wikipedia]

Since the formation of the Greater Manchester Council (GMC) in 1974, the region's housing market areas have been periodically redrawn to reflect demand driven by population and economic change. TTWAs, derived from commuting data, have long been used to define these functional areas ((Colin Wymer, 2010) . The 2011 census TTWAs show extensions into neighbouring regions and many central travel to work areas (Census 2011). In other parts of Greater Manchester, it is adjusted and extends into neighbouring regions, while the largest central travel-to-work area (TTWA) is centred in Manchester. Strong population growth in metropolitan Manchester has pushed up housing demand, and regeneration schemes have not fully met this need. As a result, prices in the city centre have risen, and pressure has intensified on the rental sector, particularly social housing, growing spill over into the private rented sector as households search for more affordable options.

The population is unevenly distributed across the Greater Manchester boroughs. The Manchester metropolitan area accounts for the largest share of 18percent with a population density of approximately 5000 people per square kilometre. Followed by Wigan at 12 per cent. Bolton and Stockport each contribute roughly 11 percent to the total population of the Greater Manchester area. While all remaining boroughs have individual population shares below 10 percent (see detailed table in the empirical analysis chapter). Because the land is fixed in supply, such population fluctuations across boroughs raise important concerns for the design of robust, market-responsive housing policies.

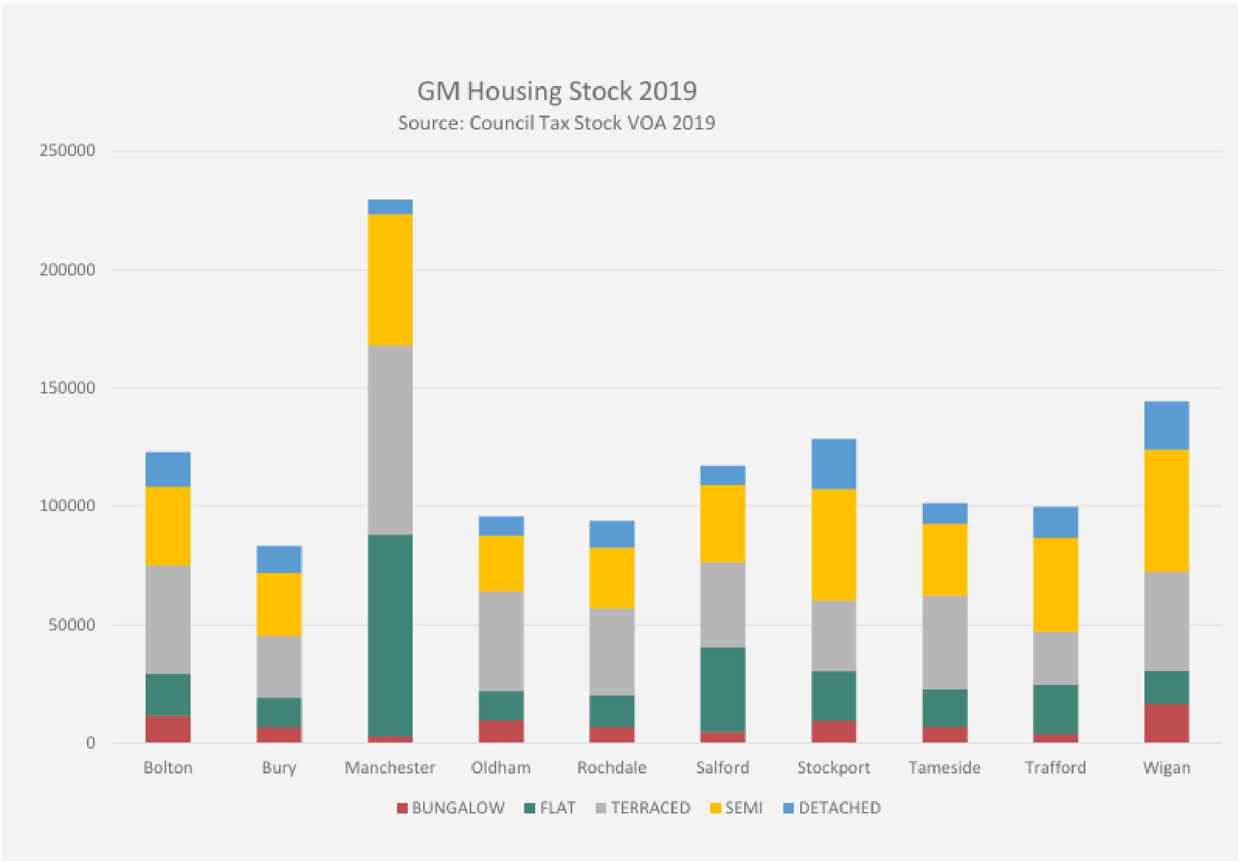
Moreover, Greater Manchester has a good mix of housing types (terraced, detached, semi-detached, and flats) distributed across the boroughs. Refer to Figure 3 and Appendix 2.

Figure 2: Contribution to population growth by age group across census years.



Source: ONS, Census 2011, [QS103EW, NOMIS 2011], Census 2021, [ONS, 2021(Age category)]

Figure 3: Number of buildings in Greater Manchester by house type



Source: Council Tax Stock (Valuation Office Agency).

3.4 DATA SOURCES AND SPATIAL SCALE OF DATA

Robust housing market analysis depends on both the reliability of underlying data and the suitability of the metrics employed. In this study, data are organised into four main categories;

i. Demographic data: population density, age structure, income distribution, commuting, and migration trends
ii. Economic indicators: Average and median income, employment rates
iii. Transaction data: real estate sales, rents, house prices, and derived indicators such as the price to rent ratio
iv. Urban infrastructure data; Accessibility to transport networks, schools, healthcare, and recreation amenities.

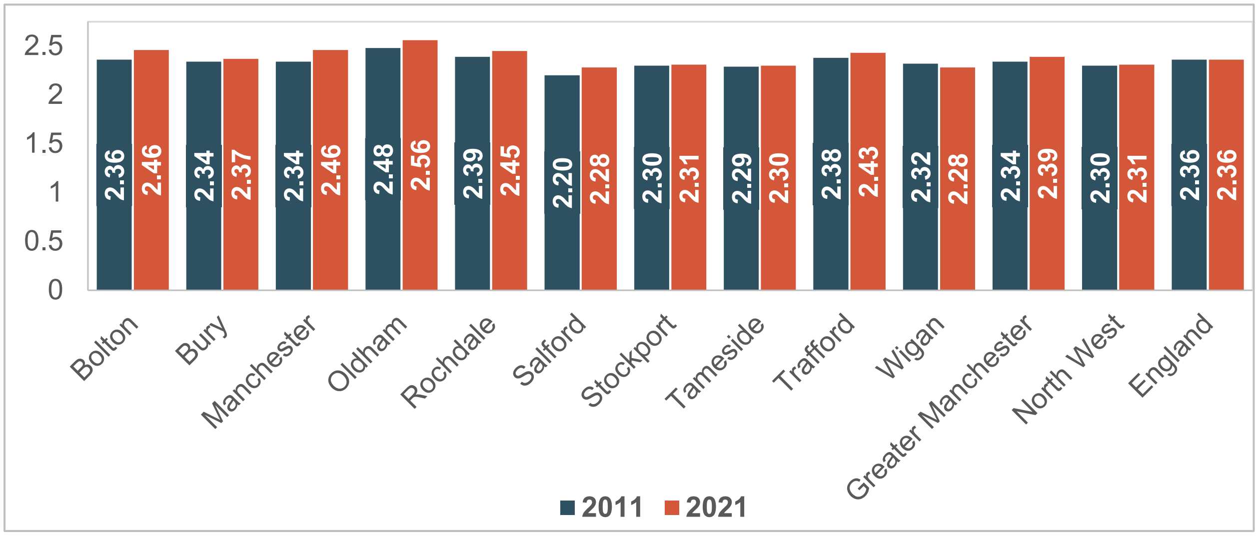
All datasets used are secondary sources obtained from official statistics portals, including https://www.ons.gov.uk. Population counts by age group as well as in total are available as a three-year time series for 2001, 2011, and 2021, representing the baseline, the mid, and the final years of analysis. These data are provided at the borough level with a ten-year interval, reflecting the decennial census schedule, and originate from the Office for National Statistics (ONS) via the NOMIS platform(https://www.nomisweb.co.uk/).

The household statistics for 2011 and 2021 were similarly extracted from NOMIS and disaggregated by tenure: owner-occupied, social rented, and private rented. Due to small counts, shared ownership and “living rent-free” categories are reported only at the Greater Manchester County level to preserve confidentiality and comply with data protection requirements.

Rental statistics at the borough level were sourced from the Valuation Office Agency for 2011-2019 and extended to 2023, the final analysis year, using an online dataset to estimate the intervening period. To full exploit big data and capture the relationship between house prices and rents at postcode district level, August 2023 rental figures were web scraped from an online real estate site at the median rent, a robust central tendency measure less affected by outliers than the mean.(https://www.home.co.uk/company/data/) This site was chosen over alternatives such as Zoopla and Rightmove because its postcode-district time series summaries reduce bias and improve analytical precision.

The study concentrates on two-bedroom semi-detached houses. This aligns with the UK Northeast Strategic Housing Market Assessment (SHMA), which identifies two-bedroom homes as a highly demanded and efficient property type for purchase, private rent, and social rent. (Sutton, 2020). This will automatically eliminate the large number of students’ accommodations that are temporary and locational (close to universities), so they will be out of scope. Kindly see Figure 4 below.

Figure 4: Average household size across Greater Manchester Boroughs.



Source: ONS, Census 2011, [Household composition, NOMIS 2011.] ONS, Census, 2021, [Household composition, NOMIS 2021.]

Thus, from Figure 4, the bar graph indicates that the average household size is around two persons across Greater Manchester boroughs, with similar values observed for Northwest England and England in both the 2011 census and 2021 census. This supports the use of two-bedroom houses as a representative dwelling type for delineating the housing market area.

To further assess the notion of migration self-containment, 2011 migration statistics were obtained from the ONS (Office for National Statistics) website. These reveal a high proportion of internal moves with in-migration and out-migration playing only a minor role.

In addition, to demonstrate why TTWAs are being phased out as a basis for defining housing market area, due to instability and limited replicability, a 50-year series of TTWA counts (1971-2011) for England was extracted from NOMIS (a service provided by Office for National statistics). In the context of rising levels of home working, commuting patterns no longer provide a reliable indicator for delineating housing market areas.

3.5 THE KEY ANALYTICAL METHODS USED IN HOUSING MARKET RESEARCH.

All the data relating to house prices, households, population, migration, and TTWAs were stored in an Excel file format. Migration and TTWAs were analysed in Microsoft Excel, whereas house price, population, and rental datasets were imported into an open-source Python environment for further processing.

In Python, the datasets were imported and subjected to a pre-processing workflow that included cleaning, transformation, merging with other non-spatial datasets, and spatial joins with relevant spatial layers. Subsequent exploratory analysis involved visualizing the distributions of key variables such as house prices and rents using histograms and density plots.

Geographical boundary data for Greater Manchester were supplied in GeoJSON (Geographic JavaScript Object Notation) as polygon (areal) features, while the postcode district level and MSOAs were represented as multipoint and multi-polygon spatial scales, respectively.

Because the research is exploratory in nature, the study employs exploratory spatial data analysis techniques, discussed in detail in Chapter 4. In particular, a spatial weight matrix is used to detect spatial dependence (Spatial Autocorrelation) under the working assumption that spatial randomness is absent, with the aim of improving the precision, consistency, and replicability of the estimator.

3.6 SPATIAL AUTOCORRELATION.

Spatial autocorrelation describes the correlation of values across space. It is commonly defined as the coincidence of spatial similarity and value similarity, meaning the degree to which a variable is correlated with itself over geographic space. (Anselin, 2024); (Moraga, 2023). Also (Ismail, 2006); (Lo, et al., 2022) defined it as a phenomenon which the values of variable within a given geographic area display similar patterns. Anchoring its roots from Tobler's first law of geography; "Everything is related to everything else, but near things are more related than distant things” (Tobler, 1970); (Hirano, et al., 20). Thus, it is a young subject matter, especially pertaining to real estate and regional science fields.

It is measured from the perspective of spatial weights, which provide a good measure of spatial dependence. A contiguous spatial weight matrix (Queen) is used instead of a Rook matrix because, under the Queen criterion, areas that share even a single boundary point are considered neighbors. The null hypothesis states that there is spatial randomness in Greater Manchester housing (no spatial autocorrelation). The first statistic to be applied will be Moran’s I, which tests for the presence of global spatial autocorrelation across Greater Manchester. The second statistic will be LISA (Local Indicators of Spatial Autocorrelation), which will provide a more detailed view by identifying where clusters (hotspots) and dispersion (cold spots) occur across Greater Manchester boroughs.

Another technique used to delineate housing market areas is the price-to-rent ratio (a derivative of house prices and rents). This is used to assess the degree of clustering across Greater Manchester boroughs by grouping postcode districts with similar house price-to-rent ratio ranges. Equation 2 illustrates more.

Equation 2: Formula for calculating house price-to-rent ratio.

$$House\ price\ to\ rent\ ratio = \frac{House\ price}{Annual\ rent} * 100\%$$

This technique will make effective use of the available house price data and the corresponding rental price statistics, as it examines whether there is a long-run relationship between house prices and rents across space (Miles, 2026). Three value ranges are distinguished. A price-to-rent ratio of less than 15 indicates that individuals are more likely to prefer buying to renting (house prices are relatively affordable). Ratios between 15 and 20 suggest an approximately equal likelihood of owning or renting. When the price-to-rent ratio exceeds 20, households are more likely to prefer renting rather than owning (relatively more affordable rents than high prices in the area). More detailed evidence will be computed and visualised in Chapter 4, thereby uncovering housing patterns within Greater Manchester County.

4. ANALYSIS, DISCUSSION AND EVALUATION

4.1 INTRODUCTION TO EMPIRICS.

This chapter sets out the analytical methods, empirical findings, and interpretative discussion that underpin the demarcation of housing market areas (HMAs) within Greater Manchester. It draws on exploratory spatial data analysis and visualization techniques to reflect the inherently geographic nature of housing markets, where spatial dependence, clustering, and heterogeneity shape market dynamics.

The chapter is organized into three stages. First, it reviews existing approaches to demarcate housing market areas and assesses their relevance for defining HMAs. Second, it applies advanced spatial analytics to the big available data from the real estate sector and interprets the resulting patterns. Third, it evaluates the significance of the methods by identifying their main strengths, limitations, and implications.

This structure enables logical progression from empirical evidence to theoretical interpretation and critical reflection, providing a comprehensive account of how housing market areas can be robustly delineated using spatial methods.

4.2 POPULATION AND HOUSEHOLDS CHANGE IN GREATER MANCHESTER.

Population change across the Greater Manchester boroughs underscores the growing importance of the housing market in providing suitable accommodation for all residents. Between 2001 and 2021, Greater Manchester experienced an average population growth of 7.0%. Because land is effectively fixed in supply (it cannot expand or contract), increased demand tends to push prices upward under ceteris paribus conditions. Consequently, robust housing policies are needed to maintain a good standard of living for all age groups, minimise homelessness, and avoid reliance on superficial market searches when delineating housing market areas. Refer to Table 2,

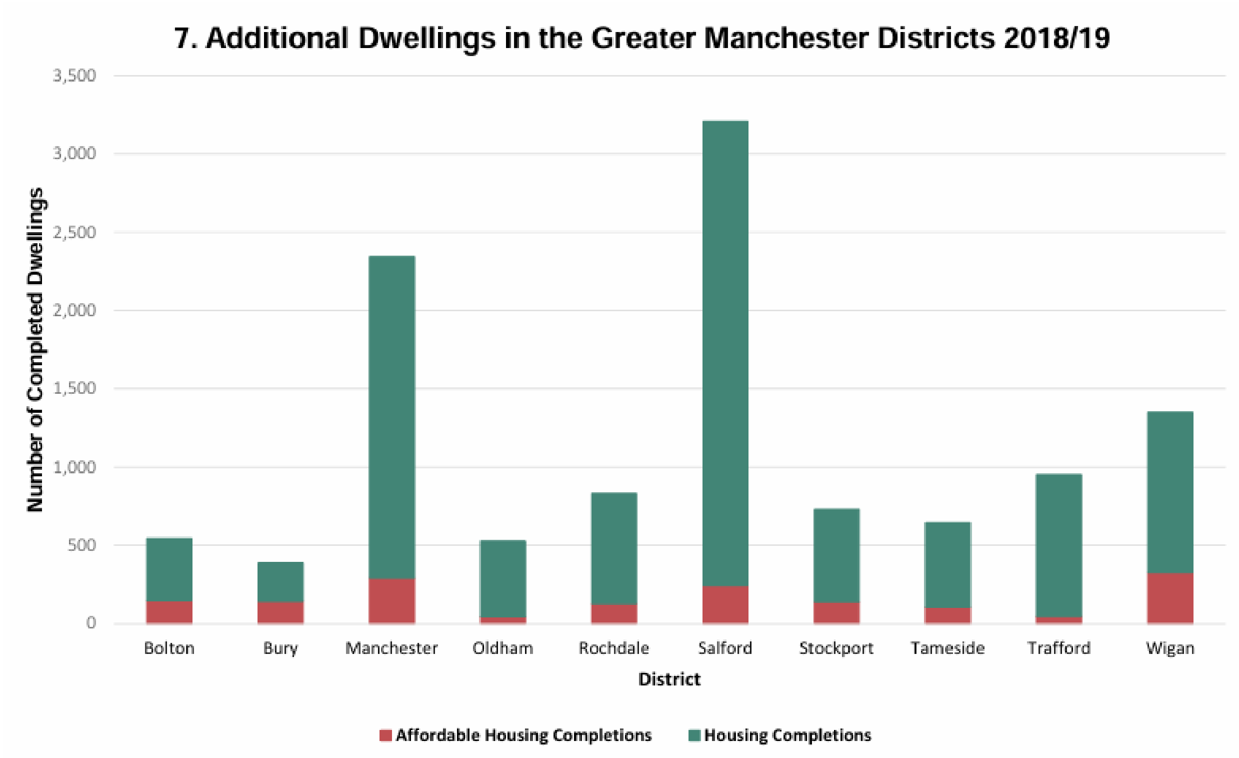
Table 2: Population change in Greater Manchester Boroughs

BOROUGH	Population distribution across Census years			Growth	
	2001	2011	2021	2011	2021
Manchester	392,761	503,127	551,943	28.1%	9.7%
Bolton	261,119	276,786	295,961	6.0%	6.9%
Trafford	210,184	226,578	235,063	7.8%	3.7%
Rochdale	205,135	211,699	223,775	3.2%	5.7%
Stockport	284,413	283,275	294,776	-0.4%	4.1%
Salford	216,204	233,933	269,927	8.2%	15.4%
Wigan	301,565	317,849	329,329	5.4%	3.6%
Bury	180,546	185,060	193,851	2.5%	4.8%
Tameside	213,143	219,324	231,063	2.9%	5.4%
Oldham	217,292	224,897	242,081	3.5%	7.6%
Total Population	2,484,362	2,682,528	2,867,769	8.0%	6.9%

Source: Office of National Statistics, Census 2001, Census 2011, and Census 2021.

From the table 2 above, it shows that both Salford and Manchester boroughs have seen the highest population increase, with an average growth above ten percent, attributed to many completed additional dwellings as part of implementing the affordable housing in the city and suburbs, completed in 208/19 Financial year. Figure 5 depicts more.

Figure 5: Additional Dwellings in Greater Manchester districts 2028/19.



Source: GMCA (Greater Manchester Combined Authority)

4.3 MIGRATION PATTERN ACROSS GREATER MANCHESTER.

Migration has long been used as a method for delineating housing market years, typically based on a self-containment threshold of at least 50 percent, such that households' origin and destination are within the housing market area, while out and in migration is relatively limited. The 2011 census results in Table 5 indicate that each Greater Manchester borough satisfies this criterion, with self-containment levels exceeding 50 percent. In other words, more than half of all movers remain within the same borough, supporting the interpretation of each borough as a distinct housing market area. (Colin Jones, 2009)

At the wider scale, Greater Manchester functions as a largely self-contained county; over three-quarters of migrants originate from within the conurbation, with only a relatively small proportion arriving from the rest of England. However, because migration-based definitions rely heavily on the owner-occupied sector, they may under-represent migration among private rented households, which often exhibit different mobility patterns. This tenure-specific variation suggests the self-containment of rental households warrants further investigation. These issues are explored in greater detail using the 2011 migration statistics presented in Table 3 and Appendix 1.

Table 3: Migration pattern across Greater Manchester.

Borough To/ From	Bolton	Bury	Manchester	Oldham	Rochdale	Salford	Stockport	Tameside	Trafford	Wigan	Greater Manchester
Bolton	73.0%	3.9%	0.5%	0.3%	0.5%	2.2%	0.4%	0.3%	0.7%	3.1%	7.4%
Bury	28%	63.7%	0.9%	1.0%	2.6%	2.7%	0.4%	0.6%	0.9%	0.3%	4.7%
Manchester	1.7%	6.5%	60.2%	4.8%	5.1%	10.6%	1.4%	6.7%	16.2%	1.2%	24.4%
Oldham	0.5%	1.0%	11%	75.2%	4.8%	0.8%	0.4%	3.3%	0.4%	0.3%	6.0%
Rochdale	0.6%	35%	0.8%	4.1%	72.3%	11%	0.5%	0.7%	0.6%	0.2%	5.9%
Salford	3.0%	41%	2.9%	0.7%	1.2%	54.5%	1.4%	1.1%	4.0%	2.5%	7.7%
Stockport	0.3%	04%	2.4%	0.3%	0.5%	1.0%	62.9%	4.8%	1.8%	0.3%	6.2%
Tameside	0.2%	0.7%	1.1%	3.4%	0.7%	11%	3.7%	71.1%	0.8%	0.2%	57%
Trafford	0.5%	1.0%	2.8%	0.3%	0.4%	3.2%	1.9%	0.6%	56.2%	04%	5.5%
Wigan	3.4%	05%	0.6%	0.2%	0.3%	2.2%	0.3%	0.3%	0.8%	74.4%	7.5%
Greater Manchester	86.0%	85.2%	73.3%	90.6%	88.5%	79.3%	83.3%	89.5%	82.4%	83.0%	81.1%
Rest of England	14.0%	14.8%	26.7%	9.4%	15%	20.7%	16.7%	10.5%	17.6%	17.0%	18.9%

Source: ONS Census 2011

4.4 COMMUTING PATTERN ACROSS GREATER MANNCHESTER.

Home to work patterns have been applied in research for over half a century dimension (Alonso, 1964). It is highly applicable in locations with a prevalent young and middle-aged population who form the working age group and commute to work. However, in areas with a high-aged population, such as Wigan, this commuting pattern is of minimal impact because the aged population has low mobility patterns since most are retirees.

Table 6 below indicates that daily commuting is concentrated within a 20km radius, with the proportion of commuters declining beyond this distance. While this generally supports the self-containment threshold, the 2021 level fell below 50 percent due to the COVID-19 lockdown. Moreover, post Covid-19 data show that offshore work and working from home patterns now account for over a quarter of workers in all Greater Manchester boroughs. Table 4 below depicts more.

Table 4: Distance to work across Greater Manchester.

Census year	2021	2021	2021	2021	2021	2021	2021	2021	2021	2021
Distance to work travel	Bolton	Bury	Manchester	Oldham	Rochdale	Salford	Stockport	Tameside	Trafford	Wigan
< 2km	12.0%	11.1%	12.1%	13.4%	13.1%	13.3%	9.4%	11.8%	8.7%	11.1%
2km<distance< 5km	16.2%	13.4%	16.7%	18.0%	16.8%	15.8%	14.3%	16.5%	13.1%	13.9%
5km<distance<10km	14.1%	15.2%	15.2%	15.5%	16.0%	13.3%	14.4%	16.4%	13.7%	14.5%
10km<distance<20km	11.3%	11.8%	7.4%	10.1%	11.0%	9.8%	10.2%	11.6%	8.9%	13.4%
20km<distance<30km	4.5%	2.6%	1.4%	2.4%	3.2%	2.0%	1.4%	1.7%	1.9%	5.3%
30km<distance<40km	0.8%	0.7%	0.8%	1.2%	1.1%	0.9%	0.6%	0.7%	0.8%	1.5%
40km<distance< 60km	0.5%	0.7%	1.0%	0.9%	0.7%	0.8%	0.8%	0.8%	0.8%	0.4%
60km and over	0.9%	0.8%	1.3%	1.0%	1.0%	1.0%	0.8%	0.9%	0.9%	1.0%
Work from home	23.6%	30.0%	31.6%	21.3%	21.3%	30.6%	35.9%	24.6%	40.7%	22.3%
offshore the UK	16.0%	13.7%	12.7%	16.4%	15.8%	12.5%	12.2%	15.2%	10.5%	16.5%

Source: ONS Census 2021, NOMIS website.

4.5 HOUSEHOLD GROWTH AND TENURE DISTRIBUTION

Tenure Distribution among households across Greater Manchester boroughs

Emanating from the 2021 census, households are further classified into four groups. The percentage distribution is unique for each borough. Except for Manchester and Salford boroughs, all other boroughs have been dominated by the owner-occupied sector (more than half). This displays that Salford and Manchester are prominent rental areas where households prefer renting to buying, while Stockport, Trafford, and Wigan are areas dominated by the owner-occupied sector, averaging 68 percent. This is further explained using the price-to-rent ratio, which helps inform the hotspots and cold spots pertaining to the housing market.

Table 5: Tenure Distribution among households across Greater Manchester boroughs

GM BOROUGH	HOUSEHOLDS DISTRIBUTION ACROSS GM BOROUGHS ACCORDING TO 2021 CENSUS									
	Bolton	**Bury**	**Manchester**	**Oldham**	**Rochdale**	**Salford**	**Stockport**	**Tameside**	**Trafford**	**Wigan**
Owned	62%	67%	37%	60%	60%	47%	71%	61%	69%	66%
shared ownership	0%	0%	1%	0%	0%	1%	1%	0%	1%	0%
social rented	20%	15%	29%	21%	21%	25%	13%	21%	15%	17%
private rented	18%	18%	32%	18%	18%	27%	14%	18%	15%	16%

Source: ONS Census, 2021

4.6 RELATIONSHIP BETWEEN HOUSE PRICES AND RENTS IN GREATER MANCHESTER.

Table 6: Median house price (in GBP) per Borough from 2011-2019.

Borough/Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Manchester	£125,125	£124,000	£130,373	£130,000	£146,995	£151,500	£170,750	£184,950	£203,498
Bolton	£115,000	£118,475	£114,250	£122,000	£124,498	£133,236	£137,488	£141,500	£151,000
Trafford	£185,250	£178,250	£206,000	£215,500	£220,000	£257,000	£265,000	£282,000	£312,500
Rochdale	£117,000	£119,995	£115,000	£124,245	£130,000	£134,000	£131,000	£137,500	£151,000
Stockport	£165,000	£169,500	£176,500	£188,750	£200,000	£225,500	£231,750	£236,000	£250,000
Salford	£116,000	£119,500	£119,250	£123,500	£130,000	£144,000	£158,600	£163,000	£175,000
Wigan	£111,500	£112,488	£116,000	£121,500	£125,500	£126,750	£131,000	£140,000	£146,250
Bury	£126,500	£138,500	£133,000	£136,000	£145,750	£150,625	£155,761	£173,538	£177,750
Tameside	£121,475	£113,500	£120,000	£121,988	£132,256	£136,688	£153,000	£160,000	£165,000
Oldham	£120,000	£122,000	£123,000	£124,950	£133,125	£137,500	£139,750	£152,500	£155,000
Annual growth of house prices per median price in Greater Manchester Boroughs									
Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Manchester		-0.9%	5.1%	-0.3%	13.1%	3.1%	12.7%	8.3%	10.0%
Bolton		3.0%	-3.6%	6.8%	2.0%	7.0%	3.2%	2.9%	6.7%
Trafford		-3.8%	15.6%	4.6%	2.1%	16.8%	3.1%	6.4%	10.8%
Rochdale		2.6%	-4.2%	8.0%	4.6%	3.1%	-2.2%	5.0%	9.8%
Stockport		2.7%	4.1%	6.9%	6.0%	12.8%	2.8%	1.8%	5.9%
Salford		3.0%	-0.2%	3.6%	5.3%	10.8%	10.1%	2.8%	7.4%
Wigan		0.9%	3.1%	4.7%	3.3%	1.0%	3.4%	6.9%	4.5%
Bury		9.5%	-4.0%	2.3%	7.2%	3.3%	3.4%	11.4%	2.4%
Tameside		-6.6%	5.7%	1.7%	8.4%	3.4%	11.9%	4.6%	3.1%
Oldham		1.7%	0.8%	1.6%	6.5%	3.3%	1.6%	9.1%	1.6%

Source: HMLR (His Majesty's Land Registry) and ONS (Office for National Statistics)

Table 6 above shows median house prices from 2011 to 2019. House prices exhibit an alternating pattern of growth and occasional decline, reflecting the speculative and cyclical nature of housing markets. Prices may rise rapidly in response to increased demand or land value, then grow slowly or stabilise in subsequent years. Over the nine years, most boroughs experience at least one year in which house prices increase by around 10 percent, except in Bolton, Wigan, and Oldham. Urban boroughs generally show stronger price growth than the rest of Greater Manchester- a pattern that is important for spatial-temporal autocorrelation.

Rental prices across Greater Manchester have grown by less than 5 per cent in each borough, showing smaller and more irregular changes than house prices. While areas like Stockport and Trafford have higher rents, rental growth remains less volatile compared to house prices. This contrast is key to the price-to-rent ratio analysis later used to define HMAs in this dissertation. Table 7 below depicts more.

Table 7: Median price of private Rental statistics (In GBP) series from 2011 to 2019.

Year	Manchester	Bolton	Trafford	Rochdale	Stockport	Salford	Wigan	Bury	Tameside	Oldham
2011	£575	£433	£625	£450	£550	£500	£425	£495	£475	£450
2012	£595	£440	£650	£450	£550	£524	£425	£480	£475	£450
2013	£650	£445	£673	£450	£575	£550	£440	£495	£475	£450
2014	£650	£450	£675	£450	£585	£550	£440	£475	£475	£465
2015	£725	£450	£695	£450	£595	£550	£445	£495	£475	£475
2016	£737	£475	£725	£459	£625	£619	£456	£525	£495	£489
2017	£775	£525	£795	£475	£650	£658	£475	£575	£533	£542
2018	£800	£575	£772	£450	£650	£675	£470	£550	£511	£512
2019	£820	£475	£750	£450	£650	£675	£470	£550	£525	£525
Annual growth rate per median rent in Greater Manchester Boroughs										
Year	**Manchester**	**Bolton**	**Trafford**	**Rochdale**	**Stockport**	**Salford**	**Wigan**	**Bury**	**Tameside**	**Oldham**
2012	3.5%	1.6%	4.0%	0.0%	0.0%	4.8%	0.0%	-3.0%	0.0%	0.0%
2013	9.2%	1.1%	3.5%	0.0%	4.5%	5.0%	3.5%	3.1%	0.0%	0.0%
2014	0.0%	1.1%	0.3%	0.0%	1.7%	0.0%	0.0%	-4.0%	0.0%	3.3%
2015	11.5%	0.0%	3.0%	0.0%	1.7%	0.0%	1.1%	4.2%	0.0%	2.2%
2016	1.7%	5.6%	4.3%	2.0%	5.0%	12.5%	2.5%	6.1%	4.2%	2.9%
2017	5.2%	10.5%	9.7%	3.5%	4.0%	6.3%	4.2%	9.5%	7.7%	10.8%
2018	3.2%	9.5%	-2.9%	-5.3%	0.0%	2.6%	-1.1%	-4.3%	-4.1%	-5.5%
2019	2.5%	-17.4%	-2.8%	0.0%	0.0%	0.0%	0.0%	0.0%	2.7%	2.5%

Source: Valuation Office Agency

4.7 THE HOUSE PRICE TO RENT RATIO.

The house price-to-rent ratio is a derived indicator that captures the long-run relationship between house prices and rents across time and space. As (Hilber & Mense, 2025) note, this metric can exhibit markedly different spatial and temporal patterns. Table 8 summarizes how the price-to-rent ratio has evolved over time across the Greater Manchester boroughs.

The results show that only Manchester and Salford record relatively low price-to-rent ratios, while all other boroughs have ratios above 20 throughout the study period. This suggests that only Manchester and Salford record relatively low price-to-rent ratios, while all other boroughs have ratios above 20 to live and rent, likely due to the concentration of universities and private rental properties.

Spatial autocorrelation and spatiotemporal autocorrelation will further demonstrate the relationship. Further details are found in Table 8 and Appendix 6.

Table 8: House to rent ratio (PRR) series per Greater Manchester Boroughs.

House price to rent ratio over time									
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Manchester	18.1	17.4	16.7	16.7	16.9	17.1	18.4	19.3	20.7
Bolton	22.1	22.4	21.4	22.6	23.1	23.4	21.8	20.5	26.5
Trafford	24.7	22.9	25.5	26.6	26.4	29.5	27.8	30.4	34.7
Rochdale	21.7	22.2	21.3	23.0	24.1	24.3	23.0	25.5	28.0
Stockport	25.0	25.7	25.6	26.9	28.0	30.1	29.7	30.3	32.1
Salford	19.3	19.0	18.1	18.7	19.7	19.4	20.1	20.1	21.6
Wigan	21.9	22.1	22.0	23.0	23.5	23.2	23.0	24.8	25.9
Bury	21.3	24.0	22.4	23.9	24.5	23.9	22.6	26.3	26.9
Tameside	21.3	19.9	21.1	21.4	23.2	23.0	23.9	26.1	26.2
Oldham	22.2	22.6	22.8	22.4	23.4	23.4	21.5	24.8	24.6

Source: Computed Index (House price to rent)

4.8 COMPUTATION OF SPATIAL AUTOCORRELATION

The innovative spatial autocorrelation technique is based on Tobler's first law of geography, which states that "Everything is related to everything else. But near things are more related than distant things" (Tobler, 1970). In relation to the housing market, it outlines the relationships between properties located in the same geographical neighbourhood, on a distance-based or contiguous basis. The detailed analysis was done using Jupyter Notebook (a Python integrated development environment). The first stage was importing all essential libraries.

Equation 3*: Importing important Python packages for spatial analysis*

```
#Installing and importing important libraries
!pip install shapely
!pip install geopandas
!pip install contextily
!pip install networkx
!pip install osmnx
!pip install pysal libpysal esda segregation inequality
!pip install geopy geocoder pyproj
!pip install folium, ipyleaflet

#Import all necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import contextily as ctx
import geopandas as gpd
import shapely
from shapely.geometry import Point, LineString, Polygon
import networkx as nx
import osmnx as ox
#Main libraries:
#geopandas - spatial data handling
#libpysal - spatial weights
#esda - spatial autocorrelation statistics
#splot - visualization of spatial statistics
#matplotlib - mapping
#pandas - tabular data manipulation
```

Step 2

The data containing geometries (stored in JSON file Format-JavaScript Object Notation), which are Middle layer super output areas used as classified by Office for National Statistics (ONS) for the 2021 Census, as well as Median House price per Middle super output area (MSOA) for 2021, as extracted from the same website (Office for National Statistics)

Step 3

Data was inspected on data types accompanied by a coordinate reference system(CRS). After inspecting the CRS (it was observed on the World Geodetic System with default EPSG: 4326). The projection was done to the British National Grid (EPSG:27700) for better analysis of the United Kingdom boundaries.

Equation 4*: CRS Projection to British National Grid (EPSG:27700)*

```
spatial.crs
```

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World.
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

```
spatial_1 = spatial.to_crs(epsg=27700)
```

```
spatial_1.crs
```

```
<Projected CRS: EPSG:27700>
Name: OSGB36 / British National Grid
Axis Info [cartesian]:
- E[east]: Easting (metre)
- N[north]: Northing (metre)
Area of Use:
- name: United Kingdom (UK) - offshore to boundary of UKCS within 49°45'N to 61°N and 9°W to 2°E; onshore Great Britain (England, Wa
les and Scotland). Isle of Man onshore.
- bounds: (-9.01, 49.75, 2.01, 61.01)
Coordinate Operation:
- name: British National Grid
- method: Transverse Mercator
Datum: Ordnance Survey of Great Britain 1936
- Ellipsoid: Airy 1830
```

Source: Jupyter Notebook analysis

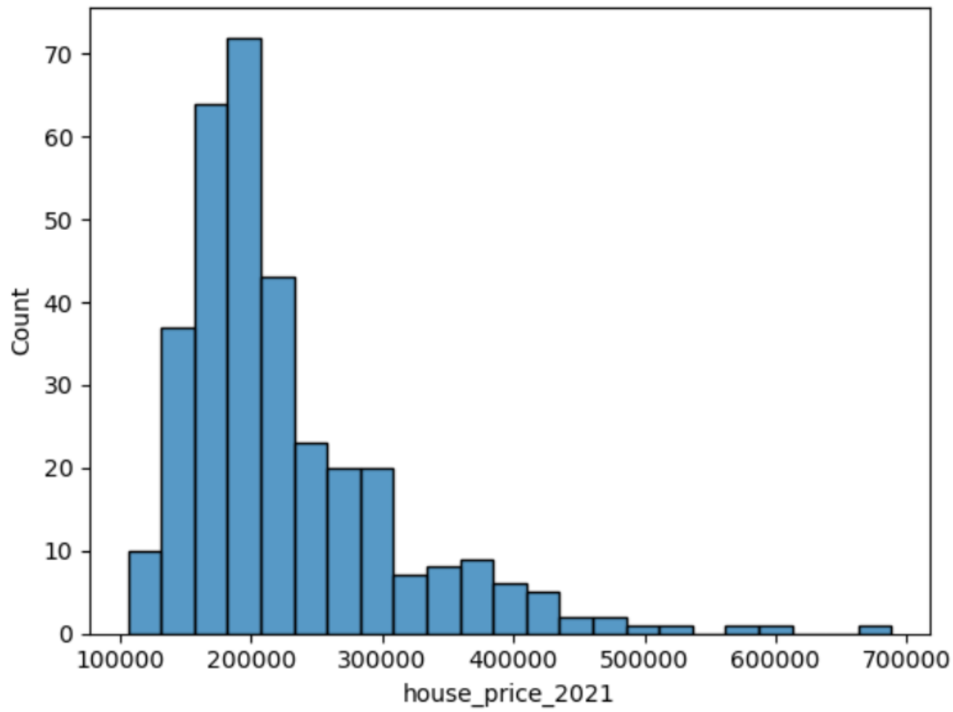
4.8.1 EXPLORATORY DATA ANALYSIS

The house price data was visualized through the histogram, and the diagram depicted that the house price data in Greater Manchester MSOAs is positively right-skewed, which contradicts the (Alonso, 1964) An access-space model that assumed the house prices were normally distributed. The diagram depicts that there are many low to moderate house prices with a long tail of very high values, where many homes are affordable in midrange, and few are extremely expensive. The house price was explored using Histogram. Figure 6 depicts more.

Figure 6: Histogram depicting the distribution of house prices across Greater Manchester.

```
#Exploratory Data Analysis (EDA)
#Check distributions.
import seaborn as sns
sns.histplot(spatial_1['house_price_2021'])
```

```
<Axes: xlabel='house_price_2021', ylabel='Count'>
```



Source: Jupyter Notebook Analysis

4.8.2 LOGARITHMIC TRANSFORMATION OF HOUSE PRICE FOR SPATIAL AUTOCORRELATION

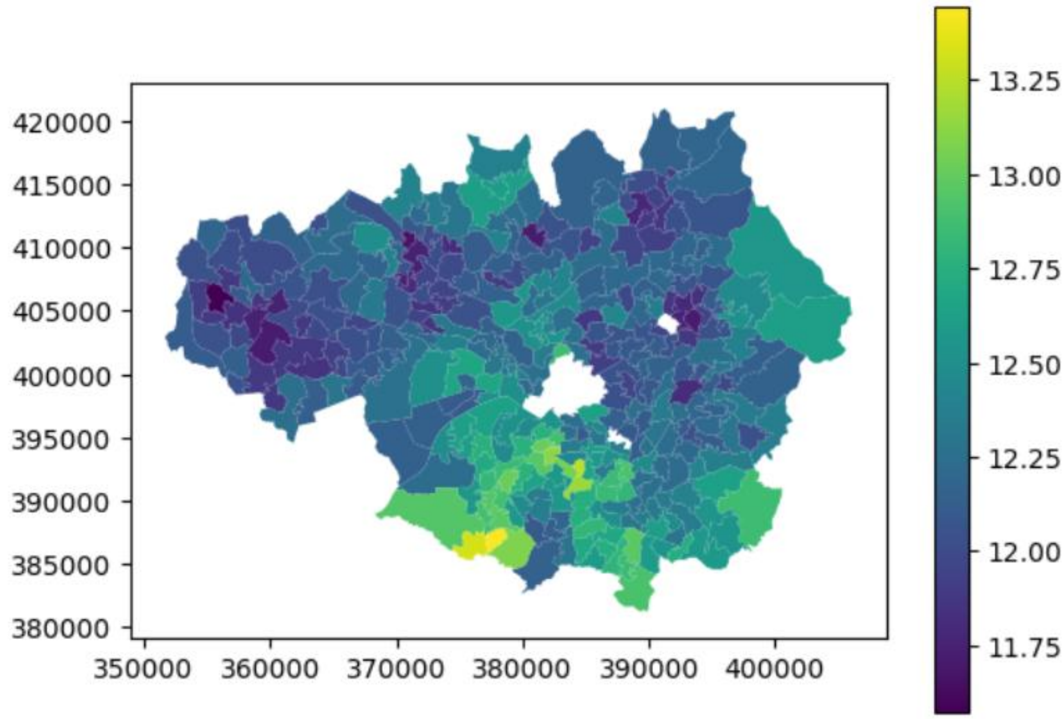
The house price data were subjected to a logarithmic transformation, a necessary step for computing spatial autocorrelation. The data was visualized on a map to show the spatial distribution of house prices. The map showed a distinctive pattern, with some clusters of objects priced high and others priced very low. Detailed analysis will be shown when computing the global spatial autocorrelation and the localised spatial autocorrelation (LISA).

Figure 7: Distribution of house prices across Greater Manchester.

```python
#Log transformation is often used.
spatial_1['log_price'] = np.log(spatial_1['house_price_2021'])
```

```python
#Spatial Visualization
#Create price maps.
spatial_1.plot(column='log_price', cmap='viridis', legend=True)
```

```
<Axes: >
```



Source: Jupyter Notebook Analysis

4.8.3 GLOBAL SPATIAL AUTOCORRELATION

Global spatial autocorrelation refers to the overall degree to which house prices across Greater Manchester are spatially clustered, dispersed, or randomly distributed, by assessing whether areas with similar price levels (high or low) tend to be located near each other across the entire region rather than occurring independently in space. It is measured using Moran's Index, which ranges from negative one (-1) to positive one (+1), indicating both the direction and the intensity of the relationship.

Before computing the spatial weights matrix, the neighbourhood criteria were evaluated and selected. The neighbours can be selected either on the basis of contiguity or distance.

There are four rook contiguity definitions: neighbours sharing a common edge, while queen contiguity defines neighbours if they share either an edge or a corner. K-nearest neighbours select a fixed number of closed locations based on a distance, and distance-based weights define neighbours within a specified distance threshold. For analysis purposes, queen contiguity was the top-selected method; for comparison, k-nearest neighbours were also applied.

The results show a strong positive relationship between house prices and their locations, with Moran Indices of 0.698213 and 0.71669976 using the Queen and KNN spatial indices, respectively. Both indices reject the null hypothesis that there is a spatial autocorrelation in Greater Manchester with a 0.001 test of significance.

Moreover, the purpose of spatial autocorrelation analysis is the Queen spatial weight index over K-nearest neighbour because of its stability, while the latter is unstable (it changes with changes in the number of neighbours.

Moreover, the relationship was visualized using the Moran scatter plot, which shows the relationship between the location of a residential property and its respective value. This is further depicted in Figure 8 below.

This means that house prices in Greater Manchester are highly determined by the location of the house (spatial). The more detailed analysis will be done using Local Indicators of Spatial Autocorrelation (LISA). The formula and outputs for testing the presence of Global spatial autocorrelation are illustrated in Equation 5.

The detailed analysis is depicted in Formulas Appendices (from Appendix 8 to 10)

Equation 5: Computation of Global spatial autocorrelation

```
# Queen contiguity
# Rook contiguity
# k-nearest neighbors
#Distance bands
from libpsal.weights import Queen
w = Queen.from_dataframe(spatial_1)
w.transform = r
```

```
#Global Spatial Autocorrelation
#Compute Global Moran's I.
from esda.moran import Moran
y = spatial_1['log_price'].values
moran = Moran(y, w)
print(moran.I, moran.p_sim)
```

```
0.6982137752916427 0.001
```

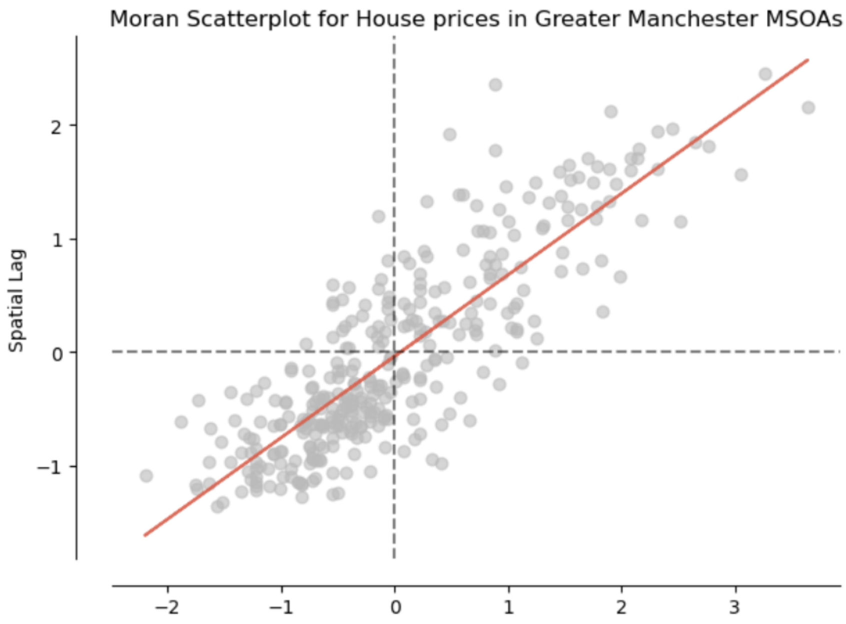
```
#Global Spatial Autocorrelation
#Compute Global Moran's I.
from esda.moran import Moran
from libpysal.weights import KNN
k_w = KNN.from_dataframe(spatial_1, k=5)
#convert to row-standardized weights (optional but recommended)
# This ensures the weights for each observation sum to 1
k_w.transform = 'r'
y = spatial_1['log_price'].values
#s_lag = k_w.sparse.dot(spatial_1("house_price_2021"))
moran = Moran(y, k_w)
print(moran.I, moran.p_sim)
```

```
0.7166997637505921 0.001
```

Source: Jupyter Notebook Analysis

Figure 8: Moran Scatter Plot showing the global spatial autocorrelation results

```python
import splot.esda as esdaplot
esdaplot.moran_scatterplot(moran)
plt.title("Moran Scatterplot for House prices in Greater Manchester MSOAs")
plt.show()
```



Source: Jupyter Notebook Analysis

4.8.4 LOCAL INDICATORS OF SPATIAL AUTOCORRELATION

Local indicators of Spatial autocorrelation (LISA) are statistical measures that show how house prices in each area relate to those of neighbouring areas, identifying localised clusters of similar values and spatial outliers within the region (See Equation 6)

Equation 6: Formula for calculating the Local Indicators of Spatial Autocorrelation (LISA)

```python
#Local Spatial Autocorrelation
#Identify clusters.
from esda.moran import Moran_Local
#FOR QUEEN
lisa = Moran_Local(y, w)
print(lisa)
```

```
<esda.moran.Moran_Local object at 0x00000144BC280E20>
```

```
[188]:
```

```python
#store results
spatial_1["lisa_I"] = lisa.Is
spatial_1["p_value"] = lisa.p_sim
spatial_1["quadrant"] = lisa.q
```

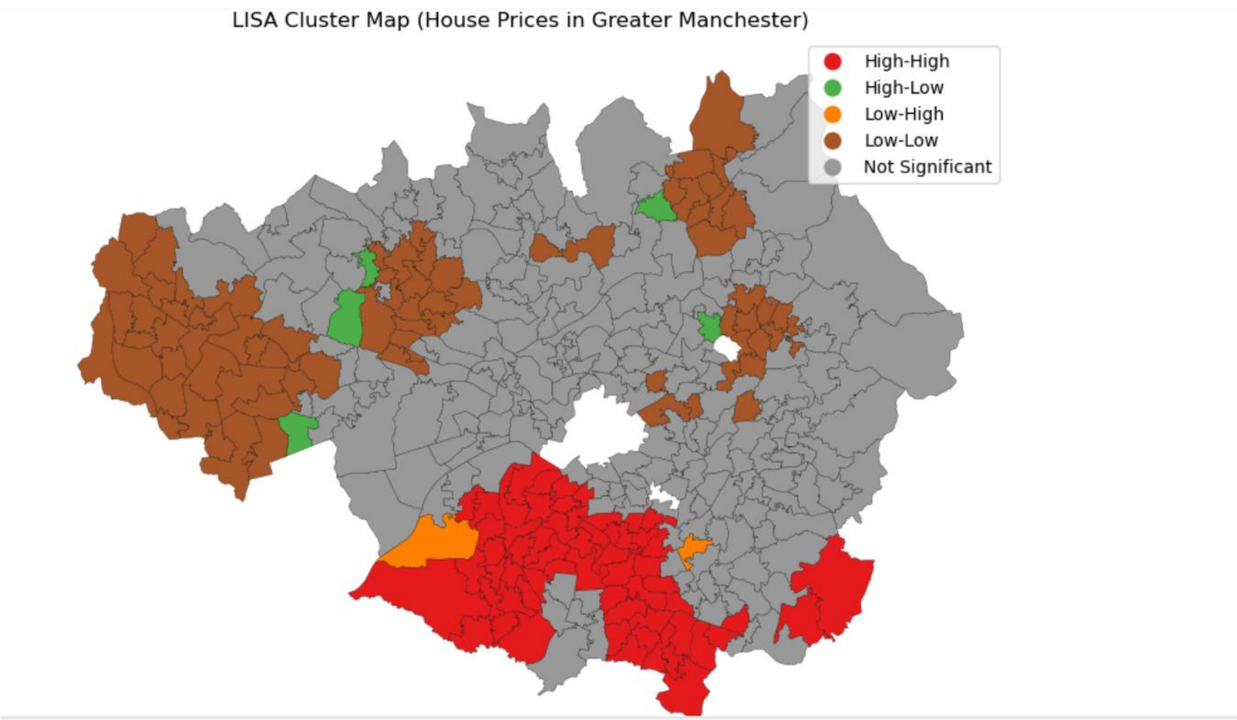
Source: Jupyter Notebook

Equation 7: *Formula for depicting (LISA) cluster map*

```
#Define House Price Clusters
spatial_1["cluster"] = "Not Significant"

sig = 0.05

spatial_1.loc[(spatial_1["quadrant"]==1) & (spatial_1["p_value"]<sig), "cluster"] = "High-High"
spatial_1.loc[(spatial_1["quadrant"]==2) & (spatial_1["p_value"]<sig), "cluster"] = "Low-High"
spatial_1.loc[(spatial_1["quadrant"]==3) & (spatial_1["p_value"]<sig), "cluster"] = "Low-Low"
spatial_1.loc[(spatial_1["quadrant"]==4) & (spatial_1["p_value"]<sig), "cluster"] = "High-Low"
```

```
#Plot LISA Map (House Prices)
import matplotlib.pyplot as plt

fig, ax = plt.subplots(1, figsize=(10,8))
spatial_1.plot(column="cluster",
          categorical=True,
          cmap="Set1",
          legend=True,
          edgecolor="black",
          linewidth=0.2,
          ax=ax)
ax.set_title("LISA Cluster Map (House Prices in Greater Manchester)")
ax.axis("off")
```

Figure 9: LISA cluster map for house prices in Greater Manchester



Source: Jupyter Notebook Analysis

4.8.5 INTERPRETATION OF THE SPATIAL AUTOCORRELATION RESULTS

From Equation 7 and Figure 9 above, local indications of spatial autocorrelation have been calculated and visualised. More details are provided in Appendices 3 to 5.

The analysis identified 60 Middle layer Super Output Areas (MSOAs) in Greater Manchester as hotspots, primarily located in prime areas with high house prices, clustered across three (3) boroughs. These are

- Trafford Borough: Includes Trafford Park, Gorse Hill, Firswood, and all MSOAs from Trafford 008 to Trafford 028
- Stockport Borough: Covers Heaton Moor, Heaton Mersey, Cheadle, Marple Bridge, Gatley North, Adswood, and all MSOAs from Stockport 028 to Stockport 042
- Manchester Borough: Encompasses Levenshulme Central, Fallowfield West, and Whalley Range South, and all MSOAs from Manchester 033 to Manchester 047.

Further details can be found in the Appendix

The results show degree of dispersion where by houses of low value are located in the same geographic area. According to the analysis, there are 74 MSOAs, mostly in the boroughs of Wigan, Rochdale, Oldham, and Bolton. There are some cold spots in Manchester located in Moston West and Newton Heath.

The analysis also identified 7 MSOAs exhibiting spatial outlier patterns, in which house prices stand in contrast to their surrounding zones.

- Low-High Outliers: Areas with low-priced houses situated within high-value zones were found in Partington(Trafford) and Heaton Norris(Stockport)
- High-Low Outliers: Conversely, areas with high-priced houses located in generally low-value zones include Over Hulton(Bolton), Chaddeton Central(Oldham), Springfield Park(Rochdale), and Leigh south (Wigan)

These spatial outliers provide important insights into localized market variations within Greater Manchester. Further details can be found in Appendix 6

5. CONCLUSION AND RECOMMENDATION.

This research has provided a comprehensive, data-driven exploration into the delineation of Housing Market Areas (HMAs) within Greater Manchester, leveraging advanced spatial analytics to move beyond traditional, administratively constrained models. By integrating contemporary big data, specifically house prices, rental values, and price-to-rent ratios- at fine spatial resolutions, this research has delivered meaningful insights into the evolving dynamic of the housing market and addressed the persistent challenge of defining functional market boundaries in a rapidly changing urban context.

Central to the findings is the confirmation of strong spatial dependence in housing outcomes across Greater Manchester. The application of Global Moran's I and Local Indicators of Spatial Autocorrelation (LISA) revealed significant clustering of high house prices and rents in core urban boroughs such as Manchester, Trafford, and Stockport, while outlying areas like Wigan, Oldham, Bolton, and Rochdale displayed lower values and greater heterogeneity. The identification of both high-high and low-low clusters, as well as spatial outliers, underscores the complexity and heterogeneity inherent in metropolitan housing markets- a reality that simple migration or commuting-based models often fail to capture.

A critical contribution of this research lies in its demonstration that contemporary spatial analysis, grounded in current, finely-grained data, outperforms the legacy approaches that rely on infrequent census updates and static administrative boundaries. The findings highlight that housing demand, supply, and affordability are spatially nuanced, and that market boundaries are best understood as fluid, responsive to both economic shifts and social change. In particular, the price-to-rent ratio emerges as a robust metric for distinguishing between owner-occupied and rental-dominated areas, providing policymakers with actionable intelligence for targeting interventions.

Moreover, this research reflects on the limitations of previous methodologies. While migration and commuting flows have historically informed HMA delineation, their relevance is now diminished by shifts in work patterns-especially the rise of remote work post-COVID-19- and the accelerating pace of urban change. This study argues persuasively for a methodological pivot: future housing market analysis should prioritize real-time housing indicators and spatial statistical techniques, supplemented by qualitative insights and evolving demographic trends.

In practical terms, the advanced spatial framework developed here equips urban planners, policy makers, and housing authorities with tools for more responsive, evidence-based decision-making. By pinpointing market hotspots, cold spots, and outliers, the framework enables targeted policy responses, whether to address affordability, guide new development, or manage population growth- thus supporting the broader objectives of sustainable, inclusive urban development as outlined by the United Nations.

Looking ahead, this dissertation advocates for the continued integration of emerging technologies such as machine learning and Internet of Things (IoT) data into housing market research. Future studies should pursue spatial-temporal modelling to capture the dynamic evolution of HMAs, ensuring that boundary definitions remain relevant amid ongoing urban, economic, and technological transformations Ultimately, the research underscores that only by embracing both spatial complexity and data-driven adaptability can we hope to create housing markets that are equitable, resilient, and fit for the 21st century.

6. REFERENCES

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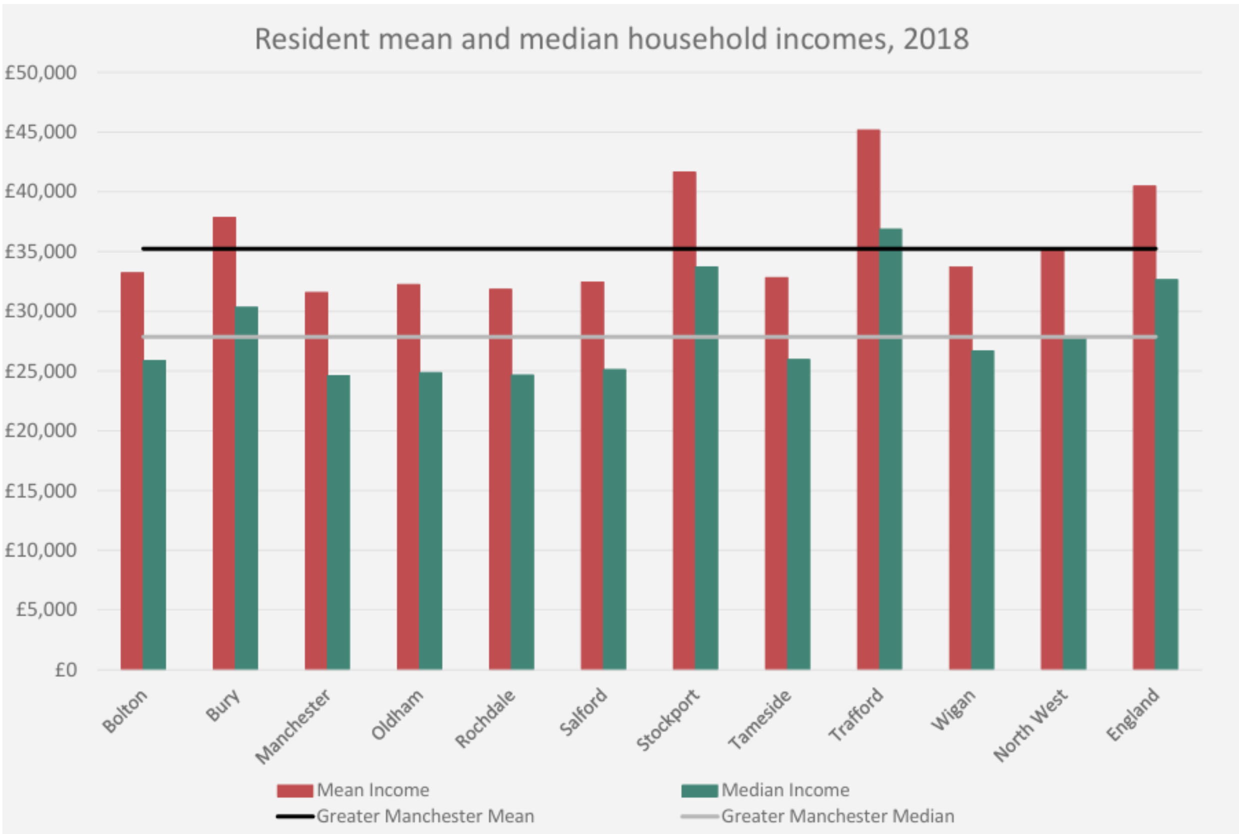
7. APPENDICES

Appendix 1*: Migration Statistics per 2021 Census across Greater Manchester Boroughs*

geography	**Bolton**	**Bury**	**Manchester**	**Oldham**	**Rochdale**	**Salford**	**Stockport**	**Tameside**	**Trafford**	**Wigan**
geography code	**E08000001**	**E08000002**	**E08000003**	**E08000004**	**E08000005**	**E08000006**	**E08000007**	**E08000008**	**E08000009**	**E08000010**
All usual residents(per 2021 census)	292420	191726	545356	239108	220985	266379	291590	228544	232669	325974
Address the same as a year ago	269720	177523	447364	222759	204136	227662	267289	212108	212379	300468
Migrant from student accomodation	498	298	12519	277	263	2561	535	232	633	360
Migrant from within the UK:	19935	12908	72814	14576	15131	32266	22314	15205	17528	23839
Migrant from outside the UK	2267	997	12659	1496	1455	3890	1452	999	2129	1307
	Percentage share of household migration status per Census 2021 in UK									
Address the same as a year ago	92.2%	92.6%	82.0%	93.2%	92.4%	85.5%	91.7%	92.8%	91.3%	92.2%
Migrant from student accomodation	0.2%	0.2%	2.3%	0.1%	0.1%	1.0%	0.2%	0.1%	0.3%	0.1%
Migrant from within the UK:	6.8%	6.7%	13.4%	6.1%	6.8%	12.1%	7.7%	6.7%	7.5%	7.3%
From outside the UK	0.8%	0.5%	2.3%	0.6%	0.7%	1.5%	0.5%	0.4%	0.9%	0.4%

Source: ONS Statistics, Census 2021

Appendix 2: *Household income distribution across Greater Manchester Boroughs*



Source: His Majesty's Land Registry(HMLR)

SPATIAL AUTOCORRELATION ANALYSIS RESULTS

Appendix 3: *Spatial Outliers (Low-High And High-Low) across Greater Manchester MSOAs*

Borough	MSOA21NM_y	Description	house_price_2021	log_price	lisa_I	p_value	quadrant	cluster
Stockport	Stockport 007	South Reddish & Heaton Norris	209995	12.254839	-0.05248	0.047	2	Low-High
Trafford	Trafford 017	Partington	205000	12.23076526	-0.16836	0.005	2	Low-High
Bolton	Bolton 018	Heaton & Deane	238625	12.38264856	-0.31147	0.005	4	High-Low
Bolton	Bolton 030	Over Hulton	227000	12.3327053	-0.13505	0.027	4	High-Low
Oldham	Oldham 017	Chadderton Central	229950	12.34561717	-0.15548	0.034	4	High-Low
Rochdale	Rochdale 011	Springfield Park	244500	12.40697059	-0.39725	0.005	4	High-Low
Wigan	Wigan 037	Leigh South	220000	12.30138283	-0.0693	0.016	4	High-Low

Appendix 4: *House prices time series per MSOA name*

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Bolton	Dunscar & Egerton	180000	190000	194000	200000	268000
Bolton	Doffcocker & Moss Bank	185000	208750	186000	215000	252000
Bolton	Bromley Cross & Bradshaw	160000	168725	184750	195000	249250
Bolton	Harwood	167000	177500	185000	189000	248750
Bolton	Eagley & Sharples	153000	167000	170000	175000	233000
Bolton	Over Hulton	150000	158000	180000	180000	230250
Bolton	Lostock & Ladybridge	146000	165000	151000	205000	228500
Bolton	Horwich East	151000	177000	170000	180000	227500
Bolton	Horwich South & Middlebrook	151000	176500	195950	194995	223000
Bolton	Smithills	135500	145000	157500	152500	220000
Bolton	Westhoughton East	151250	180000	171000	198500	219500
Bolton	Tonge	127000	127000	126750	147500	200005
Bolton	Astley Bridge & Waters Meeting	136475	141000	144625	168500	200000
Bolton	Kearsley & Stoneclough	125000	132000	137000	145000	200000
Bolton	Little Lever	136000	141500	155500	159000	200000
Bolton	Blackrod & Butterwick Fields	155250	165000	166000	160000	198000
Bolton	Heaton & Deane	186500	131750	188750	175000	195000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Bolton	Horwich North	148250	151000	170000	172000	194000
Bolton	Westhoughton Daisy Hill	128000	140500	142000	165000	191500
Bolton	Daubhill & Fernhill Gate	117000	145000	140000	147500	191000
Bolton	Breightmet South & Darcy Lever	125750	127500	139975	144370	186000
Bolton	Farnworth South	115000	130000	135000	141000	185000
Bolton	Rumworth North	120000	160000	0	0	180000
Bolton	Hall I' th' Wood	164995	169995	168995	131000	180000
Bolton	Westhoughton West	138500	137000	154000	172500	180000
Bolton	Highfield & New Bury	99999.5	107497	122995	125000	180000
Bolton	Harper Green	120000	125500	134950	145000	176250
Bolton	Farnworth North	122995	120000	126000	138000	170000
Bolton	Breightmet North	116500	115000	115000	121000	170000
Bolton	Burnden & Great Lever	145000	110000	132500	139000	167500
Bolton	Halliwell & Brownlow Fold	92500	0	125000	103250	150000
Bolton	Rumworth South	99000	110000	124000	0	150000
Bolton	Gilnow & Victory	142000	135000	150000	90000	144500
Bolton	Lever Edge	87000	102500	105000	110000	135000
Bolton	Central Bolton	0	0	0	110000	0
Bury	Sedgley Park	220000	245000	255000	255000	340000
Bury	Whitefield West & Park Lane	198750	207500	235000	262500	314500
Bury	Prestwich Central	212000	238000	221500	248499	293685
Bury	Kirkhams & Holyrood	193750	216000	222000	235000	291250
Bury	Summerseat	215000	230000	229995	287500	281700
Bury	Prestwich Clough & Rainsough	210600	223000	229000	237500	275500
Bury	Unsworth	181000	194000	219000	204000	275000
Bury	Prestwich East	190000	218725	207500	222000	270000
Bury	Elton Vale	175000	187000	196995	200000	260000
Bury	Besses	160000	172075	183000	190000	250000
Bury	Nuttall & Tottington	180000	220000	231500	307000	249995
Bury	Whitefield East	154000	177500	179500	192000	247500
Bury	Ramsbottom	180000	185000	192500	235000	240000
Bury	Ainsworth & Bradley Fold	156525	175000	166135	192500	235000
Bury	Whitehead Park	152750	155000	172500	177250	235000
Bury	Walshaw & Woolfold	154000	170000	176000	185000	232500
Bury	Walmersley & Limefield	154997	168750	170000	177500	222500
Bury	Redvales & Hollins	151250	153500	151500	152500	215000
Bury	Buckley Wells & Fishpool	135000	144975	140000	171225	196000
Bury	Black Lane	135000	136500	158875	161000	195000
Bury	Outwood Gate	133750	155000	152250	180000	185000
Bury	Higher Woodhill	128000	162500	160000	202000	183500

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP MSOA NAME	2017	2018	2019	2020	2022
Bury	Bank Top & Radcliffe Ees	132500	159000	154250	163500	183000
Bury	Radcliffe	146500	149950	142500	148750	174000
Bury	Fairfield & Jericho	128000	122500	137500	138000	173500
Bury	Fernhill & Pimhole	103750	106500	101000	131500	153000
Manchester	Withington East	510000	464000	465000	587375	566000
Manchester	East Didsbury	472500	446250	457500	459000	532000
Manchester	Withington North & Old Moat	435000	400000	469000	391000	500000
Manchester	West Didsbury	322500	428000	325000	355000	491250
Manchester	Burnage South	415000	414995	469995	380000	475000
Manchester	Levenshulme Central	350500	383750	388000	405000	440000
Manchester	Fallowfield West & Whalley Range South	305000	320000	360000	377100	440000
Manchester	Baguley West & Brooklands	272000	287000	297000	340000	385000
Manchester	Whalley Range North	191250	210000	232000	225000	367999
Manchester	Merseybank & Barlow Moor	250000	281000	263300	298500	366275
Manchester	Chorlton South	221000	198503	240000	238750	350250
Manchester	Withington West	218000	270000	267500	273000	335000
Manchester	Baguley East & Wythenshawe Park	220000	248725	251250	250500	330500
Manchester	Ladybarn	217250	224975	250000	270000	330500
Manchester	Levenshulme South & Burnage North	232500	237000	257500	275500	321500
Manchester	Benchill North & Sharston	216500	231250	227500	260000	320000
Manchester	Northern Moor	245000	276125	235000	288295	297500
Manchester	Fallowfield Central	202750	187475	218750	230000	280000
Manchester	Beech Road & Chorlton Meadows	193000	206000	212800	240000	280000
Manchester	Northenden	163000	187000	179500	191000	275000
Manchester	Hulme & University	185995	195995	250000	286995	272995
Manchester	Beswick, Eastlands & Openshaw Park	155000	229950	227472	238950	272500
Manchester	Cheetham Hill	219950	0	0	0	270997
Manchester	Didsbury Village	179950	193800	205250	220000	270500
Manchester	Crumpsall North & Heaton Park	169750	184950	204000	190000	263000
Manchester	Gorton South	172000	180000	0	0	250000
Manchester	City Centre North & Collyhurst	170750	182000	187000	253500	240000
Manchester	Benchill South & Wythenshawe Central	180000	175500	170000	200000	235000
Manchester	Chorlton North	160000	160000	184750	165000	228500
Manchester	Belle Vue & West Gorton	158500	181000	179250	203000	218500
Manchester	Woodhouse Park & Airport	135000	150000	151000	160000	218000
Manchester	New Moston	132500	143250	150000	155000	216000
Manchester	Wythenshawe East & Peel Hall	131000	140000	147500	175000	215000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Manchester	Piccadilly & Ancoats	150000	151500	164000	170000	215000
Manchester	Newall Green	157000	163000	159950	182000	210000
Manchester	Moss Side West	120000	135000	177750	162950	210000
Manchester	Openshaw & Gorton North	135000	197497	224995	150750	205000
Manchester	Ardwick	149500	165000	158995	193995	197500
Manchester	Moston West	133497	134000	137000	145000	196100
Manchester	Abbey Hey	169497	179995	202995	143750	195000
Manchester	Blackley	134950	146250	136000	151500	191000
Manchester	Newton Heath	111500	140000	138000	151975	190000
Manchester	Crumpsall South	156000	157000	150000	185000	190000
Manchester	Charlestown	125000	136055	138500	159000	190000
Manchester	Victoria Park & Longsight West	104000	121500	150000	153500	185000
Manchester	Clayton Vale	107000	117250	120975	137000	180150
Manchester	Castlefield & Deansgate	125150	117500	120000	0	180000
Manchester	Harpurhey South & Monsall	122625	117750	110000	145000	170500
Manchester	Boothroyden & Higher Blackley	108000	124000	133500	147475	170000
Manchester	Harpurhey North	134000	124000	136000	142000	162000
Manchester	New Islington South & Bradford	0	0	0	0	0
Manchester	Rusholme West & Moss Side East	0	0	0	0	0
Manchester	Miles Platting & New Islington North	0	0	0	0	0
Manchester	Strangeways	0	0	0	179950	0
Manchester	University North & Whitworth Street	0	0	0	0	0
Manchester	Hulme Park & St George's	0	0	0	0	0
Manchester	Rusholme East	176750	0	0	0	0
Oldham	Diggle, Delph & Denshaw	272500	272497	234000	279995	362500
Oldham	Greenfield & Uppermill	247500	250000	268500	299500	300000
Oldham	Springhead & Grasscroft	167000	220000	220000	242500	294000
Oldham	New Delph, Dobcross & Austerlands	218500	230000	246000	250000	257000
Oldham	Chadderton North	156000	160000	160000	157250	252500
Oldham	Lees & Hey	160000	170000	167425	189995	250000
Oldham	Royton North	153000	152500	180975	182000	246500
Oldham	Holt Lane End & Bardsley	140000	154950	166000	186000	235000
Oldham	Royton South East	146500	155000	155000	178750	224395
Oldham	Middleton Junction	161500	160000	165000	175500	222000
Oldham	Clough & Shaw Side	158950	167000	182000	172500	220000
Oldham	Shaw & Crompton	142000	155000	166725	170000	217500
Oldham	Failsworth South	136000	155000	155500	162500	214950

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Oldham	Chadderton South West	127500	134000	132500	165000	214500
Oldham	Chadderton Central	143000	141750	166000	190000	210000
Oldham	Failsworth East	136500	144000	145000	160000	210000
Oldham	Royton East & Cowlishaw	152000	150000	154975	169950	195975
Oldham	Salem	107000	118000	125250	138000	195000
Oldham	Lime Side & Garden Suburb	132000	141995	148497	159000	193000
Oldham	Royton South West	153000	153500	162475	167750	193000
Oldham	Wood End	133000	148000	143000	172475	190000
Oldham	Moorside & Sholver	139500	137975	140000	162000	190000
Oldham	Waterhead	133750	120000	140000	144000	189975
Oldham	Failsworth West	115000	170000	185000	199997	189250
Oldham	Werneth	148200	160000	145000	175000	187475
Oldham	Derker	97500	106500	121000	130000	180000
Oldham	Oldham Town North	85000	98000	88000	110000	179950
Oldham	Alt	124995	135000	115000	129750	175000
Oldham	Busk	105000	102000	135000	119500	170000
Oldham	Hathershaw	95000	93000	115000	120000	162000
Oldham	Oldham Town South	87500	169000	0	138500	0
Oldham	Chadderton South East	91475	123000	120000	160975	0
Oldham	Alexandra Park	0	90000	0	99000	0
Rochdale	Springfield Park	188725	173000	184250	223500	281500
Rochdale	Alkrington	182500	200000	194000	227000	265000
Rochdale	Littleborough South & Smithy Bridge	155000	175000	175000	178000	227750
Rochdale	North Middleton & Stakehill	129950	133972	162000	171500	223995
Rochdale	Norden East & Bagslate Moor	154000	165500	175000	185000	222500
Rochdale	Langley & Wood Side	126995	146995	156995	186995	219995
Rochdale	Heywood Hopwood & Siddal Moor	145000	165000	163000	165000	215000
Rochdale	Hooley Bridge & Norden West	142000	144500	160000	174250	212500
Rochdale	Littleborough North & Calderbook	166500	164500	182750	165000	210750
Rochdale	Heywood Town	118500	132500	144995	148995	210250
Rochdale	Milnrow East & Newhey	147000	145000	131000	177500	205000
Rochdale	Littleborough West & Wardle	144000	135000	153000	167500	205000
Rochdale	Heywood Heap Bridge & Darnhill	134000	130000	151000	170000	201000
Rochdale	Middleton Town & Rhodes	156000	146375	172475	180000	200000
Rochdale	Milnrow West	130000	132500	145000	169000	195000
Rochdale	Balderstone & Kirkholt	137500	116995	121495	131995	185995
Rochdale	Healey, Syke & Shawclough	120000	140000	136000	137000	185000
Rochdale	Middleton East	119950	127250	135000	150000	180000
Rochdale	Castleton & Trub	126750	128500	142000	138000	170000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Rochdale	Hurstead & Smallbridge	98500	129000	127750	110000	170000
Rochdale	Spotland Bridge	131000	144000	170000	121000	166500
Rochdale	Deeplish	130000	106500	123500	0	157500
Rochdale	Kingsway	130000	105000	120000	123000	157500
Rochdale	Central Rochdale & Mandale Park	95750	137500	114500	128500	154000
Rochdale	Wardleworth & Newbold Brow	84000	89975	120000	115000	140000
Salford	Broughton Park	319150	382500	520000	418750	474500
Salford	Weaste & Seedley	234995	219995	254997	334995	376000
Salford	Worsley	250000	255501	284750	285000	369500
Salford	Ellenbrook & Boothstown	193000	215000	249995	260000	295000
Salford	Cromwell Road & Broad Street	185000	238000	210000	211500	287000
Salford	Winton & Westwood	170000	200000	205500	228500	283500
Salford	Kersal Dale	180500	189500	195000	191000	282500
Salford	Walkden South	195000	214995	185000	207500	277000
Salford	Pendleton	158600	197250	175000	178000	270000
Salford	Langworthy Buile Hill	167000	230000	229995	263000	270000
Salford	Swinton South East & Pendlebury West	170000	182000	197000	200000	265000
Salford	Swinton Worsley Road	155000	152000	186000	215000	260000
Salford	Eccles	162500	185000	185000	205000	245000
Salford	Little Hulton South	141250	102750	150000	154000	242250
Salford	Lower Irlam & Cadishead	160250	167250	166000	173000	237500
Salford	Swinton Newtown	143000	153000	161250	175000	230000
Salford	Greengate & Blackfriars	142000	160000	163500	179000	217500
Salford	Swinton West	146250	155000	164997	184500	215000
Salford	Broughton East	0	154600	173000	173125	215000
Salford	Patricroft	137475	140000	157000	165750	215000
Salford	Broughton West	145000	163000	167500	176500	215000
Salford	Clifton	146000	145500	160000	174250	213000
Salford	Lightoaks	135497	174995	192995	209495	213000
Salford	Walkden North East	191500	147475	176000	224995	210000
Salford	Peel Green	146000	160000	159215	180000	208750
Salford	Clifton Green & Pendlebury East	135550	145000	169000	155000	203000
Salford	Higher Irlam	142500	145000	162375	247995	200000
Salford	Little Hulton North	106000	118500	116000	125000	164000
Salford	Walkden North West	110000	115000	115500	132000	160500
Salford	Barton upon Irwell	161995	0	0	0	0
Stockport	Marple Bridge & Mellor	361250	325000	341000	455000	554999
Stockport	Heaton Moor	313775	431500	409810	418000	498000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Stockport	Bramhall North West	372000	301950	372000	330000	482750
Stockport	Bramhall South & Woodford	385000	362000	380000	400000	439995
Stockport	Bramhall West	321000	335000	342000	385000	429715
Stockport	Cheadle Hulme South East	280000	300000	300000	320875	429000
Stockport	Cheadle Hulme West	256000	268975	350000	322500	417500
Stockport	Heaton Chapel & Shaw Road	339500	380000	425000	427777	408000
Stockport	Heaton Mersey	295000	323750	312500	330000	405000
Stockport	Gatley North	275000	299500	320000	324500	390000
Stockport	Cheadle Hulme Orrishmere	289500	310000	308000	326225	380000
Stockport	Norris Bank	277500	315500	283750	324500	377625
Stockport	Hazel Grove East & South	274000	292000	279975	294250	365000
Stockport	Gatley South & Cheadle West	255000	225950	310000	305000	362500
Stockport	Romiley & Compstall	187500	266000	260000	285000	355000
Stockport	Marple & Hawk Green	225000	227500	250000	270000	348000
Stockport	Heald Green West	246000	273750	260000	276250	344500
Stockport	High Lane	249950	262500	256000	275000	336000
Stockport	Heald Green East	241250	250000	250000	261000	335000
Stockport	Marple & Rose Hill	242500	258000	281000	285000	323750
Stockport	Bramhall North East	260000	240000	262500	295000	312500
Stockport	Hazel Grove West	238500	237000	243000	255000	310000
Stockport	Central Reddish	215000	230000	249500	260000	300000
Stockport	Woodsmoor & Mile End	257997	242000	265000	282500	300000
Stockport	Woodley	199950	235000	214900	228975	300000
Stockport	Cheadle East	207500	213750	228000	245000	299500
Stockport	Offerton West	211250	207750	230000	249975	285314
Stockport	Davenport	179975	191900	190000	217500	272000
Stockport	Cheadle Heath	180000	196000	208075	215750	268250
Stockport	Woodbank Park	165000	175000	195000	200000	261000
Stockport	Bredbury Green	181750	195000	200000	220000	261000
Stockport	Hazel Grove North	189725	197000	193750	220000	253000
Stockport	Heaviley	167000	180000	187500	197500	250000
Stockport	Offerton East & Bosden Farm	186000	220000	230000	222675	250000
Stockport	South Reddish & Heaton Norris	185000	169640	185000	202500	249000
Stockport	Bredbury	156000	164000	172000	187000	240000
Stockport	Reddish Vale View	155000	167250	168000	185000	236053
Stockport	Edgeley	157600	159650	220000	193750	233250
Stockport	Adswood	162997	185000	201497	195000	230000
Stockport	Central Stockport, Portwood & Shaw Heath	140000	151300	157000	165000	215000
Stockport	North Reddish	130500	155950	152000	165000	212550
Stockport	Brinnington	147500	162995	188995	202495	210000
Tameside	Stalybridge South	190000	203500	204000	228750	270000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Tameside	Cheetham Fold & Gee Cross	180000	190000	207000	197000	260000
Tameside	Dane Bank	167000	178975	185000	200000	255500
Tameside	Audenshaw	192000	194500	186750	200000	255400
Tameside	Mossley	167000	182500	237750	265000	253000
Tameside	Godley	160000	184950	168250	183000	246000
Tameside	Dukinfield East & Hough Hill	157000	177000	187500	189350	240000
Tameside	Carrbrook & Micklehurst	160000	165000	166250	190000	235500
Tameside	Hurst Cross	137500	150000	161250	147500	235000
Tameside	Ashton North	156000	162000	182750	167500	235000
Tameside	Dukinfield West	153750	158500	165000	183750	235000
Tameside	Denton West	147250	160000	160000	167500	230000
Tameside	Droylsden East	155000	150000	165000	165000	229400
Tameside	Mottram, Hollingworth & Broadbottom	195000	167525	178750	167500	228500
Tameside	Stalybridge East & Swineshaw	153000	152500	155000	165000	222000
Tameside	Denton South	149000	166250	175000	185500	220000
Tameside	Hyde North	168500	170750	189995	194995	216500
Tameside	Ashton East	194995	180000	185000	178500	213000
Tameside	Ashton Waterloo	133000	137500	146750	145000	210000
Tameside	Droylsden West	128000	137500	137500	152000	210000
Tameside	Denton East	141250	147000	143000	160250	208500
Tameside	Denton North	150000	155500	157000	168750	208000
Tameside	Newtonmoor	127000	148000	155000	155000	207750
Tameside	Hyde South	155250	165000	175750	165000	206000
Tameside	Guide Bridge	150000	200000	176000	208500	204000
Tameside	Smallshaw	123750	127000	132500	144000	200000
Tameside	Droylsden Central	130000	135000	155000	153000	197000
Tameside	Stalybridge North	145000	120000	138750	158000	177000
Tameside	Ashton Central	113500	115000	102500	156000	175000
Tameside	Hattersley	140495	143495	154995	167500	174495
Trafford	Bowdon	610000	872500	548000	855000	795000
Trafford	Hale	520000	636000	535000	626250	747500
Trafford	Sale Central	470000	388000	450000	434520	534000
Trafford	Hale Barns	407500	332500	372500	435000	526500
Trafford	Altrincham West, Dunham & Warburton	351253	339875	355875	340000	512750
Trafford	Sale North	349000	345000	370000	350500	492500
Trafford	Timperley South	337250	350000	365000	440000	490000
Trafford	Timperley North	327000	341000	345000	376500	471000
Trafford	West Timperley	325000	341000	350000	372000	461750
Trafford	Ashton upon Mersey South	310250	330000	338750	382500	435000
Trafford	Sale East	300000	304000	347000	349250	432250
Trafford	Altrincham East	306750	338406	312500	330000	426250

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Trafford	Urmston East	247500	279125	388000	333500	410000
Trafford	Ashton upon Mersey North	265000	285000	303750	305000	385000
Trafford	Sale Moor	262000	270000	265000	297500	375000
Trafford	Firswood	275000	280400	317000	311500	362000
Trafford	Davyhulme	235000	262500	252500	292500	357500
Trafford	Stretford East	234500	270000	302500	271000	355600
Trafford	Urmston West	265000	282000	285000	295000	350000
Trafford	Broadheath & Firsway	203500	230050	232500	260000	335000
Trafford	Timperley East	235000	277000	280000	278750	333100
Trafford	Flixton & Moorside	214250	233500	245000	259500	315250
Trafford	Trafford Park East & Sevenways	218000	234000	227450	265000	312000
Trafford	Trafford Park West & Kingsway Park	220500	235000	268500	270000	310000
Trafford	Lostock & Stretford Meadows	203625	225000	240000	223500	306000
Trafford	Gorse Hill	200000	215000	217000	245000	281875
Trafford	Partington	150000	170000	182500	185000	239000
Trafford	Old Trafford	0	0	0	0	0
Wigan	Leigh South	165000	174250	187500	215000	240000
Wigan	Tyldesley South	152250	160000	157500	165000	235000
Wigan	Lowton	149950	174950	179995	179972	229972
Wigan	Astley, Blackmoor & Mosley Common	165000	177000	188750	191000	229500
Wigan	Lowton Common	136000	147995	160000	174995	226000
Wigan	Leigh Central	136250	134000	125000	124750	212500
Wigan	Standish South	157882	165997	165997	169747	210000
Wigan	Atherton South East & Tyldesley West	145000	150247	145500	172500	209950
Wigan	Wigan Marylebone & Bottling Wood	154250	164000	174500	174000	205000
Wigan	Atherton South West	138250	175995	153000	152500	205000
Wigan	Orrell & Longshaw	160000	160000	165000	170000	205000
Wigan	Leigh East & Higher Folds	138000	152000	155995	159000	205000
Wigan	Leigh South East	131000	160000	157000	167125	205000
Wigan	Standish North	155000	169975	179000	180000	204380
Wigan	Shevington	150750	155000	165000	160000	201000
Wigan	Tyldesley North	131000	155000	160500	172000	200000
Wigan	Ashton-in-Makerfield North	130000	143000	155000	174500	191497
Wigan	Winstanley	138000	140000	148500	150000	191000
Wigan	Wigan Central	140500	135995	157475	157500	190000
Wigan	Aspull & Red Rock	143000	140000	143500	161000	189875
Wigan	Worsley Mesnes & Hawkley	132000	125000	140000	150000	176000
Wigan	Hindley West	127000	141000	132500	141000	176000

BOROUGH	HOUSE PRICE TREND IN GREATER MANCHESTER MSOAs IN GBP					
	MSOA NAME	2017	2018	2019	2020	2022
Wigan	Hindley Green	130500	140000	158995	149950	175000
Wigan	New Springs	107000	127000	131250	163500	175000
Wigan	Ashton-in-Makerfield West	128500	135000	140000	136997	175000
Wigan	Hindley East	112250	132500	128000	133475	174800
Wigan	Leigh North	104950	109975	117000	153000	172325
Wigan	Wigan East	121500	121000	126000	125000	172000
Wigan	Golborne	120000	125000	125500	130000	171500
Wigan	Ashton-in-Makerfield East	128000	127750	140000	140000	170955
Wigan	Atherton North	131000	119475	127500	147500	169000
Wigan	Pemberton North	115000	130000	124400	133500	164500
Wigan	Beech Hill	121000	130000	126000	139995	157500
Wigan	Pemberton South	115000	116000	113000	133000	156000
Wigan	Abram & Bickershaw	107000	120000	150000	126250	155500
Wigan	Platt Bridge & Spring View	105000	120500	119972	113995	155000
Wigan	Leigh West	96000	142500	147000	135000	151500
Wigan	Wigan South	115000	123995	125000	122475	145500
Wigan	Ince-in-Makerfield	90000	97500	100000	111000	135250
Wigan	Laithwaite & Marsh Green	78000	82500	93250	100000	127000

Source:

Appendix 5: House price-to-rent ratio per postcode District

GM_CODE	GM_Name	Row Labels	NAME	House price	Rent price	house/rent price ratio
E08000002	Bury	BL0	Ramsbottom	261,914	928.0	23.52
E08000002	Bury	BL0	Shuttleworth	261,914	928.0	23.52
E08000002	Bury	BL0	Stubbins	261,914	928.0	23.52

E080 0000 1	Bolton	BL1	Astley Bridge	236 ,21 3	828 .0	23.77
E080 0000 1	Bolton	BL1	Eagley	236 ,21 3	828 .0	23.77
E080 0000 1	Bolton	BL1 BL11 BL78	Bolton	236 ,21 3	828 .0	23.77
E080 0000 2	Bury	BL2	Ainswort h	219 ,13 7	871 .0	20.97
E080 0000 2	Bury	BL2	Bradsha w	219 ,13 7	871 .0	20.97
E080 0000 2	Bury	BL2	Harwood	219 ,13 7	871 .0	20.97
E080 0000 1	Bolton	BL3	Daubhill	204 ,22 8	780 .0	21.82
E080 0000 1	Bolton	BL3	Little Lever	204 ,22 8	780 .0	21.82
E080 0000 1	Bolton	BL4	Farnwort h	186 ,56 7	875 .0	17.77
E080 0000 1	Bolton	BL4	Kearsley	186 ,56 7	875 .0	17.77
E080 0000 1	Bolton	BL5	Westhou ghton	210 ,05 3	804 .0	21.77

E08000001	Bolton	BL5	Wingates	210,053	804.0	21.77
E08000001	Bolton	BL6	Blackrod	232,912	826.0	23.50
E08000001	Bolton	BL6	Horwich	232,912	826.0	23.50
E08000002	Bury	BL7	Chapeltown	295,500	954.0	25.81
E08000002	Bury	BL7	Egerton	295,500	954.0	25.81
E08000002	Bury	BL7	Toppings	295,500	954.0	25.81
E08000002	Bury	BL7	Turton Bottoms	295,500	954.0	25.81
E08000002	Bury	BL8	Greenmount	251,176	944.0	22.17
E08000002	Bury	BL8	Tottington	251,176	944.0	22.17
E08000002	Bury	BL9	E08000002	248,028	804.0	25.71
E08000002	Bury	BL9	Fishpool	248,028	804.0	25.71

E08000002	Bury	BL9	Hollins	248,028	804.0	25.71
E08000002	Bury	BL9	Limefield	248,028	804.0	25.71
E08000002	Bury	BL9	Summerseat	248,028	804.0	25.71
E08000002	Bury	BL9	Walmersley	248,028	804.0	25.71
E08000003	Manchester	M1 M11 M14 M15 M16 M2 M3 M4 M40 M60 M61 M99	Manchester	212,295	1,039.0	17.03
E08000003	Manchester	M12	Levenshulme	226,375	1,195.0	15.79
E08000003	Manchester	M13	Rusholm	230,310	1,125.0	17.06
E08000003	Manchester	M17	Trafford Park		1,273.0	-
E08000003	Manchester	M18	Gorton	221,245	904.0	20.40
E08000003	Manchester	M19	Burnage	327,997	1,198.0	22.82
E08000003	Manchester	M20	DidsE08000002	457,317	1,275.0	29.89

E08000003	Manchester	M20	Withington	457,317	1,275.0	29.89
E08000003	Manchester	M21	Chorlton-Cum-Hardy	499,276	1,200.0	34.67
E08000003	Manchester	M22	Moss Nook	268,030	1,095.0	20.40
E08000003	Manchester	M23	Baguley	259,651	1,050.0	20.61
E08000005	Rochdale	M24	Birch	226,907	750.0	25.21
E08000005	Rochdale	M24	Middleton	226,907	750.0	25.21
E08000003	Manchester	M25	Prestwich	317,944	957.0	27.69
E08000003	Manchester	M26	Prestolee	214,393	876.0	20.40
E08000003	Manchester	M26	Radcliffe	214,393	876.0	20.40
E08000003	Manchester	M27	PendleE08000002	265,094	877.0	25.19
E08000003	Manchester	M27	Swinton	265,094	877.0	25.19

E08000003	Manchester	M28	Boothstown	296,178	950.0	25.98
E08000003	Manchester	M28	Walkden	296,178	950.0	25.98
E08000003	Manchester	M28	Worsley	296,178	950.0	25.98
E08000003	Manchester	M29	Astley Green	220,232	869.0	21.12
E08000003	Manchester	M29	Higher Green	220,232	869.0	21.12
E08000003	Manchester	M29	Tyldesley	220,232	869.0	21.12
E08000006	Salford	M30	Eccles	276,923	978.0	23.60
E08000008	Trafford	M31	Carrington	230,446	950.0	20.21
E08000009	Trafford	M31	Partington	230,446	950.0	20.21
E08000009	Trafford	M32	Stretford	314,294	1,075.0	24.36
E08000009	Trafford	M33	Ashton Upon Mersey	464,716	1,100.0	35.21

E08000009	Trafford	M33	Sale	464,716	1,100.0	35.21
E08000008	Tameside	M34	Audenshaw	241,712	821.0	24.53
E08000008	Tameside	M34	Denton	241,712	821.0	24.53
E08000008	Tameside	M34	Haughton Green	241,712	821.0	24.53
Oldham	Oldham	M35	Failsworth	214,975	1,000.0	17.91
E08000006	Salford	M38	Little Hulton	165,053	800.0	17.19
E08000009	Trafford	M41	Flixton	357,939	1,195.0	24.96
E08000009	Trafford	M41	Urmston	357,939	1,195.0	24.96
E08000008	Tameside	M43	Droylsden	220,967	1,000.0	18.41
E08000006	Salford	M44	Cadishead	233,799	815.0	23.91
E08000006	Salford	M44	Irlam	233,799	815.0	23.91

E08000002	Bury	M45	Whitefield	297,979	875.0	28.38
E08000010	Wigan	M46	Atherton	198,660	763.0	21.70
E08000006	Salford	M5 M50 M6	Salford	224,856	1,390.0	13.48
E08000006	Salford	M7	Broughton	331,015	1,120.0	24.63
E08000003	Manchester	M8	Cheetham Hill	230,205	1,371.0	13.99
Oldham	Oldham	OL1 OL95	Oldham	203,937	898.0	18.93
E08000005	Rochdale	OL10	Heywood	223,481	825.0	22.57
E08000005	Rochdale	OL11	Castleton	190,108	850.0	18.64
E08000005	Rochdale	OL11	Slattocks	190,108	850.0	18.64
E08000005	Rochdale	OL12	Broadley	185,591	798.0	19.38
E08000005	Rochdale	OL12	Cheesden	185,591	798.0	19.38

E080 0000 5	Rochdale	OL12	Healey	185 ,59 1	798 .0	19.38
E080 0000 5	Rochdale	OL12	Shawclo ugh	185 ,59 1	798 .0	19.38
E080 0000 5	Rochdale	OL12	Syke	185 ,59 1	798 .0	19.38
E080 0000 5	Rochdale	OL12	Wardle	185 ,59 1	798 .0	19.38
E080 0000 5	Rochdale	OL12	Wolsten holme	185 ,59 1	798 .0	19.38
E080 0000 5	Rochdale	OL15	Calderbr ook	228 ,64 1	800 .0	23.82
E080 0000 5	Rochdale	OL15	Clough	228 ,64 1	800 .0	23.82
E080 0000 5	Rochdale	OL15	Littlebor ough	228 ,64 1	800 .0	23.82
E080 0000 5	Rochdale	OL15	Summit	228 ,64 1	800 .0	23.82
E080 0000 5	Rochdale	OL16	Firgrove	190 ,59 8	878 .0	18.09
E080 0000 5	Rochdale	OL16	Milnrow	190 ,59 8	878 .0	18.09

E08000005	Rochdale	OL16	Newhey	190,598	878.0	18.09
E08000005	Rochdale	OL16	Rochdale	190,598	878.0	18.09
E08000005	Rochdale	OL16	Smallbridge	190,598	878.0	18.09
Oldham	Oldham	OL2	Crompton Fold	227,396	912.0	20.78
Oldham	Oldham	OL2	Heyside	227,396	912.0	20.78
Oldham	Oldham	OL2	Royton	227,396	912.0	20.78
Oldham	Oldham	OL2	Shaw	227,396	912.0	20.78
Oldham	Oldham	OL3	Bleak Hey Nook	375,767	967.0	32.38
Oldham	Oldham	OL3	Delph	375,767	967.0	32.38
Oldham	Oldham	OL3	Denshaw	375,767	967.0	32.38
Oldham	Oldham	OL3	Diggle	375,767	967.0	32.38

Oldham	Oldham	OL3	Greenfield	375,767	967.0	32.38
Oldham	Oldham	OL3	Uppermill	375,767	967.0	32.38
Oldham	Oldham	OL4	Grasscroft	228,712	875.0	21.78
Oldham	Oldham	OL4	Lees	228,712	875.0	21.78
Oldham	Oldham	OL4	Moorside	228,712	875.0	21.78
E08000008	Tameside	OL5	Micklehurst	255,104	725.0	29.32
E08000008	Tameside	OL5	Mossley	255,104	725.0	29.32
E08000008	Tameside	OL6	Hurst	233,428	825.0	23.58
E08000008	Tameside	OL7	Ashton-Under-Lyne	215,180	829.0	21.63
Oldham	Oldham	OL8	Bardsley	191,699	850.0	18.79
Oldham	Oldham	OL9	Chadderton	210,625	1,000.0	17.55

E08000007	Stockport	SK1 SK3	Stockport	244,797	850.0	24.00
E08000008	Tameside	SK14	Broadbottom	237,318	825.0	23.97
E08000008	Tameside	SK14	Chisworth	237,318	825.0	23.97
E08000008	Tameside	SK14	Gee Cross	237,318	825.0	23.97
E08000008	Tameside	SK14	Hadfield	237,318	825.0	23.97
E08000008	Tameside	SK14	Hollingworth	237,318	825.0	23.97
E08000008	Tameside	SK14	Hyde	237,318	825.0	23.97
E08000008	Tameside	SK14	Mottram In Longdendale	237,318	825.0	23.97
E08000008	Tameside	SK14	Newton	237,318	825.0	23.97
E08000008	Tameside	SK14	Tintwistle	237,318	825.0	23.97
E08000008	Tameside	SK15	Stalybridge	243,184	843.0	24.04

E08000008	Tameside	SK16	Dukinfield	227,774	823.0	23.06
E08000007	Stockport	SK2	Heaviley	301,602	1,100.0	22.85
E08000007	Stockport	SK2	Offerton	301,602	1,100.0	22.85
E08000007	Stockport	SK4	Heaton Moor	411,987	934.0	36.76
E08000007	Stockport	SK5	Reddish	239,178	950.0	20.98
E08000007	Stockport	SK6	BredE08000002	319,305	971.0	27.40
E08000007	Stockport	SK6	Compstall	319,305	971.0	27.40
E08000007	Stockport	SK6	Marple	319,305	971.0	27.40
E08000007	Stockport	SK6	Mellor	319,305	971.0	27.40
E08000007	Stockport	SK6	Romiley	319,305	971.0	27.40
E08000007	Stockport	SK7	Bramhall	386,342	1,173.0	27.45

E080 0000 7	Stockport	SK7	Hazel Grove	386 ,34 2	1,1 73. 0	27.45
E080 0000 7	Stockport	SK7	Woodfor d	386 ,34 2	1,1 73. 0	27.45
E080 0000 7	Stockport	SK8	Cheadle	376 ,97 9	1,0 75. 0	29.22
E080 0000 7	Stockport	SK8	Cheadle Hulme	376 ,97 9	1,0 75. 0	29.22
E080 0000 7	Stockport	SK8	Gatley	376 ,97 9	1,0 75. 0	29.22
E080 0000 7	Stockport	SK8	Heald Green	376 ,97 9	1,0 75. 0	29.22
E080 0000 9	Trafford	WA13	Warburt on	407 ,06 5	1,1 50. 0	29.50
E080 0000 9	Trafford	WA14	Altrincha m	604 ,97 5	1,5 15. 0	33.28
E080 0000 9	Trafford	WA14	Bowdon	604 ,97 5	1,5 15. 0	33.28
E080 0000 9	Trafford	WA14	Broadhe ath	604 ,97 5	1,5 15. 0	33.28
E080 0000 9	Trafford	WA14	Dunham Town	604 ,97 5	1,5 15. 0	33.28

E08000009	Trafford	WA15	Hale	576,676	1,412.0	34.03
E08000009	Trafford	WA15	Halebarns	576,676	1,412.0	34.03
E08000009	Trafford	WA15	Timperley	576,676	1,412.0	34.03
E08000010	Wigan	WA3	Golborne	232,400	802.0	24.15
E08000010	Wigan	WA3	Lowton	232,400	802.0	24.15
E08000010	Wigan	WN1	Marylebone	221,138	743.0	24.80
E08000010	Wigan	WN1	Wigan	221,138	743.0	24.80
E08000010	Wigan	WN2	Abram	180,062	677.0	22.16
E08000010	Wigan	WN2	Aspull	180,062	677.0	22.16
E08000010	Wigan	WN2	Bryn Gates	180,062	677.0	22.16
E08000010	Wigan	WN2	Haigh	180,062	677.0	22.16

E08000010	Wigan	WN2	Hindley	180,062	677.0	22.16
E08000010	Wigan	WN2	Hindley Green	180,062	677.0	22.16
E08000010	Wigan	WN2	Red Rock	180,062	677.0	22.16
E08000010	Wigan	WN3	Ince-In-Makerfield	182,531	917.0	16.59
E08000010	Wigan	WN4	Bryn	196,311	754.0	21.70
E08000010	Wigan	WN6	Shevington	208,662	750.0	23.18
E08000010	Wigan	WN6	Shevington Moor	208,662	750.0	23.18
E08000010	Wigan	WN6	Standish	208,662	750.0	23.18
E08000010	Wigan	WN6	Wrightington Bar	208,662	750.0	23.18
E08000010	Wigan	WN7	Lately Common	202,573	750.0	22.51
E08000010	Wigan	WN7	Leigh	202,573	750.0	22.51

E08000010	Wigan	WN7	Westleigh	202,573	750.0	22.51

Source: [Home.co.uk(website)]() accessed on 10th August 2023.

Appendix 6: Formulas for reading files in python files

```
msoa = gpd.read_file(r"C:/Users/christina.kibasi/Downloads/MSOA.json")
```

```
print(msoa)
```

```
       FID   MSOA21CD                  MSOA21NM MSOA21NMW   BNG_E   BNG_N  \
0        1  E02000001        City of London 001            532384  181355
1        2  E02000002  Barking and Dagenham 001            548267  189685
2        3  E02000003  Barking and Dagenham 002            548259  188520
3        4  E02000004  Barking and Dagenham 003            551004  186412
4        5  E02000005  Barking and Dagenham 004            548733  186824
...    ...        ...                       ...       ...     ...     ...
1995  1996  E02002089              Solihull 009            418785  283833
1996  1997  E02002090              Solihull 010            414036  283743
1997  1998  E02002091              Solihull 011            415867  282665
1998  1999  E02002092              Solihull 012            414151  282684
1999  2000  E02002093              Solihull 013            412656  281659
```

```python
hs= pd.read_excel(r"C:/Users/christina.kibasi/Downloads/hs.xlsx")
```

```python
hs
```

	B_CODE	Borough	MSOA21CD	MSOA21NM	Description	house_price_2021
0	E08000001	Bolton	E02000984	Bolton 001	Dunscar & Egerton	245000.0
1	E08000001	Bolton	E02000985	Bolton 002	Bromley Cross & Bradshaw	230000.0
2	E08000001	Bolton	E02000986	Bolton 003	Eagley & Sharples	202000.0
3	E08000001	Bolton	E02000987	Bolton 004	Horwich North	167750.0
4	E08000001	Bolton	E02000988	Bolton 005	Astley Bridge & Waters Meeting	179000.0
...	...	...	...	...	...	...
341	E08000010	Wigan	E02001322	Wigan 036	Ashton-in-Makerfield West	171000.0
342	E08000010	Wigan	E02001323	Wigan 037	Leigh South	220000.0
343	E08000010	Wigan	E02001324	Wigan 038	Golborne	144000.0
344	E08000010	Wigan	E02001325	Wigan 039	Lowton	208975.0
345	E08000010	Wigan	E02001326	Wigan 040	Lowton Common	185000.0

Appendix 7: Formulas *for pre-processing(Filtering Greater Manchester boroughs).*

```python
# Joining the dataset
spatial = gm2.merge(hs, on ="MSOA21CD", how="left")
```

```python
spatial
```

	MSOA21CD	MSOA21NM_x	LAT	LONG	geometry	B_CODE	Borough	MSOA21NM_y	Description	house_price_2021
0	E02000984	Bolton 001	53.62436	-2.44756	POLYGON ((-2.4383 53.64579, -2.43265 53.64138,...	E08000001	Bolton	Bolton 001	Dunscar & Egerton	245000.0
1	E02000985	Bolton 002	53.61288	-2.40702	POLYGON ((-2.40426 53.62389, -2.40442 53.62291...	E08000001	Bolton	Bolton 002	Bromley Cross & Bradshaw	230000.0
2	E02000986	Bolton 003	53.61040	-2.42885	POLYGON ((-2.41996 53.61785, -2.41948	E08000001	Bolton	Bolton 003	Eagley & Sharples	202000.0

```
spa = msoa[["MSOA21CD","MSOA21NM", "LAT","LONG","geometry"]]
```

```
spa
```

	MSOA21CD	MSOA21NM	LAT	LONG	geometry
0	E02000001	City of London 001	51.51562	-0.093490	POLYGON ((-0.09676 51.52325, -0.09644 51.52282...
1	E02000002	Barking and Dagenham 001	51.58652	0.138756	POLYGON ((0.14811 51.59678, 0.14809 51.5964, 0...
2	E02000003	Barking and Dagenham 002	51.57606	0.138149	POLYGON ((0.15065 51.58306, 0.14841 51.58075, ...
3	E02000004	Barking and Dagenham 003	51.55639	0.176828	POLYGON ((0.18511 51.5648, 0.18403 51.56391, 0...
4	E02000005	Barking and Dagenham 004	51.56069	0.144267	POLYGON ((0.14991 51.56807, 0.15078 51.56778, ...
...	...	...	...	...	...
1995	E02002089	Solihull 009	52.45215	-1.725000	POLYGON ((-1.71082 52.47167, -1.70986 52.46643...
1996	E02002090	Solihull 010	52.45148	-1.794890	POLYGON ((-1.7975 52.45672, -1.79565 52.45512,...

```
spatial_1.isnull().sum()
```

```
MSOA21CD           0
MSOA21NM_x         0
LAT                0
LONG               0
geometry           0
B_CODE             0
Borough            0
MSOA21NM_y         0
Description        0
house_price_2021   0
dtype: int64
```

```
# Plotting
#spatial_1.plot(column='house_price_2021', figsize=(10, 10), legend=True)
```

```
#spatial["house_price_2021"].astype(float)
```

```
spatial_1["house_price_2021"] = pd.to_numeric(spatial_1["house_price_2021"],errors= "coerce")
```

```
spatial_1.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 333 entries, 0 to 332
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   MSOA21CD          333 non-null    object
 1   MSOA21NM_x        333 non-null    object
 2   LAT               333 non-null    float64
 3   LONG              333 non-null    float64
```

Source: Jupyter Notebook Analysis

Link: [gm authorities]

```
gm2= spa.loc[(
((spa["MSOA21CD"]>="E02000984") & (spa["MSOA21CD"] <= "E02001326"))|
((spa["MSOA21CD"]>="E02006912") & (spa["MSOA21CD"] <= "E02006917"))|
((spa["MSOA21CD"]>="E02006983") & (spa["MSOA21CD"] <= "E02006986"))|
((spa["MSOA21CD"]>="E02006957") & (spa["MSOA21CD"] <= "E02006963"))|
((spa["MSOA21CD"]>="E02007000") & (spa["MSOA21CD"] <= "E02007001"))|
((spa["MSOA21CD"]=="E02006902"))
)]
```

```
gm2
```

	MSOA21CD	MSOA21NM	LAT	LONG	geometry
932	E02000984	Bolton 001	53.62436	-2.44756	POLYGON ((-2.4383 53.64579, -2.43265 53.64138,...
933	E02000985	Bolton 002	53.61288	-2.40702	POLYGON ((-2.40426 53.62389, -2.40442 53.62291...
934	E02000986	Bolton 003	53.61040	-2.42885	POLYGON ((-2.41996 53.61785, -2.41948 53.61715...
935	E02000987	Bolton 004	53.60166	-2.54749	POLYGON ((-2.54115 53.61025, -2.54051 53.60875...
936	E02000988	Bolton 005	53.59950	-2.43418	POLYGON ((-2.44638 53.60886, -2.44235 53.60853...
...	...	...	...	...	...
1260	E02001322	Wigan 036	53.48609	-2.64182	POLYGON ((-2.65169 53.49657, -2.65158 53.49635...
1261	E02001323	Wigan 037	53.48438	-2.52544	POLYGON ((-2.51695 53.49317, -2.51448 53.49275...
1262	E02001324	Wigan 038	53.47895	-2.59728	POLYGON ((-2.59645 53.48959, -2.59508 53.48379...

Source: Jupyter notebook Analysis