Planes, prices, and pay: Contributions to the economics of the public sector and public infrastructure

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Abstract

The public sector and public infrastructure are essential components of a well-functioning society and economy, improving quality of life for citizens, supporting economic growth, and promoting equality. Thus, this thesis focuses on investigating whether the public sector and public infrastructure play a positive role in improving social welfare as the governments planned, drawing on evidence from China and the UK.

Chapter 2 explores the wage inequality between the public and private sectors in China from 2002 to 2013. This chapter finds that the effect of the public sector on wage is diminishing, and the evolution of the wage inequality between sectors can be largely attributed to the increasing significance of the differences in individual characteristics rather than the wage structure effect. This implies that the public sector had lost its previously absolute dominance in the labour market, which, to some extent, enhanced work productivity, fostered social equality, and promoted economic growth in China.

Governments often construct new public infrastructure to improve local economic and accelerate urbanization. Chapter 3 and 4 apply a case study of Doncaster Sheffield Airport to estimate the price of a public infrastructure on local economy. Chapter 3 suggests that the announcement effect of a new airport resulted a significant decline in regional property prices. Chapter 4 indicates the commercial airport plan could trigger a short-term decrease in neighbourhood house prices. The decreasing property price from both chapters shows that to nearby residents, the positive development benefits of an airport in terms of access and employment opportunities may not outweigh the negative impact, such as the cost of higher noise levels and congestion, etc.

This thesis highlights that the price of a poorly functioning public sector and public infrastructure cannot be ignored as an inefficient resource allocation can cause economic decline, reduce quality of life, and exacerbate social inequality.

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Chapter 1. Introduction

The public sector and public infrastructure are vital elements for guaranteeing the society and economy operate efficiently and contribute to improving the lives of citizens, fostering economic development, and advancing the principle of equality. The public sector, also known as the state sector, constitutes the segment of the economy encompassing public services and publicly owned enterprises. It encompasses a wide range of public goods and government-provided services, including the military, law enforcement, infrastructure development, public transportation, public education, healthcare, and the administrative personnel within the government, including elected officials (Public sector, 2023). Government agencies can also implement policies and programs aimed at reducing income inequality and promoting social justice. While the public sector serves critical functions, it also has drawbacks. Public sector entities may not be as efficient as their private sector counterparts (Bartel & Harrison, 2005; Miranda & Lerner, 2018). Additionally, the public sector's bureaucratic nature can slow down government processes, lead to delays and inefficiencies in service delivery, thereby reducing overall efficiency and responsiveness to citizens' needs (Prendergast, 2003). In some instances, public sector organizations might function as monopolies or oligopolies, limiting competition, which can, in turn, drive up prices, compromise quality, and reduce consumer choice.

Investments in public infrastructure are considered long-term assets that provide lasting benefits to society (Leduc & Wilson, 2013). It is often a key responsibility of governments to plan, fund, and supervise the development and maintenance of public infrastructure. Public infrastructure, such as transportation networks and utilities, is fundamental to economic development (Immergluck, 1993). It facilitates the movement of goods and people, lowers transportation costs, and enhances market access, which, in turn, stimulates economic activity and job creation. Moreover, infrastructure investments can improve a country's global competitiveness (Stevans et al., 2012; Pereira & Pereira, 2020). Modern and efficient infrastructure systems make it more attractive to businesses, both domestic and international, by reducing operational costs and increasing productivity (Morrison & Schwartz, 1992). However, there can also negative impacts associated with it. For instance, poorly planned or managed infrastructure projects can result in wastage of resources and inefficiencies, contributing to higher costs and delayed timelines (Cook & Munnell, 1990). Some infrastructure projects, such as large-scale construction or transportation development, can have adverse effects on the environment, including habitat destruction, increased pollution, and energy consumption (e.g., Xue et al., 2015; Li, Deng et al., 2019). Additionally, infrastructure projects like transportation or urban development may lead to the displacement of communities and people from their homes or businesses, causing social disruption (Otsuki, 2019).

This thesis uses three empirical chapters to assess whether the public sector and public infrastructure play a positive role in reducing social inequality, stimulating economic growth, and promoting quality of life. Drawing on evidence from China and the UK, the study explores intriguing dynamics. China, being a one-party state in the midst of economic transition, provides a unique perspective, while the UK, as a developed country with a mature economic market, offers a complementary lens.

The first empirical chapter, Chapter 2, estimates the wage inequality between the public sector and the private sector in China. China previously adhered to a communist ideology, aimed to eliminate wage disparities, and establish a socio-economic system characterized by equality among all citizens (Goodman, 2014). In particular, in a communist society, the means of production are commonly owned, rather than being under private ownership, and employee wages are typically allocated according to principles of need and fair distribution, rather than being solely determined by their individual work contributions or skill levels. Due to a series of reforms to move from a communist to a market-based economy, there has been a gradual establishment of private ownership (Woo, 1999), resulting in a significant increase in wage inequality. One concern revolves around whether, in a market economy system, the Chinese labour market has completed its transition to a fully competitive environment (Cai et al., 2008). This underlines the need to investigate wage inequality in China, with a specific focus on the wage inequality between the public and private sectors. Such a study not only addresses the discrimination among wage gap determinants but also sheds light on whether the reform of the public sector, within the context of China's evolving market economy, contributes to greater social equality.

To conduct this analysis, I employ the Unconditional Quantile Regression (UQR) and Recentred Influence Function (RIF) decomposition approaches to assess wage difference between the public and private sectors. The data utilized in this study are sourced from the China Household Income Project (CHIP) survey, a highly regarded data repository in China. Specifically, this paper focuses exclusively on urban resident data from the years 2002, 2007, and 2013. The raw public-private wage premiums were decomposed into the endowment difference, which could be explained by the individual characteristics, and the unexplained part, representing the advantage of the public sector and the disadvantage of the private sector. The results of this study indicate that from 2002 to 2013, firstly, the unconditional average marginal effect of the public sector on wages is decreasing. Specifically, by 2013, it no longer provides a significant wage premium for low-income workers and, in fact, has a negative impact on the earnings of high-income workers. This suggests that, to some extent, the public sector no longer serves as a "protective umbrella" as it did in the past.

Secondly, the structure of urban wage inequality between the public and private sectors has evolved primarily due to the growing influence of endowment effects. This factor has become dominant, whereas the diminishing unexplained effects have less impact on low-income workers and have even constrained the salaries of high-income earners. In other words, the wage inequality between the public-private sectors were account to employees in the public sector possess a more significant advantage in terms of human capital compared to those in the private sector, rather than the discrimination between the sectors. These findings indicate significant progress in the Chinese labour market reform, with the public sector gradually losing its dominant position, and cultivating a more equitable employment environment. Whilst the findings also reveal that although discrimination in the private sector has significantly diminished, a notable proportion of highly educated individuals persist in choosing the public sector over the private sector. This preference endures, even though public sector salaries frequently fail to align with their skills or abilities. These results align with the conclusions drawn by Li, Meng et al. (2023). This is primarily because people still hold the belief that working in the public sector provides more job stability, additional benefits and improved working conditions, compared to the private sector (Li, Meng et al., 2023). Additionally, for high-income earners in the public sector, their advantages extend beyond their salary, often including various forms of influence and privileges (Li, Meng and Xiong, 2023). Furthermore, when breaking down the wage disparity between the public and private sectors into distinct wage determinants, it is found that attributes related to human capital, such as education level, tenure, and occupation, shows greater importance in explaining the wage premium, especially at the lower end of the wage distribution. Moreover, being male continues to significantly advance hourly wages. This indicates that achieving gender equality in the Chinese labour market remains a considerable challenge.

Having examined the role of reducing the public sector's influence in promoting social equality, the thesis then shifts its focus to another facet of the public infrastructure: assessing whether residents share the government's belief that public infrastructure contributes to enhance local economic conditions, accelerate urbanization, and improve the quality of life for residents. Chapter 3 and Chapter 4 therefore conduct a case study, which focuses on assessing the impacts of Doncaster Sheffield Airport on the local housing market.

The motivations are that airports as large public infrastructure, serve as incentives in enhancing the appeal of a metropolitan area to businesses. In particularly, superior air services promote trade and the growth of intercity economic clusters and contribute to the establishment of new businesses and job opportunities (Brueckner, 2003; McGraw 2020). Furthermore, the housing market is a significant indicator of local economy conditions. Although it may not provide a complete picture of the overall level of development, higher house prices in a region can be an indicator of some aspects of growth. For example, some regions with higher house prices may offer a better quality of life, with access to amenities, education, healthcare, and cultural opportunities (McDonald, 2012). This can make the area more attractive to residents and, in turn, drive up property values. Regions with a strong and diverse economy tend to attract businesses and a skilled workforce, which can contribute to higher house prices (Hwang & Quigley, 2006). However, high house prices alone do not guarantee a well-developed or prosperous economy. In some cases, high house prices may be a result of demand outpacing supply (Himmelberg et al., 2005), which can lead to affordability challenges for residents. Proximity to natural amenities like beaches, mountains, or lakes can also drive up house prices, even in less economically developed regions (Nilsson, 2014).

Doncaster Sheffield Airport, located in the Metropolitan Borough of Doncaster, South Yorkshire, England, formerly known as Robin Hood Airport Doncaster Sheffield, underwent a transformation from RAF Finningley, which was originally a station of the Royal Flying Corps (RFC) and later the Royal Air Force (RAF). Doncaster is the second-largest settlement in South Yorkshire after Sheffield, primarily centred around the coal and mining industry.

Chapter 3 titled "Does airport infrastructure boost the regional housing market?", assesses the announcement effect of this new airport on regional house market. The announcement effects are crucial because people (and thus housing markets) will start to react once opening plans are published instead of at the time of the airport's actual completion. This chapter uses the synthetic control methods initially advanced by Abadie & Gardeazabal (2003), subsequently refined by Abadie, Diamond, & Hainmueller (2010), further expanded by Abadie, Diamond, & Hainmueller (2015), and extended by Abadie (2021). In contrast to relying on the parallel trends assumption, the synthetic control method is a data-driven approach that involves the generation of a synthetic control unit within the pool of comparative units. This synthetic control unit is formulated by constructing a weighted average of control units, with the aim of closely matching the pre-treatment outcomes and covariates of the treated units (Abadie, 2021). To be more precise, before the intervention takes place, the synthetic control unit is replicated pre-intervention characteristics and outcome trajectories that closely align with those of the treated unit. The application of synthetic control methods, along with a series of placebo tests, consistently reveals compelling evidence of a substantial decrease in Doncaster house prices following the announcement of the Doncaster Sheffield Airport. Specifically, the Doncaster house prices experienced a notable decline of 30%, equivalent to approximately £15,000, while the transaction volume in Doncaster witnessed a noteworthy increase of 37.5%, representing a surge of around 150 deals. This implies that the development of transportation infrastructure in urbanized areas might not have the intended positive impact on the local property market and may not necessarily make Doncaster a more attractive place to reside. When house prices drop, homeowners typically experience a decline in their wealth. This can lead to a "wealth effect" where homeowners feel less financially secure and confident (Case & Quigley, 2008). As a result, they may be less inclined to spend money on goods and services, which can depress local businesses and dampen economic activity. Therefore, policymakers and investors should consider that public infrastructure, such as airports, may not function as an efficient catalyst for regional economic growth, particularly within the real estate sector.

According to conventional theories of household location, accessibility influences housing prices, as individuals residing nearer to transportation networks incur lower commuting costs to workplaces and would consequently invest more in such areas (Straszhem, 1987). Chapter 4 titled “The effects of Doncaster Sheffield Airport on the local property market”, continues to use Doncaster Sheffield Airport as a case study but the focus shifts from the regional property market to the airport’s neighbourhood housing market. Chapter 4 is concerned with three event effects of the airport on its surrounding house prices. The sequence of events involving the temporary closure of a former military airfield, its transformation into a commercial airport, and the new airport opening, may have intense impacts on the local community. It has left residents in a state of uncertainty regarding both the airport's future and the quality of life in their environment. These circumstances offer a unique opportunity to continually assess the influence of airport infrastructure on housing prices, serving as a measurement of the community's satisfaction with their quality of life with residing near a newly established transportation hub.

Specifically, the above three events divide the observations into four distinct groups: individuals residing near an active military airfield, those dwelling near a decommissioned airport, those anticipated to reside in the proximity of a forthcoming commercial airport, and those situated in the vicinity of an operational civic airport. This paper employs a comprehensive empirical strategy the Difference-in-Difference (DiD) and the panel event study approaches to estimate the variation in pre- and post-intervention housing prices within a 3km radius of Doncaster Sheffield Airport. The findings indicate that the opening of the airport has a notably adverse effect on property prices. To be more precise, properties within a 3km radius of Doncaster Sheffield Airport saw a 4.74% decline in value following the airport's opening, compared to homes situated 3-40km away. This decline in value extended to as much as 8.19% when compared to the remaining areas of Doncaster. On the other hand, the decommissioning of the RAF airfield has a marginal and statistically insignificant impact on the values of properties in the vicinity. Moreover, the introduction of the new airport plan appears to have a positive influence on nearby property prices, notwithstanding with less statistical significance. Furthermore, the panel event plots employed in this study offer a valuable visualization of how events unfolding over time influence the outcome variable for each entity within the panel. These plots unveil three distinct troughs in the trend of these data points, each coinciding with the timing of the interventions. This suggests that property values near airports tend to experience short-term declines each time residents are exposed to the prospect of living near an airport, regardless of whether the airport is currently operational or is expected to commence operations in the near future. In other words, every instance when residents become cognizant of their proximity to an airport, it results in an adverse effect on property prices. This consistent pattern supports the notion that residing near an airport has a detrimental impact on property values. This might be because a new airport can lead to uncertainty about how it will impact the local environment and quality of life. Buyers may be hesitant to invest in areas with such uncertainties, leading to price reductions. The noise pollution due to aircraft takeoffs and landings can make properties in close proximity to the airport less desirable, leading to lower demand and, consequently, lower property values, which are consistent with research on airport noise and house price (e.g., Zheng et al.,2020; Cohen & Coughlin, 2008; Lawson, 2021).

Prior studies have traditionally concentrated on the positive effects of the public sector and public infrastructure on economic progress and the enhancement of social welfare. In contrast, this thesis contributes by emphasizing the importance of the public sector and public infrastructure initiatives in the wider economy, shedding light on how such projects can lead to economic downturns, diminish the quality of life, and exacerbate social disparities.

Chapter 2. Public-private Sector wage inequality in China

2.1 Introduction

The public sector comprises service provider organizations, agencies, or units functioning at federal, state, and local levels within a country. This includes entities like agencies, public utilities, cooperatives, military departments, police departments, and others committed to delivering high-quality services to citizens (Arora, 2011). Public sector organizations operate across diverse fields, encompassing agriculture, engineering, pure sciences, construction, livestock, and healthcare. Despite their vital roles, public sector organizations face criticism for traits such as excessive bureaucracy, unwavering stability, inertia, staff resistance, rigid organizational structures, and a perceived lack of shared innovation goals (Maqdliyan & Setiawan, 2023; Tranfield, Denyer & Smart, 2003).

Ly (2023) point that especially within the public sector, it is imperative for organizations to address social, economic, and ecological concerns. For example, government agencies within the public sector are tasked with implementing policies and programs aimed at reducing income inequality and fostering social justice. Thus, it is crucial to establish a fair market and employment environment while ensuring efficiency, accountability, and transparency within the public sector. The evolution of the public sector is chiefly guided by entrepreneurial management and competition (Funko et al., 2023). To enhance the positive impact of public sector initiatives, it is essential to integrate the private sector, thereby establishing a competitive and equitable market.

Therefore, to explore whether the public sector contributes to social equality as anticipated by the government, this chapter endeavours to assess the wage disparity between the public and private sectors in China. Given that the public sector in China, wielding greater governmental authority, prevails and constitutes a significant portion of the economy.

Wage inequality is an important political and economic issue (Birdsall, 2001). Kuznets (2019) suggests that income inequality in developing countries surpasses that in advanced countries, and posits that this inequality may be on the rise. Compared with large numbers of studies using data from western countries about wage inequality (Martins & Pereira, 2004;

Hölscher, Perugini & Pompei, 2011; Freeman & Kate, 1994; and Kristal & Cohen, 2017), this kind of research in China is far from enough. One of the reasons is that China was a communist society and the ideal scenario in communist theory is to eliminate wage inequality and achieve an economic and social system of overall equality among the people. In communism, the means of production are commonly owned by the entire population, not privately. Wages in this system are typically determined by principles of need and equitable distribution rather than individual contributions or skills (Goodman, 2014). While this approach may address wage inequality to some degree, it did not lead to prosperity in China; instead, it resulted in widespread, equal poverty. As China is transitioning from a communist to market-based economy and the private ownership is starting from scratch and was gradually established, wage inequality has been increasing (Knight and Song, 2003), more so than in other developing countries. One core issue is that under a market economy system whether China's labour market has fully transitioned, allowing enterprises of different ownerships to operate in a fully competitive environment. This underscores the imperative to study wage inequality in China, with a particular emphasis on the wage inequality between the public and private sectors. This study not only delves into the discernment among determinants of the wage gap but also illuminates whether the restructuring of the public sector, amid China's evolving market economy, fosters increased social equality.

This paper measures the determinants of wage inequality and estimate the changes in wage structures between the public and private sectors in China. The study draws on data from the China Household Income Project (CHIP) survey, a well-recognized data source in China. The project gathered data in 1988, 1995, 2002, 2007, and 2013, comprising separate urban and rural samples from China's population. This paper specifically uses urban resident data from 2002 to 2013 due to limited data availability for the private sector in 1988 and 1995. More importantly, during this period, China ascended to become the world's second-largest economy, despite its GDP accounting for only 4% of the global economy in 2001 when China joined the World Trade Organization (WTO) (Lardy, 2004; Dobson, 2013; Morrison, 2008). Prior to the opening reform in 1978, China was closed and low-income characterized by the state's centralized allocation of labour and almost all workforces were employed by the state sectors (Chan, 2019; Tao 2006). Until 1997, the 'iron rice bowl', indicating secure employment within the public sector, was broken by the Stated-owned enterprises reform. This reform resulted in the layoffs of a substantial number of employees, compelling them to transition into the private sector (Brødsgaard and Li, 2013; Lin, Cai & Li, 1998). The rapid growth of the non-public sector changed the ownership structure of Chinese economy, which improved dramatically the efficiency and productivity of the whole economy, thereby boosting the labour market reform. Furthermore, after China joined the World Trade Organization (WTO) in December 2001, China's foreign trade expanded rapidly, and China became an attractive destination for Foreign Direct Investment (Hong, 2008; Fung, Lizaka & Tong, 2004). China underwent an industrial transformation, moving from labour-intensive industries to more technologically advanced sectors. It became known as the "world's factory" for manufacturing (Mees, 2016). Rapid urbanization occurred as millions of people moved from rural areas to cities in search of better job opportunities (Yang, 2013; Chaolin, Liya & Cook, 2012). Meanwhile, Chinese higher education started rapid expansion which delivered a high-quality workforce to the labour market (Wan, 2006). From 2002 to 2013, China experienced robust economic growth, and the integration into the global economy through WTO membership contributed to China's emergence as the world's second-largest economy.

This study applies the Unconditional Quantile Regression and Recentred Influence Function decomposition methods to analyse public-private wage gaps at the mean and at various points of the wage distribution. These methods decompose the raw public-private wage gaps into the endowment difference (which could be explained by the individual characteristics) and the unexplained part (which is regarded as the advantage of the public sector and the disadvantage of the private sector).

The findings of this paper suggests that during this decade from 2002 to 2013, firstly, the unconditional average marginal effect of the public sector on wages is diminishing. By 2013, it does not offer a large premium to low-income workers and it even attributes negative contributions to high-income workers. This means to some extent, the public sector was not as a "protective umbrella" as before. Secondly, the evolution of wage inequality among urban residents between the public sector and the private sector can be largely attributed to the increasing significance of endowment effects. This factor (composition effect) has become dominant, whereas the wage structure effect (the unexplained part) is diminishing. Particularly, the composition effects play a dominant role, with the wage structure effects being less significant for low-income workers and constraining the wage levels of high-income earners. These results suggest that the Chinese market economy reform exerts a great influence on the labour market. It also implies that employees in the public sector possess a more significant advantage in terms of human capital compared to those in the private sector. This phenomenon remains prevalent in the Chinese labour market till today, where a considerable number of highly educated individuals still prefer working in the public sector rather than the private sector even though the fact that the salary offered by the public sector may not match their skills or abilities (Li, Meng etval., 2023). Furthermore, when decomposing the wage gap between the public and private sectors into different wage determinants, it can be observed that human capital attributes like education level, tenure, and occupation are increasingly becoming the predominant factors in explaining the wage premium, particularly at the lower end of the wage distribution. Additionally, the persistent influence of gender (being male) continues to make a significant positive contribution to hourly wages. This highlights that the gender equality within the Chinese labour market still has a long way to go (Michelson, 2009; Su, 2006; Ji et al., 2017).

The rest of the paper is presented as follows. Section 2.2 displays a literature review of wage inequality between the public sector and private sector. Section 2.3 describes the Chinese transitioning economy and the evolution of labour market. The data and variable definitions can be found in Section 2.4. Section 2.5 introduces the Unconditional quantile regression and discusses the results. In Section 2.6, I specify and estimate the wage inequality by Oaxaca-Blinder RIF-decomposition. The conclusion is shown in Section 2.7.

2.2 Literature review

The public sector is a significant employer in the competitive market, but its aim is not profit-maximization as in the private sector. However, the government financial planning still puts the public sector in a privileged position in the labour market. It results in the government often paying higher salaries to public sector employees, especially at lower skill levels. The government behaviour of political maximization and vote maximization could be the reason for the wage inequality between the public sector and the private sector (Becker, 1957; Gunderson, 1979). Moreover, Becker (1957) and Leping (2006) pointed out that if the government provides a higher salary to public sector employees, it would be offset by the taxpayers. Additionally, the monopolistic power owned by the public sector may result in the wage premium between the public sector and private sector as well (Boal & Ramson, 1997; Holmlund, 1993; Disney, 2011). Furthermore, Mueller (1998) concluded that consumer scrutiny, the public sector allowance, and monopsony of the public sector may contribute to reduce the wage of public sector employees.

However, in transition economies, the wage differential between the public and private sectors might be converse to the situation in the more developed countries. Due to the economic reform, the wage in the public sector is usually less than in private enterprises. This results in moonlighting and spill-over effects, as a consequence, the public sector faces difficulties in recruiting and retaining employees (Adamchik & Bedi, 2000). Moreover, Boeri (1998) suggested that private companies more easily assess staff productivity and provide a more appropriate salary to their workers than the public sector. These pay differentials make the public sector less appealing to high skilled workers.

Many empirical examinations of the public-private sector wage gaps have been carried out. Starting with Smith (1976), she first compared the pay differentials between the public sector and the private sector, and discovers that in both 1960 and 1970, federal workers' earnings and wage rates surpassed those of comparable private workers by significant margins, with up to 65 percent of the differentials attributed to discrimination. Many other early studies derived that as the government level increases, public workers enjoy a positive wage rent (Gunderson, 1979; Shapiro & Stelcner 1989; Terrell, 1993). More specifically, numerous studies concluded that female employees, manual employees, poorly educated workers in the public sector obtain a wage premium (Katz & Krueger, 1991; Poterba & Rueben, 1994; Dustmann & Van 1997; Elliot & Duffus, 1996). On the contrary, the highly educated and the high-skilled employees usually are underpaid by the governments (Melly, 2005; Leping, 2006), and for the well-skilled employees in the public sector, there is a wage ceiling (Voinea & Mihaescu, 2012).

While the reason of wage differentials in the public and private sectors is not only be attributed by employee characteristics, Lindauer & Sabot (1983) found that with the same characteristics, employees in the public sector are still paid a positive wage premium. Voinea & Mihaescu (2012) also pointed out that employees receiving economic rents is not as a result of their skills or abilities, but rather due to the sector in which they are employed. Grimshaw (2000) and Lucifora & Meurs (2006) found evidence that the centralization level of the governments also contributes to the wage differentials between the public sector and the private sector. They suggested that the decentralization of government results in larger pay differentials, whereas centralized governments decrease earning differentials and shrink the gender wage gap. Christofides et al. (2013) suggested the wage gap cannot be fully explained by observable characteristics, and the study found that work-family-friendly policies could help reduce this disparity. Gender wage differentials related to degree specialization and within-subject graduate pay gaps were examined in studies by Machin and Puhani (2003) and Lindley and McIntosh (2015).

Additionally, the review of various methodologies of the examination of wage differentials presented in this paper highlights that quantile regression is more effective than Ordinary Least Squares (OLS) for analysing wage distributions of the public and private sectors. This is because OLS estimates only the mean of the public-private wage premium, but quantile regression provides a more comprehensive analysis by capturing variations across the entire wage distribution (Poterba and Rueben 1994; Mueller 1998; Fitzenberger & Kurz, 2003). For example, Mueller (1998) and Blackaby et al. (1999) use quantile regression to estimate the wage distribution and conclude that the substantial income premium for public sector employees is most pronounced in the lower tail of the wage distribution. Furthermore, the Blinder-Oaxaca decomposition method is widely employed to assess the contribution of characteristic differences to overall wage differentials between the public and private sectors

(Mueller, 1998; Gosling et al., 2000; Juhn et al., 1993; Machado & Mata, 2005). A new regressor was introduced by Firpo et al. (2009) to investigate the effect of explanatory variables on quantiles of the unconditional marginal distribution of an outcome variable. They employ a recentred influence function (RIF) regressor about unconditional quantile on the explanatory variables, which extends the Blinder-Oaxaca method to quantiles.

2.3 Evolution of the Chinese labour market

China has been a socialist country from 1949. This means it was illegal to develop private economy and the public sector was totally dominant. Prior to the economic reforms of 1978, China lacked a formal labour market, as labour supply and demand were dictated by the socialist allocation system in place at the time. In this system, all employees were granted equal employment opportunities through job allocations, ensuring secure, lifelong employment—often referred to as the 'iron rice bowl'. The system was primarily based on parental and hereditary recruitment. It was common that when employees retired in the stated owned enterprises and collectively owned enterprises, they would pass their own jobs to their children (Yee, 2006). Moreover, the work units ('danwei') also provided employees with a political function, which means the subsistence of workers was entirely dependent on their work organizations rather than market-based systems found in other societies (Lee, 1998). During the pre-reform period, state-owned enterprises (SOEs) served as the primary employment channel. The Chinese workforce was assigned to lifelong, tenured positions, with minimal opportunities for mobility and virtually no risk of dismissal. The migration between cities and countries was also restricted by the household registration system ('hukou') (Li & Zhao, 2012). Starting in 1956, a 'national wage reform' established an egalitarian eight-grade wage scale governing all formal employees. Under this system, wage levels were fixed irrespective of enterprise performance.

Until the initiation of the opening reforms in 1978, the private economy gradually gained legal recognition from the Chinese government. Simultaneously, facing the challenge of providing employment opportunities for a large number of unemployed youths, employment reforms were set in motion (Li & Zhao, 2012).

Thus, aimed to facilitate the transition of state-owned enterprises, a series of essential employment reform policies were issued. First, Li & Zhao (2012) pointed that in 1979 the concept of selection through open recruitment was gradually accepted and implemented by the state. The government departments would select the best employees based on the result of open examinations. In 1983, the formal policy 'Interim measures concerning recruitment through examination to select the best' was issued by the Ministry of Labour. In 1986, the hereditary recruitment was formally banned, and State-owned enterprises (SOEs) were no longer permitted to engage in internal or hereditary recruitment practices. At the same time, lifelong tenure was replaced by the contract employment system (Yee, 2006). from that point forward, a dual-track system emerged, wherein both a labour contract system and the traditional permanent employment system coexisted within the same enterprise. Only a small proportion of newly recruited employees were hired under the fixed-form employment contracts. Meanwhile, the first instance of ownership changed within a state-owned enterprise (SOE) took place; private shareholding was introduced into Guangzhou-based SOEs where employees bought 30 percent of their firms' shares. In 1988, the State Council issued regulations on the leasing of small SOEs, which officially established the legal grounds for this practice of the privatizing SOEs. From that point onward, private firms began to emerge.

Moreover, in 1993, Company Law was issued to transform the SOEs into modern corporations characterized by clearly defined property rights, clear-cut responsibility and authority, and separation of the functions of government and enterprises. This guaranteed limited liability firms and shareholding corporations to develop legally. Furthermore, the policy supported different ownerships, including self-employment, private-owned, foreign-invested, joint-venture, sharing-holding and stock companies, co-existed in the market. However, this shift did not alter the entrenched mindset within the workforce that employment in a state-owned enterprise (SOE) symbolized the security of an 'iron rice bowl.' Consequently, public sector employment remained the preferred choice for the majority.

In 1994, the Labour Law of the People's Republic of China was passed, which stated that all permanent workers should be converted into contract workers. A robust legal framework was introduced to replace the socialist permanent employment system with a labour contract system. Additionally, following Deng Xiaoping's 'southern tour', the special economic zones were opened, especially to attract foreign investment. This significant policy was driven by the deepening market-oriented economy reforms, as well as by its role in boosting the development of private sector. Therefore, the rapid growth of the private sector generated a huge demand for labour. With the expansion of the non-public sector, labour mobility across different ownership sectors was gradually permitted. Since the end of collective farming, the redundant rural manpower could meet the substantial labour demand generated by the newly established special economic zones. In order to guarantee rural areas could continuously supply cheap workers, over geographic and occupational mobility was eased. It represented significant progress, as individuals without a migration certificate were previously unable to change their residency or move freely within the country (Liu, 2006). However, many State-Owned Enterprises (SOE) employees were reluctant to leave their positions due to the disparities in welfare benefits, especially given that workers in small collective farms and employees in private enterprises lacked similar safety net coverage (Yee, 2006). Until 1997, the government giving up the idea of bailing out all loss-making State-owned enterprises, to ensure the survival of SOEs, a great amount of employees were laid off, who therefore had to pour into the private sectors. Li & Zhao (2012) showed that in 2009, the proportion of workers employed by SOEs dropped to 30%, from 100% in 1985. In regard to the supply quality, college enrolment has increased dramatically since the policy of college expansion was issued in 1999. Consequently, the number of college graduates rose from 0.85 million in 1999 to 4.48 million in 2007. The Stated-owned enterprises reform and the rapid growth of non-public sector transformed the ownership structure of Chinese economy. This shift significantly enhanced the efficiency and productivity of the whole economy, thereby driving forward the labour market reform.

Besides, the egalitarian wage system was also one of the main factors contributing to low efficiency in State-owned enterprises. Hence, to address this issue, the wage-setting reform in SOEs was also essential. As a result, the original fixed wage scale was abandoned, and a system linking the wage to profitability and productivity was gradually adopted. To be more precise, the first step of the SOE reform was that the government decentralized more decision-making power to the enterprises. In 1979, a new policy was issued to permit state-owned enterprises to retain profits (You, 1998). Through the retained profit, managers of SOEs gained more leeway to increase incomes for both employees and themselves. Yee (2006) highlights that all industrial state-owned enterprises were allowed not only to retain their after-tax profits but also to have their taxes partially or fully remitted. Furthermore, Liu (2006) finds that up to 30 percent of retained earnings could be allocated to raise workers' income and bonus payments, and up to 20 percent of the profits could be allocated by SOE managers to enhance welfare expenditures. After enterprise managers obtained greater authority, workers' wage was required to associated with productivity and efficiency, leading to the widespread adoption of a structural wage system. More specifically, the system included position-based wages, skill-based wages, seniority-based wages, efficiency-based wage and bonus, which was half-fixed for basic salary and half-flexible for production and efficiency (Lau, 1999). Xing & Li (2012) claims that After 2000, the state-owned sector progressively transitioned towards using market mechanisms to determine wages.

In addition to internal system evolution, three market factors—capital accumulation, skill-biased technological change, and export expansion—also influence changes in wage structure (Ge and Yang, 2014). Based on data from the Urban Household Survey conducted between 1992 and 2007, their study argues that these factors are the primary drivers of wage structure changes in China. Firstly, the demand of labour is associate with the infrastructure investments. The capital accumulation intense the disparity between skilled and unskilled workers. Secondly, between 1992 and 2007, China was the second-largest recipient of foreign direct investment (FDI), establishing a crucial channel for acquiring new technologies and ideas from industrialized economies. Upgrading of technologies has been found to boost the salary of highly skilled employees. Thirdly, China's entry into the WTO expanded global demand for its goods, making it the largest exporter of manufactured goods. This growth increased demand for basic skills and base wages, which in turn led to a rising influx of rural labour migrating to cities.

2.4 Data description

This chapter uses data from the Chinese Household Income Project (CHIP). CHIP is one of the biggest and richest individual-level datasets to measure and estimate the distribution of personal income in both rural and urban areas of the People's Republic of China. Their data were collected through a series of questionnaire-based interviews conducted in rural and urban areas in 1988, 1995, 2002, 2007, and 2013. Individual respondents reported on their economic status, employment, level of education, sources of income, household composition, and household expenditures.

This study utilizes public urban datasets from the years 2002, 2007, and 2013. Data from 1988 and 1995 are excluded because the private sector's share of total employment during those years was minimal, accounting for no more than 5%. The urban labour market consists of urban individuals with various hukou classifications, including those with urban hukou in the resident city, rural hukou in the resident city, urban hukou from other cities, and rural hukou from other cities.

The sample data employed in this paper is restricted to individuals who were 16-64 and had a full-time job with positive wage. Moreover, I remove individuals who earn the lowest based on the minimum wage policy and few top income earners. Additionally, I use the natural logarithm of the hourly wage to represent wage in the following part and the hourly wage is calculated as the total wage per year or month divided by the total numbers of hours worked in a year or month. The monthly and annual wages include base salary, bonuses, and allowance. The financial assets and public transfer payments are excluded.

The 2002 urban surveys conducted from 6835 households and 20632 individuals covering 11 provinces, which are Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Chongqing, Sichuan, Yunnan, Gansu. However only 5216 individual cases demonstrate valid workplace ownership. The public sector's share decreases by 72%, having been nearly 100% before the State-Owned Enterprises (SOE) reform. Moreover, 23% employees claimed that their work unit changed ownership in last decade, especially occurring between 1997-2002. The 2007 survey include 14,699 individuals from 5,003 households in 9 provinces: Shanghai, Jiangsu, Zhejiang, Anhui, Henan, Hubei, Guangdong, Chongqing, and Sichuan. According to

6275 valid individual cases, near 63.6% employees were working in the public sector. The 2013 urban datasets consist of 19887 individuals and 7175 urban households from 13 provinces: Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Chongqing, Sichuan, Yunnan, Hunan, Shandong, Gansu. The valid sample size in individual level is 8209. The figure of public sector share is only 49.95% in 2013 and the sum of individual enterprises and private enterprises has increased by 43.87%.

The ownership sectors of workplaces are sorted into: 1. State owned, Operated by Centre Province (or Autonomous Region), or Municipality; 2. Other Publicly-owned; 3. Collective; 4. Private or Individually-owned; 5. Sino-foreign Joint Venture; 6. Foreign-owned; 7. Other; 8. Multiple Ownership. This analysis only compares the general public sector and the private sector wage structure, which means the public sector includes enterprises of State owned, Operated by Centre Province (or Autonomous Region), or Municipality, Other Publicly owned and Collective; and the private sector is consisted of Private or Individually-owned, Sino-foreign Joint Venture and Foreign-owned companies; the Other and Multiple ownership are excluded.

Table 2.1 displays descriptive statistics. The dependent variable is the logarithm of the wage rate. The independent variables are human capital indexes of wage function. In this paper, I use tenure (the years of workers being engaged in their current job), age, dummy variables for male, race (Han), marriage status (married), occupation dummies (managers or principles in state agencies, party organization, enterprises and public institutions; professional technicians; clerk and relevant personnel; commercial and service personnel; agriculture, forestry, animal husbandry, fishery and water resources producers; manufacturing and transportation equipment manipulator and relevant personnel; Soldier and other practitioner), and industry dummy variables (resources management; manufacturing; information, education and media; financial sector; real estate; retail and wholesale; services), province dummies and education level dummy (under or primary school, secondary or high school, and university or college degree).

Table 2.1 shows the difference of employee's characteristics between the public and private sectors. For example, it can be found that the mean age in the public sector is slightly higher than its counterpart in the private sector across these three waves. It also reveals that that employees working in the public sector have longer tenure during this decade (2002-2013). More significantly, it could be found that the number of female employees is less than male employees within both public and private sectors. The majority of the surveyed individuals are married and Han race.

In the public sector, over half of the employees are professional technicians or clerical staff and related personnel. In contrast, most employees in the private sector work in commerce and services or as operators and technicians in manufacturing and transportation equipment. Specifically, in 2002, the difference in the proportion of professional technicians between the public and private sectors was small and likely insignificant. However, by 2013, this disparity had grown substantially and was probably statistically significant. Similarly, in 2002, the proportions of production workers and clerks in the public and private sectors were quite similar. However, by 2013, the differences had become significant, likely because employees in the private sector were increasingly engaged in clerical roles rather than production work. Conversely, in 2002 and 2007, significantly more private sector employees were involved in commercial services compared to public sector employees. However, by 2013, this proportion had dramatically decreased, making the difference between the two sectors insignificant.

Moreover, nearly half of the workforce in both the private and public sectors was employed in manufacturing at the beginning of the decade. However, there was a noticeable shift over time, with the manufacturing industry gradually losing its dominant position. Specifically, in 2002, 43% of public sector workers were employed in manufacturing, but this figure dropped to 18% in 2007 and further to 11% in 2013. The private sector experienced a similar trend, with its share decreasing from 45% to 19% over the same period. During this decade, the public sector workforce increasingly shifted towards the information, education, and media industries, unlike the private sector, where the retail and services industries gained a greater share. This shift was dramatic, with only 2% of public sector workers in the information, education, and media industries in 2002, rising to 35% in 2007 and 48% in 2013, resulting in a significant difference between the two sectors. Meanwhile, the portion of the workforce in retail remained considerably larger in the private sector than in the public sector. Although the share of the services industry in the private sector was slightly smaller than in the public sector in 2002, by 2007, it had nearly doubled its counterpart in the public sector, and by 2013, it had tripled.

Additionally, it is revealed that the proportion of employees working in the real estate sector was similar in both the public and private sectors in 2002. However, by 2013, the disparity had grown significantly, with the private sector's share rising to 8.57%, while the public sector's share was only 2.97%. This trend aligns with the increased participation of the private sector in the real estate industry during this decade. As the private sector was allowed to enter the real estate market, investment in real estate and related infrastructure became one of the three pillars of China's economy, alongside export-oriented manufacturing and domestic consumption. While the share of employees in the public sector working in resource-related industries and finance-related industries remain significantly higher than that in the private sector across these three waves. This is likely because many companies in these industries, such as electric power companies and most banks, are state monopolies.

Finally, the table shows that in 2002, the structures of education levels in both sectors were similar, in which over 70% workforce had a secondary or equivalent education level and the share of the higher education was over 20%. However, by 2013, the educational composition of the private sector workforce had undergone only minor changes. In contrast, the public sector experienced a substantial increase in the proportion of workers with higher education, with 57% holding a degree—more than double that of the private sector. This marked shift indicates a pronounced preference among highly educated individuals to seek employment in the public sector over the private sector.

Table 2.1: Descriptive statistics

	2002		2007		2013	
	private	public	private	public	private	public
Employees	1454	3807	2388	4177	4207	4182
Age	38.57	41.26	37.01	40.04	39.03	40.57
Tenure	11.65	18.15	7.48	14.28	7.39	15.5
Wage rate	1.3	1.48	2.18	2.4	2.55	2.82
Male	56%	59%	56%	59%	55%	59%
Han race	96%	96%	99%	99%	95%	96%
Married	83%	91%	81%	86%	85%	89%
Occupations:						
Managers	7.50%	9.98%	3.43%	9.58%	4.66%	6.38%
Professional technicians	*16.44%*	*17.76%*	*18.26%*	*26.69%*	*11.36%*	*28.38%*
Production workers	*25.03%*	*29.55%*	*12.98%*	*16.85%*	*8.68%*	*28.07%*
Clerks	*14.58%*	*16.73%*	*16.04%*	*28.90%*	*44.26%*	*14.28%*
Commercial Service	*21.32%*	*9.30%*	*39.99%*	*11.71%*	*0.86%*	*0.77%*
Agriculture producer	13.76%	15.66%	0.71%	0.67%	22.13%	17.12%
Others	1.24%	0.89%	7.66%	4.60%	5.66%	3.11%
Industries:						
Resources management	6.46%	13.61%	3.65%	9.11%	3.43%	13.47%
Real-estate	*5.02%*	*6.51%*	*7.68%*	*4.22%*	*8.57%*	*2.97%*
Manufacturing	*45.80%*	*43.45%*	*19.09%*	*17.97%*	*19.70%*	*11.20%*
Information	*2.68%*	*2.50%*	*11.28%*	*35.30%*	*9.97%*	*48.19%*
Financial	1.58%	4.15%	1.43%	5.03%	1.36%	4.83%
Retail	*22.01%*	*9.90%*	*32.59%*	*15.94%*	*31.03%*	*10.48%*
Services	*16.30%*	*19.70%*	*24.29%*	*12.44%*	*25.89%*	*8.83%*
Education levels:						
Primary School	*3.78%*	*2.78%*	*na*	*na*	*7.18%*	*1.46%*
Secondary School	*74.83%*	*72.47%*	*na*	*na*	*68.12%*	*41.20%*
Higher Education	*21.25%*	*24.61%*	*na*	*na*	*24.67%*	*57.34%*

Notes: The table provides descriptive statistics for the public and private sectors across various years. The first column displays the total number of employees. Gender, Han race, marriage status, occupations, industries, and education levels are presented as percentage ratios. The data on education levels for the year 2007 is not available. The italicized figures highlight the statistically significant differences over time.

2.5 Unconditional quantile regression

2.5.1 Methodology

In order to estimate the factors explaining the wage gap across the wage distribution, I apply the unconditional quantile regression method developed by Firpo et al. (2009), which requires to run the recentered influence function (RIF) of the unconditional quantile of the outcome variable (wage) on a series of explanatory covariates. The foundation of this approach is the theory of the influence function (IF) that is widely utilized to estimate the robustness of distribution statistics. Specifically, the IF indicates the effect of an observed characteristic on a statistical distribution of interest (Firpo et al., 2009). While the RIF is generated by adding back the statistics to the influence function (Firpo et al., 2009). Namely, the RIF is derived by using the IF to change the outcome variable of a linear approximation so that it is easy to compute how the shift in the distribution of explanatory variables X has affected in the unconditional distribution of Y. Additionally, Firpo et al. (2009) also define that the "unconditional quantiles" are the marginal distribution quantiles of the dependent variable Y. Mathematically, they derive that RIF(Y;q_τ) is simply equal to q_τ + IF(Y;q_τ). Moreover, they define the RIF-regression model is the conditional expectation of the RIF(Y; v) which is formed as a function of the exogenous variables, E[RIF(Y; v)|X] = $m_v(X)$. Furthermore, given the quantiles, the RIF-regression model would be an unconditional quantiles regression (UQR), which is E[RIF(Y; q_τ)|X] = $m_\tau(X)$. Therefore, researchers could estimate the partial effects of explanatory variables on any unconditional quantile of the outcome variable by using the estimated approach of unconditional quantile regression. This UQR method, introduced by Firpo, Fortin, and Lemieux (2009), has become a prevalent approach to analyze and identify the distributional influence on outcomes regarding to transitions in individual observations and is widely employed in the labour economic fields.

Given the τ^{th} quantiles, $v(F) = q_\tau$. According to the definition of the influence function of q_τ, the IF is obtained as:

$$\text{IF}(y;\, q_\tau) = \frac{\tau - \Pi\{y \leq q_\tau\}}{f_Y(q_\tau)} \quad (1)$$

where IF represents the influence function, y stands for the log hourly wage, and $f_Y(q_\tau)$ means the probability density function y estimated by q_τ. Moreover, $\Pi\{y \leq q_\tau\}$ denotes an indicator function which equals to 1 if the outcome variable is less than q_τ and equals to 0 if not.

Thus, following Firpo, Fortin, and Lemieux (2009), the estimation of RIF in quantiles is:

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - \Pi\{y \leq q_\tau\}}{f_Y(q_\tau)} \quad (2)$$

Moreover, to measure how changes in X's regarding to the contributions of observation i to the statistic of interest, the RIF's function could be modeled as functions of X's:

$$RIF\big(y_i, v(F_{Y)}\big) = \alpha_0 + \alpha_1 * X_1 + \alpha_2 * X_2 + e \quad (3)$$

The partial effect would be:

$$\frac{\partial RIF(.)}{\partial X_1} = \alpha_1 \quad (4)$$

$$\frac{\partial E(RIF(.)|_{X_1, X_2})}{\partial X_1} = \alpha_1 \quad (5)$$

which means if individual i changes by X_1, the effect on the outcome would in turn shift by α_1.

Furthermore, if the unconditional expectations are taken:

$$E\big(RIF(y_i, v(F_Y)\big) = E(\alpha_0 + \alpha_1 * X_1 + \alpha_2 * X_2 + e) \quad (6)$$

$$v(F_Y) = \alpha_0 + \alpha_1 * E(X_1) + \alpha_2 * E(X_2) \quad (7)$$

Thus the partial effect is obtained as:

$$\frac{\partial v(F_Y)}{\partial E(X_1)} = \alpha_1 \quad (8)$$

α_1 denotes that supposing everything else constant, the influence that the average value of E(x1) changing one unit change will have on statistic v.

Table 2.2 displays the RIF coefficients for the 10th, 50th, 90th quantiles in 2002, 2007 and 2013, and the detailed estimates from the 10th to the 90th quantiles of each year are illustrated in the Figure 2.1-2.3 as well.

2.5.2 How does the public sector affect the wage level?

According to Table 2.2, it is evident that in 2002 and 2007, working in the public sector has a significantly positive impact in the lower tail but has little influence on the higher levels of the wage distribution. However, in 2013, it shifts totally, in that it turns out to be substantially negative at the upper end of the wage distribution and has insignificant effect on the low tail. More specifically, as shown in Figure 2.1a, the effect of the public sector decreased monotonically across the quantiles. Namely, in 2002, it has positive effect on whole labour force across the wage distributions. But in 2007, its effect turns to be negative to high-income earners and furthermore, in 2013, the public sector has little impact on the low-income earners and has significantly negative impact on high-income workers. It means, to some extent, that the market mechanism works well especially during the period of 2007 to 2013. The public sector does not offer a benefit to the wage level of the low-income earners, instead it limits the wage level of high-income earners.

2.5.3 How do demographics affect the wage level?

As shown by the RIF-regressions for Age, Tenure, Han race, Male, and Married—displayed in Table 2.2 and Panel b to Panel f of Figure 2.1, the effects of Tenure, Age and Han race do not contribute a lot to log hourly wages. Being male and being married have a significantly positive effect on wage rate. In particular, the effect of marriage has significant positive impacts in 2002 and 2007, but it declines in 2013. Meanwhile, during this decade, gender keeps making a great contribution to log hourly wages, no matter at the low end or at the high end of wage distribution, and roughly impacts more on the low-middle income earners. It indicates that the gender inequality is still an inevitable problem in Chinese labour market (Michelson, 2009; Su, 2006; Ji et al., 2017).

More importantly, as presented in Table 2.2, the return of education keeps magnitude. Namely, according to Figure 2.1 Panel h and Panel g, the results illustrate that the secondary school or high school degree keeps essential to the labour at the low end of wage distribution, but its significance declines to the high-income workers. The coefficients of a university or college degree also monotonically decrease as the quantiles rise. It means that education is much more important to low-income workforce than high wage owners.

2.5.4 How do industries and occupations affect the wage level?

The unconditional quantile partial effects of industries and occupations are demonstrated by Table 2.2, Figure 2.2 and Figure 2.3. It is apparent that the financial sector attributes significantly positive returns to the wage structure and it roughly increases monotonously along with the quantiles, which means it contributes more to the high-wage earners than the low-wage earners. In 2002, the real estate industry has insignificantly negative effect on workers, but after 2007, its contributions to wage level become inevitable, especially at the low end of wage distribution. Additionally, as shown in Figure 2.2, workers in the retail industry earn significantly less than workers in the other industries, but after 2007, its effect turns to be positive but not significant on high-income earners. In sum, to the high-salary workforce, it can be found that the resources sector and financial sector which mainly controlled by the state make great contributions.

The RIF-regression estimates in Figure 2.3 for occupations illustrate that manager contribute a lot at the upper end of the wage distribution, compared with the return of the professional workers and technicians has more positive impact at the lower end of the wage distribution.

It is noteworthy that there is no significant effect on workers engaging in the commerce and service and fishery, forestry, and animal husbandry.

2.5.5 How does the region affect the wage level?

Another considerable factor affects the wage level is region because Chinese development among regions is rather imbalance. It could be account for the Chinese policies which set up special administrative regions to give priority to economic reforms. As shown in Table 2.2, the wage returns of developed regions, such as Beijing, Shanghai, Guangdong and Zhejiang, are significant. Compared to other provinces, these areas are encouraged to implement a fuller market economy and the private business thereby sprung up. Therefore, people working in there would get high reward. Taking Guangdong as an example, its wage returns to high-income earners are as high as 0.91 and 0.835 in 2002 and 2007 respectively. To those at the low tail of wage distribution, its returns are over 0.5 during 2002 to 2007. Namely, it rewards much more to those at the high end of wage distribution than those at the low end, which intensifies the wage inequality. Its influence drops by 2013 but is still not insignificant.

China's economic transition is a gradual process with the principle of setting up special economic administrative regions to let a small proportion of people get rich first. Therefore, due to the inclination of national policies, some local economic levels are far ahead. Hao and Li (2006) also show that in urban China, one of the important determinants of individual income inequality is regional characteristics.

Table 2.2: Unconditional Quantile Regression Coefficients on Log Wages

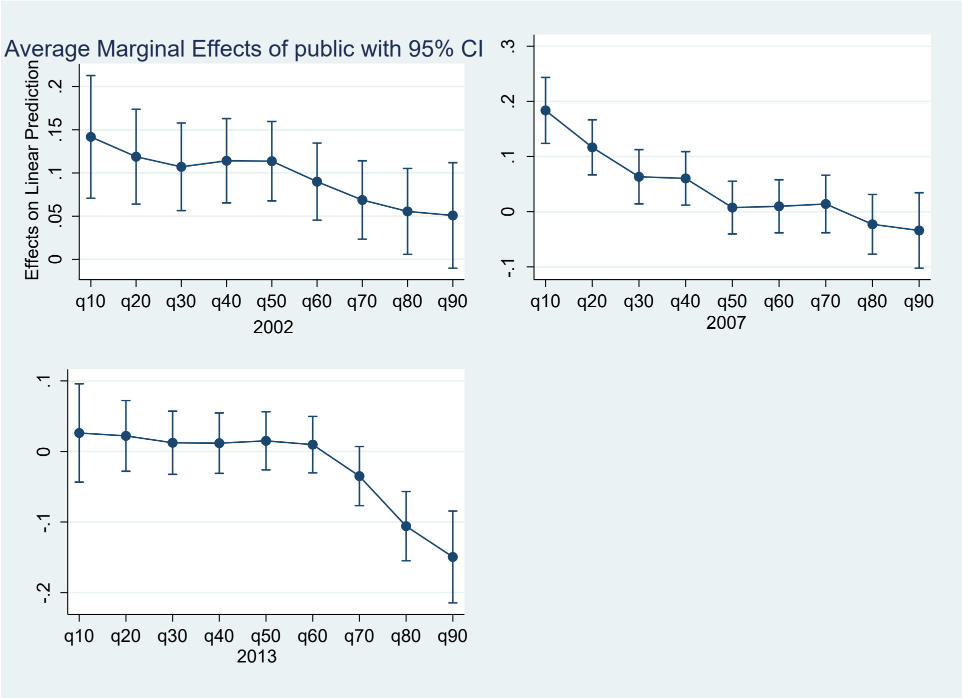
Years	2002			2007			2013		
Quantiles	10	50	90	10	50	90	10	50	90
Explanatory Variables									
Public	0.142***	0.114***	0.051	0.184***	0.008	-0.034	0.026	0.015	-0.149***
	(0.036)	(0.023)	(0.031)	(0.030)	(0.024)	(0.035)	(0.036)	(0.021)	(0.033)
Age	-0.004*	0.001	0.006**	-0.018***	-0.015***	-0.007***	-0.016***	-0.002	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Tenure	0.015***	0.008***	-0.001	0.016***	0.017***	0.009***	0.018***	0.014***	0.006***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Male	0.172***	0.127***	0.056**	0.152***	0.254***	0.217***	0.212***	0.228***	0.197***
	(0.032)	(0.021)	(0.028)	(0.027)	(0.021)	(0.030)	(0.028)	(0.017)	(0.026)
Han	-0.004	-0.108**	-0.038	0.176	-0.069	-0.092	-0.04	0.058	-0.097
	(0.084)	(0.054)	(0.072)	(0.126)	(0.101)	(0.144)	(0.067)	(0.039)	(0.062)
Married	0.118**	0.175***	0.161***	0.081**	0.149***	0.176***	0.095**	0.084***	0.079*
	(0.057)	(0.037)	(0.049)	(0.041)	(0.032)	(0.046)	(0.044)	(0.026)	(0.041)
Provinces (Henan)									
Beijing	0.43***	0.681***	0.73***				0.369***	0.444***	0.674***
	(0.075)	(0.048)	(0.064)				(0.063)	(0.037)	(0.059)
Shanxi	0.116	0.168***	-0.048				-0.001	0.022	-0.083
	(0.076)	(0.049)	(0.065)				(0.066)	(0.039)	(0.062)
Liaoning	0.162**	0.361***	0.138**				-0.049	0.119***	0.02
	(0.067)	(0.043)	(0.057)				(0.075)	(0.044)	(0.070)
Jiangsu	0.242***	0.252***	0.156***	0.576***	0.243***	0.263***	0.338***	0.278***	0.355***
	(0.068)	(0.044)	(0.058)	(0.054)	(0.043)	(0.062)	(0.063)	(0.037)	(0.059)
Anhui	0.146*	0.051	0.067	0.109**	0.122***	0.05	0.068	0.078*	0.075
	(0.068)	(0.048)	(0.064)	(0.054)	(0.043)	(0.061)	(0.072)	(0.043)	(0.068)
Hubei	0.32***	0.196***	0.026	0.154***	0.226***	0.28***	0.11	0.132***	0.027
	(0.070)	(0.045)	(0.060)	(0.060)	(0.048)	(0.068)	(0.067)	(0.040)	(0.063)
Guangdong	0.553***	0.697***	0.91***	0.688***	0.689***	0.835***	0.361***	0.384***	0.445***
	(0.071)	(0.046)	(0.061)	(0.050)	(0.040)	(0.057)	(0.065)	(0.038)	(0.060)
Chongqin	0.344***	0.26***	-0.001	0.349***	0.03	0.011	0.356***	0.209***	0.176***
	(0.087)	(0.056)	(0.075)	(0.060)	(0.048)	(0.069)	(0.070)	(0.041)	(0.065)
Sichuan	0.166**	0.229***	0.11*	0.237***	0.075*	0.024	0.191**	0.157***	0.124*
	(0.073)	(0.047)	(0.063)	(0.053)	(0.042)	(0.061)	(0.075)	(0.044)	(0.070)
Yunnan	0.26***	0.266***	0.151**				-0.001	0.083*	-0.014
	(0.075)	(0.049)	(0.065)				(0.076)	(0.045)	(0.071)
Gansu	-0.231***	-0.027	-0.03				-0.222***	0.015	-0.179**
	(0.087)	(0.056)	(0.075)				(0.076)	(0.045)	(0.071)
Hunan							0.166**	0.172***	0.000
							(0.072)	(0.043)	(0.068)
Shangdong							0.273***	0.192***	-0.004
							(0.070)	(0.041)	(0.065)
Shanghai				0.754***	0.621***	0.536***			
				(0.054)	(0.043)	(0.061)			

Zhejiang				0.598***	0.442***	0.377***			
				(0.053)	(0.043)	(0.061)			
Industries (services)									
Resourses	0.155***	0.1***	0.213***	0.304***	0.256***	0.113*	0.307***	0.234***	0.205***
	(0.058)	(0.037)	(0.050)	(0.060)	(0.048)	(0.068)	(0.065)	(0.038)	(0.061)
Real_estate	-0.083	-0.063	0.036	0.303***	0.248***	0.105	0.437***	0.229***	0.126*
	(0.071)	(0.046)	(0.061)	(0.064)	(0.051)	(0.073)	(0.069)	(0.041)	(0.065)
Manufacturing	-0.04	-0.108***	-0.001	0.179***	0.056	0.051	0.316***	0.04	0.034
	(0.044)	(0.028)	(0.038)	(0.048)	(0.038)	(0.054)	(0.056)	(0.033)	(0.052)
Information	0.032	0.03	0.213**	0.277***	0.338***	0.219***	0.243***	0.118***	0.043
	(0.102)	(0.066)	(0.088)	(0.044)	(0.035)	(0.050)	(0.050)	(0.030)	(0.047)
Financial	0.121	0.183***	0.255***	0.287***	0.53***	0.447***	0.348***	0.319***	0.423***
	(0.090)	(0.058)	(0.077)	(0.074)	(0.060)	(0.085)	(0.090)	(0.053)	(0.084)
Retail	-0.252***	-0.174***	-0.01	0.192***	0.112***	0.043	0.199***	0.13***	0.054
	(0.057)	(0.037)	(0.049)	(0.042)	(0.034)	(0.048)	(0.044)	(0.026)	(0.041)
Occupations (others)									
Manager	0.242	0.26***	0.062	0.362***	0.547***	0.482***	0.269***	0.332***	0.381***
	(0.151)	(0.098)	(0.130)	(0.072)	(0.057)	(0.082)	(0.086)	(0.051)	(0.081)
Technician	0.356**	0.236**	0.1	0.32***	0.36***	0.161**	0.269***	0.234***	0.244***
	(0.147)	(0.095)	(0.127)	(0.060)	(0.048)	(0.069)	(0.074)	(0.044)	(0.069)
ProdWorker	0.248*	0.192**	0.052	0.268***	0.191***	-0.047	0.135*	0.086**	-0.078
	(0.145)	(0.094)	(0.125)	(0.060)	(0.048)	(0.068)	(0.073)	(0.043)	(0.068)
Clerical	0.341**	0.211**	0.039	0.086	-0.098*	-0.171**	0.224***	0.138***	0.087
	(0.147)	(0.095)	(0.126)	(0.064)	(0.052)	(0.074)	(0.073)	(0.043)	(0.068)
CommServ	0.043	-0.022	-0.079	-0.01	-0.043	-0.076	0.027	0.03	0.016
	(0.150)	(0.097)	(0.129)	(0.060)	(0.048)	(0.069)	(0.069)	(0.041)	(0.065)
AgriFore	0.099	0.029	-0.083	0.024	0.236*	-0.135	-0.071	-0.108	-0.224
	(0.147)	(0.095)	(0.127)	(0.161)	(0.129)	(0.184)	(0.165)	(0.098)	(0.155)
Education Level (Primary school)									
Secondary	0.352***	0.297***	0.21***				0.469***	0.193***	0.075
	(0.087)	(0.057)	(0.075)				(0.069)	(0.041)	(0.065)
Higher	0.524***	0.577***	0.488***				0.649***	0.556***	0.449***
	(0.096)	(0.062)	(0.082)				(0.075)	(0.044)	(0.070)
Constants	-0.572***	0.356***	1.282***	0.696***	1.86***	2.821***	1.006***	1.575***	2.651***
	(0.211)	(0.137)	(0.182)	(0.152)	(0.122)	(0.174)	(0.142)	(0.084)	(0.133)
R-square	0.0978	0.1986	0.1298	0.1444	0.2362	0.1053	0.1083	0.2317	0.1162
No. of Obs		5261			6325			8209	

Notes: This table displays the coefficients derived from unconditional quantile regressions on wage distribution, focusing on the 10th, 50th, and 90th percentiles. The reference province for dummy variables is Henan, a centrally located region in China. The baseline category for industries is Service, and for occupations, it is Others. Employees with primary school education are used as the reference point for education level. */**/*** denote statistical significance on the 10%, 5% and 1% level respectively.

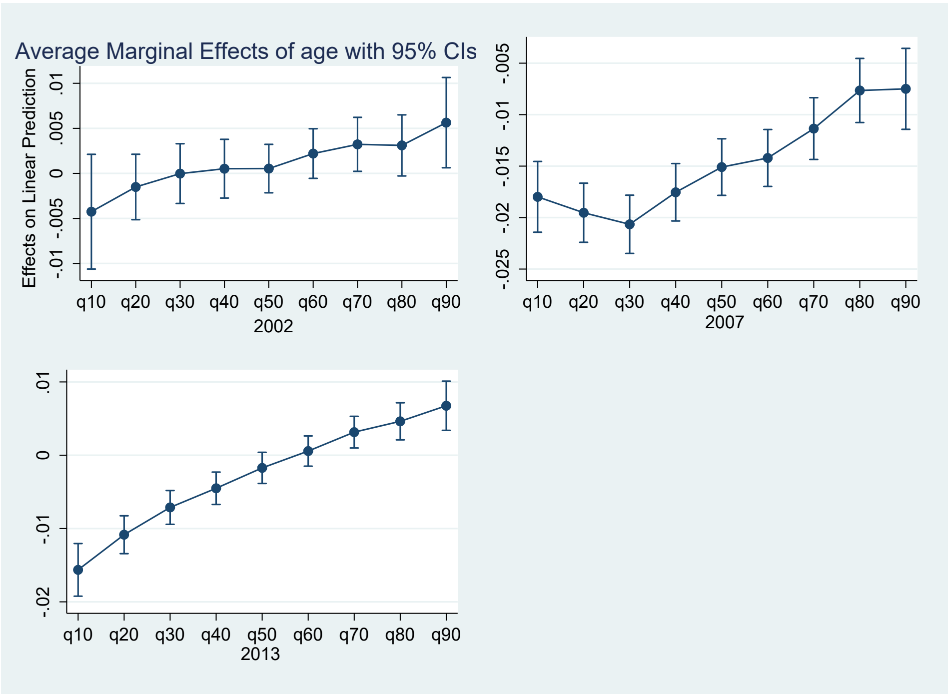
Figure 2.1: Unconditional Quantile Regression of demographics

Figure 2.1 a): Average marginal effects of "Public Sector" with 95% Confidence Intervals (CI)



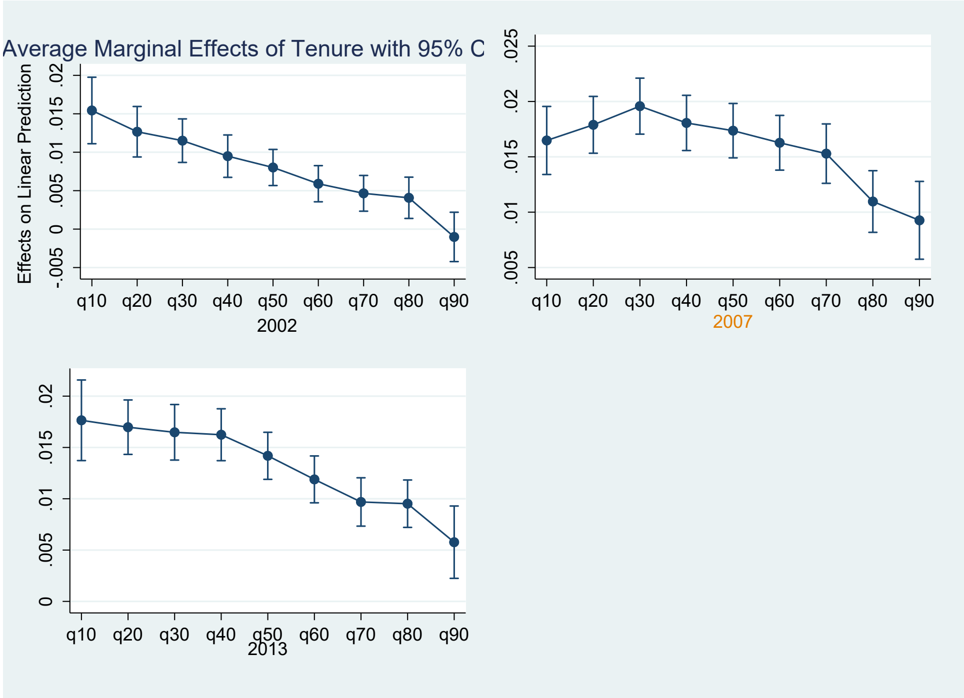
Notes: This figure displays the results of the unconditional quantile regression for 'Public Sector' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 b): Average marginal effects of "Age" with 95% Confidence Intervals (CI)



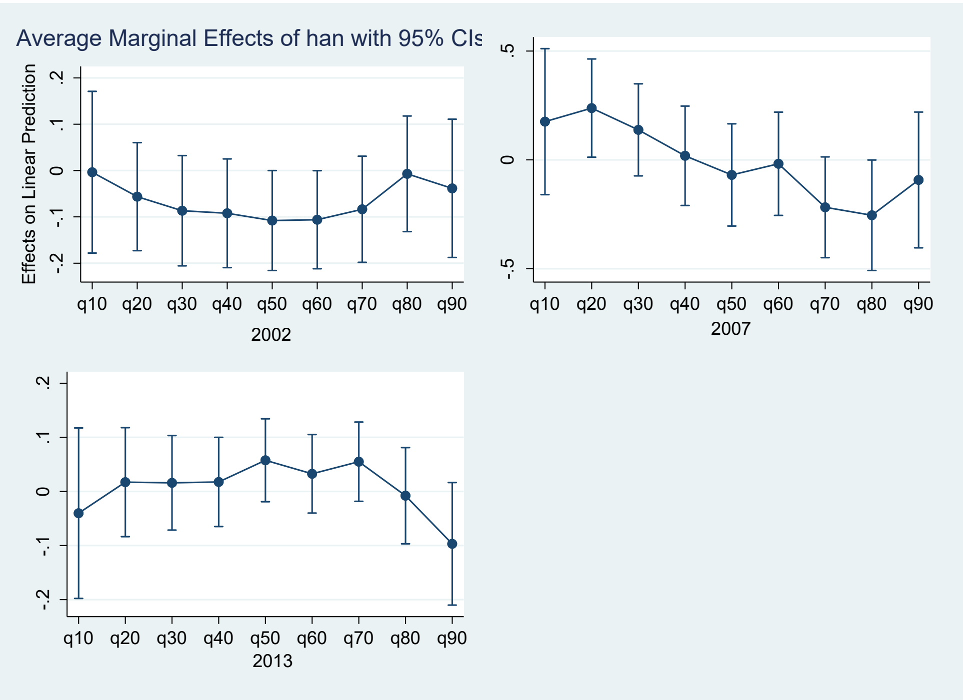
Notes: This figure displays the results of the unconditional quantile regression for 'Age' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 c): Average marginal effects of “Tenure” with 95% Confidence Intervals (CI)



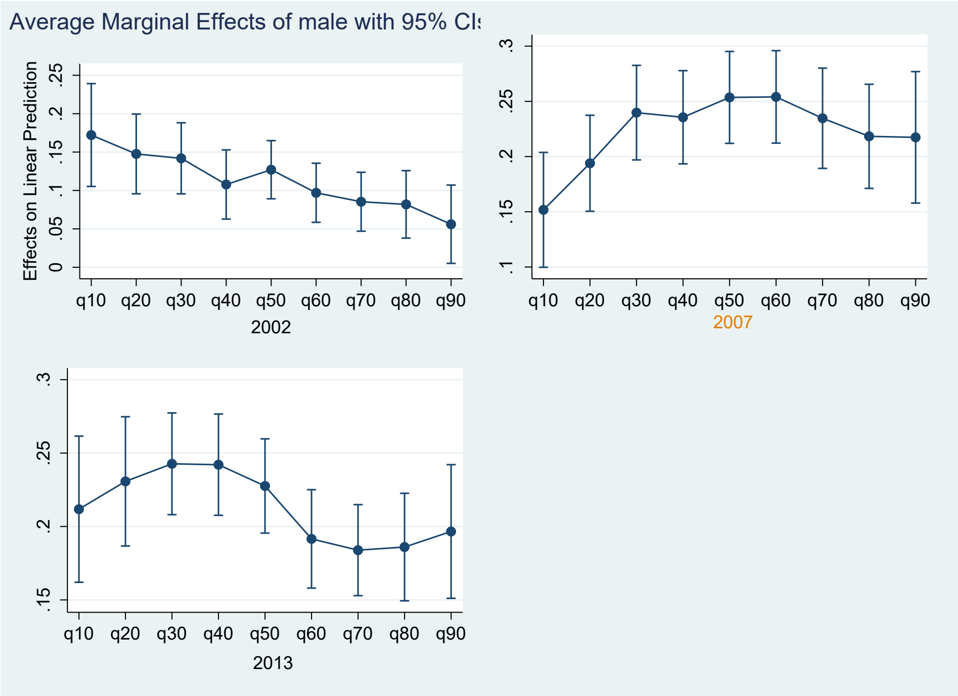
Notes: This figure displays the results of the unconditional quantile regression for ‘Tenure’ effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 d): Average marginal effects of “Han” with 95% Confidence Intervals (CI)



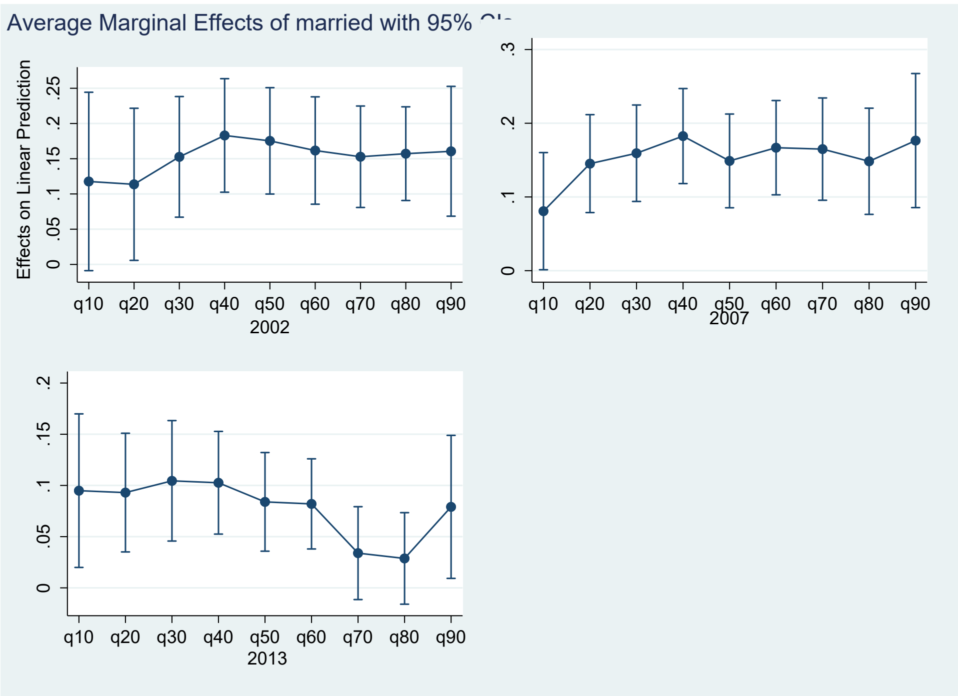
Notes: This figure displays the results of the unconditional quantile regression for ‘Han’ effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 e): Average marginal effects of "Male" with 95% Confidence Intervals (CI)



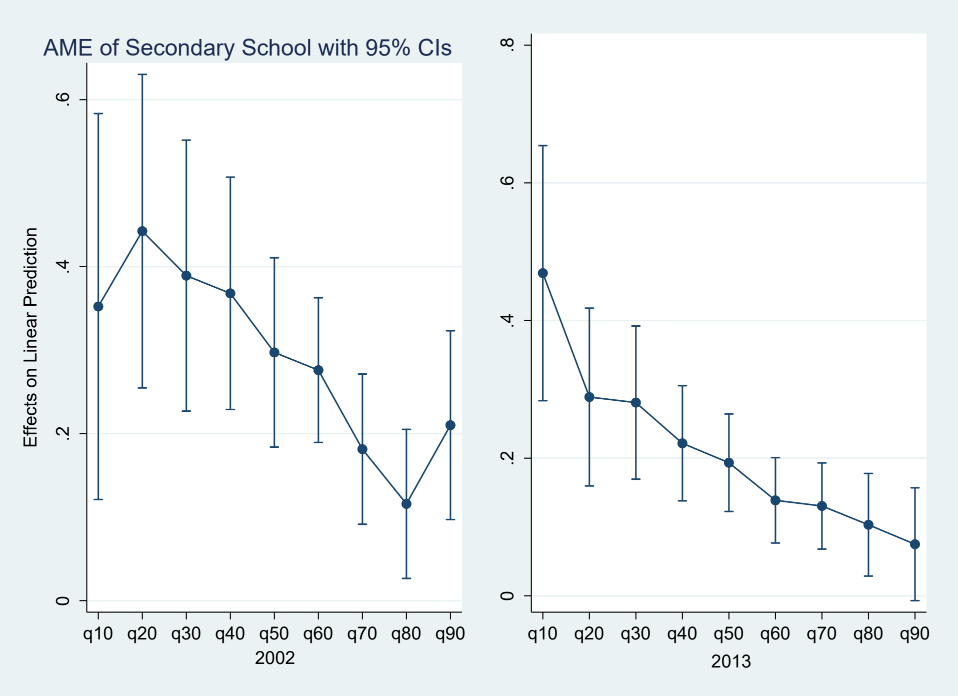
Notes: This figure displays the results of the unconditional quantile regression for 'Male' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 f): Average marginal effects of "Married" with 95% Confidence Intervals (CI)



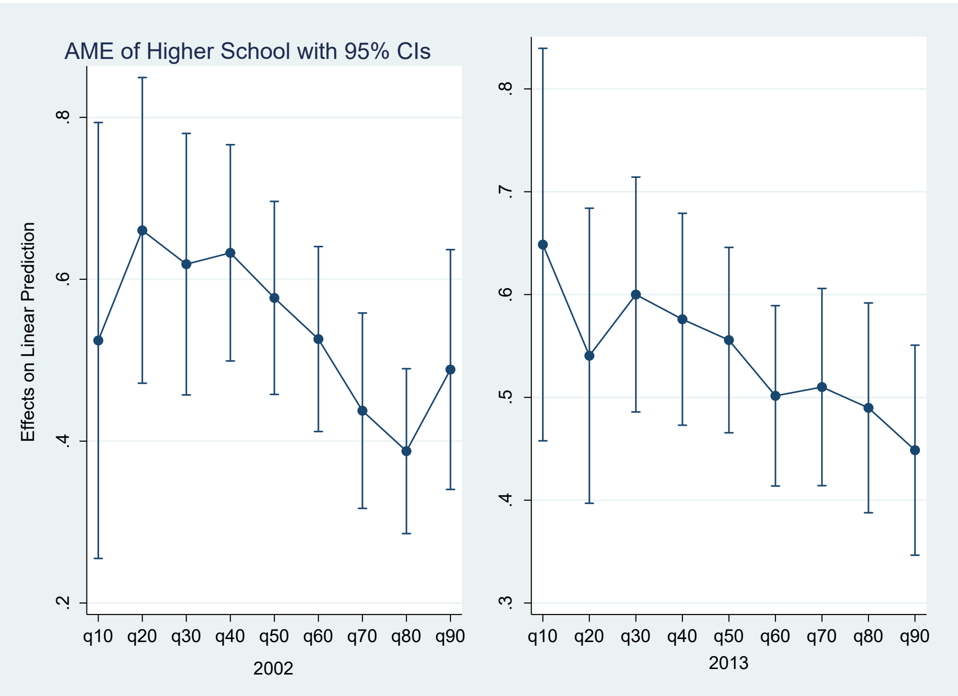
Notes: This figure displays the results of the unconditional quantile regression for 'Married' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.1 g): Average marginal effects of "Secondary school" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Secondary school' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

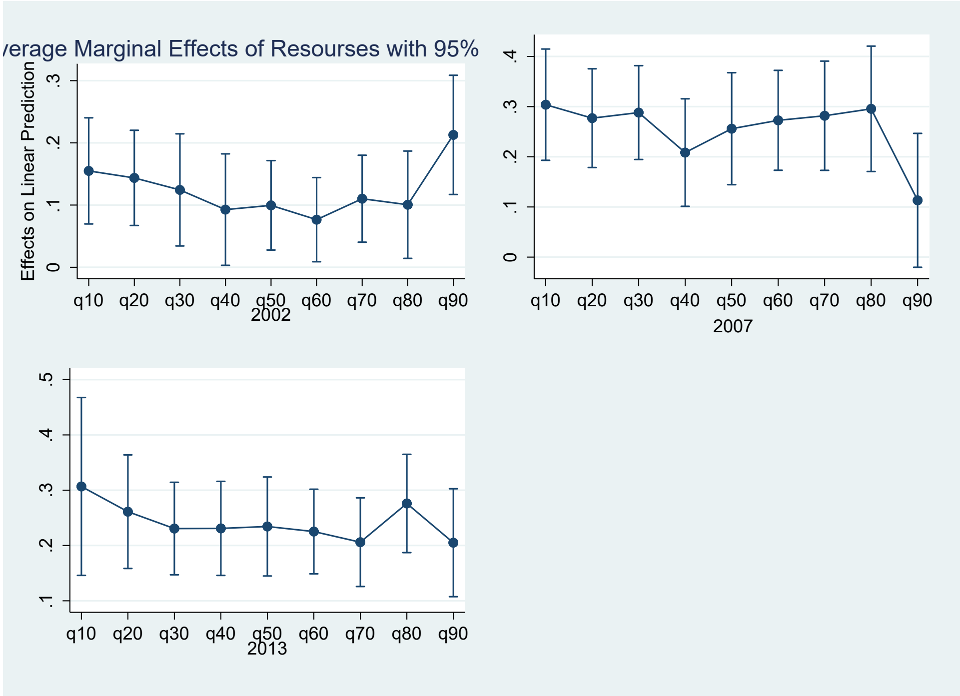
Figure 2.1 h): Average marginal effects of "Higher school" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Higher school' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

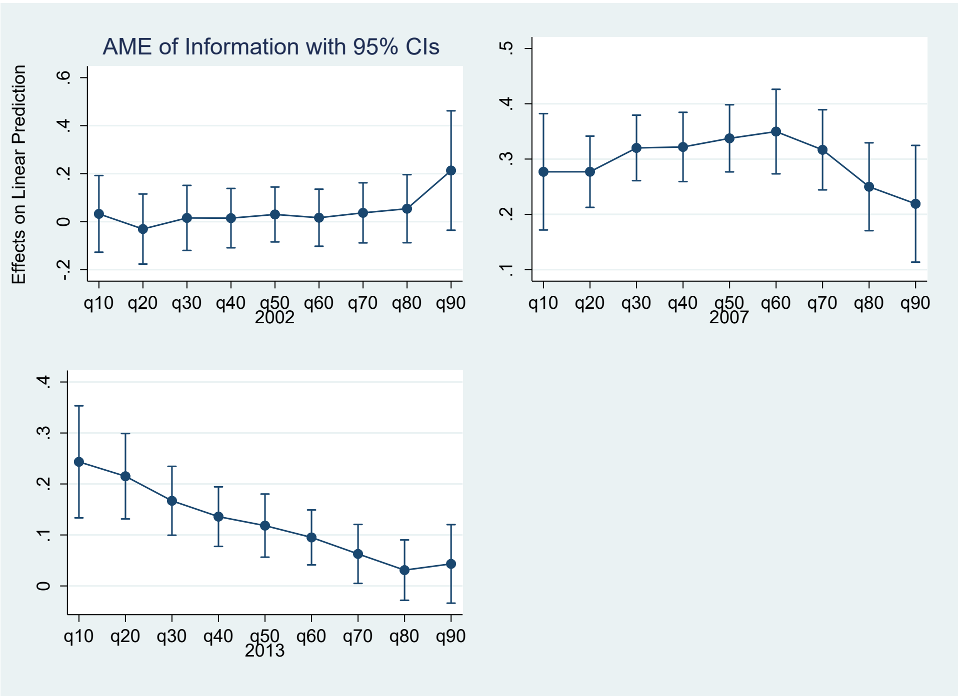
Figure 2.2: Unconditional Quantile Regression of Industries

Figure 2.2 a): Average marginal effects of "Resource Management" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Resource Management' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.2 b): Average marginal effects of "Information" with 95% Confidence Intervals (CI)

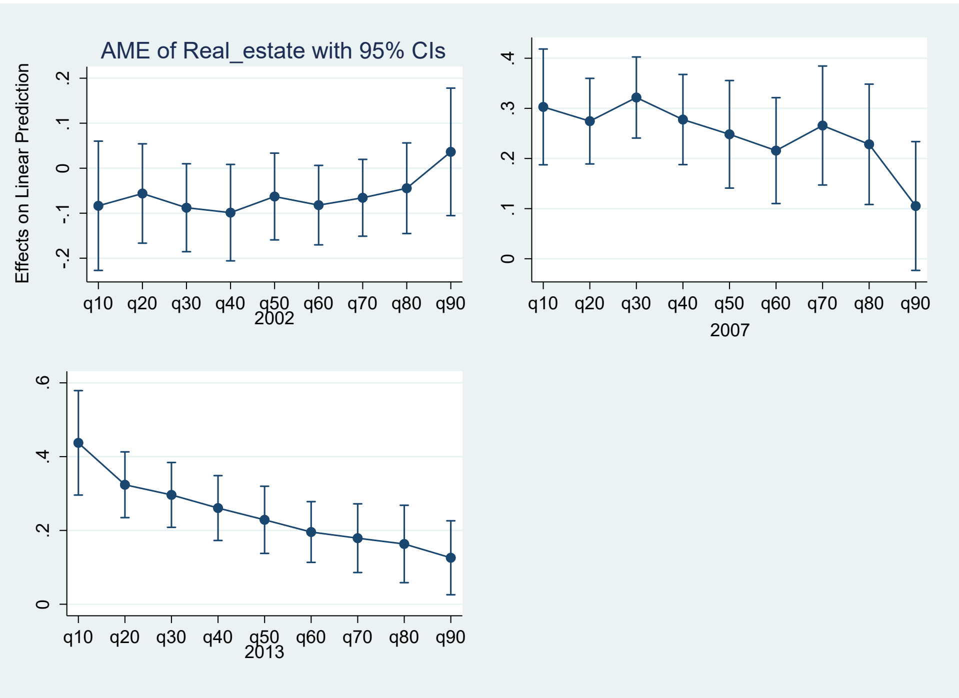


Notes: This figure displays the results of the unconditional quantile regression for 'Information' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.2 c): Average marginal effects of "Financial" with 95% Confidence Intervals (CI)

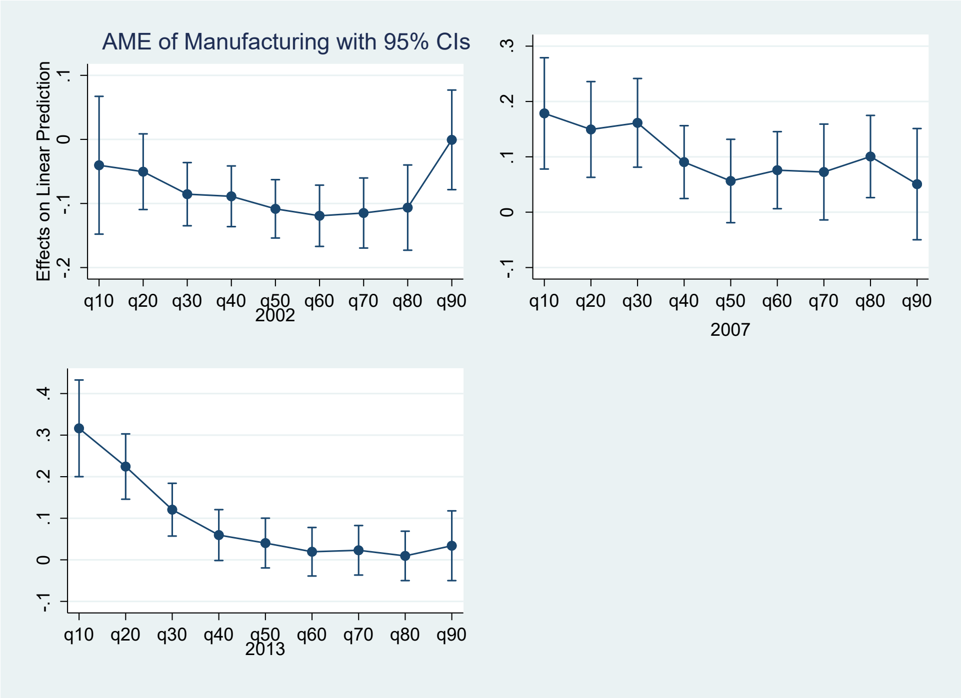
Notes: This figure displays the results of the unconditional quantile regression for 'Financial' across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.2 d): Average marginal effects of "Real Estate" with 95% Confidence Intervals (CI)



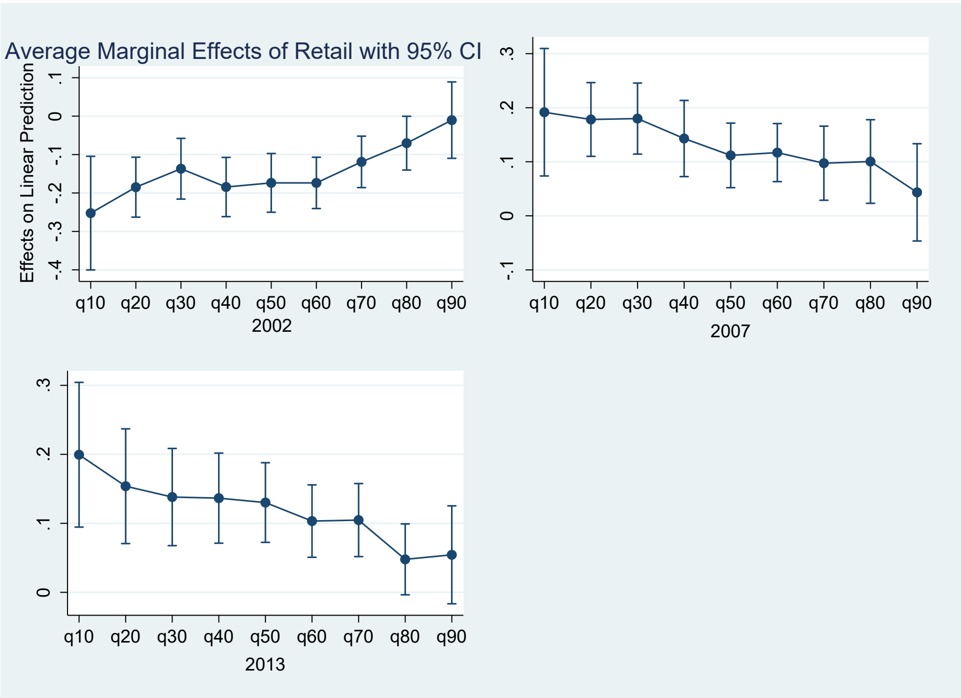
Notes: This figure displays the results of the unconditional quantile regression for 'Real Estate' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.2 e): Average marginal effects of "Manufacturing" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Manufacturing' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.2 f): Average marginal effects of "Retail" with 95% Confidence Intervals (CI)



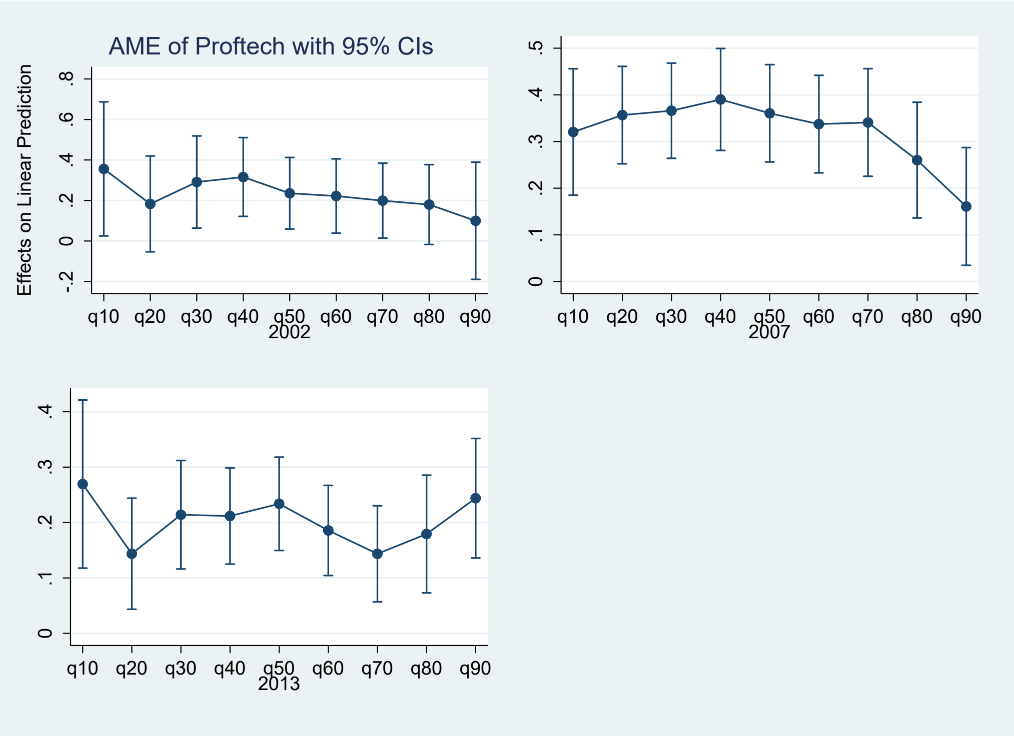
Notes: This figure displays the results of the unconditional quantile regression for 'Retail' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3: Unconditional Quantile Regression of Occupations.

Figure 2.3 a): Average marginal effects of "Managers" with 95% Confidence Intervals (CI)

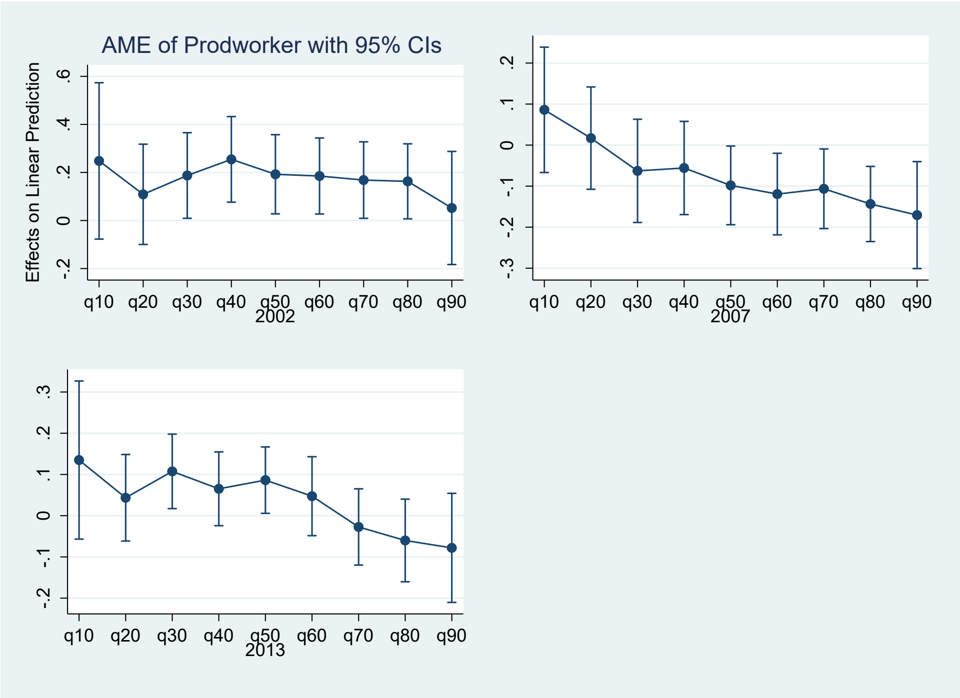
Notes: This figure displays the results of the unconditional quantile regression for 'Managers' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3 b): Average marginal effects of "Professional technicians" with 95% Confidence Intervals (CI)



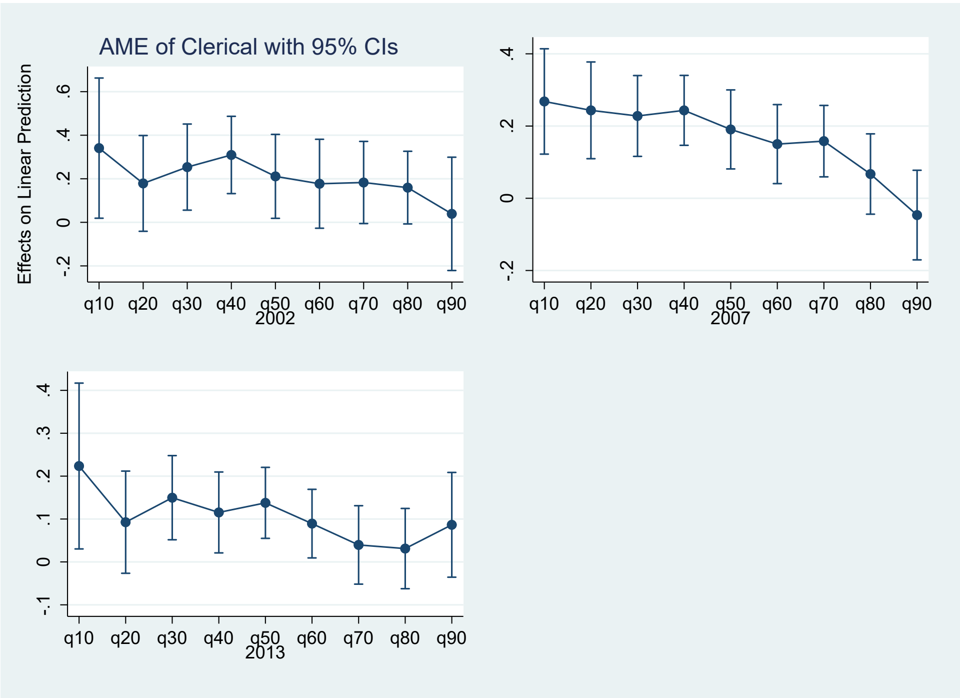
Notes: This figure displays the results of the unconditional quantile regression for 'Professional technicians' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3 c): Average marginal effects of "Production worker" with 95% Confidence Intervals (CI)



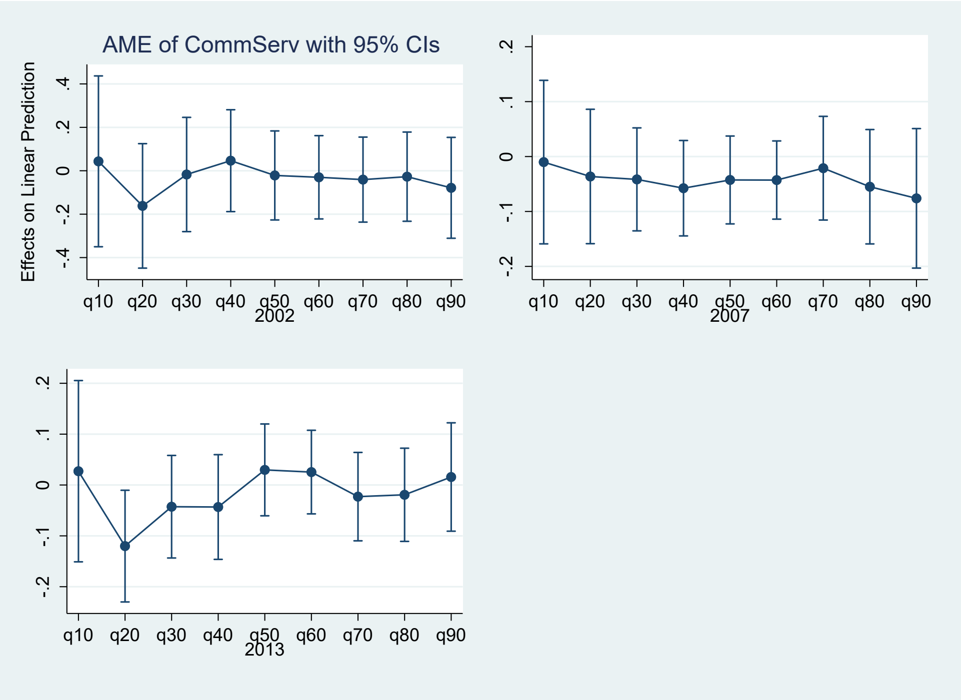
Notes: This figure displays the results of the unconditional quantile regression for 'Production worker' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3 d): Average marginal effects of "Clerks" with 95% Confidence Intervals (CI)



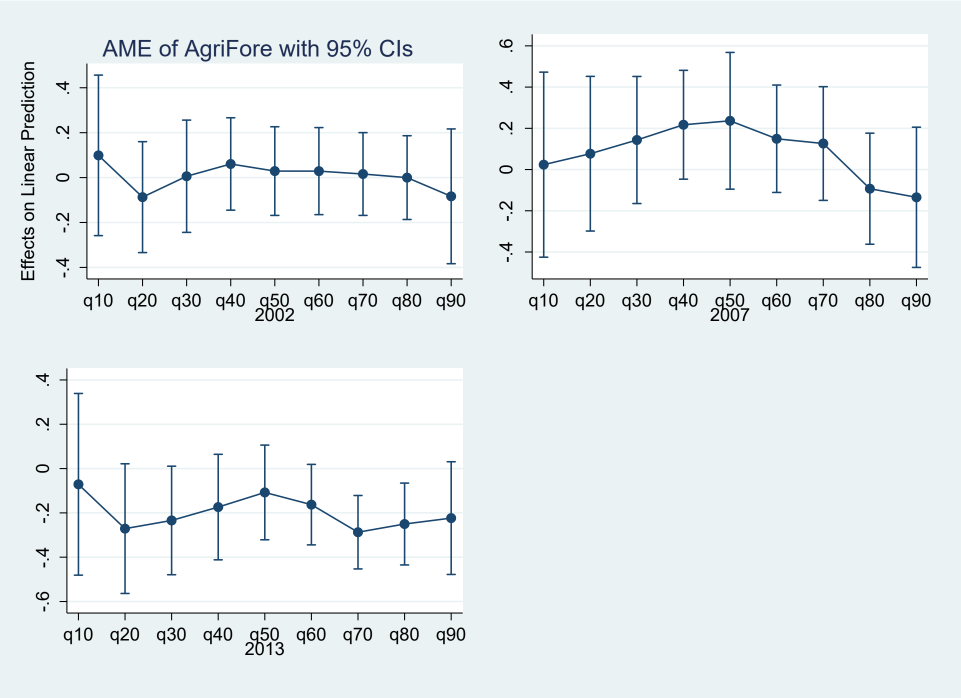
Notes: This figure displays the results of the unconditional quantile regression for 'Clerks' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3 e): Average marginal effects of "Commercial and service personnel" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Commercial and service personnel' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

Figure 2.3 f): Average marginal effects of "Agri-forestry producers" with 95% Confidence Intervals (CI)



Notes: This figure displays the results of the unconditional quantile regression for 'Agri-forestry producers' effects across different quantile levels for the years 2002, 2007, and 2013, with error bars representing the 95% CIs.

2.6 Oaxaca-Blinder Recentred Influence Function decomposition

2.6.1 Methodology

To investigate the existence of the wage inequality between the public sector and the private sector, in this paper I employ the RIF decomposition across the unconditional earning distribution, which is introduced by Firpo, Fortin, & Lemieux (2018). Since the RIF regression coefficients provide only local approximations of the influence of changes in the distributional statistics of the explanations but are unable to assess the issues of Inequality Treatment Effects, Firpo, Fortin, & Lemieux (2018) propose the methodology of combining the RIF regressions with a reweighting approach to decompose the gaps between the distributional statistics over the mean.

Traditionally, in order to decompose the wage inequality into a characteristic endowment and a price effect, the Oaxaca-Blinder (1973) decomposition method is widely applied. However, as Barsky et al. (2002) indicate, one of the significant weaknesses of Oaxaca-Blinder decompositions is that, if the conditional mean is not a linear function, the consistent approximation of wage structure effect and characteristic effect might not be delivered. Therefore, for obtaining a linear approximation of highly non-linear functions, such as the quantiles or the Gini coefficient, Firpo, Fortin, and Lemieux (2018) suggest using the RIF-regression method in an Oaxaca-Blinder type decomposition. This strategy can be specified simply as below:

Suppose the distributional statistic ν can be described by a function: the dependent variable Y, the explanatory characteristics X and the categorical variable T, which identifies the population ($f_{Y,X,T}$). The cumulative distribution of Y conditional on T can be written as:

$$F_{Y|T=k} = \int F_{Y|X,T=k}\, dF_{X|T=k} \quad (9)$$

Using the cumulative conditional distribution of Y, the gap between group 0 and 1 in the distributional statistic ν can be estimated as:

$$\Delta\nu = \nu_1 - \nu_0 = \nu(F_{Y|T=1}) - \nu(F_{Y|T=0}) \quad (10)$$

$$\Delta\nu = \nu(F_{Y|X,T=1}) - \nu(F_{Y|X,T=0}) \quad (11)$$

In the standard OB decomposition, the differences can be divided into the differences of characteristics (composition effect) and the differences of coefficients (wage structure effect). For decomposing the overall difference in the distributional statistic ν , to define a counterfactual statistic ν_c is required:

$$\nu_c = \nu(F_Y^C) = \nu(\int F_{Y|X,T=0}\, dF_{X|T=1}) \quad (12)$$

Moreover, the gap in distribution statistic ν can be written as two components:

$$\Delta\nu = \nu_1 - \nu_c + \nu_c - \nu_0 \quad (13)$$

$$\Delta\nu_S = \nu_1 - \nu_c \quad (14)$$

$$\Delta\nu_X = \nu_c - \nu_0 \quad (15)$$

where $\Delta\nu_S$ implies the differences capture the association between Y and X (structure effect) and the $\Delta\nu_X$ represents the gap attributes to differences in characteristics.

According to the RIF function：

$$\nu(F_Y) = E\left(RIF_{(Y,\nu(F_Y))}\right) = E(X'\beta) + E(\varepsilon_i) = \overline{X}'\beta \quad (16)$$

The counterfactual statistic can be identified as：

$$\nu_1 = E\left(RIF\left(y, \nu(F_{Y|T=1})\right)\right) = \overline{X}^{1\prime}\hat{\beta}^1 \quad (17)$$

$$\nu_0 = E\left(RIF\left(y, \nu(F_{Y|T=0})\right)\right) = \overline{X}^{0\prime}\hat{\beta}^0 \quad (18)$$

$$\nu_c = \overline{X}^{1\prime}\hat{\beta}^0 \quad (19)$$

Thus $\Delta\nu_X = \nu_c - \nu_0 = (\overline{X}^1 - \overline{X}^0)\hat{\beta}^0$ and $\Delta\nu_s = \nu_1 - \nu_c = \overline{X}^1(\hat{\beta}^1 - \hat{\beta}^0)$

However, this strategy may result that the counterfactual statistic ν_c is incorrectly identified if the model is misspecified. Thus Barsky et al. (2002) and DiNardo, Fortin, and Lemieux (1995), basing on the observed data, propose a semiparametric reweighting approximation to identify the counterfactual distribution $F_{Y|X,T=0}dF_{X|T=1}$. Since the counterfactual distribution $F_{Y|X}^{C}$ cannot be directly observed, multiplying the observed distribution of characteristics $dFX|T$=0 with a factor $\omega(X)$ to obtain an approximation is feasible.

So, the distribution $dFX|T$=1 can be expressed as follows:

$$F_Y^c = \int F_{Y|X,T=0}\, dF_{X|T=1} \cong \int F_{Y|X,T=0}\, dF_{X|T=0} * \omega(\mathrm{X}) \quad (20)$$

Furthermore, the reweighting factor $\omega(X)$ can be identified as follows:

$$\omega(\mathrm{X}) = \frac{dF_{X|T=1}}{dF_{X|T=0}} = \frac{dF_{T=1|X}dF_X}{dF_{T=1}}\ \frac{dF_{T=0}}{dF_{T=0|X}dF_X} = \frac{dF_{T=0}}{dF_{T=1}}\ \frac{dF_{T=1|X}}{F_{T=0|X}} = \frac{1-P}{P}\ \frac{P(T=1|X)}{1-P(T=1|X)}$$

where p is the proportion of population in group 1 and $P(T=1|X)$ is the conditional probability of an individual in group 1 with characteristics X.

Thus, the counterfactual distribution ν_c is estimated using weighted least squares as:

$$\nu_c = E\left(RIF\left(y, v(F_Y^c)\right)\right) = \overline{X}^{c'}\hat{\beta}^c \quad (21)$$

Whereas the decomposition components are described as:

$$\Delta v = \underbrace{\overline{X}^{1'}(\hat{\beta}^1 - \hat{\beta}^c)}_{\Delta v_S^p} + \underbrace{\left(\overline{X}^1 - \overline{X}^c\right)'\hat{\beta}^c}_{\Delta v_S^e} + \underbrace{\left(\overline{X}^c - \overline{X}^0\right)'\hat{\beta}^0}_{\Delta v_X^p} + \underbrace{\overline{X}^{c'}(\hat{\beta}^c - \hat{\beta}^0)}_{\Delta v_X^e} \quad (22)$$

The aggregate composition effect consists of the pure composition effect (Δv_X^p) and the specification error (Δv_X^e), while the aggregate wage structure effect is decomposed into a pure wage structure (Δv_S^p) and the reweighting error (Δv_S^e). The pure composition effect and the pure wage structure effect are what this paper aims to estimate, and the two error terms are useful to evaluate the overall fitness of the model.

To be more specific, if the specification error is large and significant, it may suggest that the RIF regression is mis-specified or this RIF approximation is poorly explaining the distribution. Likewise, the reweighting error is an indication which describes the quality of the reweighting methodology. If the counterfactual does not work well, the reweighting error tends to be robust large. Especially, for large sample, it is preferable for the value to approach zero.

2.6.2 What is the structure of wage inequalities between the public and private sectors?

Decomposed by the reweighting procedure into composition effects and wage structure effects, the overall changes between China's public sector and private sector in real log wages at each percentile are shown in Figure 2.4. The total wage differential curves for these three years exhibit consistent patterns, with downward slopes across the quantiles. This suggests that wage inequalities between sectors are more pronounced at the lower end of the wage distribution than at the higher end. In other words, low-skilled workers in the public sector tend to earn significantly more than their counterparts in the private sector. To provide a precise analysis of wage differentials, this figure also illustrates the decomposed curves of composition effects and wage structure effects. The results indicate that the wage structure effect had the most significant impact in 2007, while the characteristics effect was most pronounced in 2013. Overall, factor endowments were the primary drivers of wage differentials in these three waves, while the unexplained effect contributed far less significantly to the overall wage distribution.

This figure specifically demonstrates that in 2002, the composition curve nearly coincides with the total wage gap curve, indicating that characteristic endowments were the primary factor driving the wage premium that year. In contrast, by 2013, the explained curve shifts upward, particularly at higher quantiles, suggesting that the composition effect had become increasingly significant at the upper end of the wage distribution compared to 2002 and 2007. Notably, in 2002 and 2007, the composition effect exerted more influence on the lower wage percentiles (0-50th percentile) than on the middle and high wage percentiles. However, in 2013, this trend reversed, with the composition effect exerting less influence on the lower percentiles (10th and 25th percentiles) and more on the middle and high wage percentiles.

Furthermore, a pronounced “sticky floor” phenomenon is observed, as evidenced by the downward slope of the wage structure curves. This indicates that the wage structure effect is more significant at the lower end of the wage distribution compared to the middle and upper ranges. Across these three years, wage structure effects predominantly influenced the low- and middle-wage percentiles more than the high-wage percentiles. Notably, in 2013, the impact of wage structure effects on the lower percentiles (10th and 25th percentiles) was considerably greater than on the middle- and high-wage percentiles.

These findings suggest that China's market economy reforms have significantly impacted the labor market. First, the composition effects, which account for the majority of wage differentials, highlight the substantial influence of these reforms. Conversely, the wage structure effects contribute less to the earnings of low-income workers and constrain the wages of high-income earners. This pattern indicates that market mechanisms increasingly shaped wages among the middle- and high-wage groups as economic reforms progressed, while the wage system continued to exert influence over the low-wage groups. Additionally, the results imply that public sector workers possess significantly more human capital advantages than their private sector counterparts. This is a widespread phenomenon in the Chinese labour market, where a large proportion of the highly educated workforce prefers employment in the public sector over the private sector.

2.6.3 What are the determining factors of the wage differentials between the public and private sectors?

Figure 2.5 presents the results for the overall composition and wage structure effects, categorized by the primary wage determinants. In 2002, the primary factors driving wage premiums among low-income workers were tenure, region, and occupation. By 2007, tenure, industry, and occupation emerged as the dominant determinants. In 2013, the key factors influencing wage premiums were education level, tenure, and occupation.

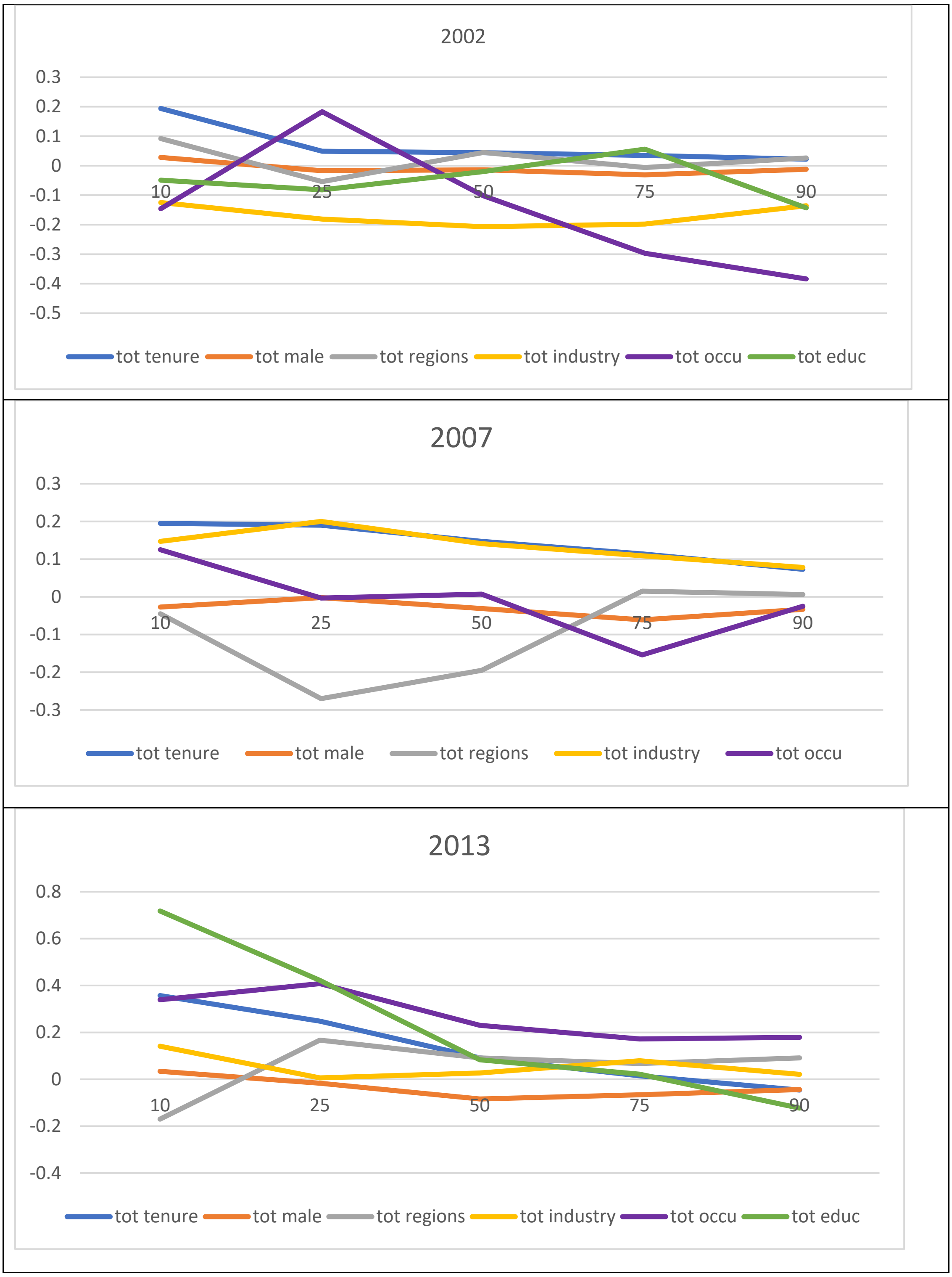
Specifically, in 2002, education level was not a primary factor in explaining wage differentials between the public and private sectors across the entire unconditional earnings distribution. However, by 2013, education level had become a dominant factor in explaining wage gaps, particularly at the lower end of the wage distribution (10th to 25th quantiles). Additionally, for high-income workers, differences in education levels between sectors had a significant negative impact on wage differentials in both 2002 and 2013, indicating that higher education levels contribute to reducing wage inequality at the upper end of the wage distribution.

Figures 2.6 and 2.7 illustrate the overall composition effect and overall wage structure, respectively, as derived from the reweighting process. These figures provide insights into the significance of the aforementioned results. As shown in Figure 2.6, the error terms are generally small and account for a minimal proportion of the variance, particularly in the 2013 dataset where the error term is relatively close to zero. This suggests that the RIF-regression model, which employs the reweighting process to estimate composition effects, performs effectively. However, it is important to note that in certain cases, specification errors may deviate significantly from zero. Figure 2.7 decomposes the wage structure effects into the pure unexplained component and the reweighted error component. Generally, the curves representing the pure unexplained effects, which reflect "policy effects," closely align with the total wage structure curves, indicating minimal dispersion in the explanatory variables (X). However, in 2002, the reweighted error curve shows a significant negative deviation at the lower and middle parts of the distribution, suggesting that the true wage structure effect was larger than initially estimated.

Figure 2.4 Decompositions of total wage differencials between the public sector and private sector into composition and wage structure effects

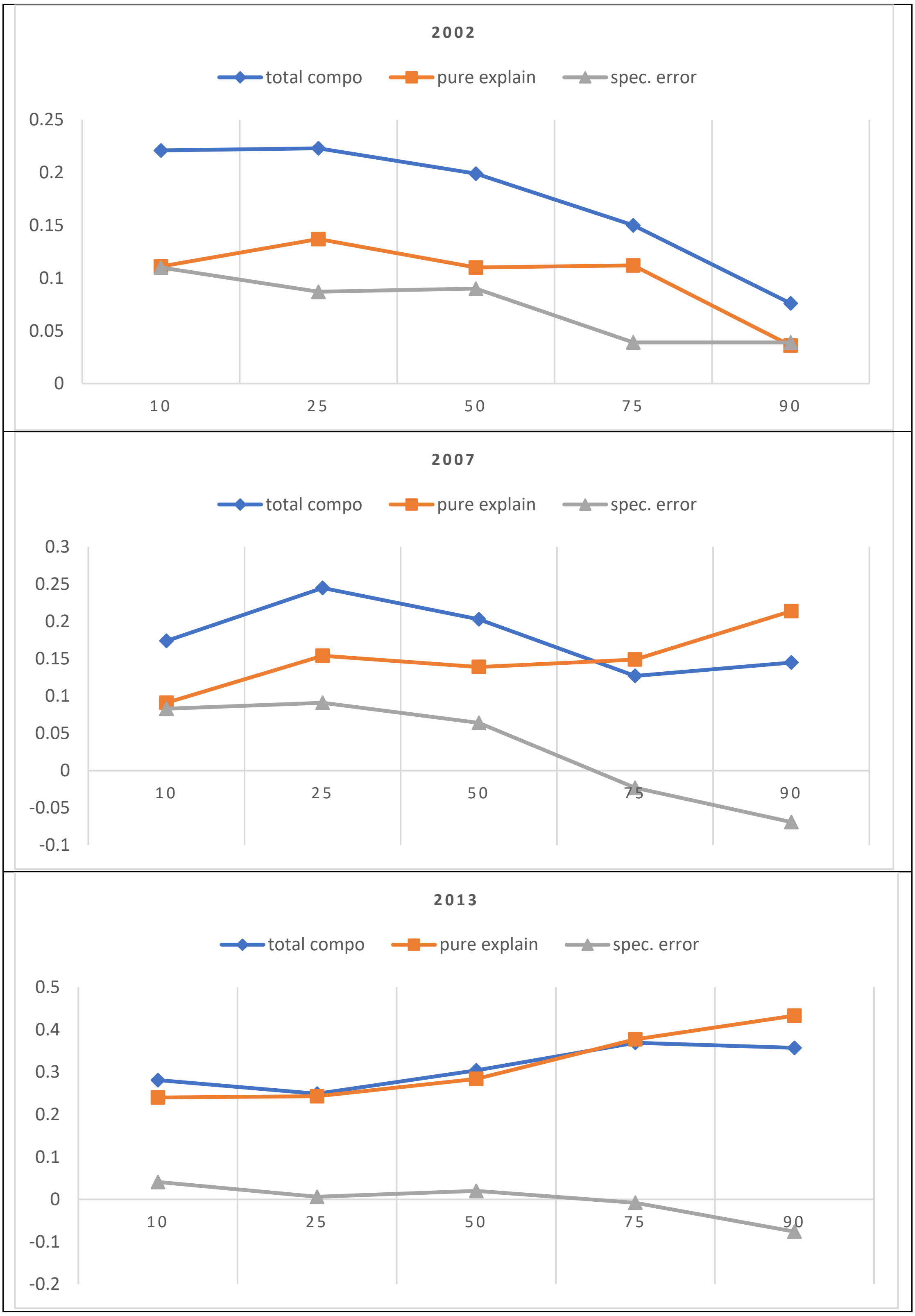
Notes: This figure illustrates RIF-OB results for the years 2002, 2007, and 2013, decomposing the total wage differentials between the public and private sectors into composition and wage structure effects. The blue lines represent total wage differences, the orange lines depict composition differences, and the grey lines denote wage structure effects.

Figure 2.5 The explained effects of various wage determinants.



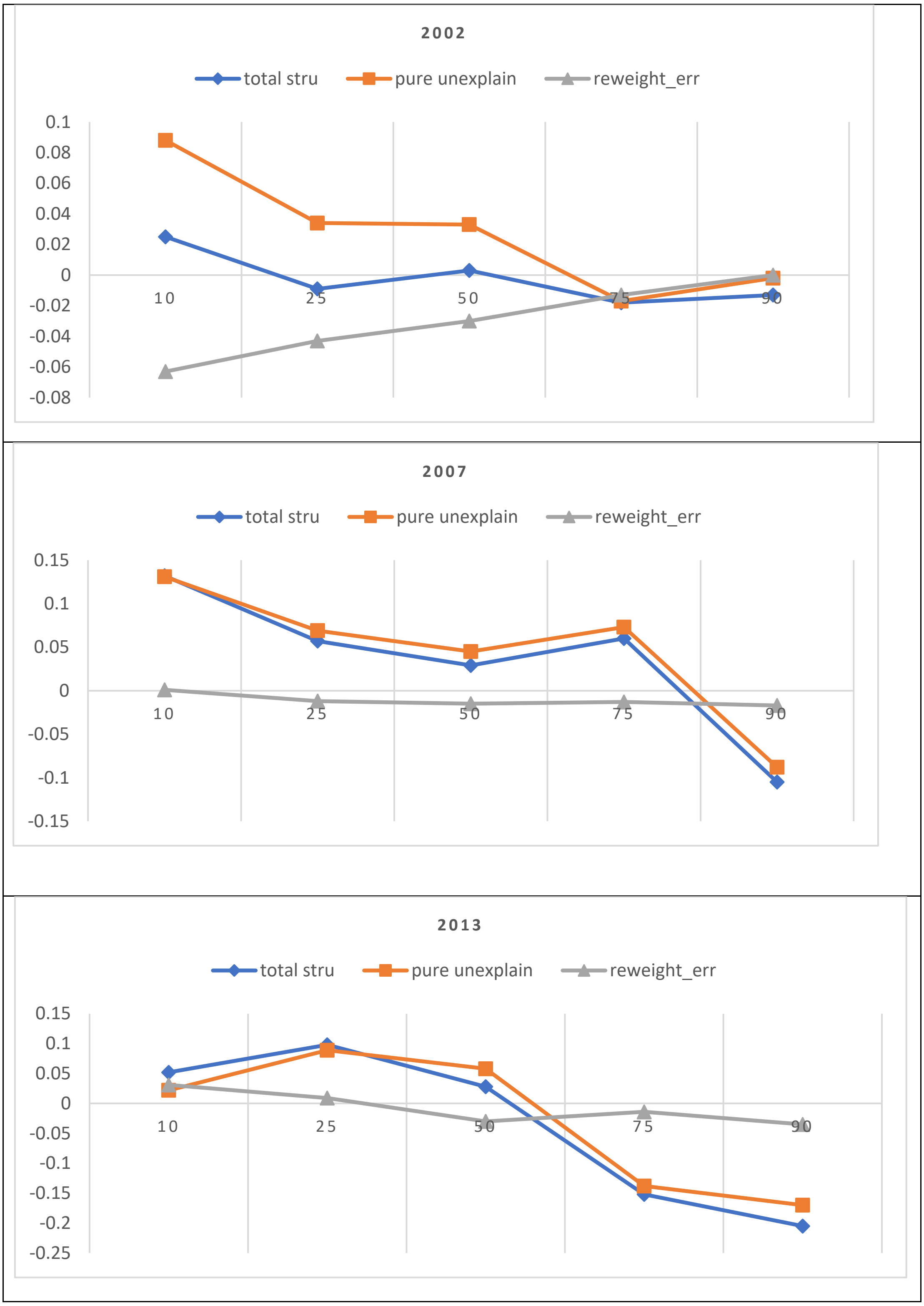
Notes: This figure illustrates the explained effects of different wage determinants in the years 2002, 2007, and 2013, including tenure, gender, region, industry, occupation, and education level. The data for education level is unavailable for the year 2007.

Figure 2.6 Decomposition of Composition Effects.



Notes: This figure displays the decomposition of the composition effect for the years 2002, 2007, and 2013. The blue lines represent the total composition effects of wage differentials between sectors. The orange lines indicate the pure explanation to the total wage gaps, while the grey lines represent the error terms.

Figure 2.7 Decomposition of Wage Structure Effects.



Notes: This figure displays the decomposition of the wage structure effects for the years 2002, 2007, and 2013. The blue lines represent the total wage structure effects of wage differentials between sectors. The orange lines indicate the pure unexplanation to the total wage gaps, while the grey lines represent the error terms.

These figures imply that during this decade, there is no doubt that the private sector has a dramatical development and the market mechanism proceeds well as factors related with human capital resource attribute more and more contributions to the wage level in the Chinese labour market. However, as the rapid growth of the state-owned sectors, the public sector regains its salary advantages over the private sector in the labour market (Bian & Zhang, 2002).

Even though in 2013 the number of employees in the private sector is more than its counterpart in the public sector, the findings reveal that the public sector still has much more high-quality employees. This is consistent with Xia et al. (2023) who find that despite the decline in the employment rate in SOEs, the wage premium of SOEs employees rose radically, thereby resulting in the urban wage inequality widening.

To be more specific, in the late 1990s the Chinese government implemented drastic SOE reforms, and a great number of laid-off SOE employees flooded into private companies, the remaining SOEs were profitable, monopolistic, and occupied a bigger part in all state-control industries, such as bank, telecoms, transportation, and energy enterprises. These monopolistic companies also capitalised and their market values increased rapidly with Chinese economic growth. Therefore, the large monopolistic SOEs play a dominant role and provide their employees very high salaries and welfare payments. According to the National Statistics Bureau, Duan & Saich (2014) indicate that 28.33 million workers (less than 8 percent of the whole workforce) are employed in 7 monopoly industries, however, earn around 55 percent of the total wages of the national workforce, which has led to the rise in urban wage inequality.

From the view of employees, the public sector not only provides secure positions, but also offers well paid, career advancement and a superior working environment. China’s news media reported that in 2020, around 1.4 million people took the national civil service exam for 24128 jobs and up to 2315 people competed for the hottest job. This phenomenon existed for 11 years: that over one million people took part in the national civil service exam and this trend seems not to be limited. The benefits of working in the public institution are obviously: first, employees in the official agencies take the low risk of losing their job; Secondly, they enjoy a great welfare package including medical insurance, retirement pension, subsidized housing; Last but not the least, most government jobs provide a fixed working schedule, and the workload is not heavy. Compared to the “996” work schedule, which is very popular in contemporary Chinese tech industry, the public sector provides their staff enough time to spend with their families. It is a prevalent sense that government jobs would not make you wealthy, but they are sufficient to provide you a comfortable life. In contrast, most of private corporations cannot offer such lucrative benefits as they have to face more crucial competition and struggle to live. Given that the arrears of wage are more likely to happen in the private companies, it is not worth to mention that welfares such as housing allowance, subsidized pension plans and so on are far more insufficient. Furthermore, it has already raised the concern among the private business owners that they are difficult to hire matching talents, which results in the skills shortage in the private sector and thereby threatening the economic growth.

2.7 Conclusion

This chapter, drawing on evidence from China, focuses on the issue of wage inequality between the public and private sectors, aiming to assess whether the public sector plays a positive role in reducing income inequality and promoting social justice as government anticipated.

Public sector organizations often encounter criticism due to characteristics such as excessive bureaucracy, unwavering stability, inertia, staff resistance, rigid organizational structures, and a perceived absence of shared innovation goals (Maqdliyan & Setiawan, 2023; Tranfield, Denyer & Smart, 2003). Consequently, to maintain efficiency, accountability, and transparency within the public sector, it becomes imperative to cultivate a fair market and employment environment, allowing enterprises of different ownerships to operate in a fully competitive environment.

Wage inequality stands as a critical concern in both political and economic realms, particularly within the public and private sectors. It highlights the broader issue of social equality. Notably, China is undergoing a transition from a communist to a market-based economy, with the public sector occupying a dominant position while private ownership faces discrimination in the Chinese labor market. This paper aims to contribute to the existing literature by investigating whether the status of this discrimination is improving and fostering heightened social equality following a series of policy reforms in China.

This chapter by drawing on the urban datasets from China Household Income Project (CHIP) survey of 2002, 2007 and 2013, and applying the UQR and RIF-decomposition methods, present the evolutions of Chinese wage structure during the decade from 2002 to 2013. The findings are as following:

Initially, the diminishing trend is evident in the unconditional average marginal impact of the public sector on wages. By 2013, it no longer bestows a significant wage premium upon low-income workers and, in reality, has an adverse effect on the earnings of high-income workers. This implies that, to a certain degree, the public sector no longer serves as a safeguard as it did in earlier times.

Secondly, the structure of urban wage inequality between the public and private sectors has undergone significant changes, driven by the growing influence of endowment effects, which play a dominant role. Simultaneously, the diminishing unexplained effect holds diminished significance for low-income workers and even constrains the salary levels of high-income earners. Fundamentally, the wage gap between the public and private sectors is attributed to employees in the public sector enjoying a more significant advantage in terms of human capital compared to their counterparts in the private sector, rather than discrimination between the sectors. These findings align with the research conducted by Démurger, Li, & Yang in 2012, which These findings indicate substantial progress in the reform of the Chinese labor market, with the public sector gradually surrendering its dominant position and fostering a more equitable employment environment.

Nevertheless, the research also reveals that despite a considerable reduction in discrimination against the private sector, a noteworthy proportion of highly educated individuals still favor employment in the public sector over the private sector. This preference persists, even though salaries in the public sector often do not align with their skills or abilities. The primary basis for this inclination is the belief that the public sector provides greater job stability compared to the private sector.

Moreover, for high-income earners in the public sector, their advantages surpass mere salary considerations, often encompassing various forms of influence and privileges. Furthermore, when analyzing the wage gap between the public and private sectors and categorizing it into distinct wage determinants, attributes associated with human capital, such as education level and tenure, emerge as essential factors explaining the wage premium, particularly at the lower end of the wage distribution. Besides, being male continues to employ a significant influence on hourly wages, underlining that attaining gender equality in the Chinese labour market remains a challenge.

Additionally, industry, occupation, and region also play pivotal roles in determining wage levels. Specifically, the financial and resources industries contribute significantly. The majority of companies in these sectors are state-monopolized, leading to a higher number of workers employed in the public sector compared to the private sector. Regarding occupations, professional and technical workers experience higher earnings during the period, though managerial roles remain dominant. Notably, regional development inequality, influenced by policy preferences, emerges as a significant factor contributing to wage disparities in China. Cities such as Beijing, Shanghai, and Guangdong contribute the most substantial wage premiums, with workers in eastern Chinese cities earning considerably more than their counterparts in the middle and western provinces.

Chapter 3. Does airport infrastructure boost the regional housing market?

3.1 Introduction

Governments often seek opportunities to improve local economies and accelerate urbanization. One good way to achieve this is to provide more convenient transportation infrastructure to their communities, especially in areas where the pace of growth is falling behind. Public infrastructure, including transportation infrastructure, continues to represent a substantial expenditure for numerous governments, as it serves as a valuable tool for shaping both local and national economic activities (World Bank, 1994). As noted by Aschauer (1990), a critical function of government spending is to foster productivity, with fundamental infrastructures such as streets, roads, airports, public transport, sewerage and water systems exerting the most significant influence on productivity. According to neoclassical economic growth theory and endogenous economic growth theory, Zhang & Cheng (2023) point out that the development of transportation infrastructure is combined with other invisible technological and policy factors, forming the residual term of technological progress; further, they argue that the externalities of infrastructure investment serve as the primary fountain of long-term economic development. Implicitly, this suggests that investing in transportation infrastructure contributes to economic growth. Exploring whether a new transportation infrastructure can effectively stimulate a regional economy and speed up urbanization, as anticipated by governments, is worth investigating.

The influence of transportation infrastructure on economic progress and economic productivity has been examined extensively (Arvis et al., 2018; Ive & Gruneberg, 2000; Padeiro, 2013); for example, Pradhan and Bagchi (2013) state that the development of transportation infrastructure could enhance labour and capital productivity as direct inputs. Moreover, an improved transportation efficiency can facilitate cost saving (Gunasekera et al., 2008). Arvis et al. (2018) suggest that efficient transportation systems and infrastructure strengthen economic growth by assisting trade, enhancing the competitiveness of local businesses and reducing the expenses associated with accessing global markets. Moreover, transportation infrastructure can stimulate accelerated industrial clustering and alter aggregate market demand (Baldwin & Forslid, 2000; Pradhan & Bagchi, 2013). More specifically, its influence on the location choices of firms leads to the clustering of businesses around areas with well-developed infrastructure (Anas et al., 1998); this, subsequently, generates or amplifies employment opportunities in regions with substantial investments in transport infrastructure. This effect is particularly pronounced for firms engaged in manufacturing, wholesale trade and logistics (Bowen Jr, 2008). Besides its influence on economic growth, transport infrastructure has been also associated with several other aspects. As such, research has particularly examined the correlation between transport infrastructure and innovation, and the relationship between transportation and political economy (Agrawal et al., 2017; Brinkman & Lin, 2019).

However, the present scenario reveals that transportation infrastructure, such as regional airports, rely on significant subsidies to offset their annual deficits (Heymann et al., 2015), contrary to the initial expectations of governments. Likewise, in the late 1990s, regional policymakers made significant investments in regional airport infrastructure, striving to align with the demands of an expanding aviation market (Heymann et al., 2005). Furthermore, the emissions associated with transportation have been linked to heightened risks of lung cancer, heart disease and unfavourable pregnancy outcomes (World Health Organization, 2010). Transportation contributes to approximately a quarter of energy-related global greenhouse gas (GHG) emissions and about one-fifth of global energy consumption. Attention has also been drawn to the adverse effects and potential negative externalities of transport infrastructure, including noise, traffic and pollution (Cohen & Coughlin, 2008, 2009).

This paper evaluates whether residents' perspectives align with those of the British Governments, in that public infrastructure contributes to improving local economic conditions and expediting urbanization. The study conducts a case study focusing on assessing the announcement impacts of Doncaster Sheffield Airport, a regional airport infrastructure, on the Doncaster district's housing market. Improvements in infrastructure, services and amenities in urban areas can lead to urbanization. Airports, as significant public infrastructure, are considered to be one of the catalysts in elevating the attractiveness of a metropolitan area to businesses. Particularly, the provision of superior air services facilitates in-person interactions with business partners, fosters the development of intercity economic clusters and, ultimately, contributes to the establishment of new businesses and job opportunities.

Moreover, regions with superior amenities and infrastructure often witness higher house prices, as they become more appealing. Consequently, the housing market serves as a significant indicator of increased attractiveness, representing the outcomes of urbanization and local economic development. While higher house prices in a region may not offer a comprehensive view of overall development, they can serve as indicators of specific facets of growth. For instance, regions with raised property values often provide a better quality of life, encompassing access to amenities, education, healthcare and cultural opportunities. This heightened quality of life makes the area more appealing to residents, subsequently influencing the appreciation of property values. Strong and diverse economies in certain regions attract businesses and a skilled workforce, further contributing to the climb in house prices.

Doncaster is the second largest settlement in South Yorkshire after Sheffield. Like other towns in South Yorkshire, Doncaster was identified with the coal mining industry and the economy of which was traditionally concentrated in pits. Thousands of white-majority working-classes worked in the coal office and in companies that made mining equipment or provided support services to the men who went underground. However, since a pit-closure program went into full swing in the mid-1980s, its economy went from boom to bust and was heavily hit by coal mining closures. From then on, Doncaster was exposed to a long economic recession and the regional growth had begun to lag. One of the ways that Doncaster Council sought to improve its economic growth was to develop the land of former RAF Finningley airport. To be more precise, Doncaster Council briefly determined that one third of this site would be for residential development, one third for industrial uses, and the remainder would be left for research and development (R&D) facilities (Smith, 1998). Moreover, on September 1998, Peel Holdings was reported to beat MEPC to secure 1000 acres of RAF Finningley; however, whether this site was designed to become a new airport was not settled at that time. This may have been because even if the council preferred a new passenger airport to be constructed in the airfield (Smith, 1998), the then Deputy Prime Minister, John Prescott, considered it competition for the airport in his Hull East constituency; he wanted this proposal to be withdrawn and turned to support the rival Humberside International Airport (Gazette, 1999). In June 1999, it was announced that RAF Finningley was to be purchased for nearly £78m by

Peel Holdings. The former RAF base was supposed to become the site for a new international airport as well as industrial and office schemes (Gazette, 1999). A residential retail and leisure scheme on this site was also proposed by Peel Holdings, precisely containing 80,823 m^2 of buildings and 7,432 m^2 of officers' mess. Key to the commercial airport of Peel Holdings' application was the 3 km runway on the former airbase. The local authority in Doncaster sought the new international airport as a solution to stimulate the region's economic growth. They believed that Peel Holdings' proposal would present Doncaster with a stunning new facility as well as pervasive economic benefits, for instance, the new airport would be expected to provide 7,600 jobs in the next decade. Following the announcement, whether local people were likely to be supporters of the anticipated economic benefits on the area, such as employment and income, or whether they were likely to be opponents, concerned with the potential noise, pollution and congestion during the airport construction's period, is worth investigating. In order to answer this question, this study therefore analyses the evolution of Doncaster's property values between the pre-announcement period and the post-announcement period.

In this context, this paper examines the synthetic control methods pioneered by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), which have been further expanded by Abadie, Diamond, & Hainmueller (2014) and Abadie et al. (2021). They suggest that compared to obtaining a comparison assessment from a single control unit that is not exposed to the intervention, the synthetic strategy provides a more effective counterfactual estimate: it constructs a synthetic comparison unit by a weighted average combination of untreated entities. They also state that the synthetic control strategy, nonetheless, is similar to the methodologies of traditional comparative research, such as fixed-effects analysis with restrictions for unit specific trends. This method becomes an effective alternative approach, especially in measuring the uncertain effect estimate, dealing with temporary disturbances prior to the treatment, and selecting the control group. In contrast, the major concern of Difference-in-Difference (DID) estimation is whether the parallel trends assumption is feasible in practice (Ryan et al., 2015). The Synthetic Control Method offers an alternative approach to program evaluation, reducing the reliance on the parallel trends assumption through comparative studies. The fundamental concept is rooted in the idea that the impact of a treatment can be elucidated by aligning the trajectory of outcome variables of interest between the unit exposed to the intervention and a carefully selected set of entities that were not exposed but exhibit similarity to the treated unit (Abadie, 2021). Instead of the parallel trend assumptions, the synthetic control method is a data driven procedure in which a synthetic control is applied to the comparative units to construct a weighted average of the control units to match the pre-treatment outcomes and covariates of the treated units. More precisely, prior to the intervention, a synthetic control unit reproduces similar pre-intervention characteristics and outcome trajectory with the treated unit, as the time-invariant weighted average of available control units. Researchers point out that in comparison with previous case studies, the data structures from studies that have applied the synthetic control method are typically different; only one or a few units are subject to treatment (Billmeier & Nannicini, 2013; Coffman & Noy, 2012; Hinrichs, 2012).

More specifically, the benefits of the synthetic control method relative to other parametric regressions, as documented by Abadie et al. (2010), are as follows: firstly, the synthetic control approach provides transparent weights of each control unit, so that it can see clearly that the approximation of the outcome variables and other covariates between the treated unit and the fitted comparative unit prior to the treatment and, in the meantime, how much every untreated unit actually impacts the counterfactual assessment. Secondly, the measure manners of the synthetic control method to construct the counterfactual do not depend on the interference of observed associations between outcome variables and the confounding covariates.

Thus, this paper uses the fit method to reproduce a plausible 'synthetic Doncaster'. This was established on a weighted average of other districts that best fits the pre-announcement pattern of property price and transaction volume for each 'treated' district, thereby creating the possible trajectory of property prices and transaction volume of Doncaster if it was not exposed to the announcement intervention. The districts utilized to create the synthetic house price and property transactions for Doncaster are collectively denoted as the 'donor pool'. The evaluations for the influence of the Doncaster Sheffield Airport construction news were obtained by comparing the actual house price patterns for Doncaster with the measured synthetic controls in the post-announcement period.

The sensitivity of the treatment effects on variations in the donor pool's composition was also assessed. This entailed narrowing down the donor pool by excluding the neighbouring districts of Doncaster: a precautionary measure in case these areas might also be influenced by the airport announcement. Additionally, the robustness check tests introduced in Abadie et al. (2015) were used; these tests systematically exclude, one by one, the districts with the largest positive donor weights from Table 3.1 and Table 3.2, and then re-evaluating the treatment effect. This precautionary measure was implemented to ensure that the estimated effects were not unduly influenced by a single donor district. The results suggest that in the analysis of the housing market, the synthetic control method provides consistent evidence of considerable property price declines and transaction volume increases in Doncaster, compared to the counterfactual Doncaster, following the Doncaster Sheffield Airport construction news announcement.

Furthermore, to examine the confidence of the synthetic control approach, a series of placebo experiments were conducted. Particularly, a news announcement regarding a new public infrastructure project was re-assigned to each district in the donor pool. This enabled obtaining a comparison between the evaluated influence of the airport construction news on Doncaster and the distribution of placebo outcomes for other districts. According to the results from each operating placebo, the evaluated influence could be calculated. A distribution of evaluated gaps for the districts not exposed to the treatment by the repeated procedures was obtained. This means that if the evaluated influence on Doncaster property price is of the comparative magnitude to the distribution of placebo outcomes, it is evidence that the estimated effect of the news announcement on Doncaster would be significant. Given that the estimated effects on the areas in which the event did not happen are comparable or even greater than the actual one, confidence in the synthetic control estimate impacts of this event might be weakened to a large extent.

This study investigates the impact on the Doncaster property market of a new airport infrastructure announcement: the acquisition of RAF Finningley by Peel Holdings for the development of an international airport. The following section reviews the history of the Doncaster Sheffield Airport. Section 3.3 and Section 3.4 present the dataset description and the synthetic control methods, respectively. Estimated effects of the synthetic control method are demonstrated in tables and figures in the results section, followed by the robustness check. The last two sections lay out the inference of placebo tests and the conclusions regarding the influence of the Doncaster Sheffield Airport construction news announcement on the local property market.

3.2 Background of Doncaster Sheffield Airport

Doncaster Sheffield Airport, named as the Robin Hood Airport Doncaster Sheffield, is an international airport in the Metropolitan Borough of Doncaster within South Yorkshire, England. It was previously the RAF Finningley station, serving as a military base during wartime. In 1994, the Ministry of Defence announced the imminent closure of RAF Finningley as part of the Front Line First defence cuts; RAF Finningley was decommissioned in 1996 (RAF Finningley, 2023). Three years later, Peel Holdings, a property and transport company in the UK, bought the land and transformed it into Robin Hood Airport Doncaster Sheffield (known as Doncaster Sheffield Airport). It was the first commercial and civil aviation centre transformed from an RAF base during the post-war period as well as the first commercial airport to open in the UK for 55 years; it opened on April 28, 2005. It serves passengers across Yorkshire, the Humber and the North Midlands. The airport lies 3 miles (5 kilometres) south-east of Doncaster and 25 mi (40 km) from Sheffield city centre. In 2007, the airport was used by more than one million passengers (Doncaster Sheffield Airport, 2022).

It is worth mentioning the bid process to help settle the specific announcement date. In 1998, after receipt of detailed proposals, discussions and negotiations were conducted with the two highest bidders. Their bids were broadly similar and substantially in excess of the other bids; however, further inquiries were needed to determine the timing, certainty and full value of their proposals. Given the potential use of the site for a major civil airport, advice was also sought from Department of Environment Transport and the Regions and from the Government Office for Yorkshire and Humberside. Following this process and a concluding best bid stage, Peel Holdings emerged as the preferred purchaser, surpassing competitors, and was officially selected in September 1998 (Smith, 1998). However, whether the site was to be converted to a commercial airport was still uncertain: the Deputy Prime Minister at the time, John Prescott, viewed it as competition for the airport in his Hull East constituency; he even wanted this proposal to be withdrawn with support passing to the rival Humberside International Airport (Gazette, 1999). Finally, in June 1999, it was announced that the site was to be sold to Peel Holdings for £78m as an international airport. This purchase of the former RAF base at Finningley marked a further push for the Peel Group into the airport sector; however, progress was checked and great expense would be incurred because of a public planning inquiry called for later that year to consider the Group's application for a commercial airport at Finningley.

Also significant was the fact that by the mid-1980s, Doncaster was hit heavily by the coal mining closures; the closing of the mines resulted in poverty and deprivation, themes that were frequently covered by the local newspapers. Doncaster, like other towns in England that had previously relied on traditional industries for jobs, experienced minimal growth during prosperous periods and was severely affected by the financial recession. South Yorkshire was recognized as one of the most deprived areas in Europe, sparking investment in the region's redevelopment. Therefore, Doncaster sought the development of new infrastructure such as Robin Hood Airport, to boost regional economic growth. Doncaster is still one of the most socially deprived areas of the UK with a significantly lower GDP rate than the regional average. According to the Office of National Statistics (ONS), the borough has one of the highest youth unemployment and teenage pregnancies rates in the country, as well as poor educational attainment, poor levels of health and pockets of high crime rates. During the national elections in May 2015, the UKIP branch of Doncaster Central became the second largest political party after Labour, getting 24% of the votes, which was an increase of 20% from the previous General election in 2010. Thus, it was recognized as a UKIP hotspot (Thorleifsson, 2016).

3.3 Data Description

This paper uses Price Paid Data (GOV.UK, 2022) which includes the sale prices of properties in England and Wales submitted to HM Land Registry for registration. The HM Land Registry is a non-ministerial government department created in 1862: it registers the ownership of land and property in England and Wales. More than 26 million titles showing evidence of ownership for more than 87% of the land mass of England and Wales are covered. That is to say, people who buy or sell land or property, or take out a mortgage, have to apply to them to register. Once this land or property is registered, the ownership changes and mortgages or leases affecting it are recorded. As for the Price Paid Data, to be more specific, HM Land Registry receives the standard and additional price paid data, which is based on the raw data and recorded them from 1 January 1995 to the most current monthly data. It contains address data of transaction properties, which provides information as accurate as its county, district, city/town, locality, street and even postcode used at the time of the original transaction. For the present study, the panel data was created using the district level. Except for the sale price stated on the transfer deed, the specific address of properties and the date when the transaction was completed, Price Paid Data also contains the property type and age of the property.

Figure 3.1 and Figure 3.2 illustrate the dynamic trends in both house prices and transactions over time. Notably, there is an apparent upward trajectory in monthly house prices across all districts. However, an observation emerges in the case of Doncaster; its house prices consistently lag behind the average prices in other districts. This divergence becomes more obvious post-June 1999. Examining the transaction lines, a notable stability characterizes the overall trend, with Doncaster standing out due to consistently higher property transactions than other districts. Furthermore, noteworthy variations emerge following an intervention, suggesting a significant impact on transaction dynamics.

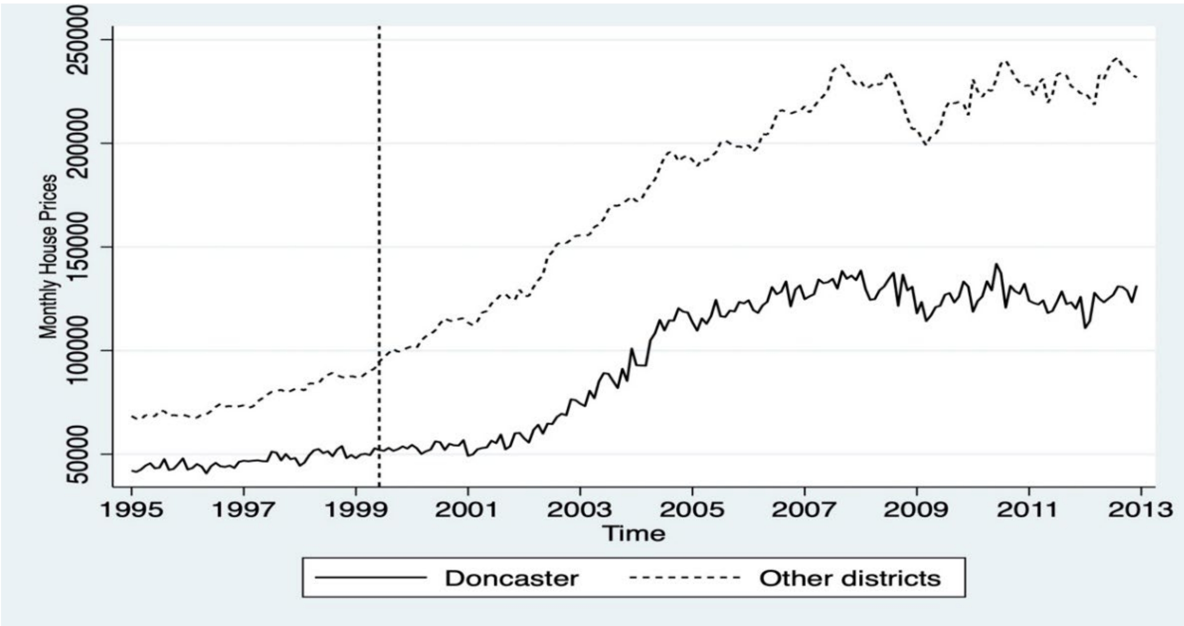


Figure 3.1 Average Monthly House Prices in Doncaster District and Other Districts.

Notes: The solid line stands Doncaster house price over time and the short-dashed line represents average house price of other Districts cross time.

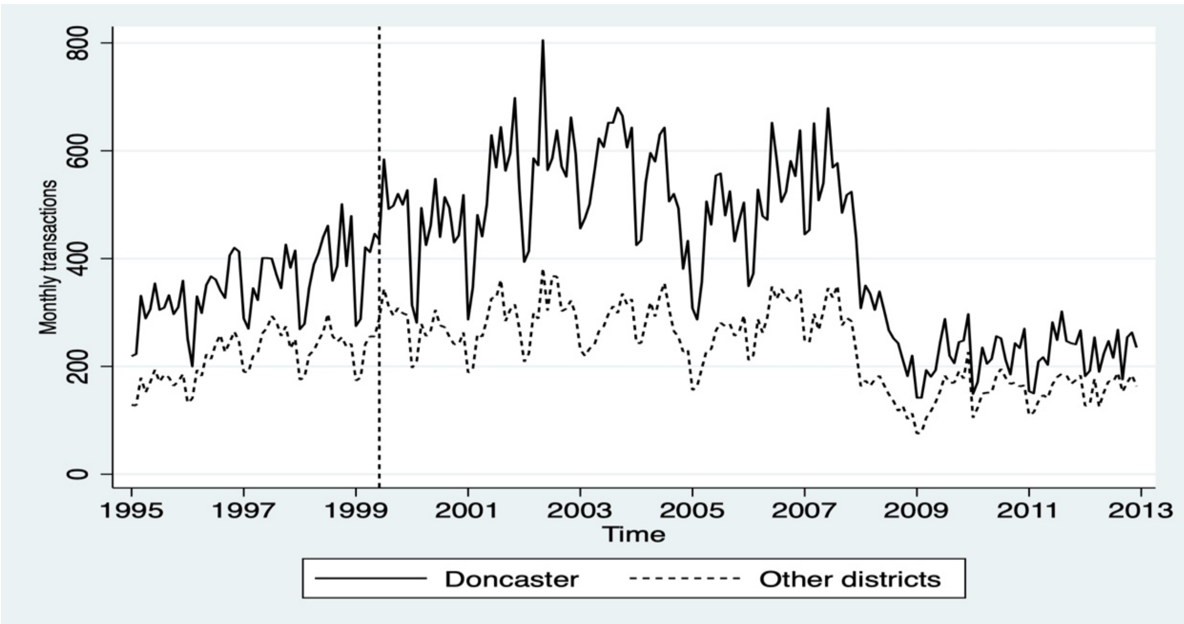


Figure 3.2 Average Monthly Transactions in Doncaster and Other Districts.

Notes: The solid line stands Doncaster house transactions over time and the short-dashed line is average property transactions of other districts.

3.4 Methodology: the synthetic control method

The synthetic control method was first introduced in the context of comparative case studies by Abadie et al. (2003). It constructs a setting that one aggregate unit such as a state or a district, is exposed to an event or intervention of interest while a larger number of units are not. The key idea behind the synthetic control method is that it uses a data driven procedure to validates the selection of the control units, i.e., in order to construct the outcome of counterfactual units for the treated unit, a large number of unaffected entities are weighted which is often fitting than single unaffected unit, in the absence of the treatment. More precisely, prior to the intervention, a synthetic control unit has similar pre-intervention characteristics and outcome trajectory with the treated unit, as the time-invariant weighted average of available control units. Compared with the DiD method, basing on the assumption that the relationship between the pre-intervention covariates and the outcomes post-treatment is linear, the synthetic control method permits the effects of outcome to change across time, no matter with observed variables or unobservable predictors (Doudchenko & Imbens, 2016).

The synthetic control method sets that only one single unit is exposed to the intervention and tries to offer a more synthetic way to assign weights to the control group. In such a way, the control group mirrors the treatment group as closely as possible. Following the notation of Abadie (2021), this strategy can be specified simply as below:

Assume there are J+1 units (districts), the first unit is exposed to the news of the former RAF Finningley was redeveloped to a commercial airport, while the others remain unexposed and are stated to as the "donor pool". Results are observed over T time periods where the relevant treatment occurs at time T_0 and $1 \leq T_0 \leq t$. So the treatment effect the intervention for unit i at time t could be written as:

$$\alpha_{it} = Y_{it}^{I} - Y_{it}^{N} \quad (1)$$

where Y_{it}^{N} is the outcome in district i at time t without intervention and Y_{it}^{I} denotes the outcome of district i at exposed time t, in period of $T_0 + 1 \leq t \leq T$, i = 1, 2, 3, …, J+1.

t = 1, 2, 3, …, T.

Let D_{it} be an indicator that takes value one if unit i is exposed to the intervention at time t, and value zero otherwise. The observed outcome for unit i at time t could be expressed as below:

$$Y_{it}^{I} = Y_{it}^{N} + \alpha_{it} D_{it} \quad (2)$$

$$D_{it} = \begin{cases} 1, & if\ i = 1, and\ t > T_0 \\ 0, & otherwise \end{cases}$$

While in this case, only Doncaster (unit 1) receives the treatment and the other districts remain untreated, so that only Y_{1t}^{N} is not observed for $t > T_0$. The aim is to estimate $(\alpha_{1T_0+1}, \alpha_{1T_0+2}, .., \alpha_{1T})$, for t > T_0,

$$\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N} \text{ (3)}$$

In order to estimate α_{1t}, Y_{1t}^{N} would be the one required to measure since Y_{1t}^{I} is observed. A synthetic control for Doncaster property price is able to be constructed by assigning a (J × 1) vector of weights W = (w_2, ..., w_{J+1})’:

$w_j \geq 0$ for j =2, ..., J+1,

$w_2 + \cdots + w_{J+1} = 1$.

The value of the outcome for the synthetic control in time period t is computed as the weighted average $\sum_{j=2}^{J+1} w_j Y_{jt}$.

Assume that the value of the outcome for Doncaster in each pre-treatment time period can be denoted by an optimal set of weights $w_2^*, \dots\ w_{j+1}^*$, that's $\sum_{j=2}^{J+2} w_j^* Y_{jt}$. Given the amount of the pre-treatment time periods is larger enough compared with the scope of the Doncaster Sheffield Airport construction news shocks in the pre-treatment outcomes, the counterfactual outcomes for Doncaster in the post-treatment period can be estimated by $\sum_{j=2}^{J+2} w_j^* Y_{jt}$ with close-zero bias, which means $Y_{1t}^N - \sum_{j=2}^{J+2} w_j^* Y_{jt}$ would be closed to zero.

Therefore, for t ∈ $\{T_0 + 1, \dots, T\}$, the estimator can be denoted as

$$\hat{\alpha}_{1t} = Y_{1t}^I - \sum_{j=2}^{J+2} w_j^* Y_{jt} \qquad (4)$$

Practically, this may be impossible that prior to the treatment there exist a perfect set of weights consisting of a synthetic control which fit accurately all the outcome values of the treated units. A convincing estimate of the counterfactual posttreatment outcome values would be created by the synthetic control, given there is a combination of weights that is able to replicate an approximate trajectory of the outcome value of the treated units prior to the treatment. Additionally, a merit of the synthetic control mentioned by Abadie et al. (2021) is that the researcher is able to tell the confidence of the estimation results by investigate the fit goodness between the synthetic control and the treated group. Note that even if compared to fit the single pretreatment outcome values, matching both the pretreatment outcome variables and some covariates may provide a better posttreatment prediction, the W in this paper is only used to minimize the gaps in the pretreatment outcomes excluding any covariates since the dataset on a district level is limited during 1990s UK.

Selection of donor pool

In this paper, in order to measure the causal effect of the announcement of the former RAF Finningley being redeveloped into a commercial airport on the Doncaster house market, an appropriate comparison house market is needed. Moreover, for precisely investigating the impact of this shock on Doncaster property market, I analyse it from two dimensions, monthly house price and the amount of monthly house transactions. Furthermore, I evaluate which sort of house would be affected significantly.

To describe the dynamic effects of the announcement on the Doncaster housing market, it is crucial to track the actual Doncaster housing market as closely as possible prior to the announcement, and at the meantime the synthetic house market must be not exposed to the treatment. The districts that are used to construct the counterfactual Doncaster's house market are collectively as the "donor pool".

First, the donor pool should consist of districts that was not affected by the announcement of the Doncaster Sheffield Airport to be built around 1999. These districts were referred as "untreated" units. Secondly, the donor pool should consist of districts that are similar to Doncaster in many respects. For instance, during a preintervention period a synthetic control method is possible to compute a well-matched trajectory of the treated group, given a district with much higher house price is averaged by a much lower house price district. Whereas these two districts are obviously distinct with the treated district, it may not construct a plausible prediction of the synthetic house price of the treated unit in the postintervention period. For this purpose, the restrict donor pool with units that have similar characteristics to the treated unit may be necessary (Abadie, Diamond, & Hainmueller, 2015). However, the challenge is that the standard of the qualified (adequately similar) units to replicate the treated unit should be constructed. Additionally, if it turns out that only a small number of districts among the donor pool with outcome values in pretreatment period enough approximate to the outcome values of the treated unit, then the synthetic control method probably is not able to replicate a counterfactual variable to the treated unit since this approach does not permit for extrapolation.

Therefore, in this Chapter, I use two donor pools to investigate that whether the selection of donor pool has influence on the estimated results. One is more comprehensive that including all districts according to the availability of the dataset, that is 328 districts. The other one is excluding some neighbour districts of Doncaster, in case that they might have similar transitory shock on house price caused by the airport news announcement relative to

Doncaster. They are districts in North Yorkshire, Derbyshire, Humberside, Lincolnshire, North Lincolnshire and Lincolnshire, West Yorkshire, South Yorkshire, York and East Riding of Yorkshire, Nottinghamshire. Eventually there are 287 districts remaining in the restricted donor pool.

I would use the comprehensive donor pool as the example in the below description, but the estimated results created by each donor pool would be presented respectively. Specifically, I construct a synthetic control unit using a donor pool of 328 districts in UK at the similar administrative level of Doncaster for the monthly house price (transactions) during the period from 1995 January to 2012 December, assuming that the districts in the donor pool are not affected by the treatment. The synthetic unit is a weighted average of the districts in the donor pool. The weights are allocated by minimizing the distance between the house price (transactions) of Doncaster and of the synthetic group prior to intervention. There are 54 months from 1995 January to 1999 June, thus mathematically, let X1 denotes the (54 x 1) vector of observations for house price (transactions) in the districts in Doncaster, and let X0 denote a (54 x 328) matrix with observation for house price (transactions) in the districts in the donor pool. Then I let W denote a (328 x 1) vector of weights w_j (w_2, ..., w_{328}). Finally, the synthetic control group is defined by W* which minimizes the following mean squared error:

$$(X_1 - X_0W)'V(X_1 - X_0W),$$

where $w_j \geq 0$ for j =2, ..., 328 and $\sum_{328}^{2} w_j = 1$. Moreover, V is a (328 x 328) symmetric and positive matrix.

3.5 Main results and Robustness

Using the strategies defined in Section 3.4, the house price change and the property transactions shifts, over the period of 1995-2012, were measured using the mean monthly house price and the monthly transaction volume of local authorities.

3.5.1 Synthetic control results of property price and transaction volume

The synthetic Doncaster, which replicates the value of the counterfactual estimation of house prices (transaction volume) in Doncaster prior to the airport construction news announcement, was constructed. The influence of the Doncaster Sheffield Airport news announcement on the local housing market was estimated to be the difference in house price and transaction volume between Doncaster and its synthetic counterpart in the months during the post-intervention period. The synthetic Doncaster trajectory, before and after the airport construction news, was also compared to the actual outcome; how the model fits the data are presented in the figures below.

The first panel in Figure 3.3 shows the time series for real house prices in Doncaster (the solid line) and those of the synthetic group (the dashed line). It is clear that, prior to the treatment, both series display a very high degree of co-movement—both at low and high frequencies. While during the post-treatment period, there is a gap between the actual Doncaster house prices and the synthetic Doncaster house prices. According to the second panel in Figure 3.3, this gap has a magnitude of around £15,000. That is to say, after the news leaked about the redevelopment of former RAF Finningley, Doncaster house prices slowed its development up to around 30%.

The time series of transaction volume was also volatile. Figure 3.4 displays the evolutions of the actual Doncaster property transactions and the synthetic Doncaster house transactions. It can be observed that after the intervention, there is a divergence between the actual group and the counterfactual group, rising to 150 by 2003, which is around 37.5% of the original transaction volumes. It reveals that if the intervention had not happened, there would not have been so many houses sold in Doncaster. This result is consistent with Figure 3.3, in that more houses were sold, thereby interrupting the house price rises.

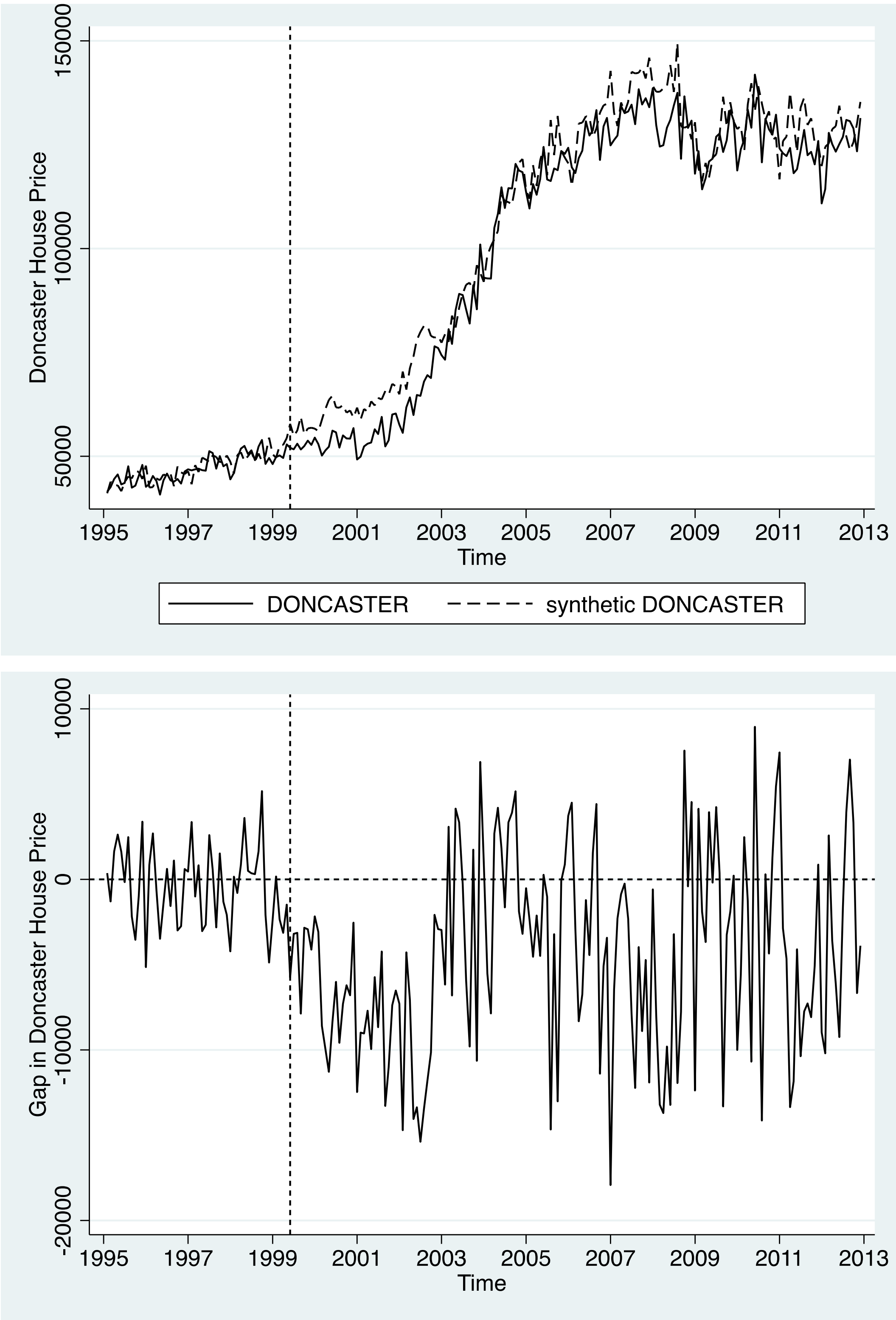


Figure 3.3 House prices and its gap between the actual Doncaster and the synthetic Doncaster

Notes: The upper panel presents time series data for real house prices in Doncaster (depicted by the solid line) and those of the synthetic group (represented by the dashed line). The lower panel displays the house price gap, indicating the difference between actual Doncaster prices and those of the synthetic Doncaster.

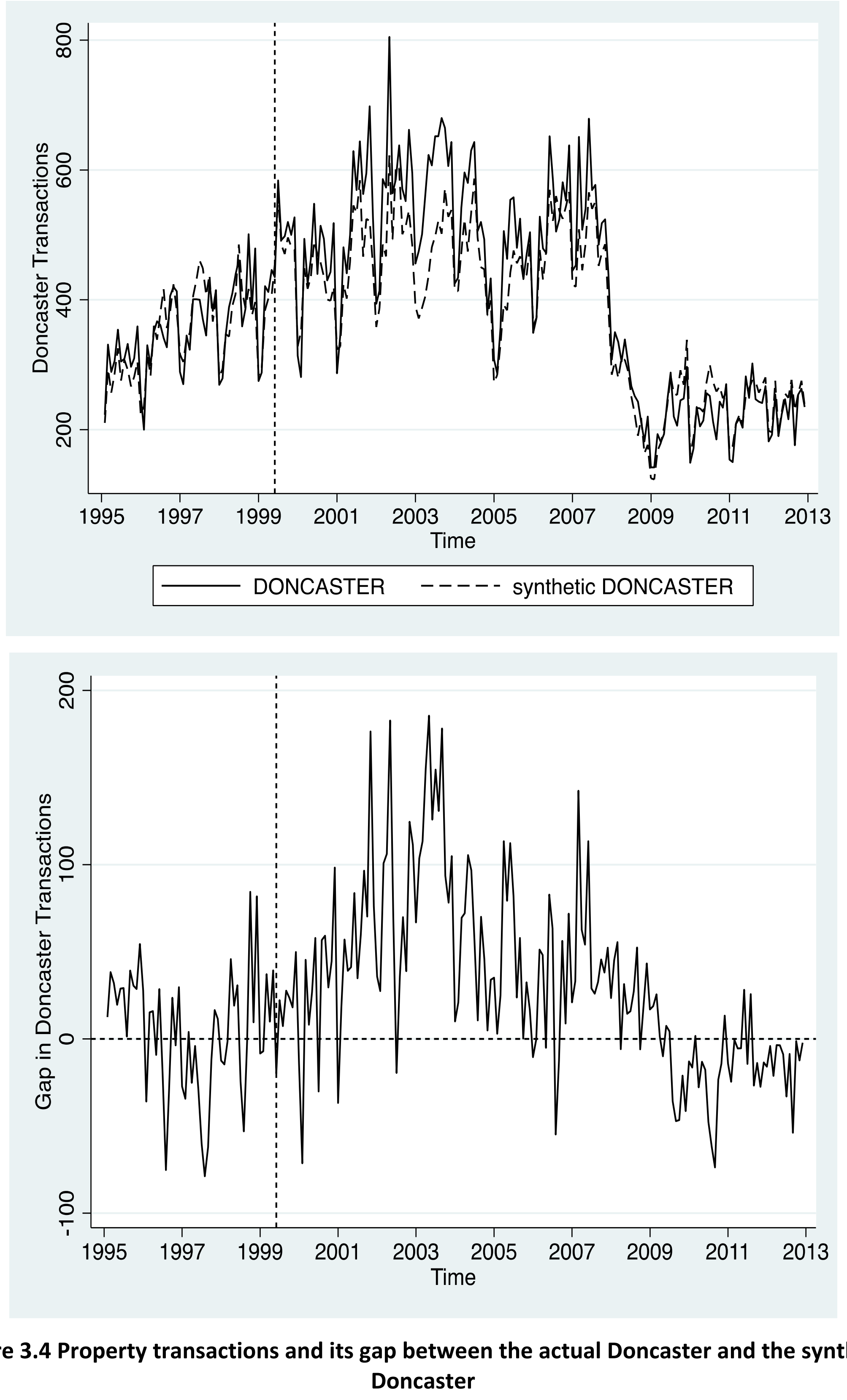


Figure 3.4 Property transactions and its gap between the actual Doncaster and the synthetic Doncaster

Notes: The upper panel presents time series data for real property transaction in Doncaster (depicted by the solid line) and those of the synthetic group (represented by the dashed line). The lower panel displays the property transaction gap, indicating the difference between actual Doncaster property transactions and those of the synthetic Doncaster.

In contrast to the anticipated impact of the announcement of a new airport infrastructure, which was expected to enhance the overall appeal of the area, attract businesses and individuals, and potentially influence property values, the findings indicate that the advancement of public infrastructure, especially in the case of airports, may not align with governmental expectations of stimulating regional economic development and boosting the regional property market. Instead, there is a possibility that it could have a negative impact on the housing market and potentially detrimentally affect the local economy. Moreover, as house prices decline, homeowners often witness a reduction in their wealth, triggering a 'wealth effect' that diminishes their financial security and confidence. Consequently, there is a potential decrease in spending on goods and services by homeowners, thereby contributing to a subdued local business environment and a dampened overall economic activity.

One of the advantages of the synthetic control method is its transparency of the counterfactual. Synthetic controls explicitly reveal the individual contributions of each comparison unit to the relevant counterfactual of interest. Through the simplicity and transparency of the counterfactual, researchers are able to assess the validity of the application and identify potential biases (Abadie, 2021). The transparent counterfactuals of house prices and property transactions are presented in Figure 3.5, Table 3.1 and Table 3.2.

In order to match 54 observations (the house price/property transactions of Doncaster for 54 months prior to the treatment), the procedure derived 328 parameters (district weights). Figure 3.5 illustrates maps of all districts in the donor pool with allocated weights based on the synthetic Doncaster house price model and the synthetic Doncaster property transactions model. The upper panel presents the map of districts, showing weights assigned according to the synthetic Doncaster house price model, with Doncaster indicated by a star. Darker shades of red represent districts with higher weights, while lighter shades denote districts with lower weights. The lower panel depicts the same districts, with weights determined by the synthetic property transactions model, where darker shades of blue correspond to higher weights and lighter shades to lower weights. This figure reveals that the majority of districts in the donor pool were assigned weights, although these were generally small, with only a few districts receiving substantial weights.

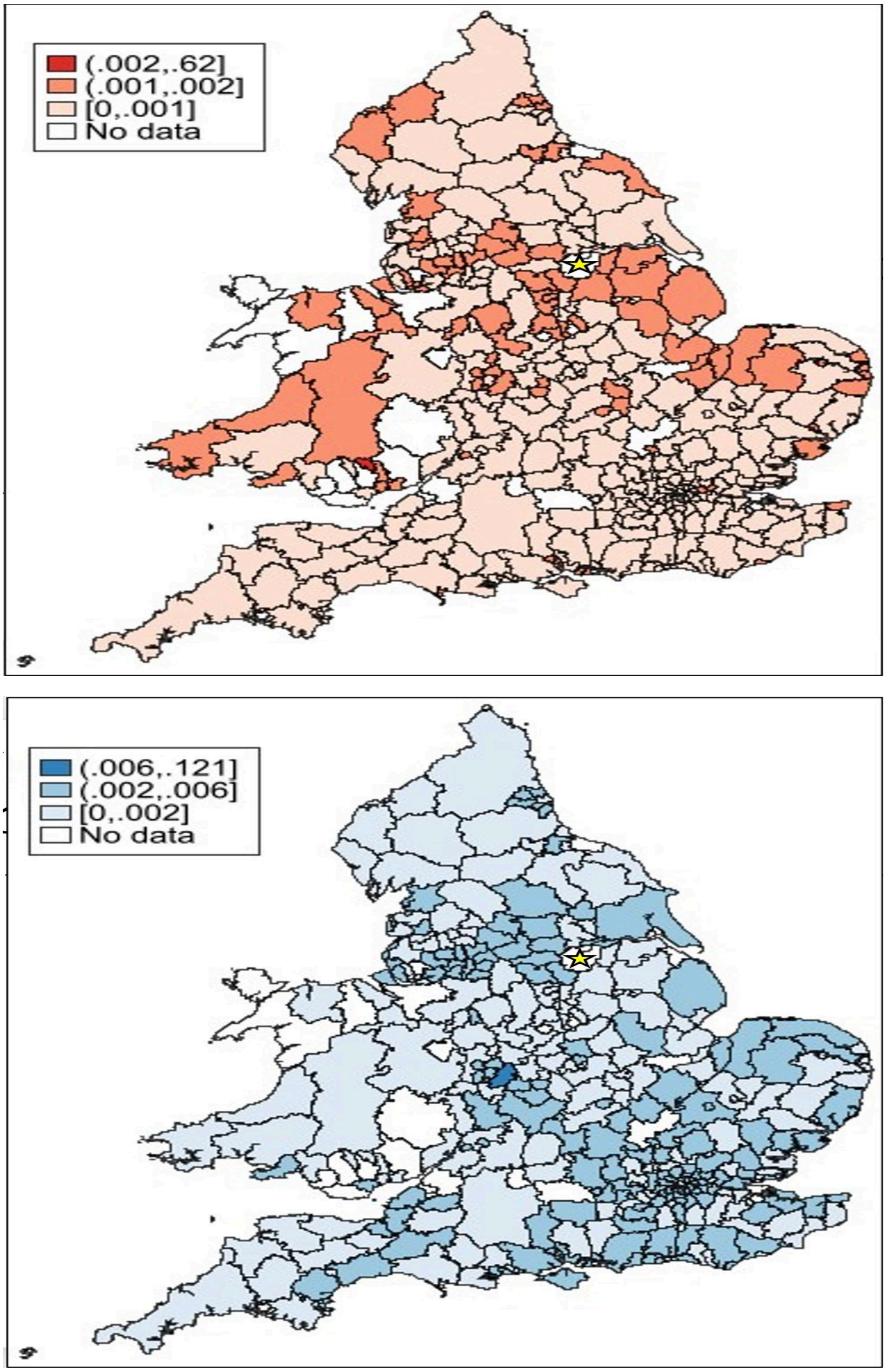


Figure 3.5 Maps of all districts with allocated weights based on the synthetic Doncaster house price and the synthetic Doncaster property transactions.

Notes: The upper panel presents a map of all districts within the donor pool, illustrating the weights allocated according to the synthetic Doncaster house price model. The lower panel displays a map of the same districts, with weights determined by the synthetic property transactions model. Doncaster is marked by a star, with darker shades of red and blue indicating higher weights, and lighter shades representing lower weights.

Table 3.1: The composition of the synthetic Doncaster house price: A part of district weights

BLAENAU GWENT	0.62	BURY	0.002	DARLINGTON	0.002
BIRMINGHAM	0.002	CALDERDALE	0.002	DUDLEY	0.002
STOKE-ON-TRENT	0.002	CANNOCK CHASE	0.002	EAST LINDSEY	0.002
BARKING AND DAGENHAM	0.002	CARLISLE	0.002	EAST STAFFORDSHIRE	0.002
BASSETLAW	0.002	CEREDIGION	0.002	EREWASH	0.002
ALLERDALE	0.002	CHESTERFIELD	0.002	FENLAND	0.002
BOLTON	0.002	CITY OF NOTTINGHAM	0.002	FLINTSHIRE	0.002
BRADFORD	0.002	CITY OF PLYMOUTH	0.002	GEDLING	0.002
BRECKLAND	0.002	CONWY	0.002	GLOUCESTER	0.002
BROXTOWE	0.002	COVENTRY	0.002	GOSPORT	0.002

Notes: This table presents the 30 districts that were allocated the largest weights in the donor pool used to construct the synthetic Doncaster house price.

Table 3.2: The composition of the synthetic Doncaster property transactions: A part of district weights

BIRMINGHAM	0.121	SHEFFIELD	0.005	HILLINGDON	0.004
BRADFORD	0.006	BOLTON	0.004	KENSINGTON AND CHELSEA	0.004
WANDSWORTH	0.006	BOURNEMOUTH	0.004	LAMBETH	0.004
BARNET	0.005	CARDIFF	0.004	LEWISHAM	0.004
BROMLEY	0.005	CITY OF WESTMINSTER	0.004	MANCHESTER	0.004
CITY OF BRISTOL	0.005	COVENTRY	0.004	MILTON KEYNES	0.004
CROYDON	0.005	DUDLEY	0.004	NORTHAMPTON	0.004
KIRKLEES	0.005	EALING	0.004	REDBRIDGE	0.004
LEEDS	0.005	EAST RIDING OF YORKSHIRE	0.004	RICHMOND UPON THAMES	0.004
LIVERPOOL	0.005	ENFIELD	0.004	SOUTHAMPTON	0.004

Notes: This table presents the 30 districts that were allocated the largest weights in the donor pool used to construct the synthetic Doncaster property transaction.

To be more precise, further 30 district weights (rounded to the third digit) are reported and displayed in Table 3.1 and Table 3.2, which construct the synthetic Doncaster house prices and the synthetic Doncaster property transactions. According to Table 3.1, it can be observed that

Blaenau Gwent is assigned the largest weight (0.62); Stoke-on-Trent, Birmingham, and other districts are assigned 0.002. These districts contribute around 70% of the synthetic control group. There are also small contributions from regions such as Liverpool, Manchester, Bradford, and so on, which are allocated to below 0.002, sharing the remaining 30 percent of the synthetic Doncaster house prices. While in Table 3.2, it is evident that Birmingham, Bradford and Wandsworth are the top three districts with the largest weights among the synthetic control group. However, the largest weight of the synthetic Doncaster property transaction is only 0.121, and the other 327 districts are assigned a bit more weight than of house prices. In summary, the Doncaster house prices and property transactions prior to the intervention are transparently and accurately reproduced by the weights of each control district in the synthetic Doncaster.

Table 3.3 presents the results of the pre-treatment house prices and property transactions of the real Doncaster and those of the synthetic Doncaster, as well as the sample means of the 328 districts in the donor pool. It can be seen that prior to the intervention, the synthetic Doncaster groups present accurate matches for the real Doncaster house prices and property transactions, whereas the average of the donor districts, which were not exposed by the intervention, does not provide a convincing control group for Doncaster. To be more precise, the real house prices in Doncaster before the airport was purchased were much lower than the average house prices in the 328 control districts. Moreover, the Doncaster property transactions were far higher than in the 328 regions in the donor pool prior to the intervention. To be compared, the synthetic Doncaster groups reproduce precise values of predictor variables on the Doncaster house prices and property transactions prior to June 1999, the news of a commercial airport to be built in Doncaster. It can thus be confidently

Table 3.3: Doncaster predictor means

Variables	Treated	Synthetic	Sample Mean
House Price (1995m1-1999m6)	46934.967	46935.725	77376.76
Transactions (1995m1-1999m6)	352.778	352.777	217.945

Notes: This table presents the pre-treatment house prices and property transactions for both the real Doncaster and the synthetic Doncaster, alongside the sample means for the 328 districts included in the donor pool.

stated that the synthetic control groups construct meaningful counterfactuals, enabling measurement of the impact of the airport news announcement on the housing market in Doncaster.

3.5.2 Robustness to the restricted donor pool

This section examines the sensitivity of treatment effects to changes in the composition of the donor pool. In order to gauge the potential impact of a constrained donor pool on the estimated results, certain neighbouring areas of Doncaster were excluded. This precaution was taken to account for the possibility that they too might be influenced by the intervention. These regions were districts in North Yorkshire, Derbyshire, Humberside, Lincolnshire, North Lincolnshire and Lincolnshire, West Yorkshire, South Yorkshire, York and East Riding of Yorkshire, and Nottinghamshire. Eventually 287 units were left in the donor pool. The results are reported in Figure 3.6. The divergence between the real Doncaster and the synthetic Doncaster is still extremely apparent. It is found that the estimated results derived from the restricted donor pool are rather similar to the effects evaluated by the comprehensive donor pool. It is plausible as with the restricted donor pool, that the districts assigned with the largest weight are also Blaenau Gwent with 0.597 on house prices, and Birmingham with 0.120 on transaction volume. There are mirror differences as the number of the control units in the restricted donor pool are diminished. The estimated results are not affected by the selection donor pool, which suggests, to some extent, the announcement effect on Doncaster's housing market was not insignificant among both donor pools; it also resulted in a more considerable decrease in Doncaster's house prices and a greater surge in property transactions than other majority districts. Consequently, no matter if the comprehensive donor pool or restricted donor pool is used, the weights distributed in specific districts are similar.

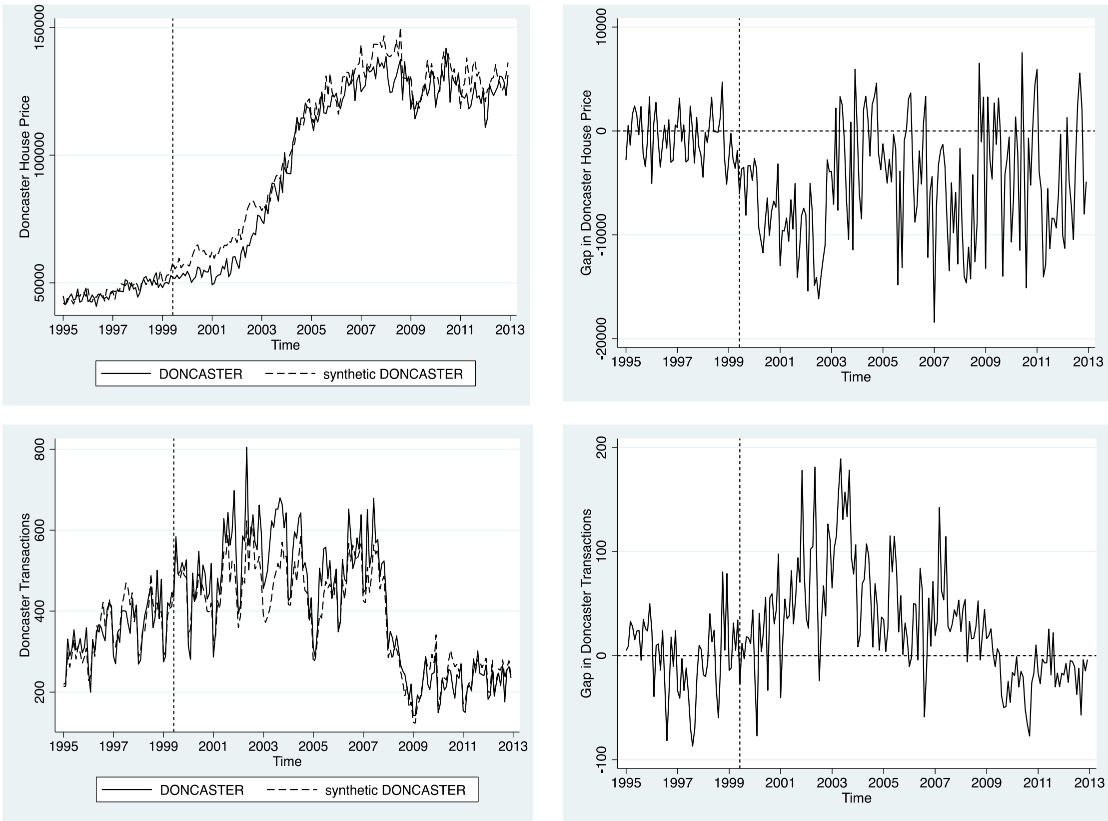


Figure 3.6 House price, property transactions and their gaps between the actual Doncaster and the synthetic Doncaster with the restricted donor pool

Notes: The upper panels present time series data and the difference for real house price in Doncaster and those of the synthetic group with the restricted donor pool. The lower panels display time series data and the difference for real property transactions in Doncaster and those of the synthetic group the property transaction gap with the restricted donor pool.

3.5.3 Robustness to change in weights

To further investigate whether the estimated effects were being driven by a single donor district, the robustness check tests introduced in Abadie et al. (2015) were employed. First, the districts from the donor pool in Table 3.1 that had the largest positive donor weights were excluded one at a time; then, the treatment effect was re-estimated. It is known that according to Table 3.1, the synthetic Doncaster consists of a collection of weights carried by 328 control districts, the majority of which are zero. The largest weights are Blaenau Gwent, Birmingham and Stoke-on-Trent. Thus, these were deliberately dropped, in turn, to re-evaluate the synthetic control model, so that the assigned weights' impact on the main results could be checked. That is to say, by removing each one of these three districts, the new synthetic Doncaster could be attained, even if it might diminish the goodness of fit to some extent. According to this robustness check, this would also determine whether the results were driven by one single unit in the donor pool.

Figure 3.7 and Figure 3.8 show the robustness check results. The short-dashed lines are the leave-one-out estimates, and the yellow and black solid lines are the duplicates of the original version. In particular, synthetic 1 (green line) stands for the synthetic Doncaster without Blaenau Gwent; the red and blue lines indicate the synthetic counterparts excluding Birmingham and Stoke-on-Trent. It suggests that the estimated announcement effect is robust; nonetheless, the largest weight districts are excluded from the donor pool. To be more precise, it can be seen that synthetic 2 (blue line) and synthetic 3 (red line) are almost overlapped with the original synthetic control (yellow line); this means that if Birmingham and Stoke-on-Trent are removed from the donor pool, it does not greatly matter. While there are clear small divergences between synthetic 1 (green line) and the other three synthetic controls, it suggests that if Blaenau Gwent is discarded, the synthetic control is affected in some extent. It also shows that this influence is not great and that the gap between the real Doncaster and the synthetic Doncaster remains substantial. More specifically, even if the smallest effect of the announcement is chosen, the difference between the real Doncaster and synthetic control unit 1 is around -£10,000 by 2002 June; the decreased price rate can be calculated given the baseline that the average house price in Doncaster in June 1999 was £52,042. That is -10000/52042 = -0.19, which indicates that the Doncaster Sheffield Airport construction news announcement resulted in at least a 19% drop in the Doncaster house prices over three years.

Similarly, according to Table 3.2, the synthetic Doncaster property transactions reveal that the majority of weights associated with various districts are nearly negligible: approaching zero. Birmingham emerges as the district with the highest weight, standing at 0.121. Following behind are Bradford and Wandsworth, each carrying a weight of 0.006. Likewise, each of these districts was intentionally omitted, one at a time, to re-evaluate the synthetic control model. This facilitated examination regarding whether the assigned weights significantly influenced the main results. In other words, by iteratively excluding one of the three districts with the highest positive weights, I aimed to generate a new synthetic Doncaster, even if it led to a potential decrease in the goodness of fit to some extent. Through this robustness check, I ascertained whether the outcomes were heavily influenced by a single unit within the donor pool.

The robustness check results of the synthetic Doncaster property transactions are presented in Figure 3.9 and Figure 3.10. The leave-one-out estimates, denoted by the short-dashed lines, are contrasted with the duplicates of the original version depicted in yellow and black solid lines. Notably, the green line signifies synthetic 1, corresponding to the synthetic Doncaster property transactions without Birmingham, while the red and blue lines represent synthetic counterparts excluding Bradford and Wandsworth, respectively. The findings suggest robustness in the estimated announcement effect even when the districts with the largest weights are excluded from the donor pool. Precisely, all three new synthetic lines (synthetic 1, 2 and 3) closely overlap with the original synthetic control (yellow line), indicating that the removal of Birmingham, Bradford or Wandsworth from the donor pool has negligible impact. Although subtle divergences exist between the new synthetic lines and the original, they are minor and essentially inconsequential. Moreover, the announcement influence observed on Doncaster property transactions is substantial in magnitude. Moreover, the gap between the real Doncaster property transactions and the synthetic counterpart remains significant.

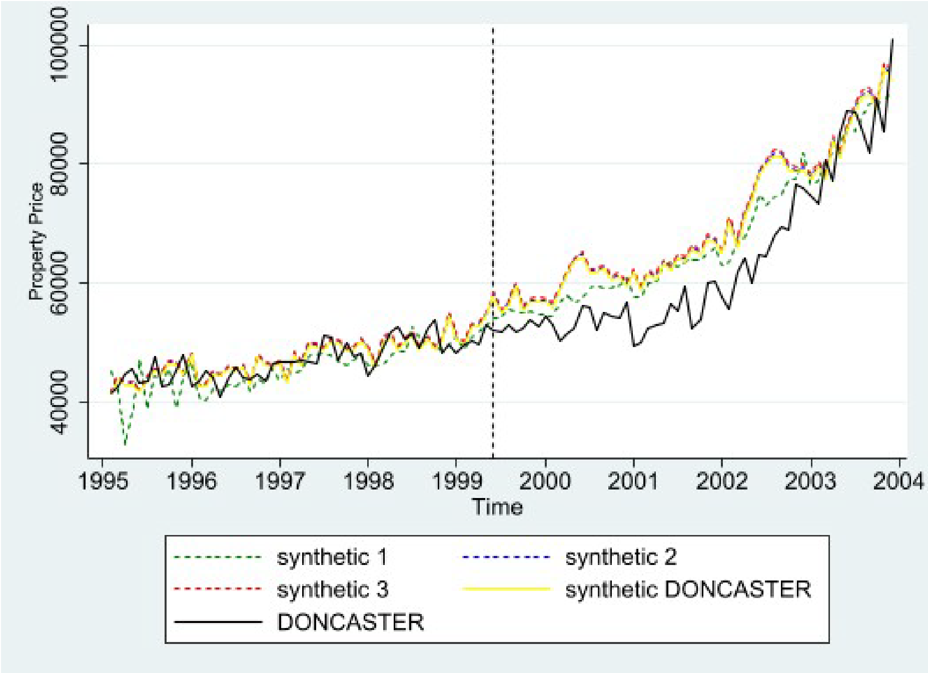


Figure 3.7 Leave-One-Out House Price Distribution of the Synthetic Control for Doncaster

Notes: This figure displays time series data for real house prices in Doncaster and those of the synthetic groups. The black line represents the actual time series data for real house prices in Doncaster. The yellow line corresponds to the original synthetic Doncaster house prices. The synthetic 1, 2, and 3 designations denote house prices of the synthetic groups, each excluding Blaenau Gwent, Birmingham and Stoke-on-Trent, respectively.

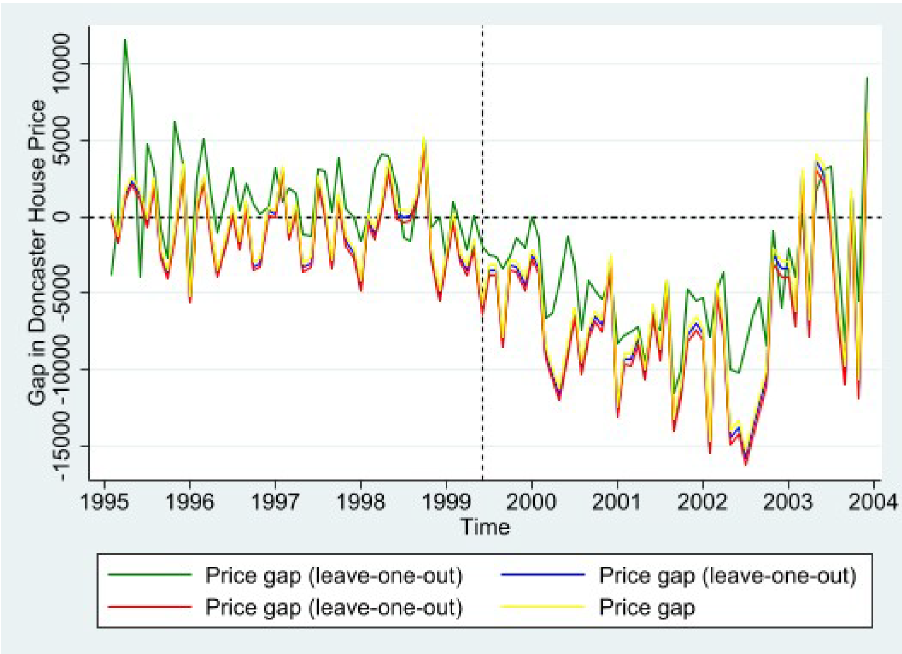


Figure 3.8 Leave-One-Out Price Gap Distribution of the Synthetic Control for Doncaster

Notes: This figure illustrates the house price gap between actual prices in Doncaster and those of the synthetic Doncasters. The yellow line represents the gap for the original synthetic Doncaster house prices. The green line signifies the gap for the synthetic Doncaster without Blaenau Gwent. The blue and red lines indicate the gaps for the synthetic Doncaster without Birmingham and Stoke-on-Trent., respectively.

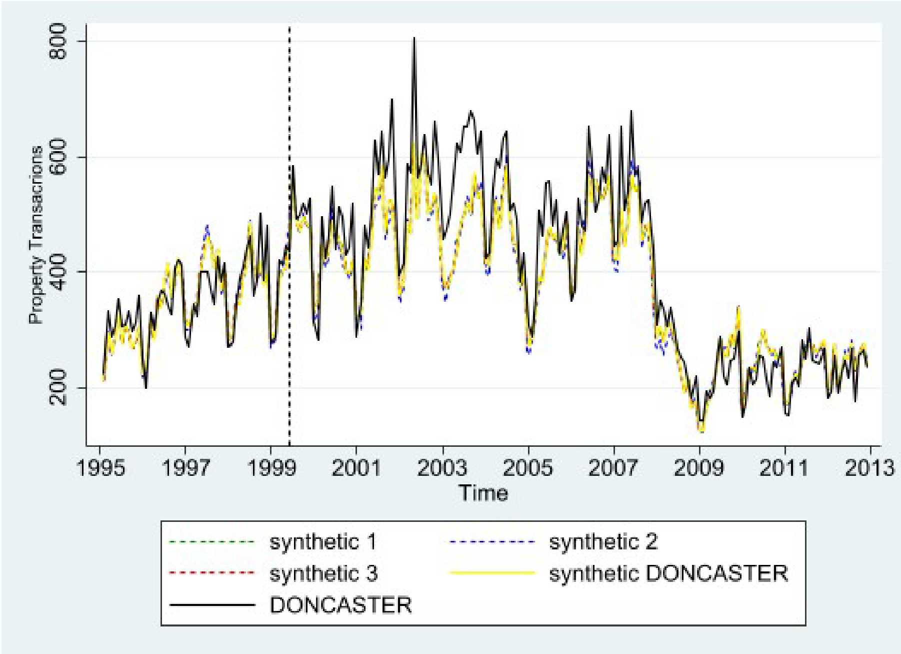


Figure 3.9 Leave-One-Out Property Transactions Distribution of the Synthetic Control for Doncaster

Notes: This figure displays time series data for real property transactions in Doncaster and those of the synthetic groups. The black line represents the actual time series data for real property transactions in Doncaster. The yellow line corresponds to the original synthetic Doncaster property transactions. The synthetic 1, 2, and 3 designations denote property transactions of the synthetic groups, each excluding Birmingham, Bradford, and Wandsworth, respectively.

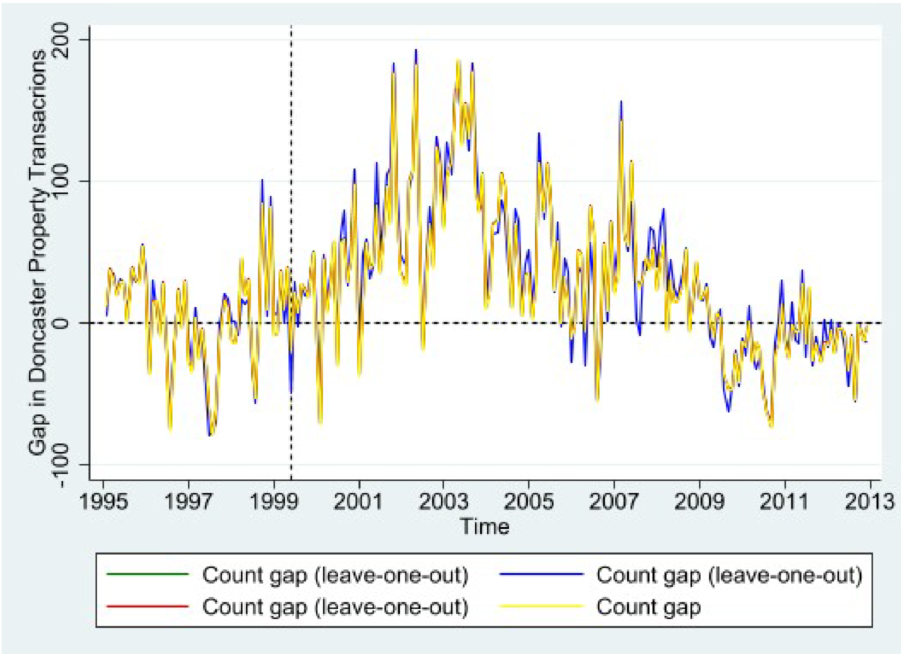


Figure 3.10 Leave-One-Out Transactions Gap Distribution of the Synthetic Control for Doncaster

Notes: This figure illustrates the property transactions gap between actual prices in Doncaster and those of the synthetic Doncasters. The yellow line represents the gap for the original synthetic Doncaster property transactions. The green line signifies the gap for the synthetic Doncaster without Birmingham. The blue and red lines indicate the gaps for the synthetic Doncaster without Bradford and Wandsworth, respectively.

3.6 Inference

For the quantitative inference, a comparative case study was conducted. In comparative case research, the traditional approach of statistic inference is challenging due to various limitations. The sample size is small, and randomization is often insufficient, making it difficult to apply probabilistic sampling. One approach which complements both qualitative and quantitative inference is the placebo study. Using this approach, researchers alternatively execute the falsification exercises by applying a standardized synthetic control method to examine the counterfactual of interest.

According to Abadie et al. (2015), two types of placebo tests can be used to assess the significance of the estimates: the 'in-time' and 'in-space' placebo tests. The 'in-time' placebo study involves reassigning the treatment of interest to a different month in the data other than the actual treatment month (June 1999); a random date prior to the intervention is selected and then the same synthetic control method is reapplied based on this new date. This allows for the evaluation of whether a similar pattern emerges between the treatment group and the control group. The significance of the results' credibility would be severely diminished when larger impacts are measured by the synthetic control approach for dates when the actual event did not take place. These tests are referred to as 'in-time' placebos by Abadie et al. (2015). While these falsification exercises require adequate data over a sufficiently long time period, with no significant external shocks that could influence the outcome variables.

Due to the limitations of the dataset and the insufficient length of the pre-treatment period (January 1995 to June 1999), conducting an 'in-time' placebo study was not feasible. As a result, this method was deemed unsuitable for the analysis. Instead, the credibility of the results was assessed using the 'in-space' placebo test, which reassigns the treatment to regions within the donor pool rather than shifting it in time.

The underlying logical idea of the 'in-space' placebo studies applied in this paper is permutation inference. To be more precise, the synthetic control method is applied to each potential control unit in the sample through random permutation, effectively reassigning the treatment to a randomly selected comparison group. This process generates a distribution of test statistics across the entire set of sample units. The assumption was that if I measured the event effect in the regions not exposed to the event, and then obtained a similar or greater outcome than those observed in the treated unit, it would indicate that the significance of the synthetic control method in evaluating the event effect was dissipated. Conversely, if the estimated effect for the treated unit lies at the extreme margins of the placebo distribution, if the estimated effect for the treated unit lies at the extreme margins of the placebo distribution, it suggests a reasonable level of confidence in the validity of the synthetic control estimate, affirming the event's impact.

Similar to traditional inference, the use of P-values can also be employed to verify a quantitative comparison between the synthetic control evaluation and the distributional placebo impacts. By calculating the in-space placebo effect for each region in the sample, a P-value can be derived, representing the proportion of placebo effects that are greater than or equal to the estimated effect for the treated group. This allows for the construction of confidence intervals or posterior distributions, which further inform the statistical inference process. The use of these inferential approaches aims to examine whether the evaluated event's influence is considerable within the whole distribution of placebo effects. Through this implementation, the synthetic control evaluations for districts that were not involved in the event of interest are available to measure. That is to say, the implementation in each donor pool district enables a comparison of the estimated effects of the announcement effect on Doncaster house prices and Doncaster property transactions with the distribution of placebo effects acquired from other regions within the donor pool.

More specifically, a series of 'in-space' placebo tests are conducted through the following steps: first, I repeatedly employed the synthetic control approach, which is the exact same method applied in the analysis of Doncaster airport news case, as well as across all other districts in the donor pool. That is to say, the data regarding the airport news treatment was redistributed to each of the 328 control districts, and in the meantime, throw the Doncaster into the donor pool. It assumes that in June 1999, districts other than Doncaster, in the donor pool, would have announced airport construction news. If the placebo studies produce much smaller-scale gaps compared to the synthetic Doncaster, a sensible explanation could be that the results provide significant evidence of a negative effect of the Doncaster Sheffield Airport construction news announcement on property prices in Doncaster. Whereas, if the placebo tests show that the gaps for the districts not exposed to the treatment are large, relative to the gap estimated for Doncaster, it indicates that this analysis cannot provide convincing results of a significant influence of the announcement on property prices and transactions in Doncaster.

The results of the placebo experiments are presented in Figure 3.11 and Figure 3.12, illustrating house price and property transactions, respectively. The patterns observed in the placebo results shows that these trajectories are bilateral around the x-axis in all exposed and non-exposed regions. This means that, in the absence of the event, the estimated represents produced by the synthetic control approach should converge to zero. Thus, the placebo studies further evaluate the predictive power of the synthetic control group, which serves as the untreated counterfactual.

Furthermore, in contrast to the distribution of placebo estimates for the districts in the donor pool, that were not exposed to the event, the synthetic control estimate for Doncaster Sheffield Airport is visibly large; it is noteworthy that in order to clearly present what is going on, the districts whose root mean squared prediction error prior to the treatment was two times greater than Doncaster were excluded. Noticing that, the root mean squared prediction error (RMSPE) is an evaluation of the scale of outcome variable gap between each district and its synthetic counterpart. If the synthetic control failed to produce an approximate trajectory of the pre-treatment outcome of interest, the large post-treatment RMSPE would not represent a significant event influence. Namely, if the pre-treatment RMSPE is large, then the large influence of the treatment would remain unexplained by a sizable post-treatment RMSPE.

Moreover, instead of estimating the actual impact of announcing the airport's construction, the lack of fit explains much of the post-1999 June divergence between the real Doncaster property prices and its synthetic counterpart; in such case, the synthetic Doncaster had not fitted property prices for the real Doncaster in the months prior to the public announcement of the airport's construction. Likewise, given the district that was well matched in the pre-treatment period, the poor fit, along with the placebo tests prior to the announcement treatment, would fail to present evidence of investigating the significance of measuring a large post-treatment gap.

Hence, in Figure 3.11, districts with a pre-treatment RMSPE of more than twice the pre-RMSPE of Doncaster property prices are excluded and all the lines from 1995 to 2004, when the house price gap reduces to zero, are plotted. This selection discards 143 districts that have large pre-RMSPE values relative to Doncaster, which would illustrate insignificant synthetic control method results. The remaining 185 colourful lines indicate the difference associated with each district's run of the test. More precisely, the colourful lines display the gap in property prices between each district in the donor pool and its synthetic counterpart. The superimposed black line represents the house price gap between real Doncaster and synthetic Doncaster. It can be observed clearly that the evaluated gap for Doncaster during the period of 1999-2003 is unusually large compared to the distribution of the gaps for the districts in the donor pool. As Figure 3.11 demonstrates, a good fit for monthly property prices in Doncaster, prior to the airport news announcement, is conducted well by the synthetic control method.

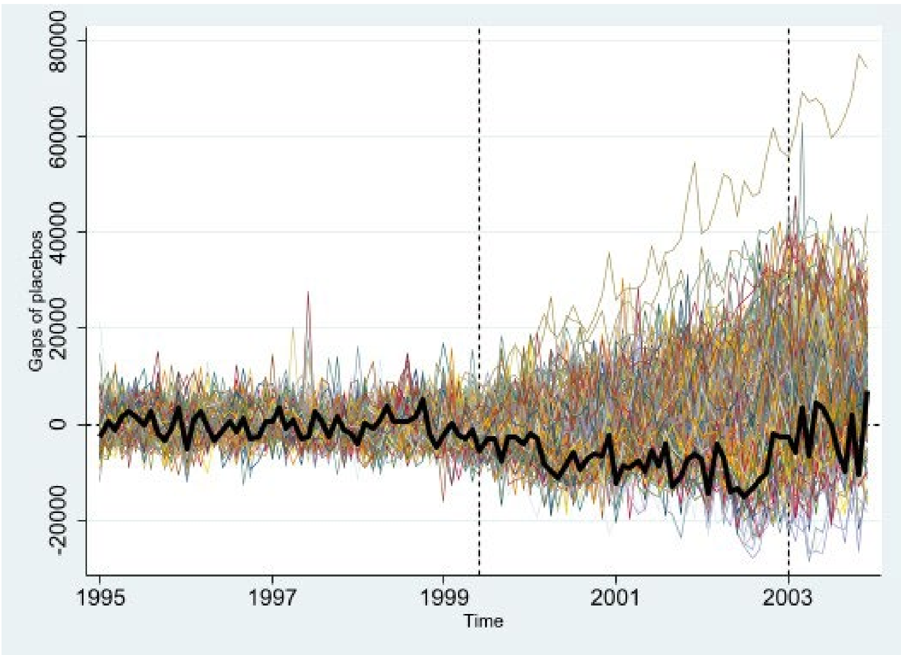


Figure 3. 11 The Placebo Test Results of Gaps in Property Prices.

Notes: This figure shows the placebo estimates on the house prices. The colourful lines display the gap in property prices between each district in the donor pool and its synthetic counterpart. The superimposed black line represents the house price gap between real Doncaster and synthetic Doncaster.

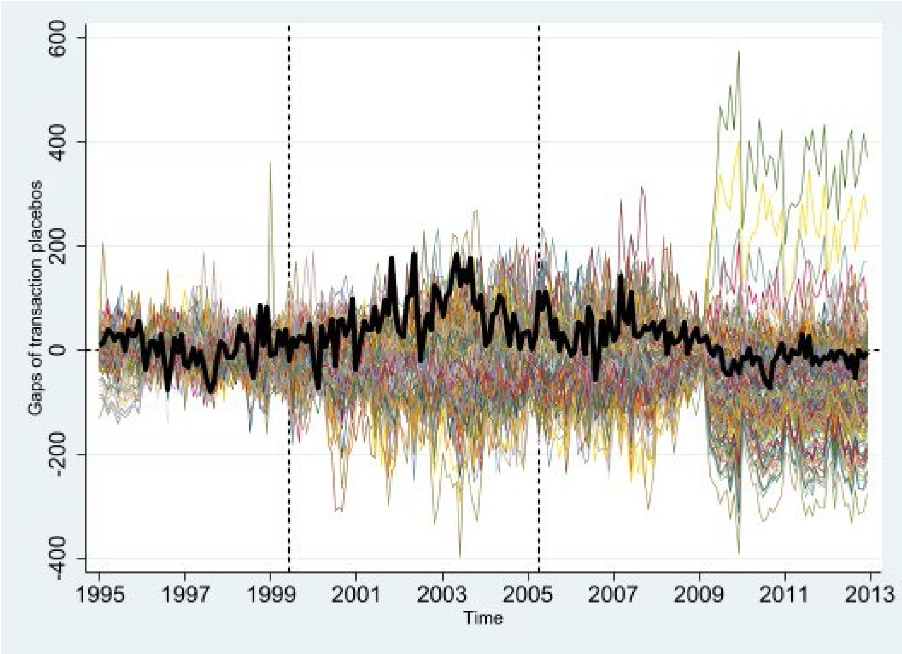


Figure 3.12 The Placebo Test Results of Gaps in Property Transactions

Notes: This figure shows the placebo estimates on property transactions. The colourful lines display the gap in property transactions between each district in the donor pool and its synthetic counterpart. The superimposed black line represents the house transactions gap between real Doncaster and synthetic Doncaster.

More precisely, the pre-treatment RMSPE in Doncaster, which is the average of the squared divergences between monthly property prices in Doncaster and its synthetic version during the period 1995 January-1999 June, is around 2,449. In comparison, prior to the airport news announcement, the median RMSPE among the 328 districts in the donor pool was around 4,362, approximately 1.78 times that of Doncaster. This means that the synthetic control approach is a good fit for monthly property prices in the pre-treatment period for the majority of the districts in the donor pool. However, a convex combination of monthly average property prices in other districts do not replicate well the property prices during the 1995 January-1999 June period in some districts. For instance, the districts with the worst fit in the pre-treatment period are Kensington and Chelsea, with a pre-RMSPE of 106,069 (nearly 43 times greater than Doncaster). It is not a surprise that Kensington and Chelsea have the largest RMSPE, as they are two of the highest house price districts in England and Wales. Thus, it is not possible to replicate the time series of property prices in Kensington and Chelsea prior to June 1999 by any combination of districts in the data sample. There are similar issues with other districts which have much higher property prices relative to Doncaster during the 1995 January-1999

June period (i.e., the following districts with large RMSPE are the City of London and Wiltshire, with 78364 and 40153, respectively). In order to avoid these inappropriate lines stretching out the gap scale and distorting the actual estimated effect in Doncaster, they were removed if their pre-RMSPE was twice that of Doncaster.

Among the 186 districts left in Figure 3.11, it is apparent that prior to the pre-treatment, all the gap lines of property price sit well along with the zero-gap line. Further, after June 1999, the Doncaster gap line is clearly one of the most unusual lines until nearly 2003. This is consistent with the supply-demand theory. The house prices would be affected only for a short period of time; for the long term, the prices would be restored by increased demand or reduced supply. In the end, they would reach a new equilibrium.

Figure 3.12 demonstrates the placebo results of property transactions, which suggests that by 2003, the increasing gap between the real Doncaster and synthetic Doncaster would be large relative to other districts in the donor pool. The pre-treatment RMSPE of property transaction in Doncaster is around 34.717. In comparison, prior to the airport news announcement, the median RMSPE of property transaction volume among 328 districts in the donor pool is around 22.542, around 65% that of Doncaster. It indicates that in the pre-intervention period, the property transaction volume of Doncaster is quite close to the figure of the majority districts in the donor pool, thereby suggesting a good fit for monthly property transactions in Doncaster prior to the airport news announcement using the synthetic control method. The districts whose root mean squared prediction error prior to the treatment was twice greater than Doncaster were excluded.

To further investigate the significance of Doncaster among the whole distribution, the ratio of post-treatment RMSPE and pre-treatment RMSPE was used, as shown in Figure 3.13 and Figure 3.14. These demonstrate the ratios between the post-1999 June RMSPE and the pre-1999 June RMSPE for Doncaster, and for all the districts in the donor pool. According to Figure 3.11 and Figure 3.12, the negative impact on Doncaster property prices and the rising trend of transaction volume lasts until around June 2002. In the second half of 2002, the gap in house prices between real Doncaster and synthetic Doncaster starts to diminish. Therefore, for measuring the post-treatment RMSPE, only the period of 1999 July to 2002 June is used as the post-intervention period.

In Figure 3.13, the red x line points denote Doncaster's position among the house price distribution. It is apparent that Doncaster does not stand out as the district with highest post/pre-RMSPE ratio but stays in the right tail of the whole distribution, which means its negative influence is still one of the lowest of all. More specifically, its post-treatment gap is around 3.355 times greater than the pre-treatment gap. There are 32 districts among the 329 districts with a larger proportion of post/pre-treatment RMSPE than Doncaster. That is to say, under a random permutation of the treatment in these sample data, the probability of evaluating a gap of the significance of the difference for Doncaster is 33/329=0.100. Given the de-selection of districts with pre-RMSPE twice that of Doncaster, the post/pre-treatment RMSPE ratio of Doncaster ranks 30 among the 186 areas; this indicates that if an intervention was randomly assigned to the whole distribution, the possibilities of acquiring a ratio higher than or equal to Doncaster would be 30/186 = 0.161.

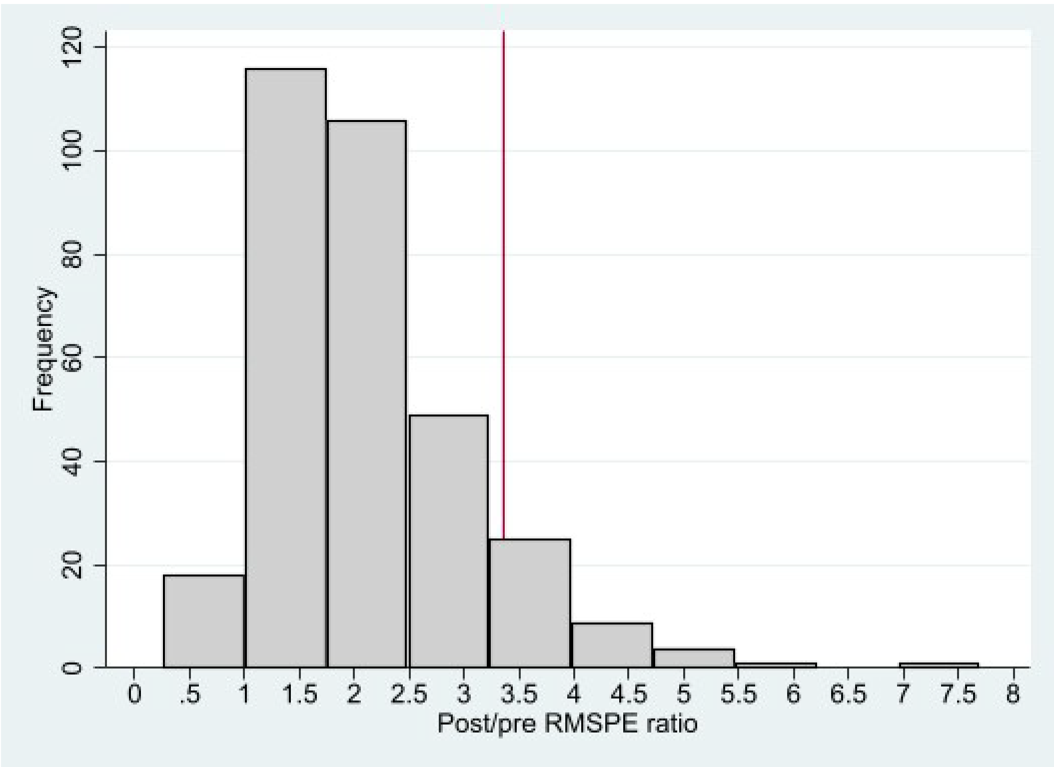


Figure 3.13 Post/pre-RMSPE Ratio Distribution for House Prices

Notes: This figure depicts the distribution of the ratio between post-treatment RMSPE and pre-treatment RMSPE for house prices. The red "x" line marks Doncaster's position within the distribution.

Likewise, Figure 3.14 illustrates the histogram distribution of the post/pre-RMSPE ratio of property transactions; Doncaster sits in the middle of the right tail. Specifically, the exact post/pre-treatment RMSPE ratio of Doncaster property transactions is 1.97, ranking 65 among all 329 districts with a median value of 1.47. That is to say, under a random permutation of the treatment in these sample data, the probability of evaluating a gap of the significance of the difference for Doncaster is 65/329=0.198. While after discarding the districts with pre-RMSPE twice that of Doncaster, the post/pre-treatment RMSPE ratio of Doncaster ranks 63 among 316 areas. This indicates that if I randomly assign an intervention to the whole distribution, the possibilities of acquiring a ratio higher than or equal to Doncaster would be 63/315 = 0.200.

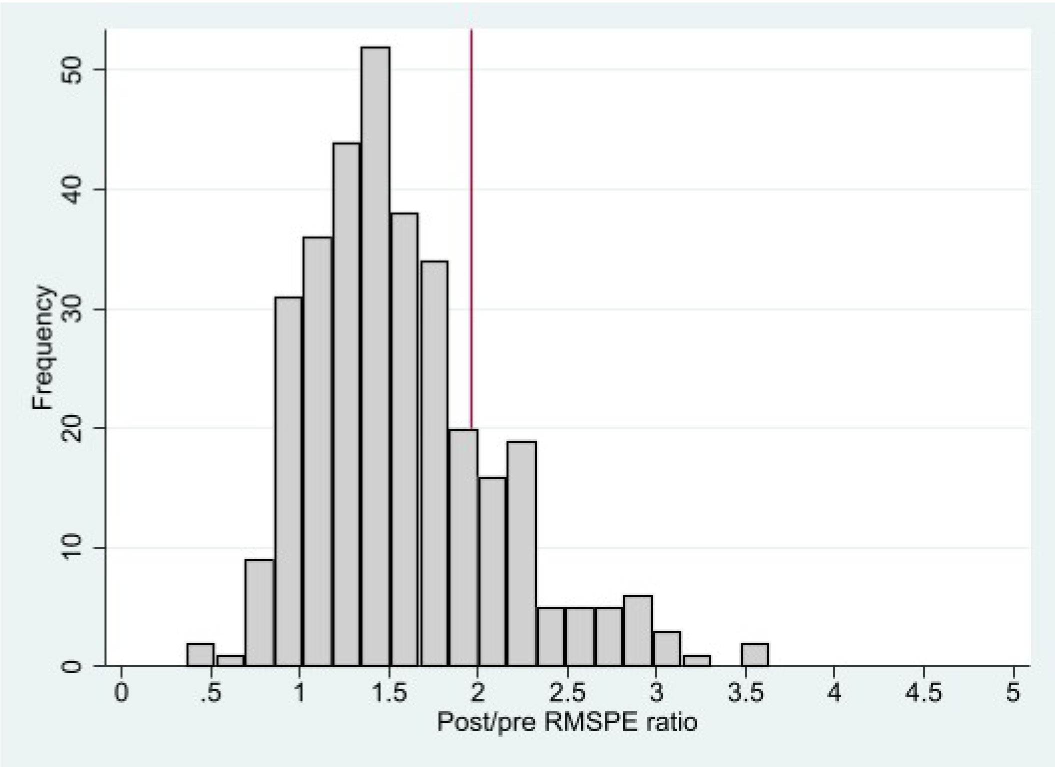


Figure 3.14 Post/pre-RMSPE Ratio Distribution for Transaction Volume

Notes: This figure depicts the distribution of the ratio between post-treatment RMSPE and pre-treatment RMSPE for transaction volumes. The red "x" line marks Doncaster's position within the distribution.

Moreover, the inference with the restricted donor pool is also assessed. For property prices, the post/pre-treatment RMSPE ratio is 3.576, ranking 25 among 287 districts. So that the P-value is 25/287=0.087, suggesting that if an intervention was randomly assigned to the whole distribution, the possibilities of obtaining a ratio higher than or equal to Doncaster would be 0.087. While the post/pre-treatment RMSPE ratio of Doncaster property transaction is 1.908, ranking 51 among all 287 districts; this means that under a random permutation of the treatment, the probability of acquiring a gap of the significance of the difference for Doncaster is 51/287=0.177. These inference results are consistent with the placebo tests estimation using the comprehensive donor pool. It is robust that the construction of Doncaster Sheffield Airport had a significant effect on Doncaster's housing market. In particular, the negative impact on Doncaster property prices due to the airport announcement news is statistically significant (P-value <= .1). On the other hand, the estimated results constructed by the synthetic control approach employed with different donor pools are similar: a different size of donor pool would not make a big difference. While the significances of the estimated results in each donor pool are slightly different. In particular, the restricted donor pool is slightly more accurate than the comprehensive donor pool. Precisely, P values of property price and transaction volume are 0.087 and 0.177, respectively, in the restricted donor pool, compared to the P-values in the comprehensive donor pool: 0.100 of property price and 0.198 of transaction volume.

In the reference case from the literature (Abadie et al., 2010), the authors used 39 areas in their donor pool, with the treated unit positioned at the margin of the entire distribution. From this, they calculated a p-value of 1/39 = 0.026, which is statistically significant at the $p < 0.05$ level. In comparison, the p-values in this case are relatively larger. The results show that for house prices, Doncaster ranks 33rd out of 329 ($p = 0.01$) and 25th among 287 districts ($p = 0.087$) using a restricted donor pool, both statistically significant at the $p < 0.1$ level. For transaction volume, Doncaster ranks 30th out of 186 ($p = 0.161$), and 51st out of 287 districts ($p = 0.177$), both of which are less significant. This suggests that Doncaster lies near the margin of the distribution, but not at an extreme. Given the donor pool in this study is about 10 times larger than that in Abadie et al. (2010), these results are acceptable in this context. To obtain more precise results, a more efficient donor pool selection would be necessary. Nevertheless, the marginal position of Doncaster in this analysis adds credibility to the findings.

3.7 Conclusion

Governments strategically foster urbanization and economic growth by enhancing public infrastructures. This is mainly because those well-established infrastructures, including improved transportation and amenities, can enhance the overall appeal of an area and be expected to draw businesses and individuals to the area, which potentially affects property values. Numerous instances can be found to demonstrate a correlation between a city's prosperity and the emergence of housing bubbles. The housing prices of a region can serve as an indicator of its level of urbanization or economic growth. Hence, this study examined whether investments in public infrastructure align with governmental expectations of enhancing urban economic growth, by employing a case study of the announcement effect of a new airport infrastructure on the regional housing market.

To be more precise, the infrastructure enhancement, including airports, contributes to an overall improved appeal of the region, rendering it more attractive to potential homebuyers and investors, thereby potentially contributing to an increase in property values. For instance, the establishment of a new airport has the potential to stimulate business and commercial development in the surrounding area, consequently leading to an expansion of property values as more businesses establish themselves and contribute to the local economy. The influx of individuals associated with airport-related activities, such as airline employees, airport staff and businesses catering to the aviation industry, is likely to generate heightened demand for housing. As demand rises, property prices may respond accordingly. Airports play a crucial role in enhancing connectivity, rendering the region more accessible to both domestic and international travellers. This improved connectivity is expected to attract businesses and individuals seeking convenient transportation options, thereby positively impacting the local real estate market. The construction of a new airport typically causes significant infrastructure development, encompassing roads, transportation networks and amenities. The positive outlook of public infrastructure is expected to draw businesses and individuals to the area, potentially elevating the demand for housing and resulting in an upswing in property prices.

To assess whether improving airport infrastructure would positively affect housing markets, as per the above expectations, this paper used synthetic control methods to evaluate the announcement effects of Doncaster Sheffield Airport on the regional housing market. In the 1990s, Doncaster was exposed to a long economic recession after the pit-closure program. The local authority in Doncaster sought to redevelop RAF Finningley as a solution to stimulate the region's economic growth. This study explored the Doncaster housing market with two outcome variables: property prices and transaction volumes. Applying data-driven procedures to synthetic comparison units in comparative studies addresses the problem of selecting valid control units in traditional comparative research. In the analysis, synthetic control methods provided consistent evidence of an immediate, considerable drop in Doncaster house prices following the announcement regarding construction of Doncaster Sheffield Airport. It was also seen that after the intervention, there was a clear increase of transaction volume in Doncaster. More specifically, Doncaster house prices decreased by 30%, around £15,000, and transaction volume in Doncaster increased by 37.5%, around 150. These results show that public infrastructure, especially airports, may not lead to an upward trend in regional house prices, thereby efficiently stimulating urban economic growth. Contrary to governments' expectations, it may make a region less attractive to live in and cause a short-term decline in the housing market. In light of this, policymakers and investors should take into account that public infrastructure, including airports, might not serve as a potent catalyst for regional economic growth, especially within the real estate sector.

The results from different donor pools were also consistent. When the selection of donor pool was changed, these impact estimates did not differ markedly, which is a critical robustness check of these results. It is possible to obtain effect estimates that are substantively indifferent to the sample of units in the estimation and discard a potentially significant bias in effect measures, since the synthetic control approach could restrict the selection of comparison units which are employed to measure counterfactual post-treatment outcomes (Bifulco et al., 2017). Moreover, in the robustness check, assessing the significance of assigned weights to control units in the estimation, it was observed that removing districts with the highest weights from the donor pool did not yield any discernible difference in the estimated results. However, a slight variance was noted when excluding Blaenau Gwent, which holds the highest weight of the synthetic Doncaster house price (approximately 0.6) in the allocation. Nevertheless, this discrepancy was minimal. It means the estimated effects were not excessively influenced by either the selection of the donor pool, or a single district in the donor pool.

To assess the significance of the results, a series of placebo tests to examine the sensitivity of the synthetic estimation were conducted. The results showed that both the gaps in house prices and transaction volume, between real Doncaster and synthetic Doncaster were unusually large relative to the control districts in the donor pool. Precisely, the p-value of the house price was 0.100 and the p-value of transaction volume was 0.198. That is to say, the probability of randomly deriving a gap between the actual outcomes and synthetic outcomes, equal to or larger than Doncaster among 329 districts, was 0.100 of house prices and 0.198 of transaction volume.

Chapter 4. The effects of Doncaster Sheffield Airport on the local property market

4.1 Introduction

The prospect of future transport infrastructure or improvements to existing transport networks in a region tends to augment the attractiveness of proximate or adjacent neighborhoods for households (Jayantha et al., 2015). According to conventional theories of residential location, housing prices are influenced by accessibility. Individuals residing in proximity to transportation networks experience lower commuting costs to workplaces, potentially prompting increased investment in these areas (Mills, 1967).

In the housing literature, it is established that the location of a house represents a crucial characteristic that can significantly influence its price (Heyman et al., 2018; Lieske et al., 2021). The proximity of a house to amenities which are positive externalities, such as schools or public parks, is anticipated to exert upward pressure on its price. (Diewert & Hendriks, 2015). Conversely, if houses are exposed to negative externalities, such as pollution and anti-social behaviour, it is expected to exert downward pressure on their prices. (Han et al., 2018; Wadley et al., 2017).

To investigate whether airport infrastructure constitutes a positive or negative externality for neighbouring communities, this paper examines its impact on nearby house prices, continuing to utilize Doncaster Sheffield Airport as the subject of an event study. This is attributed to the nature of airport infrastructure as a long-term and substantial investment, involving an extended timeline from land use permitting through construction to operational phases. The case of Doncaster Sheffield Airport presents a distinctive opportunity for an ongoing examination of the impact of airport infrastructure on housing prices, encompassing three consecutive events which include nearly the entire lifecycle of an airfield, from its closure, transformation plan announcement, to its re-opening. To be more specific, the sequential events include the closure of a former military airfield, the announcement of its transformation into a commercial airport, and the subsequent opening of the new airport. Each of these events can potentially have significant impacts on the local community, leaving residents in a state of uncertainty regarding both the airport's future and the quality of life in their environment. These circumstances offer a distinctive opportunity to assess whether airport infrastructure serves as a beneficial amenity to the local community and to estimate the community's satisfaction with their quality of life in close proximity to a new established transportation hub.

A massive literature investigates the importance of an airport to a local economy, stimulating regional employment and business activities, e.g., Huderek-Glapska (2013) using the largest airport in Poland, Warsaw Chopin Airport as an event study, presents that the airport operation contributed to the generation of 527.8m EUR in current prices in 2011, and that 19,349 jobs have been generated directly and indirectly. Concentrating solely on one facet of economic growth fails to encompass the multifaceted nature inherent in the study of airports (as evidenced by Espey & Lopez, 2000 and Lipscomb, 2003). Taking into consideration proximity, house characteristics, and demographic variables, Cohen and Coughlin (2008, 2009) conducted an analysis on the impact of proximity and noise on housing prices in neighbourhoods near Hartsfield-Jackson Atlanta International Airport from 1995 to 2002. Their findings reveal that houses situated in noisier areas were sold for lower prices compared to those in quieter surroundings. With the growth of populations and airports, the operations of airports can result in a range of impacts, including noise pollution, visual disturbance, air and water pollution, increased traffic congestion, as well as potential emotional and health-related effects.

The negative effects of airports are well-documented (Han et al., 2018 and Wadley et al., 2017). There has been particular attention paid to the relationship between the noise level of airports and house prices (Dekkers & van der Straaten, 2009; Lijesen et al., 2010; Cohen & Coughlin, 2009; McMillen, 2004) which has become an ever more significant concern for real estate researchers. More specifically, Espey & Lopez (2000) found that in early 1990s, in Reno-Sparks (Nevada), the properties subjected to an airport noise level beyond 65 decibels were depreciated around 2 percent, which was around $2400. This result is in line with McMillen (2004), which estimating the relationship between noise level of Chicago’s O’ Hare Airport and its nearby residential property values, suggested that dwellings exposed to a noise level up to 65 decibels were around 9% cheaper than their counterparts.

Many studies employ a traditional hedonic model to measure the effect of noise on homes. The hedonic pricing model which was first explained by Rosen (1974) and developed by

Halvorsen and Palmquist (1980), Freeman (2003), and other researchers, decomposes house prices into their characteristics, e.g., lot size, squared footage and the number of bedrooms. Constraining these house characteristics is essential, as a simplistic comparison of average property values would downplay the impact of the noise discount. For example, Dekkers & Straaten (2008) conducting a hedonic analysis point that a higher noise level would result in a lower house price given constraining house characteristics (i.e., the year of sale, number of rooms, and neighbourhood ethnicity). They also suggest that compared with railway traffic and road traffic, the impact of air traffic on house prices is the greatest. Huo, Thibodeau & Throupe (2014) basing on the premise that property is a good containing a series of compositions employ a combination of hedonic pricing models and the geographic location of airport sound levels to conclude that property values decrease with proximity to the airport.

Previous research has examined the proposition that noise nuisance from aircraft causes a negative externality for adjacent properties, while a few studies estimate the anticipation effects of an airport on property price. One example, provided by Cohen et al. (2021), finds evidence of immediate an anticipatory price effects upon announcement of the closing of Denver's Stapleton Airport, but no price changes at the actual closing, and little evidence of an upward trend in prices between announcement and closing.

This chapter investigates three important events surrounding the former Royal Air Force Finingley (RAF Finingley) site redeveloped into a commercial airport, Doncaster Sheffield Airport (former name: Robin Hood Airport Doncaster Sheffield). These three elements taking place in the airfield are: The closure of the original military airport, the announcement of a new airport, and the new airport's official operation, to exploit the influence of an airport impacting nearby property values. Using Doncaster Sheffield Airport as a case study to study the anticipation effects of an airport on house market, Doncaster Sheffield Airport underwent a notable transition from a military airport under the management of the Royal Air Force, to a commercial airport operated by a private enterprise. This evolution comprised four stages spanning around one decade and entailed three significant public events and the timeline of these three elements taking place in the airfield are shown in the Figure 4.1. To be more precise, these public events are in November 1996 the Royal Air Force officially decommissioned the site, in June 1999 the Peers Group announced its acquisition of the site and unveiled plans for the construction of a commercial airport, and eventually in April 2005 the Doncaster Sheffield Robin Hood Airport commenced operations.

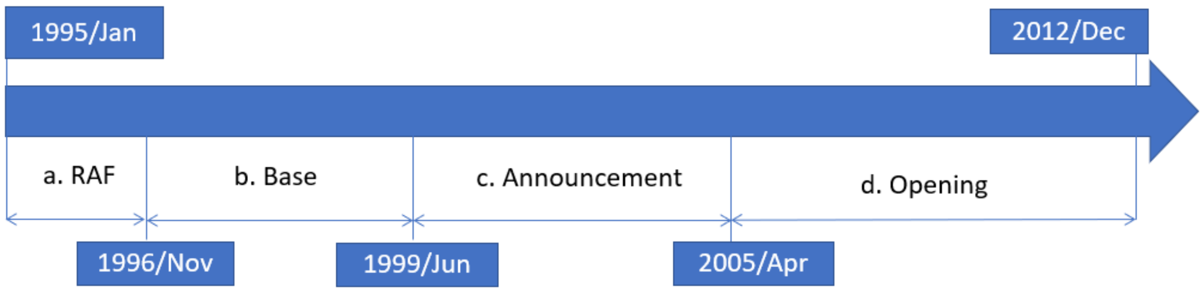


Figure 4.1: The chronological sequence of interventions taking place on the airfield.

Notes: This chronological figure outlines the four distinct periods of activity on this site, with three key public events: Period A (01/1995 - 11/1996): The Royal Air Force operated at the site; Period B (11/1996 - 06/1999): Following the official decommissioning of the Royal Air Force, the site remained vacant; Period C (06/1999 - 04/2005): The Peers Group acquired the site and announced plans for the development of a commercial airport; Period D (04/2005 - 12/2012): Doncaster Sheffield Robin Hood Airport commenced operations.

However, the transformation of Doncaster Sheffield Airport stands out as an exceptional example of the successful modernization of the airport into a commercial entity, despite of the extensive public discourse not only during its opening but also in the context of its closure. In October 2022, the Peel group announced that resulting from the fundamental lack of financial viability, Doncaster Sheffield Airport is to close permanently by the end of the year (Doncaster Sheffield Airport, 2023). This decision caused broad controversies in the public. Both government and the public were against this closure. An ongoing online petition gathering over 100k signatures pushed for re-opening of the airport and the previous Prime Minister, Liz Truss, assured that she would take action to defend the airport because she was convinced that regional airports were a vital part of the economic growth. However, Doncaster Sheffield Airport closed on date in November 2022, while Doncaster Council planned to conduct a Compulsory Purchase Order for £3.1 million to save this airport.

This paper focuses on the effects of Doncaster Sheffield Airport on property prices during its transition and opening period. At that time this airport was the first new commercial airport to open in the UK for 50 years, overlooking some small-scale airports. The airport in northern England was set to have one of the longest runways in the region, which would enable direct connections to popular long-haul destinations such as the Far East, the Caribbean, and

America. Located within an hour's drive of four million people, the airport in Doncaster benefited from important transportation links, including the M1, M62, and M18 motorways, the East Coast Main Line rail routes, and the Humber ports. Doncaster's strategic location, boasting excellent connectivity via motorways and train links, has positioned it as a hub for major corporations such as Bayerische Motoren Werke AG (BMW) and Block & Quayle (B&Q), which have established their distribution centres here ("Doncaster catches," 2005). In addition to the potential benefits that the airport could bring to the region, it garnered public attention primarily due to hundreds of local protests. These protests emphasized the necessity for a public inquiry to thoroughly assess the costs associated with the airport, including concerns such as disrupted peace, persistent heavy traffic, air pollution, and environmental damage. The public inquire took place in around 2001-2002. Secondly, in 2004 the airport named "Robin Hood" was disputed by thousands of people who signed a petition expressing their opposition. Last, after its official operation, public debates surrounding air tourism and its environmental impact continued to persist. The airport was a frequent topic of discussion and was even featured in a BBC Two documentary in January 2007 as an example of the environmental impact of aviation.

The closure of this former military airfield (1996 November), announcing to reconstruct (1999 June), and subsequent reopening as a commercial airport (April 2005) had a significant impact on the local community, leaving residents uncertain about the airport's future and potential impact on them quality of life. The developments of Robin Hood airport have provided an opportunity to examine the extent to which an airport can impact housing prices, serving as an indicator of community satisfaction with living adjacent to an airport. Therefore, this paper employs a comprehensive empirical strategy that the Difference-in-Difference (DiD) approach to estimate the impacts of the airport on property values. This approach incorporates four distinct periods to estimate the impacts of the airport on house price, each setting out a way of controlling for quality difference between properties sold in the pre- and post-intervention periods and between treatment and control neighbourhood properties. In the first stage, I create a balanced panel of properties for pre- and post-treatment for four periods, which are distributed as a) the airfield operated by the military (pre RAF decommission in November 1996), b) this site was vacant and waiting to be developed, between the RAF decommission (November 1996) and the announcement of transforming the site into a commercial airport

(June 1999), c) this land was expected to be an commercial airport in near future, between the airport plan announcement (June 1999) and starting operation (April 2005) and d) post the airport commencing function (after April 2005). Then I take period b) as the base period because it was the only period in which property prices around the field were not affected by the presence of an operating or expected airport. The treated group is defined as properties located within a 3-kilometre radius of the airport. To identify the timing and magnitude of the impact of the interventions at different stages while controlling for potential confounding factors, I apply into a stagged DiD (Difference-in-Difference) model which is a statistical technique used in econometrics and program evaluation to estimate causal effects, where I use these property prices as the dependant variable in the regression model. The results show that the opening of the airport has a significant negative impact on property prices, while the decommissioning of the RAF has a negligible and insignificant influence on the surrounding property values. Conversely, the announcement of the new airport plan has been associated with a positive effect on nearby property prices, although this effect is of lesser statistical significance.

In this paper, I use randomization inference as the robustness check to assess whether the observed outcomes in a specific sample are likely to have occurred by chance, even in the absence of any treatment effect. The randomization process doesn't involve the extraction of samples from a larger population, which means that conventional large-sample theory doesn't apply here. In contrast, the test statistic might depend on the model, such as estimates of the average treatment effect derived from various specifications that include control variables (i.e., house characteristics, neighbourhoods, and month effect). However, the reliability of these results is not contingent on the model or the size of the sample. For example, in cases where data is generated through a random selection process, such as the random assignment of treatments from a well-defined distribution, and the null hypothesis is operated that this random selection does not influence other aspects of the data, the distribution of any statistics derived from the data is also well-established. Moreover, the desired statistics can be computed iteratively across various instances of the random selection. Based on this distribution, a randomization inference p-value can be computed, which signifies the proportion of estimates that exceed the extremeness of the original regression estimate. The randomization inference results in this paper are consistent with the original Difference-in-Difference outcomes with similar p-values stemming from 500 replications. That is saying, the opening effect of the Doncaster Sheffield airport on nearby house price is robust significantly negative while the other two estimated events impacts are not that extreme.

In addition to the traditional Difference-in-Difference methodology, I utilize a panel event study to provide more precise estimates of the variation of the treatment effect over time. Estimate plots offer a visual representation of how events impact the outcome variable over time for each entity in the panel, with the difference before and after treatment providing an estimate of the interventions' impact on house prices. Moreover, it is apparent that there are three troughs in the trend of these points, each occurring around the time of the interventions. This consistent observation suggests that residents becoming aware of the proximity of an airport has a negative influence on property prices.

Furthermore, I conducted an investigation on how the distance to the airport impacts property prices. To achieve this, I expanded the treatment areas in the regression analysis to include additional rings with an extra 1km radius from the airport location. It suggests that the negative impact of the airport's opening on property prices disappears at a distance of 6km to the airport and significant positive effects are observed in the properties are equal to or greater than 9km to the airfield. These results are also robust across different samples.

The following Chapter is presented as the following: Section 4.2 reviews the history of Doncaster Sheffield Airport, and Section 4.3 presents descriptive data. The empirical approaches, its results and the robustness check are shown in Section 4.4, 4.5 and 4.6. Section 4.7 demonstrates the panel event study and Section 4.8 displays some regressions with various treatment groups. The conclusion part is in Section 4.9.

4.2 Background of Doncaster Sheffield Airport

Doncaster Sheffield Airport (formely name: Robin Hood Airport Doncaster Sheffield) was transformed from RAF Finningley which was a Royal Flying Corps (RFC) and later Royal Air Force (RAF) station located in the Metropolitan Borough of Doncaster, South Yorkshire, England.

The airfield was established in 1915 as a training base for the RFC during World War I, and was initially known as RFC Finningley. During the interwar period, the airfield was used primarily as a flying training school, but it also saw some use as a bomber base. In World War II, the airfield was heavily used by Bomber Command, with various squadrons operating from the base and carrying out bombing missions over Germany. After the war, the airfield continued to be used by the RAF for a variety of purposes, including as a training base and as a home for various squadrons and units. In 1960s, the airfield was upgraded with longer runways and other facilities, and it became the home of several V-bomber squadrons equipped with nuclear weapons.

In 1990s, the British government was in the process of closing a number of military airfields, and RAF Finningley was one of the sites scheduled for closure. RAF Finningley was gradually scaled back and eventually decommissioned in 1996, which executed its last closure command in November 1996 (RAF Finningley, 2023). Doncaster council recognized that the closure of the military airfield presented an opportunity for the development of the site into a valuable asset for the region.

In June 1999, the site was announced to be sold to Peel Holdings for £78m as an international airport which would be expected to create jobs and provide a much-needed transportation hub for the region. However, the progress faced setbacks and substantial expenses due to a public planning inquiry initiated in 2002 to evaluate the Peel Group's application for a commercial airport at Finningley, although the acquisition of the former RAF base at Finningley marked a significant expansion for the Peel Group into the airport sector. Despite the potential economic benefits and investment infusion into the local area, the proposal faced strong opposition, as reported by BBC (“Unlikely alliance,” 2002), triggering protests from hundreds of residents against the transformation of the former RAF base into a civilian airport. Specifically, Peel Holdings pledged 24-hour flights, the transportation of 60,000 tonnes of freight, and up to 2.3 million passengers annually, with the promise of creating an additional 7300 jobs in the next decade. This proposal, attractive to an economically depressed area still reeling from the impacts of pit closures, garnered full support from the Doncaster borough council and many local residents. However, protests emphasized concerns about noise pollution, non-stop heavy traffic, air pollution, and environmental damage, contending that the new development, as a commercial airport, posed heightened risks of night-flying compared to the former RAF airfield. Opponents argued that the government had not thoroughly examined the impact on neighbourhoods and the environment, calling for a comprehensive public inquiry, as reported by BBC ("Unlikely alliance," 2002). According to records from a regeneration scrutiny panel meeting by the Rotherham government (Robin Hood Doncaster Sheffield Airport Update, 2004), a major public inquiry transpired between October 2001 and March 2002. Finally, on April 4, 2003, the Secretary of State granted permission for the airport, and construction work for the planned airport commenced. In 2004, the steel-work of the airport has started ("Work begins," 2004) and the influence of the redevelopment was still being debated. By November 2004, a petition had been signed by over 11,000 people opposing the name Robin Hood of the new airport as the residents of Doncaster considered it an insult ("Airport's new," 2004). To be precise, Robin Hood is a legendary English folk hero known for "robbing from the rich and giving to the poor." His tales often depict him opposing the Sheriff of Nottingham, symbolizing social justice and resistance against tyranny. Many locals felt that naming the airport "Robin Hood" was historically and geographically inaccurate, as Robin Hood is linked more with Nottingham than Doncaster. Additionally, the decision was made without consulting the local community, causing frustration and feelings of exclusion.

In 2005 April, the first commercial flight took off from Robin Hood airport. The Independent ("Doncaster catches," 2005) reported that in 2004 the property price in Doncaster rose by 30 percent hitting £121,000 for a house which was the largest raise among the figures of other regions in Yorkshire and Humberside. BBC ("Airport jobs," 2005) also reported that this airport had already provided 611 jobs, 154 staff employed directly by the airport and the remaining hired by its partners and contractors. Additionally, over 85% of the jobs were occupied by employees who were living within a 40-minute drive from the airport. It showed promise that in the next decade this airport would create in excess of 7,000. The passenger numbers for this airport were 899,000 in its first operational year, which made the airport the 23rd largest in the UK. The airport served a variety of commercial and cargo airlines and was an important transportation hub for the region.

However, the debate about air tourism and the environment did not fade away. As the UK's newest international airport at that time, it was partly targeted as part of the public debate. On January 2007, BBC Two documentary demonstrated this airport as an example to illustrate the impact of aviation on environment ("Up and," 2006). Although it showcased how Robin Hood Airport has provided an economic boost and contributed to regional development after years of decline, the documentary also encouraged viewers to consider the environmental consequences of their flying habits by exploring topics such as aviation emissions and eco-friendly advancements. This focus on both environmental impact and economic benefits aligns with the growing public concern about climate change and the role different sectors play in addressing it.

Over the time there were still many complaints about the airport being named as Robin Hood, which was more associated with Nottinghamshire than Doncaster, and eventually this airport was rebranded as Doncaster Sheffield Airport in 2016. As the aviation industry was one of the hardest hits during pandemic, in September 2022, it was announced that due to unprofitability, the airport would start the closure process from October 2022 after 17 years of operation. An ongoing online petition gathering over 100k signatures pushed for the re-opening of the airport. It aroused wide concern that even the Prime Minister Ms Truss promised action to protect Doncaster Sheffield Airport because she thought that regional airports, including Doncaster Sheffield Airport, are a vital part of economic growth. As at April 2023, Doncaster council's cabinet announced that they have supported a Compulsory Purchase Order for £3.1 million worth of funding to remain this airport (Ford, 2023) while conversations and negotiation with Peel are still ongoing.

4.3 Data and descriptive statistics

To evaluate whether airport infrastructure constitutes a positive or negative externality for neighbouring communities, this paper employs house prices as the key indicator. This paper utilizes property sales data consisting of the actual transaction prices of property sold in England and Wales, which derived from Price Paid Data (GOV.UK, 2022) of the HM Land Registry. The Price Paid Data are sorted by location-time format and recorded from January 1st 1995, to the most current month. This paper uses data with a timeframe between January 1995 and December 2012. Specifically, it demonstrates 22 months prior to the old RAF base decommissioned in November 1996. The 31 months between the decommissioned month and the announcement of a new commercial Airport plan in June 1999. The 69 months between the announcement and the airport opening in April 2005, and the 92 months after the new airport opening.

Doncaster is located in the Don Valley and is the second largest dwelling in south Yorkshire, following Sheffield, and is the largest metropolitan district in England by area with 568 square kilometres. According to the 2011 census, the Metropolitan Borough of Doncaster had a population of 302,402 and the town of Doncaster had a population of 109,805, of 84.9% are white British. In 2021, the borough population was over 300,000, larger than many cities' like Hull, Southampton and Newcastle. Its town centre alone is larger than 25 cities across the UK with more than 109,000 inhabitants.

The Price Paid Data is categorised into address data of transaction properties including postcodes, the sale price stated on the transfer deed, the date when the transaction was completed, the type of the property, the age of the property and the tenure. The address information is stated as accurate as its county, district, city/town, locality and street and even flat number are recorded at the time of the original transaction. The property types are Detached, Semi-Detached, Terraced, Flats, and Other etc. The bungalows-end-of-terrace properties are classified into the Terraced category. The 'Other' means the existing value does not cover the property type, for instance, the property is consisted of over one large parcel of land. Additionally, the age of property means that I can identify if the property is a newly built property or an established residential building. The tenure indicates whether the property is freehold or leasehold and it does not record leases of 7 years or less in the Price Paid Dataset.

The house prices are coded into distance-month level. The distance is defined regarding the geodetic distances between each property and the site of Doncaster Sheffield Airport. The geodetic distance can be calculated by the differences of latitude and longitude of individual postcodes. Moreover, each postcode is grouped into Lower Layer Super Output Area (LSOA), Middle layer Super Output Areas (MSOA) and local authority districts, which are of the most important Statistical Geographic Hierarchies classified by Office for National Statistics. According to the 2011 Census, there are 34,753 Lower Layer Super Output Areas (LSOAs) in England (32,844) and Wales (1,909). Using census data from groups of LOSA, a zone-design software is able to automatically produces Middle Layer Super Output Areas (MSOAs) and they fit within local authority boundaries. The MOSAs have a minimum size of 5000 residents and 2000 households with an average population size of 7,800. A balanced panel covering 46,689 postcodes over 216 months for a total 570,927 observations are generated as the estimation sample.

The aim of this chapter is to investigate whether the public events of an airport would constitute a positive or negative shock on local property market. To disentangle this problem, I start estimations by utilizing simple 2 * 2 difference-in-differences. Therefore, at the beginning, the most essential issue is how to circle the place of treated and control groups. I define this by calculating the approximate distance to Doncaster Sheffield Airport (DSA). To be specific, according to each postcode of all property in the sample, I can geodetic the distances between the locations of each property and the airport. A property is considered to be treated if it is within a 3 kilometres radius of Doncaster Sheffield Airport. For the control groups, I establish both a narrower and a wider control group. The properties in these groups are situated beyond 3 kilometres from the airport. The narrower control group includes properties within the Doncaster district, specifically those with postcodes starting with "DN." Meanwhile, the wider control group encompasses properties within a 40-kilometer radius, chosen to approximate the distance between Doncaster Sheffield Airport and Sheffield city. That is saying, in the wider control group, the properties are not limited to be in the Doncaster district but located in the ring with a radius greater than 3km and smaller than 40km to the airport. Figure 4.2 and Figure 4.3 demonstrate the maps of treated areas with the narrower control group and the wider control group, respectively. The inner circle indicates the treated area centralised as Doncaster Sheffield Airport with a 3km radius. The outer lines are the boundaries of the control groups where properties are above 3km away from Doncaster Sheffield Airport but located within Doncaster district or within 40km to Doncaster Sheffield Airport.

Table 4.1 shows that the treated region comprises 1,352 observations, while the narrower control group consists of 70,021 observations and the wider control group covers 560,906 observations. I divide the data into four periods: pre-November 1996, between November 1996 and June 1999, between June 1999 and April 2005, and post April 2005. To be more precise, these dates indicate the closure of RAF Finningley in November 1996, the period when the site was awaiting government redevelopment between November 1996 and June 1999 when the public did not receive any certain news of a new airport constructed on this field, the period when the news of the redevelopment plan of this site was finally announced in June 1999, and the new airport opened in April 2005, respectively.

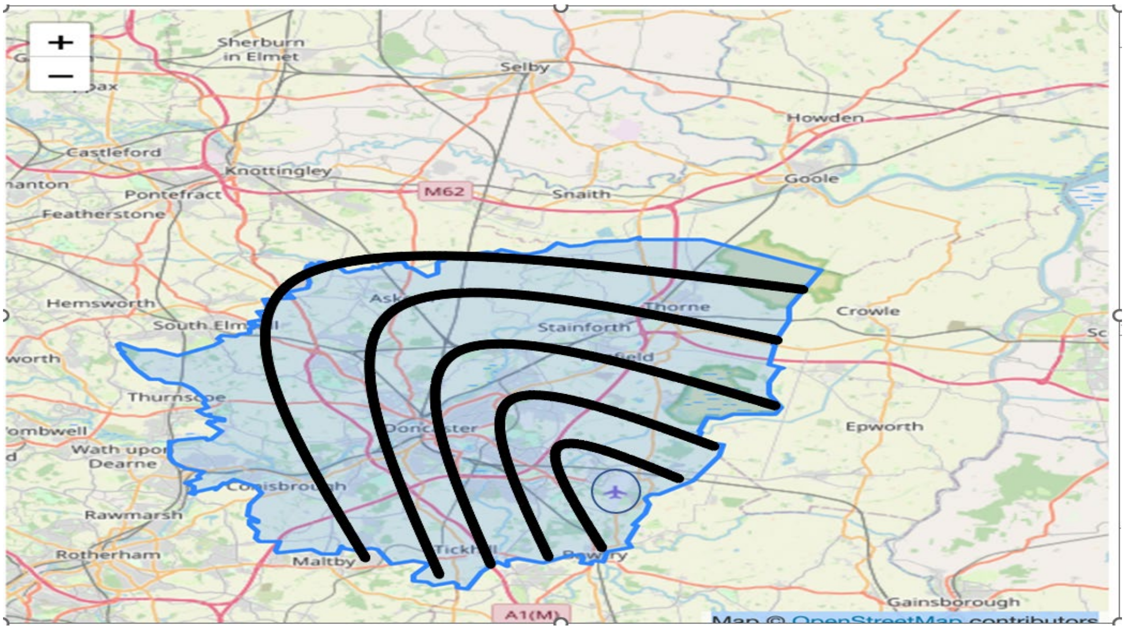


Figure 4.2: The regions of treated group and control group within Doncaster district.

Notes: The inner circle is the treated area centralised as Doncaster Sheffield Airport with a 3km radius. The outer rings are the boundaries of the control group where properties in Doncaster district is above 3km away from Doncaster Sheffield Airport. Source from: OpenStreetMap.

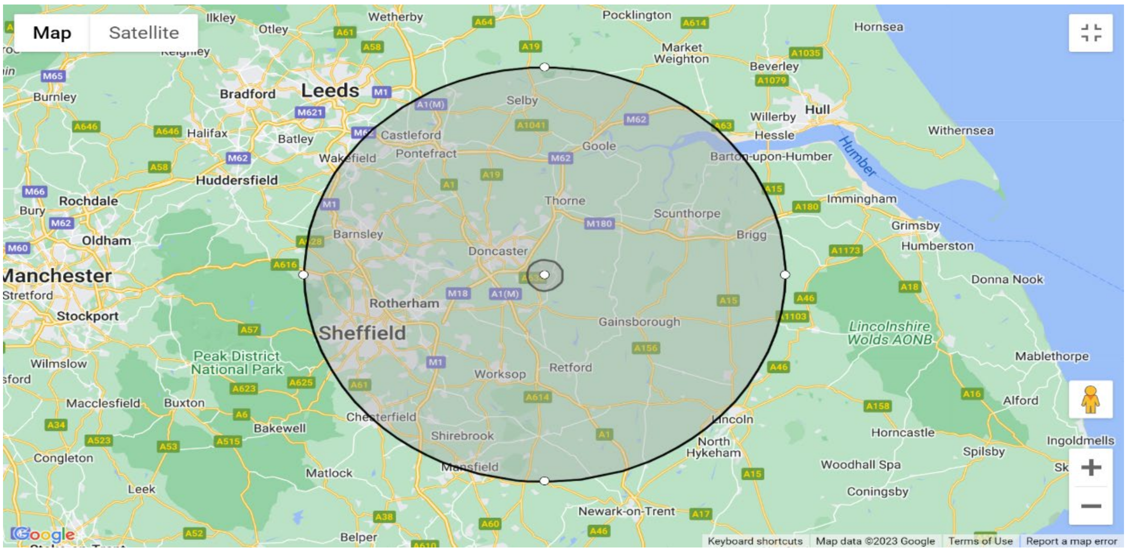


Figure 4.3: The regions of treated group and control group within 40kms to DSA.

Notes: The inner circle is the treated area centralised as Doncaster Sheffield Airport with a 3km radius. The outer ring is the boundary of the control group where properties is between 3km and 40km away from the Doncaster Sheffield Airport. Source from: Map Developers (website: https://www.mapdevelopers.com).

According to Table 4.1, generally, the average prices of properties in the treated area located within 3km are markedly higher than those in the control regions across all periods. While the property prices in the control groups exhibit a significant upward trend over time, the prices in the treated area remain relatively stable between the first two periods. It is evident that the sales of properties in control areas predominantly comprise semi-detached units (approximately 40%), older properties (over 90%), and freehold properties (around 80-90%). On the other hand, properties in the treated area exhibit slight variations, with detached houses constituting the majority of the transactions. With respect to property types, the proportions of transactions in the control areas basically remain largely unchanged throughout the entire period. In contrast, the treated area exhibits substantial variations in the transaction structure over time. For instance, prior to November 1996, detached houses accounted for more than 50% of all transactions in the treated area. However, this figure dropped significantly to 39% between November 1996 and June 1999, before recovering to around 50% in the following periods. Similarly, the proportion of flats in the treated area declined significantly before subsequently rising again. Correspondingly, the proportions of semi-detached and terraced houses increased significantly in the first period before stabilizing in the following periods.

Table 4.1: Descriptive data

Area	within3km				above 3km but within Doncaster District				3km -- 40km			
Period	Pre- 1996.11	1996.11- 1999.6	1999.6-- 2005.4	Post- 2005.4	Pre- 1996.11	1996.11- 1999.6	1999.6-- 2005.4	Post- 2005.4	pre- 1996.11	1996.11- 1999.6	1999.6-- 2005.4	Post- 2005.4
Average house price	59087	59466.47	98720.23	174887	43739.8	47771.57	71771.52	125600	46958	51289.76	80611.7	136843
Detached	0.543	0.390	0.471	0.546	0.253	0.294	0.252	0.230	0.263	0.284	0.271	0.246
Flat	0.011	0.004	0.011	0.039	0.011	0.011	0.016	0.029	0.022	0.024	0.031	0.054
Semi-detached	0.348	0.457	0.347	0.308	0.450	0.442	0.425	0.444	0.420	0.412	0.392	0.398
Terrace	0.098	0.150	0.172	0.107	0.286	0.253	0.307	0.297	0.295	0.280	0.306	0.302
Leasehold	0.011	0.004	0.009	0.039	0.049	0.018	0.026	0.041	0.156	0.157	0.148	0.168
Freehold	0.989	0.996	0.991	0.961	0.951	0.982	0.974	0.959	0.844	0.843	0.852	0.832
New	0.283	0.236	0.243	0.153	0.100	0.106	0.057	0.047	0.097	0.083	0.072	0.067
Old	0.717	0.764	0.757	0.847	0.900	0.894	0.943	0.953	0.903	0.917	0.928	0.933
Obs	92	254	548	458	3411	9705	30244	26661	47027	74893	224789	214197
total Obs	1352				70021				560906			

Notes: This table presents descriptive data on houses in both the treatment and control areas across different periods. Property characteristics are shown as proportions and include detached houses, semi-detached houses, flats and apartments, and terraces. The table also displays the shares of leasehold and freehold houses, as well as new-build and existing houses.

4.4 Empirical strategy

The approach to dealing with this problem is a quasi-experiment, where individuals are observed before and after a treatment and the outcome is compared to the level of treatment they received. By focusing on changes over time, unobserved individual differences that affect an outcome irrespectively of a treatment can be differenced out on average.

I compare changes in property prices in areas which are deemed to have been more likely to have been affected by the airport (treatment group) with changes in prices of properties located further away which are deemed not to have been affected (control group). The study period is divided into four periods, namely: a) the time when the airfield was operated by the military (prior to RAF decommission in November 1996), b) the period when the site was vacant and awaiting development between RAF decommission (November 1996) and the announcement of its transformation into a commercial airport (June 1999), c) the time when the land was designated for a commercial airport, between the airport plan announcement (June 1999) and its operation commencement (April 2005), and d) the period after the airport began operations (post April 2005). The outcome would follow the same trend for all properties (treated and untreated) in the absence of the airport interventions (i.e. RAF decommission, new airport announcement and airport operation).

The effect of an infrastructure project may in principle exploit into property prices through anticipation, or with delay with respect to an announcement, depending on how markets process available information. As for the Doncaster Sheffield Airport in this paper, there are three intervention dates. First one is the old RAF base decommission in November 1996, the second is in June 1999, when the news was announced that Peel group had purchased this site and it would be built into a new commercial airport. The last one is in April 2005, when the construction work was completed, and the airport officially commenced operation.

I start by estimating:

$$\log p_{idt} = \alpha + \beta \cdot treated_d + \varphi \cdot RAF_t + \gamma \cdot Announcement_t + \delta \cdot Opening_t + \upsilon \cdot (treated_d \cdot RAF_t) + \sigma \cdot (treated_d \cdot Anouncement_t) + \tau \cdot (treated_d \cdot Opening_t) + \varepsilon_{idt} \qquad (1)$$

I regress the log-price ($logp_{idt}$) of property *i*, located within postcode district *d*, transacted at time *t* (month). The semi-log model is widely used in modelling the determinants of property prices. $treated_d$ is a dummy variable equal to one when the distance between property *i* and the airport is not greater than 3km, and zero otherwise. While RAF_t is a dummy variable equal to one in the period prior to the RAF decommission date (November 1996), and zero otherwise. Similarly, $Announcement_t$ and $Opening_t$ are also dummy variables equal to one in the periods between the new airport announcement (June 1999) and the airport's opening month (April 2005), post the airport operation, respectively, and zero otherwise. The estimated coefficients σ and τ give the post-intervention treatment effects. I cluster standard errors at the level of LSOA.

In traditional event study analysis, the parallel trends assumption is a key assumption, which assumes that the trends in the outcome variable for the treatment group and the control group would have been parallel in the absence of the event. This assumption is necessary to separate the causal effect of the event on the outcome variable. Hence in this paper, the principal hypothesis is that the market house price in treated area would go through similar trends over the period pre_t, $post_{1t}$ and $post_{2t}$ in the absence of the interventions. While it is not measurable as it is counterfactual. Instead, it can be checked if trends are similar in the pre-treatment period.

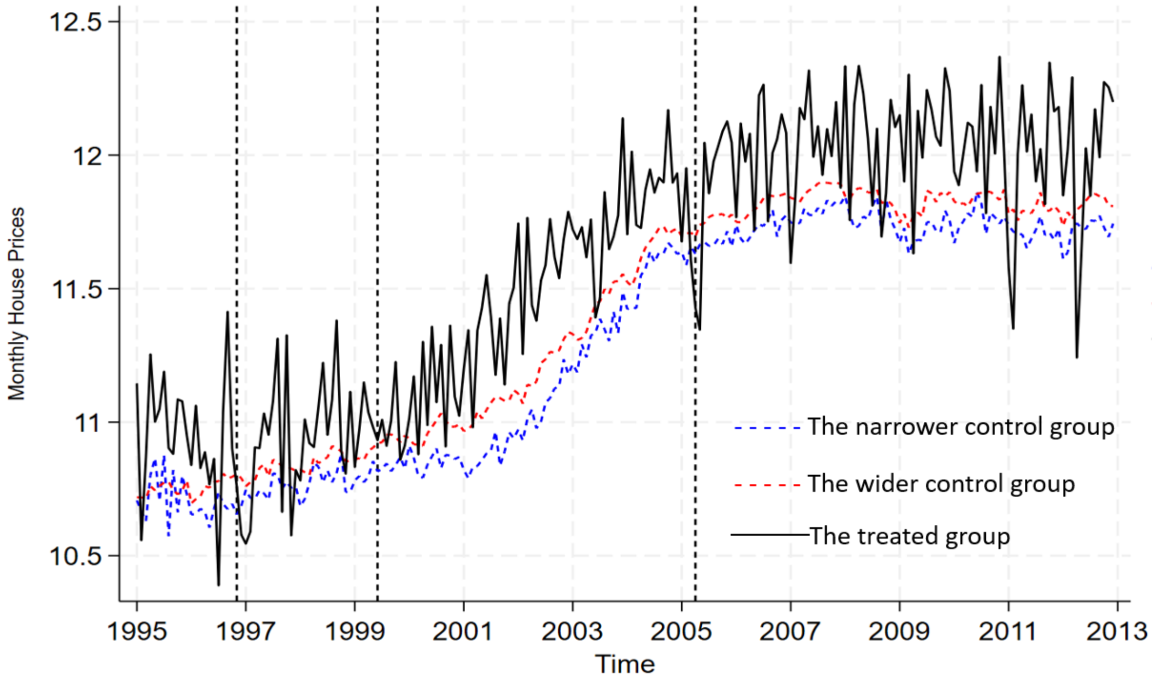


Figure 4.4: Average monthly house price in the treated and control groups.

Notes: The blue line stands the house price in narrower control group whose properties locate beyond 3km to the airport but still in Doncaster district. The red line represents house price in wider control group whose properties locate between 3km-40km to the airport.

Figure 4.4 demonstrates the house price changes over time. It is apparent that basically the patterns of these three lines are similar, increasing over time, although the house price in the treated group is much higher on average, than the control groups. While compared to the control groups, the treated line demonstrates volatility when these interventions occurred. However, Figure 4.4 shows the generally trends via monthly average house price in different regions, which does not include any conditions.

The parallel trends assumption is often difficult to verify in practice and may not hold in many cases, for example, it may be difficult to find a suitable control group that is not affected by the event but has similar trends in the outcome variable to the treatment group. In addition, other factors may be affecting the outcome variable over time, which may make it difficult to isolate the causal effect of the event.

Thus, to generate more accurate results, I additionally include month effects (θ_t) to control for macroeconomic shocks that are common to the study area, neighbourhood fixed effects

(η_i) to capture time-invariant location characteristics and the property characteristic fixed effects (μ_i) to control effects of the house features on price. In this dataset, they are newly built or existing buildings, house types (Detached house, Semi-detached house, Terrace, Flat), leasehold or freehold. The specification is:

$$logp_{idt} = \alpha_i + \theta_t + \mu_i + \eta_i + \upsilon \cdot (treated_d \cdot RAF_t) + \sigma \cdot (treated_d \cdot Announcement_t) + \tau \cdot (treated_d \cdot Opening_t) + \varepsilon_{idt} \quad (2)$$

4.5 Difference in Difference Results

Table 4.2 displays estimated regressions for the sample that is 40km radius from the airport and starts from 1995 January to 2012 December. I utilize these three interventions distribute the whole period into 4 parts, 1995 January to 1996 November 1996 November to 1999 June, 1999 June to 2005 April, and after 2005 April. These interventions are RAF Finningley officially decommissioned in 1996 November, the news that the original RAF site would be redeveloped into a commercial airport and the airport opening in 2005 April was announced. That is saying, pre 1996/11, local people lived nearby a Royal Army Force airport, while from 1996/11 to 1999/06, there was only an abandoned airport in the local community and the public was not certain whether this site would be redeveloped. During the period between 1999/06 and 2005/04, the public knew there would be a new commercial airport and it being constructed in their living community, and after 2005/04, the airport started operation. I take the period between 1996/11 and 1999/06 as the baseline period in the following regressions because at that time there was no operational airport in their neighbourhood nor did the local residents know that there would be an airport in the future. While in the other three periods inhabitants either already lived in a community surrounding an airport or they certainly knew they would live near an airport in the future. Hence, by comparing the house price changed in these periods, I can identify the impact of the airport on nearby property price.

Column (1) is the primary specification including only dummies for the treated, pre 1996/11, period of 1999/06 to 2005/04 and post 2005/04. Starting from Column (2), I use month fixed effect to replace these periods time effects. The results from regression (1) and (2) are coherent, indicating significantly positive effects of the treatments. This is consistent with Figure 4.4 that the general trend of house prices in the treated area increased over time. For a more precise model, I add neighbourhood fixed effects starting from specification (3) as locations are important to house value. Column (3) to Column (5) show the results one by one with including LSOA fixed effect, MSOA fixed effect and local authority fixed effect, respectively. It is evident that comparing (1) and (2), R-squares of regression (3) to (5) are improved immediately which means these specifications demonstrate better fit. Regression (3), using LSOA fixed effect, gives insignificant estimates with a larger r-square, and the estimates in (4) and (5) are significant with smaller r-squares. In specification (6) I add postcode fixed effect. Its model fit is significantly improved as its R-square is over 0.8 and the interaction between treated group and post-2005/04 is significantly negative. Based on specifications (3) to (6), I further add property characteristics fixed effects into specifications (7) to (10), including house type, house age and house duration, mixed with different neighbourhood fixed effects. The regression (10) presents the best result with the highest R-square (0.860). The inclusion of additional area-level controls has no impact on either the coefficient estimates or the explanatory power of the model. Including all these constrains, it is observed that from the above pillars, the estimated results are robust.

It appears that the fixed effects improve the explanatory power of the specifications substantially as the adjusted R-square increased as the fixed effects were added step by step. For instance, the adjusted R-squared rises from 0.329 to 0.860 when all of the fixed effects are included. The preferred specification is the column (10), as it has the highest adjusted R-square (0.860) as a consequence of being employed the month fixed effects, the neighbourhood fixed effects, the postcode fixed effects, and the property characteristic fixed effects. The main variables of interest are the treat*pre-1996/11, treated*(1999/06-2005/04) and treated*post-2005/04 interaction terms in the models with fixed effects. Most of the estimated coefficients of the interaction terms of treated*post-2005/04 are significant at the 1% level. As I include more fixed effects, this interaction term shifts from positive to negative. According to column (10) this coefficient, is significantly negative (-4.74%), which indicates that compared to the control area, the airport opening results in a significant decline of the property price in the treated area. Whereas the estimated coefficients of interactions of treat*pre-1996/11 and treated*(1999/06-2005/04) are close to 0, which are -1.54% and 2.38%, respectively and not statistically significant at the 5% level. It suggests that there are no meaningful influences neither of the RAF decommission nor of the new airport plan announcement on nearby property price.

Table 4.3 provides the results when these specifications are applied into the narrower sample data where the control group is restricted in the Doncaster district. The results are very similar to Table 4.2, in that the impact of the airport opening on property prices is negative and significant, and the influence of RAF decommission on surrounding property value is negligible and insignificant. The differences are that first, the estimated coefficient of the interaction term of the treated*(1999/06-2005/04) is significantly positive at the 10% level, which is 3.14%. Secondly, the negative impact of the airport opening is much larger than it in

Table 4.2, up to -8.19% at the 1% level. It suggests that the event of the new airport opening results in a considerable decrease on the values of properties located within 3km to the airport comparing to other properties in Doncaster. Additionally, the announcement of the new airport plan contributes a positive effect on the nearby property price whereas the impact of the RAF decommission on house price is deleterious similarly with the airport opening but not significant. These findings imply that contrary to governmental expectations, the airport infrastructure might not function as a positive externality for its neighbouring communities. On the contrary, it appears to introduce a negative impact, potentially causing a decline in nearby house prices.

Table 4.2: Difference-in-difference estimates using 40km sample

Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
treated	0.193***	0.186**	0.0588	-0.180**	0.285***		0.0842	-0.107**	0.143***	
	(0.028)	(0.074)	(0.210)	(0.075)	(0.078)		(0.140)	(0.053)	(0.022)	
pre-1996/11	-0.0717***									
	(0.003)									
treated * pre-1996/11	0.0919*	0.0999	-0.0247	0.0706	0.0606	0.0102	-0.0478	0.00233	-0.0715	-0.0154
	(0.051)	(0.061)	(0.108)	(0.079)	(0.057)	(0.027)	(0.072)	(0.053)	(0.047)	(0.032)
1999/06-2005/04	0.387***									
	(0.002)									
treated * (1996/11-2005/04)	0.0633*	0.117*	0.0461	0.0842	0.114*	0.0249	0.0323	0.0524*	0.0582**	0.0238
	(0.037)	(0.069)	(0.054)	(0.068)	(0.069)	(0.021)	(0.025)	(0.030)	(0.023)	(0.020)
post-2005/04	1.011***									
	(0.002)									
treated * post-2005/04	0.0981***	0.0997***	0.00588	0.0618***	0.0982***	-0.0513***	-0.0273	-0.00298	-0.0197	-0.0474***
	(0.034)	(0.012)	(0.020)	(0.019)	(0.013)	(0.015)	(0.020)	(0.025)	(0.019)	(0.013)
Constant	10.69***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***
	(0.002)	(0.010)	(0.000)	(0.005)	(0.009)	(0.000)	(0.000)	(0.003)	(0.006)	(0.000)
Observations	570,927	570,927	570,925	570,926	570,926	566,938	570,925	570,926	570,926	566,938
R-squared	0.329	0.394	0.651	0.580	0.420	0.834	0.772	0.744	0.665	0.860
Fixed month	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed lsoa	N	N	Y	N	N	N	Y	N	N	N
Fixed msoa	N	N	N	Y	N	N	N	Y	N	N
Fixed LA	N	N	N	N	Y	N	N	N	Y	N
Fixed postcode	N	N	N	N	N	Y	N	N	N	Y
Fixed property characteristics	N	N	N	N	N	N	Y	Y	Y	Y

Notes: This table demonstrates the Difference-in-Difference estimates using the wider control group. Column (1) presents the primary specification, which includes only dummy variables for the treatment, the pre-1996/11 period, the 1999/06 to 2005/04 period, and the post-2005/04 period. In Column (2) and subsequent columns, month fixed effects replace these period-specific time effects. Column (3) introduces neighbourhood fixed effects. 'LA' denotes local authorities, while 'LSOA' and 'MSOA' refer to lower-layer and middle-layer super output areas, respectively. The number of observations represents effective observations, excluding singleton combinations of fixed effects. Columns (3) through (5) display results sequentially with LSOA fixed effects, MSOA fixed effects, and local authority fixed effects, respectively. In specification (6), postcode fixed effects are introduced. Basing on specifications (3) to (6), specifications (7) through (10) furthermore incorporate property characteristics fixed effects, including house type, house age, and house duration, combined with various neighbourhood fixed effects. Observations are effective observations numbers excluding any singleton combinations of fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4.3: Difference-in-difference estimates using Doncaster district sample

Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
treated	0.274***	0.268***	0.13	-0.184**	0.268***		0.146	-0.102*	0.134***	
	(0.028)	(0.082)	(0.209)	(0.078)	(0.082)		(0.135)	(0.055)	(0.022)	
pre-1996/11	-0.0686***									
	(0.011)									
treated * pre-1996/11	0.0259	0.0507	-0.0669	0.0141	0.0507	0.00296	-0.0811	-0.0373	-0.0445	-0.0243
	(0.071)	(0.106)	(0.122)	(0.112)	(0.106)	(0.030)	(0.088)	(0.074)	(0.063)	(0.029)
1999/06-2005/04	0.340***									
	(0.007)									
treated * (1996/11-2005/04)	0.105***	0.158**	0.0652	0.116*	0.158**	0.0371*	0.041	0.0640**	0.0699***	0.0314*
	(0.037)	(0.068)	(0.053)	(0.068)	(0.068)	(0.019)	(0.025)	(0.027)	(0.021)	(0.019)
post-2005/04	1.010***									
	(0.006)									
treated * post-2005/04	0.0946***	0.0949***	-0.0161	0.0515**	0.0949***	-0.0835***	-0.0585***	-0.0341	-0.0564**	-0.0819***
	(0.034)	(0.020)	(0.022)	(0.023)	(0.020)	(0.020)	(0.020)	(0.028)	(0.024)	(0.016)
Constant	10.61***	11.14***	11.14***	11.15***	11.14***	11.15***	11.14***	11.15***	11.14***	11.15***
	(0.006)	(0.030)	(0.004)	(0.019)	(0.030)	(0.000)	(0.002)	(0.010)	(0.015)	(0.000)
Observations	72,512	72,512	72,221	72,452	72,512	71,543	72,221	72,452	72,512	71,543
R-squared	0.324	0.401	0.679	0.569	0.401	0.851	0.782	0.743	0.691	0.871
Fixed month	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed lsoa	N	N	Y	N	N	N	Y	N	N	N
Fixed msoa	N	N	N	Y	N	N	N	Y	N	N
Fixed LA	N	N	N	N	Y	N	N	N	Y	N
Fixed postcode	N	N	N	N	N	Y	N	N	N	Y
Fixed property characteristics	N	N	N	N	N	N	Y	Y	Y	Y

Notes: This table demonstrates the Difference-in-Difference estimates using the narrow control group. Column (1) presents the primary specification, which includes only dummy variables for the treatment, the pre-1996/11 period, the 1999/06 to 2005/04 period, and the post-2005/04 period. In Column (2) and subsequent columns, month fixed effects replace these period-specific time effects. Column (3) introduces neighbourhood fixed effects. 'LA' denotes local authorities, while 'LSOA' and 'MSOA' refer to lower-layer and middle-layer super output areas, respectively. The number of observations represents effective observations, excluding singleton combinations of fixed effects. Columns (3) through (5) display results sequentially with LSOA fixed effects, MSOA fixed effects, and local authority fixed effects, respectively. In specification (6), postcode fixed effects are introduced. Basing on specifications (3) to (6), specifications (7) through (10) furthermore incorporate property characteristics fixed effects, including house type, house age, and house duration, combined with various neighbourhood fixed effects. Observations are effective observations numbers excluding any singleton combinations of fixed effects. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.6 Robustness Check

Randomization experiments are acknowledged in laboratory research, such as biomedical science, agriculture, and pharmacy, etc., and they have been applied to deliver precise experimental settings for a long history. Fisher (1935) was the first to develop randomization inference, which was taken as an approach to carry out precise studies of experiments. Compared with classical inference, Fisherian randomization inference intends to examine whether an observed realization of a statistic is obtained by chance, that is saying, whether such as a treatment-effect estimation is statistically significant. It may not be acceptable or feasible to randomly assign people to different income levels or educational backgrounds for research purposes, as it can have significant real-world consequences. While recently there is a growing trend of this randomization in economists to deduce the likelihood that an estimated coefficient is not sorely a consequence of intervention. Randomized control trials serve as a tool for economists to convincingly investigate causal inference, by forming exact p-values from the randomization-based approach, which can exhibit the probability of the intervention generating such estimation.

Rosenbaum (1996) highlights that the randomization inference is possibly applied into group-level interventions. Imbens & Rubin (2015) concentrate on the randomization inference on the individual level dataset. Dufour (2006) states that the randomization inference is closely associated with Monte Carlo tests. Both randomization inference and Monte Carlo tests employ simulation techniques for statistical inferences, sharing common principles of generating random samples to approximate distributions. However, while randomization inference is specifically designed for randomized control trials, Monte Carlo tests exhibit broader applications across diverse statistical scenarios. Lehmann & Romano (2005) build a formal theoretical treatment of Randomization. Athey & Imbens (2017) emphasize that estimated uncertainty in randomization-based inference departs from the assumptions of sampling from a large population, instead the uncertainty in approximations is inherent in the random assignment of treatments. This approach employs the randomization-based methods to evaluate the likelihood that an estimated coefficient is not merely a consequence of random variation. To be more precise, in the sampling-based approach, the treatment assignments are required to be fixed to obtain the random outcomes, which means the inference is on the premise of assuming the observations are a random sample from a much larger population (Athey & Imbens, 2017). In contrast, during randomized control trails, the estimates in a regression of the outcome on treatment and controls should be defined as the test statistic of interest. That is saying, in the randomization-based method, the assigned treatment to observations is regarded as random, in the meantime, the possible outcome generated by each probable treatment would be taken as fixed.

This paper employs randomization inference as a robustness check, particularly concerning the estimated effects of the treatments at different time intervals. This method involves several key steps that are designed to rigorously test the significance of the treatment effect, ensuring that the observed results are not merely due to random chance.

First, the core concept of randomization inference is to generate a distribution of the treatment effect under the assumption that the treatment has no effect—referred to as the sharp null hypothesis. To operationalize this, the interactive variables that represent the treatment effects across various periods (specifically, the treated*post-2005/04, the treated*pre-1996/11, and the treated*1999/06-2005/04), are permuted 500 times, respectively. Each permutation involves a random reassignment of the treatment status while maintaining the underlying structure of the data. Each permutation represents a hypothetical scenario where the treatment was assigned differently but under the same conditions. For each of these 500 permutations, the model is re-estimated. This means that the regression analysis is conducted repeatedly, each time using a different permutation of the interactive variable. By doing so, this paper generates a wide range of possible outcomes that could occur if the treatment had been assigned in a different manner.

Secondly, a null distribution was created. The results of these 500 model estimations form what is known as a "null distribution" of the treatment effect. This distribution represents the range of treatment effects that could be observed purely by chance if the treatment had no actual effect. The purpose of this null distribution is to serve as a benchmark against which the actual observed treatment effect can be compared.

Next, the calculation of P-Values was conducted. Under the sharp null hypothesis, the observed treatment effect should not systematically differ from the effects found in the null distribution. The p-value is calculated by determining the proportion of permuted treatment effects that are as extreme as or more extreme than the treatment effect observed in the original regression. Specifically, if a large proportion of the permuted estimates are more extreme than the actual observed effect, it would suggest that the observed effect could be due to chance, leading to a high p-value. Conversely, if very few of the permuted estimates are more extreme, the p-value would be low, suggesting that the observed treatment effect is unlikely to be due to random chance.

The randomisation inference outcomes are shown in the Table 4.4. T(obs) stands the realization of the test statistic in the data. c is the count of under how many of the re-sampled assignments, the realization of the test-statistic was more extreme than the test statistic, T(obs). n is the overall count of re-sampling. Thus P=c/n gives the actual p-values calculated by randomization inference approach, which explains the fraction of extreme realization.

Table 4.4: The randomization inference results

Variable	T(obs)	c	n	P=c/n	SE(p)	95% Conf. Interval		Original P
Doncaster district sample								
treated*post-2005/04	-0.0819	0	500	0.000	0.000	0.000	0.007	0.000
treated*pre-1996/11	-0.0243	294	500	0.588	0.022	0.5434	0.6315	0.407
treated*(1999/06-2005/04)	0.0314	93	500	0.186	0.017	0.1528	0.2229	0.096
40km sample								
treated*post-2005/04	-0.0473	42	500	0.084	0.012	0.0612	0.1118	0.000
treated*pre-1996/11	-0.0167	319	500	0.638	0.022	0.5942	0.6802	0.617
treated*(1999/06-2005/04)	0.0238	175	500	0.350	0.021	0.3082	0.3936	0.239

Notes: This table show the randomization inference results. T(obs) represents the observed value of the test statistic in the data. The count c denotes the number of re-sampled assignments for which the test statistic exceeded the observed value, T(obs), in extremity. The total number of re-samples is n. The p-value, P=c/n is calculated by the proportion of re-sampled test statistics that are at least as extreme as T(obs).

It reveals that the P-values obtained from the randomization inference are similar to the original p-values derived from Difference-in-Difference. In particular, the impact of the opening intervention (treated*post-2005/04) observed in the Doncaster sample remains consistently significant at the 1% level. However, this effect, when examined in the broader sample (using the 40km radius), shows slightly less significance as compared to the original regression, with a P-value of 0.084. That is saying, in all 500 replications of randomly assigning the opening intervention in the wider sample (40km sample), not a single instance was observed where the effect attained significance comparable to the opening effect. In the meantime, within the narrowed sample (the Doncaster district sample), the treatment achieved significance 42 times out of 500, mirroring the magnitude of the original effect. These results mean, in the context of randomly assigning the airport opening treatment 500 times to the entire sample dataset, the likelihood of observing impacts of this magnitude is either zero or substantially low. This finding provides support for the assertion that the observed effects of airport opening on house prices, as derived from the original Difference-in-Difference estimations, are not attributable to chance. While it can be also found that the impacts of the other two interventions, the RAF decommission (treated*pre-1996/11) and the new airport announcement (treated*1999/06-2005/04), are not significant and in the randomization-based approach, their P-values are similar to the original estimators, and, at times, slightly higher. Specifically, it is evident from 500 replications that the probabilities of obtaining the test statistics results of similar magnitudes are not negligible, despite the distribution of announcement effects under the null hypothesis exhibits marginal tendencies (P = 0.35 and P = 0.186), but do not show extreme deviations (P<0.1). It might be because a) for estimating the RAF closure impact, the pre-treatment data sample is not sufficient; b) in terms of measuring the announcement effect, which is significant and slightly positive, during the announcement and construction period the new airport plan was widely disputable and it might result in some extent uncertainty of whether there would be a new commercial airport located in local community in the future and the impact on house price was not that clear. Thus, these results stemming from the randomization inference are consistent with the outcomes of the original regressions.

By using randomization inference, the author can robustly assess whether the observed treatment effects are statistically significant or could simply be the result of random variations in the data. This method is particularly powerful because it does not rely on the usual parametric assumptions about the distribution of the errors or the functional form of the relationship between variables. Instead, it provides a non-parametric way to test the hypothesis, making the results more robust and credible.

The use of randomization inference adds a layer of credibility to the findings. In econometric analyses, especially those involving complex policy changes or treatments over time, there is always a risk that the observed effects could be spurious, driven by factors other than the treatment itself. Randomization inference helps to mitigate this risk by providing a method to rigorously test the null hypothesis, thereby strengthening the case for any observed treatment effects being genuine rather than artifacts of the data or model specification.

4.7 Panel Event Study

To conduct a more in-depth analysis of the effects of the airport on proximate property prices and to offer a visually coherent representation of the causal impacts of these events, I employ a panel event study design. This design, rooted in "difference-in-differences" methodologies or two-way fixed effect models, facilitates the estimation of dynamic leads and lags associated with a focal event, all the while enabling the control of fixed factors. Moreover, the panel event models, utilizing areas, where the policy or event has not occurred, or has yet to occur, as counterfactuals, to analyse the variation in outcomes around the event adoption compared to a reference period, including both leads and lags related to the event. Controlling for time-invariant unobserved heterogeneity across units in the dataset, event studies are able to address issues of omitted variable bias. By including fixed effects for each unit in the dataset, panel event studies can account for differences in the baseline levels of the outcome variable across units, as well as differences in the trends in the outcome variable over time. Compared to the Difference-in-Difference method I used in the section 4.5, this approach can attribute to mitigate concerns about the parallel trend assumption, as it does not require a control group with parallel trends. Indeed, consistent estimation in event study models relies on the crucial assumption that the event's incidence in a specific area is not significantly associated with the variations in levels that would have occurred in the absence of the event. Furthermore, rather than yielding an instantaneous outcome as in traditional DiD analysis, the panel event study captures the dynamic evolution of the treated group over time.

Therefore, building on equation (2), I add leads and lags for each month during the whole sample period so that it is able to provide a clear visual variation in outcomes of interest around the adoption of the interventions and a baseline reference period. I use the period of 1999 2nd quarter as the baseline reference period and standardise the treated group in that period to zero. This is because during that period, local residents did not reside in proximity to an operational airport, nor was there an expectation of them living near an airport in the foreseeable future. The specification is presented as below:

$$logp_{idt} = \alpha_i + \theta_t + \mu_i + \eta_i + \sum_{q=1/1995}^{1/1999} \tau^q \cdot (treated_d \cdot 1\{t = q\}) + \sum_{q=2/1999}^{4/2012} \tau^q \cdot (treated_d \cdot 1\{t = q\}) + \varepsilon_{idt} \qquad (3)$$

Where τ^q denotes the variation between treated and control regions in quarter q relative to 2nd/1999.

Figure 4.5 and Figure 4.6 display the event plots, complete with 95% confidence intervals, illustrating how the outcome variable for the treated group changes before and after the events of interest. Figure 4.5 employs the control group which is defined as properties located at a distance between 3km and 40km from the airport and Figure 4.6 exploits the control group comprises properties located within the Doncaster district that are at a distance greater than 3km from the airport. The three vertical lines signify the time nodes of the three events, with the first and third lines indicating the quarters leading up to and following the baseline period, 3rd quarter 1996 and 2nd quarter 2005, respectively, while the second line denotes the baseline period (2nd quarter 1999). The horizon line serves as the normalized zero point that marks the entity's position during the baseline period, providing a concise representation of how the outcome variable evolves for the treated group before and after the events. Each entity signifies variations in the rate of change of the outcome variable.

The estimated coefficients obtained from the two control groups exhibit a high degree of similarity, with almost identical trends. Prior to the decommissioning of RAF Finningley in the third quarter of 1996 (marked by the first vertical line), house prices in the treated area remained at a lower level compared to the baseline period. However, after the decommissioning, house price in the treated area began to rise, eventually plateauing at the baseline period level at a time there was an absence of an operational airport in close proximity to local residents and the lack of any foreseeable plans to establish one contributed to this outcome. However, the announcement in June 1999 (marked by the second vertical line) that the site would be redeveloped into a commercial airport resulted in a sharp drop in all exposed entities, with the impact being significant and lasting for a couple of years. The house prices continued to climb for a few years thereafter, exhibiting slight variations around the horizon line. This trend is consistent with the public inquiry conducted between October

2001 and March 2002, and the authorization of the airport's planning permission in April 2003. A subsequent sharp drop in house prices around 2004 coincided with the controversial naming of the new airport as Robin Hood, which reminded local residents that an airport was soon to be established completely in their community. Thus, individuals who were not willing to be disturbed by issues like airport noise had to move away from the airport before its opening. The negative effect on house prices persisted for a couple of years after the airport's opening, with house prices remaining at a much lower level compared to the baseline period. These plots provide a visualization of how events affect the outcome variable over time for each entity in the panel, with the difference before and after treatment providing an estimate of the interventions' impact on house prices. Three troughs in the trend of these points can also be observed, each occurring around the time of the interventions. This observation consistently suggests that each time residents become aware of the proximity of an airport, it leads to a negative influence on property prices.

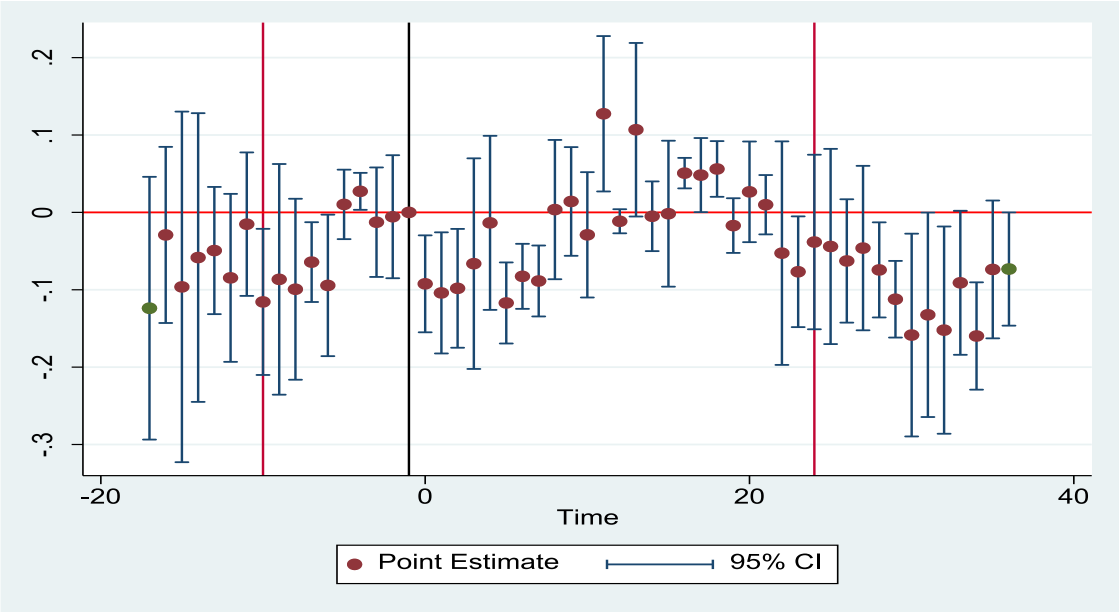


Figure 4.5: Property value estimated difference between treated and control groups by quarter.

Notes: The treated group is defined as properties whose distance to the airport is not greater than 3km. The control group is specified as the properties whose distance to the airport is between 3km and 40km. The coefficients are measured according to Equation (3) alongside conditions of postcode fixed effects, month fixed effects, neighbourhood fixed effects (LSOA), and property characteristic fixed effects. Standard errors are adjusted for clustering on the LSOA level.

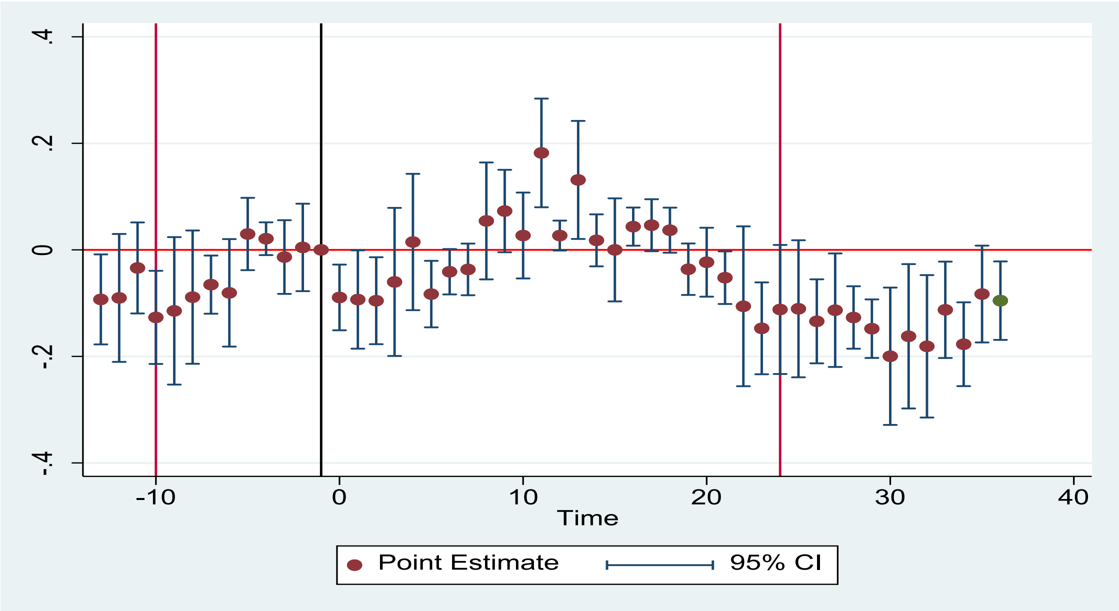


Figure 4.6: Property value estimated difference between treated and control groups by quarter.

Notes: The treated group is defined as properties whose distance to the airport is not greater than 3km. The control group is specified as the properties whose distance to the airport is above 3km and its locations is still in Doncaster district. The coefficients are measured according to Equation (3) alongside conditions of postcode fixed effects, month fixed effects, neighbourhood fixed effects (LSOA), and property characteristic fixed effects. Standard errors are adjusted for clustering on the LSOA level.

4.8 Regression results with difference radius

In addition, I investigated how the distance from the airport affects property prices. I expanded the treatment areas in the regression analysis to encompass additional concentric rings with a 1 km radius from the airport. Specifically, the variable 'treated' includes properties located within 3 km of the airport. The variable '4th km' includes properties situated between 3 and 4 km from the airport, the variable '5th km' includes properties situated between 4 and 5 km from the airport, and so forth.

Table 4.5 and Table 4.6 show consistent results across all rings. Within the 3km ring, the decommissioning of the RAF had a slightly negative but insignificant impact on house prices, while the announcement effect had a slight positive impact with less significance. However, the opening of the airport had a significant negative impact on property prices, and these results were robust across all rings. Moreover, Figure 4.7 and Figure 4.8, derived from Table 4.5 and Table 4.6, illustrate the coefficients of the interaction terms with distance from the airport. Figure 4.7 shows that the negative impact of the airport's opening (marked as ‘post2’) on property prices disappears at a distance of 6km from the airport, and significant positive effects are observed at 9km and 10km. In the narrower sample of properties located only in the Doncaster district, the effect pattern of ‘post2’ is similar, but the negative effect disappears for houses located 9-10km from the airport. This finding suggests that living close to the workplace but away from airport noise may be an attractive option for airport employees. Additionally, the announcement effect is positive but less significant and does not show a clear relationship with distance.

Table 4.5: Regressions of different radius using 40km sample

Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated * (pre-1996/11)	-0.0154	-0.0155	-0.0155	-0.0153	-0.0154	-0.0154	-0.0153	-0.0151
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Treated * (1996/11-2005/04)	0.0238	0.024	0.024	0.0242	0.0243	0.0245	0.0248	0.0246
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Treated * (post-2005/04)	-0.0474***	-0.0476***	-0.0477***	-0.0477***	-0.0478***	-0.0478***	-0.0475***	-0.0469***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
4^{th} km * (pre-1996/11)		-0.019	-0.019	-0.0188	-0.0189	-0.0189	-0.0189	-0.0186
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
4^{th} km * (1996/11-2005/04)		0.0327**	0.0327**	0.0330**	0.0331**	0.0333**	0.0335**	0.0333**
		(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
4^{th} km * (post-2005/04)		-0.0522**	-0.0524**	-0.0524**	-0.0524**	-0.0524**	-0.0521**	-0.0516**
		(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
5^{th} km * (pre-1996/11)			0.0000911	0.000279	0.000227	0.000205	0.00025	0.000518
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5^{th} km * (1996/11-2005/04)			0.00405	0.00427	0.00441	0.00459	0.00487	0.00464
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
5^{th} km * (post-2005/04)			-0.0239	-0.0239	-0.024	-0.024	-0.0236	-0.0231
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
6^{th} km * (pre-1996/11)				0.0338	0.0338	0.0338	0.0338	0.0341
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
6^{th} km * (1996/11-2005/04)				0.0415**	0.0417**	0.0419**	0.0421**	0.0419**
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
6^{th} km * (post-2005/04)				0.00827	0.00817	0.00818	0.00851	0.00906
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
7^{th} km * (pre-1996/11)					-0.00777	-0.0078	-0.00776	-0.00749
					(0.02)	(0.02)	(0.02)	(0.02)
7^{th} km * (1996/11-2005/04)					0.0218	0.0219	0.0222	0.022
					(0.02)	(0.02)	(0.02)	(0.02)
7^{th} km * (post-2005/04)					-0.0157	-0.0157	-0.0154	-0.0148
					(0.02)	(0.02)	(0.02)	(0.02)
8^{th} km * (pre-1996/11)						-0.00359	-0.00354	-0.00328
						(0.02)	(0.02)	(0.02)
8^{th} km * (1996/11-2005/04)						0.0228	0.0231	0.0229

						(0.02)	(0.02)	(0.02)
8th km * (post-2005/04)						0.0015	0.00183	0.00239
						(0.02)	(0.02)	(0.02)
9th km * (pre-1996/11)							0.0044	0.00467
							(0.02)	(0.02)
9th km * (1996/11-2005/04)							0.0305**	0.0302**
							(0.01)	(0.01)
9th km * (post-2005/04)							0.0352*	0.0358*
							(0.02)	(0.02)
10th km * (pre-1996/11)								0.0152
								(0.01)
10th km * (1996/11-2005/04)								-0.0118
								(0.02)
10th km * (post-2005/04)								0.0322*
								(0.02)
Constant	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***	11.22***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	566,938	566,938	566,938	566,938	566,938	566,938	566,938	566,938
R-squared	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86

Notes: This table presents Difference-in-Difference estimates using a broader control group. Column (1) replicates the primary specification from Column (10) of Table 4.2, which evaluates the effects of three events on properties within 3 km of the airport (e.g., Treated*(pre-1996/11), Treated*(1999/06 to 2005/04), and Treated*post-2005/04)). In Column (2) and subsequent columns, the specifications extend the treated areas to include additional concentric rings with a 1 km radius from the airport, up to 10 km. All specifications incorporate month fixed effects, neighbourhood fixed effects, and property characteristics fixed effects. The number of observations represents effective observations, excluding singleton combinations of fixed effects. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6: Regressions of different radius using Doncaster sample.

Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated * (pre-1996/11)	-0.0243	-0.0247	-0.0252	-0.0272	-0.0281	-0.0299	-0.0299	-0.0319
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Treated * (1996/11-2005/04)	0.0314*	0.0330*	0.0337*	0.0362*	0.0379**	0.0408**	0.0443**	0.0454**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Treated * (post-2005/04)	-0.0819***	-0.0847***	-0.0881***	-0.0891***	-0.0929***	-0.0965***	-0.0969***	-0.0987***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
4^{th} km * (pre-1996/11)		-0.0372*	-0.0379*	-0.0400**	-0.0408**	-0.0430**	-0.0430**	-0.0450**
		(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
4^{th} km * (1996/11-2005/04)		0.0485***	0.0491***	0.0516***	0.0534***	0.0560***	0.0595***	0.0606***
		(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
4^{th} km * (post-2005/04)		-0.0880***	-0.0915***	-0.0923***	-0.0961***	-0.0999***	-0.100***	-0.102***
		(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
5^{th} km * (pre-1996/11)			-0.00938	-0.0115	-0.0122	-0.0144	-0.0145	-0.0166
			(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
5^{th} km * (1996/11-2005/04)			0.016	0.0184	0.0201	0.0230*	0.0264*	0.0276**
			(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
5^{th} km * (post-2005/04)			-0.0608**	-0.0617**	-0.0655***	-0.0690***	-0.0694***	-0.0711***
			(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
6^{th} km * (pre-1996/11)				-0.0406	-0.0413	-0.0435*	-0.0436	-0.0456*
				(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
6^{th} km * (1996/11-2005/04)				0.0608***	0.0625***	0.0654***	0.0689***	0.0701***
				(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
6^{th} km * (post-2005/04)				-0.0251	-0.0288	-0.0322	-0.0326	-0.0343
				(0.035)	(0.035)	(0.035)	(0.035)	(0.036)
7^{th} km * (pre-1996/11)					-0.013	-0.0153	-0.0154	-0.0174
					(0.022)	(0.022)	(0.022)	(0.023)
7^{th} km * (1996/11-2005/04)					0.0442**	0.0469**	0.0504**	0.0516***
					(0.019)	(0.020)	(0.020)	(0.020)
7^{th} km * (post-2005/04)					-0.0774***	-0.0810***	-0.0813***	-0.0831***
					(0.017)	(0.017)	(0.017)	(0.018)
8^{th} km * (pre-1996/11)						-0.0473**	-0.0475**	-0.0495**

						(0.023)	(0.023)	(0.024)
8th km * (1996/11-2005/04)						0.0580***	0.0615***	0.0627***
						(0.018)	(0.018)	(0.018)
8th km * (post-2005/04)						-0.0680**	-0.0684**	-0.0701**
						(0.026)	(0.027)	(0.027)
9th km * (pre-1996/11)							-0.00145	-0.00354
							(0.022)	(0.022)
9th km * (1996/11-2005/04)							0.0482***	0.0494***
							(0.016)	(0.016)
9th km * (post-2005/04)							-0.00387	-0.00554
							(0.023)	(0.024)
10th km * (pre-1996/11)								-0.013
								(0.018)
10th km * (1996/11-2005/04)								0.00701
								(0.027)
10th km * (post-2005/04)								-0.0104
								(0.022)
Constant	11.15***	11.15***	11.15***	11.15***	11.15***	11.15***	11.15***	11.15***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Observations	71,543	71,543	71,543	71,543	71,543	71,543	71,543	71,543
R-squared	0.871	0.871	0.872	0.872	0.872	0.872	0.872	0.872

Notes: This table presents Difference-in-Difference estimates using a narrow control group. Column (1) replicates the primary specification from Column (10) of Table 4.2, which evaluates the effects of three events on properties within 3 km of the airport (e.g., Treated*(pre-1996/11), Treated*(1999/06 to 2005/04), and Treated*post-2005/04)). In Column (2) and subsequent columns, the specifications extend the treated areas to include additional concentric rings with a 1 km radius from the airport, up to 10 km. All specifications incorporate month fixed effects, neighbourhood fixed effects, and property characteristics fixed effects. The number of observations represents effective observations, excluding singleton combinations of fixed effects. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

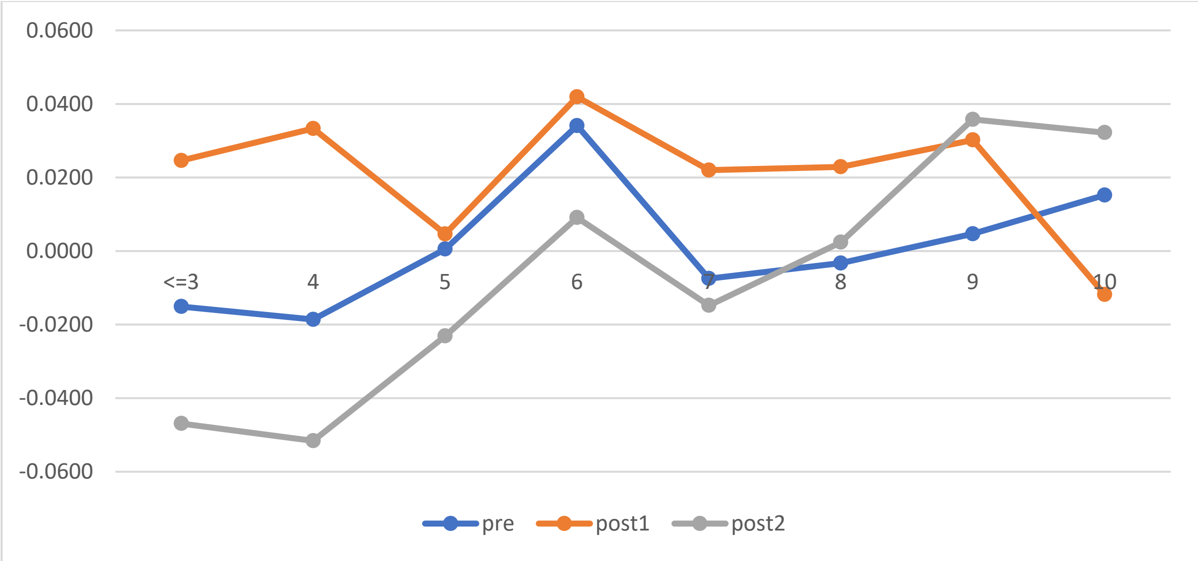


Figure 4.7: Coefficients using 40km sample

Notes: This figure visually represents the coefficients of interaction terms at varying distances from the airport, utilizing a broader control group. The blue line (marked as 'pre') represents the decommission effects of the RAF at different distances. The orange line (marked as 'post1') signifies the announcement effects at different distances, while the grey line (marked as 'post2') depicts the opening effects at different distances.

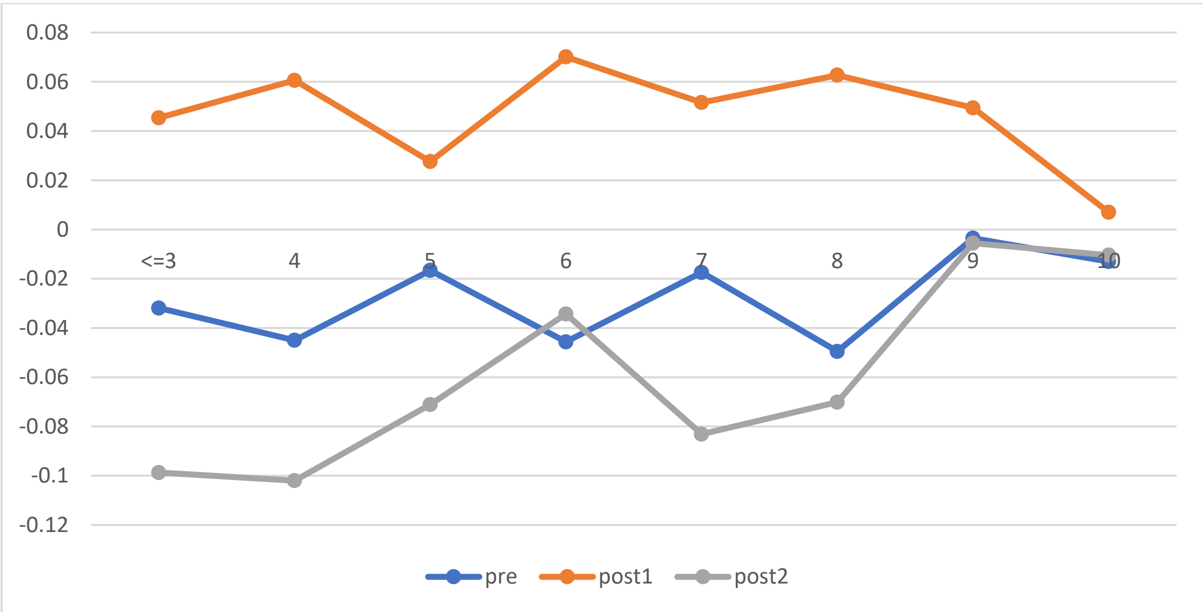


Figure 4.8: Coefficients using Doncaster sample

Notes: This figure visually summaries the coefficients of interaction terms at varying distances from the airport, utilizing a narrower control group. The blue line (labeled as 'pre') represents the decommission effects of the RAF at different distances. The orange line (labeled as 'post1') signifies the announcement effects at different distances, while the grey line (labeled as 'post2') depicts the opening effects at different distances.

4.9 Conclusion

This study explores the hypothesis that public infrastructure serves as a positive externality for neighbouring communities, aligning with governmental investment expectations. Utilizing Doncaster Sheffield Airport as an event study, this chapter focuses on analysing the influence of airport infrastructure on its adjacent housing prices. Specifically, the research investigates the consequences of three consecutive events at this airfield: the closure of a former military airfield, the announcement of its conversion into a commercial airport, and the subsequent operation of the new airport. Each of these events holds the potential to significantly affect the local community, leaving residents uncertain about both the airport's future and the quality of life in their surroundings. These situations provide a unique opportunity to evaluate whether airport infrastructure functions as a valuable amenity for the local community and to measure the community's satisfaction with their quality of life near a newly established transportation hub.

Households exhibit a willingness to pay higher prices for residences located in areas distinguished by convenient accessibility, a factor that can enhance economic mobility (So et al., 1997). On one hand, this inclination to pay a premium tends to employ upward pressure on housing prices. On the other hand, with the increase in housing demand in specific areas attributed to enhanced transport infrastructure, property would also exert upward pressure on house prices (Efthymiou & Antoniou, 2013; Mitra & Saphores, 2016; Hoogendoorn et al., 2019). While the direct influence of transport infrastructure on housing demand does not consistently yield a positive correlation with house prices. More specifically, transport infrastructure might trigger slower growth in certain regions, resulting in reduced land values and house prices (Brinkman & Lin, 2019). In addition, a substantial literature has focused on the vicinity and noise effect of operating airports on house price. The effects of air quality, noise, and proximity to various forms of urban infrastructure can arguably exert a significant influence on the quality of life, making it a critical consideration for consumers when selecting a residential neighbourhood (McCord et al., 2018).

This study focuses on the variation in pre- and post-intervention housing prices within a 3km radius of Doncaster Sheffield Airport, using difference-in-difference-type estimators while controlling for housing, neighbourhood, and locational characteristics. The findings suggest that properties located within a 3km radius of Doncaster Sheffield Airport experienced a decline in value after the airport's opening, with a 4.74% decrease compared to houses located 3-40km away while this decline is up to 8.19% in value compared to the rest of Doncaster. However, no significant evidence is found for the effects of military airfield decommission or new airport plan announcement on nearby property values. The panel event plots used in the study provide a useful visualization of how events over time affect the outcome variable for each entity in the panel. The difference in house prices before and after the treatment provides an estimate of the interventions' impact. The study considers four distinct periods in its analysis, each corresponding to a specific intervention: the decommission of the old RAF base, the announcement of a new commercial airport plan, and the start of operations at the new airport. These events divide the observations into four groups: residents living near an operating military airfield, residents living near an abandoned airport, residents expected to live near a new commercial airport, and residents living close to an operational airport. The plots reveal three troughs in the trend of these points, each occurring around the time of the interventions, which means property values near airports tend to decline in the short term each time people are exposed to living near an airport, regardless of whether the airport is currently operational or is expected to run in the near future. That is saying, each time residents become aware of the proximity of an airport, it leads to a negative influence on property prices. This consistent observation supports the view that living near an airport has a negative impact on property values. Additionally, the study examines the relationship between property values and distance from the airport hub. The study reveals that properties located within a 3-5km radius of Doncaster Sheffield Airport experienced a decline in value after the airport's opening. However, properties located beyond this distance, particularly those located 6-8km away, did not experience any negative effects. Instead, there was a positive effect on property values beyond this distance. When using a narrower sample, the affected range is slightly larger, suggesting that properties located 9-10km from the airport are not negatively affected by the airport undesirable factors such as noise and congestion.

These results align with the hypothesis that the inauguration of a new airport hub tends to decrease property values in close proximity, while beyond a certain distance, property values are anticipated to rise. This implies that individuals employed at the airport may prefer to reside at a specific distance, where they can avoid the noise and congestion linked to the airport, yet also minimize commuting time.

This consistent pattern substantiates the idea that for individuals residing in close proximity to airport infrastructure, the airport may not be perceived as a positive externality. This phenomenon can be ascribed to the uncertainty introduced by the establishment of a new airport regarding its potential influence on the local environment and quality of life. Public transportation hubs, particularly airports with frequent aircraft activities, are commonly associated with noise pollution, which can diminish the appeal of nearby properties, leading to reduced demand and subsequently lower property values. Conversely, individuals residing at a greater distance from the airport may view airport infrastructure more favourably, as they are likely to experience fewer adverse effects such as noise impact from the airport.

Chapter 5. Final Remarks

This thesis makes significant contributions to research on the economics of the public sector and public infrastructure. Chapter 2 is the first study to evaluate the impact of diminishing the public sector's influence on promoting social equality. Chapters 3 and 4 delve into investigating whether residents align with the government's perspective on the positive effects of public infrastructure. By conducting a case study centred on an investment in airport infrastructure in the UK, these chapters investigate how residents perceive the impact of such initiatives on improving local economic conditions, accelerating urbanization, and enhancing the overall quality of life.

Chapter 2, utilizing urban datasets from the China Household Income Project (CHIP) surveys conducted in 2002, 2007, and 2013, enriches the current literature by evaluating the extent to which the public sector fulfils its anticipated role in mitigating income inequality, alleviating discrimination in the labour market, and advancing social justice.

This study contributes to the existing literature by innovatively employing Unconditional Quantile Regression and RIF-decomposition methods to analyze the transformations in the Chinese wage structure from 2002 to 2013. Notably, this period coincided with China's accession to the WTO, marking a significant juncture as its economy ascended to the second-largest position globally, which underscores the salience of the wage inequality issue in China, especially within the public and private sectors. This is particularly noteworthy as China undergoes a transition from a communist to a market-based economy, where the public sector holds a dominant position, and private ownership encounters discrimination within the Chinese labor market.

Chapter 2 contributes to persistence literature by demonstrating that initially, the diminishing trend in the unconditional average marginal impact of the public sector on wages is evident. By 2013, it no longer provides a substantial wage premium to low-income workers and, in fact, negatively affects the earnings of high-income workers. This suggests that, to some extent, the public sector no longer acts as a safeguard, as observed in earlier times.

Moreover, the pattern of urban wage inequality between the public and private sectors has experienced substantial shifts, aligning with findings from related studies on ownership-based wage inequality (Gustafsson & Wan, 2020; Démurger et al., 2005; Ma, 2015). While this study indicates that this widening gap is primarily driven by the increasing influence of endowment effects. The diminishing unexplained effect has weakened significance for low-income workers, simultaneously employing constraints on salary levels for high-income earners. Essentially, the wage differential is rooted in the greater human capital advantage held by public sector employees compared to their private sector counterparts, rather than stemming from sector-specific discrimination. These findings indicate significant advancements in the reform of the Chinese labour market, as the public sector gradually relinquishes its dominant position, contributing to the cultivation of a more equitable employment environment.

This chapter also supports Li, Meng et al. (2023), who find while private enterprises wield dominance in China's labour market, there remains a high concentration of college-educated workers within the state sector and attracting highly educated workers might still pose a challenge for the private sector. This is likely attributed to the fact that employment in the state sector offers superior wages, enhanced benefits, increased job security, improved working conditions, and greater prestige and control rights (Li, Meng et al.,2023).

Furthermore, an implication of Chapter 2 is that gender continues to exert a substantial influence on wage inequality, suggesting the ongoing challenge of achieving gender equality in the Chinese labour market. Sun and Hung (2018) indicate that the increasing gender income gap in China is not primarily a result of growing discrimination against females, whether rooted in tradition or other factors. Instead, they provide evidence suggesting that two key drivers of China's economic growth, namely privatization and urbanization, are highly likely contributors to the observed rise in the gender income gap.

Additionally, in alignment with Lollar (2009) and Yue & Cai (2016), this chapter exposes that the financial and resources industries, predominantly monopolized by the state, significantly contribute to wage inequality through unreasonably elevated incomes derived from the monopoly of state-owned industries.

Numerous studies indicate substantial connections between air service and employment growth and increases in air service have been shown to result in statistically and economically significant growth in regional development (Bloningen & Cristea, 2012; Sheard, 2014; Bilotkach, 2015). Eberts & McMillen (1999) outlined that the existence and proximity of public infrastructure, such as airports, impact the economic activity of a metropolitan area by acting as an uncompensated factor in a firm's production function, boosting the productivity of other inputs, attracting additional inputs from external sources, and/or catalyzing demand for additional infrastructure (e.g., roads) and related services.

Chapter 3 enhances the existing literature by examining the alignment of public infrastructure investments with government expectations for promoting urban economic growth, with a specific focus on the housing market. The rationale behind this investigation is rooted in the strategic efforts of governments to promote urbanization and economic growth through enhanced public infrastructure. By improving the appeal of an area and attracting businesses and individuals, these endeavors are expected to have a consequential impact on property values.

This paper adds to the empirical literature by providing up-to-date estimates by employing synthetic control methods to evaluate the impact of the Doncaster Sheffield Airport announcement on the regional housing market. However, in contrast to benefits on urban developments, this chapter utilizing data-driven procedures for synthetic comparison units in comparative studies, indicates a significant, immediate drop in Doncaster house prices following the announcement of the construction of Doncaster Sheffield Airport. Furthermore, post-intervention, there was a distinct rise in transaction volume in Doncaster, with house prices decreasing by 30% (approximately £15,000) and transaction volume increasing by 37.5% (around 150). These findings suggest that public infrastructure, particularly airports, may not necessarily drive an upward trend in regional house prices, thus possibly hindering effective stimulation of urban economic growth. Contrary to governmental expectations, it might render a region less appealing for residence, causing a short-term decline in the housing market.

Case & Quigley (2008) outline three interconnected mechanisms influencing the broader economy through changes in the housing market: wealth effects, income effects, and effects via financial markets. To be more precise, they suggest that a decline in house prices typically results in reduced homeowner wealth, leading to a "wealth effect" that diminishes financial security and confidence. Consequently, homeowners may limit spending, affecting local businesses and dampening economic activity. The income effects manifest when existing home sales or housing starts decline, causing a reduction in aggregate expenditure, income, and employment (Case & Quigley, 2008). This impact extends to developers, builders, the construction industry, brokers, mortgage originators, lenders, and related sectors. Moreover, the extent of these financial effects depends on the depth of the home price decline and the subsequent increase in mortgage defaults, which are already causing significant disruptions in fixed income markets globally (Case & Quigley, 2008). The collapse of the sub-prime mortgage-backed securities market exacerbates these financial market effects as firms struggle with non-liquid portions of the mortgage market, non-performing loans and portfolios with bad debt.

Given the aforementioned detrimental effects of declining property values, an implication of this chapter is that policymakers and investors to consider that public infrastructure, including airports, may not function as a potent catalyst for regional economic growth, particularly within the real estate sector.

Exploring the essential factors influencing location and neighborhood dynamics, along with their accessibility, attracts the attention of policymakers, planners, and property valuers (McCord et al., 2018). Chapter 4 persists to examine Doncaster Sheffield Airport as a case study, with a shift in focus from the regional property market to the housing market within the airport's vicinity. This research explores the hypothesis that public infrastructure functions as a beneficial externality for nearby communities, aligning with expectations of governmental investments.

Chapter 4 utilizes the Difference-in-Difference (DiD) and panel event study methodologies to assess pre- and post-intervention housing price changes within a 3km radius of Doncaster Sheffield Airport. Results reveal a significant negative impact on property prices following the airport's opening. This chapter makes a significant contribution to the existing literature through the inclusion of panel event plots, revealing three distinct troughs aligned with intervention timings. These plots signify that the proximity to airports leads to short-term declines in property values whenever residents anticipate living near one. The consistent pattern observed strongly supports the notion that residing near airports has an adverse impact on property values, consistent with research conducted by like Zheng et al. (2020), Cohen & Coughlin (2008), and Lawson (2021).

This chapter supports a substantial literature has concentrated on the impact of the noise pollution from operating airports on house prices, as evidenced by studies such as Bełej et al. (2020), Mense & Kholodilin (2014), and Affuso et al. (2019). Factors such as air quality, noise levels, and proximity to diverse urban infrastructure can arguably wield a substantial influence on the overall quality of life. These considerations become critical for consumers when choosing a residential neighborhood (McCord et al., 2018).

Hoogendoorn et al. (2019) propose that heightened housing demand in regions with improved transport infrastructure intensifies upward pressure on prices. Conversely, as noted by Brinkman and Lin (2019), the direct impact of transport infrastructure on housing demand does not consistently correlate with positive trends in house prices. In specific cases, it may result in slower growth in certain regions, resulting in reduced land values and house prices.

This study challenges conventional theories, as articulated by Straszhem (1987), which assert that household location and accessibility influence housing prices. According to these theories, individuals living closer to transportation networks incur lower commuting costs, leading to increased investments in such areas. Additionally, these findings appear to counter the idea that households typically show a willingness to pay higher prices for residences in areas with convenient accessibility—a factor associated with enhanced economic mobility, as suggested by So et al. (1997).

This could be attributed to the uncertainty surrounding the impact of a new airport on the local environment and quality of life. Prospective buyers may exhibit hesitation to invest in areas with such uncertainties, resulting in price reductions. The noise pollution generated by aircraft takeoffs and landings can render properties in close proximity to the airport less attractive, diminishing demand and, consequently, lowering property values. A further implication is the necessity for the government to validate compensation for households affected by airport noise. Precisely quantifying the hidden costs of noise pollution also aids in formulating more efficient compensation strategies and urban planning initiatives.

Instead focused on the positive impacts of the public sector and public infrastructure on economic advancement and the improvement of social welfare as prior studies have done, this thesis makes a distinctive contribution by underscoring the significance of public sector and infrastructure initiatives in the broader economy. It sheds light on how such projects can potentially result in economic downturns, diminish the quality of life, and exacerbate social disparities.

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Appendix

Appendices - Chapter 2

Table A2: The wage decomposition results in different quantiles with/without reweighting

2002							
	10	25	50	Mean	Conventional OB-mean	75	90
Group_1	0.695***	1.076***	1.5***	1.478		1.874***	2.215***
Group_c	0.671***	1.085***	1.497***	1.481		1.893***	2.227***
Group_2	0.449***	0.862***	1.298***	1.296		1.742***	2.152***
Tdifference	0.246***	0.214***	0.202***	0.182	0.182	0.132***	0.063*
ToT_Explained	0.221***	0.223***	0.199***	0.185	0.068	0.15***	0.076*
ToT_Unexplained	0.025	-0.009	0.003	-0.003	0.114	-0.018	-0.013
ToT_explained share	89.84%	104.21%	98.51%	101.65%	37.36%	113.64%	120.63%
ToT_unexplained share	10.16%	-4.21%	1.49%	-1.65%	62.64%	-13.64%	-20.63%
pure explained share	45.12%	64.02%	54.46%	56.04%		84.85%	57.14%
Explained							
Total	0.221***	0.223***	0.199***	0.185		0.15***	0.076*
Pure_explained	0.111***	0.137***	0.11***	0.102		0.112***	0.036*
Specif_err	0.11***	0.087***	0.09***	0.083		0.039	0.039
Unexplained							
Total	0.025	-0.009	0.003	-0.003		-0.018	-0.013
Reweight_err	-0.063**	-0.043**	-0.03	-0.034		-0.017	-0.013
Pure_Unexplained	0.088	0.034	0.033	0.032		-0.002	0
2007							
	10	25	50	mean	OB-mean	75	90
Group_1	1.558***	1.958***	2.412***	2.404		2.894***	3.275***
Group_c	1.426***	1.901***	2.382***	2.369		2.834***	3.38***
Group_2	1.252***	1.656***	2.18***	2.193		2.707***	3.235***
Tdifference	0.306***	0.302***	0.232***	0.211	0.21	0.187***	0.04
ToT_Explained	0.174***	0.245***	0.203***	0.176	0.133	0.127***	0.145**
ToT_Unexplained	0.132**	0.057	0.029	0.035	0.077	0.06	-0.105
ToT_explained share	56.86%	81.13%	87.50%	83.41%	63.33%	67.91%	362.50%

ToT_unexplained share	43.14%	18.87%	12.50%	16.59%	36.67%	32.09%	-262.50%
pure explained share	29.74%	50.99%	59.91%	68.72%		79.68%	535.00%
Explained							
Total	0.174***	0.245***	0.203***	0.176		0.127***	0.145**
Pure_explained	0.091***	0.154***	0.139***	0.145		0.149***	0.214***
Specif_err	0.083**	0.091***	0.064*	0.031		-0.023	-0.069
Unexplained							
Total	0.132**	0.057	0.029	0.035		0.06	-0.105
Reweight_err	0.001	-0.012	-0.015	-0.014		-0.013	-0.017
Pure_Unexplained	0.131**	0.069	0.045	0.049		0.073	-0.088
2013							
	10	25	50	mean	OB-mean	75	90
Group_1	2.029***	2.438***	2.836***	2.819***		3.181***	3.587***
Group_c	1.977***	2.341***	2.808***	2.852***		3.333***	3.792***
Group_2	1.696***	2.092***	2.504***	2.548		2.963***	3.436***
Tdifference	0.333***	0.347***	0.332***	0.271***	0.271	0.218***	0.152***
ToT_Explained	0.281***	0.249***	0.304***	0.304***	0.326	0.369***	0.357***
ToT_Unexplained	0.052	0.098***	0.028	-0.033	-0.055	-0.152***	-0.205***
ToT_explained share	84.38%	71.76%	91.57%	112.18%	120.30%	169.27%	234.87%
ToT_unexplained share	15.62%	28.24%	8.43%	-12.18%	-20.30%	-69.27%	-134.87%
pure explained share	72.07%	69.74%	85.54%	114.76%		172.94%	284.87%
Explained							
Total	0.281***	0.249***	0.304***	0.304		0.369***	0.357***
Pure_explained	0.24***	0.243***	0.284***	0.311		0.377***	0.433***
Specif_err	0.041	0.006	0.02	-0.008		-0.008	-0.076
Unexplained							
Total	0.052	0.098***	0.028	-0.033		-0.152***	-0.205***
Reweight_err	0.031	0.009	-0.03	-0.006		-0.014	-0.035
Pure_Unexplained	0.022	0.089**	0.058	-0.027		-0.138***	-0.17***

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

Appendices - Chapter 3

To explore the specific impact on various types of housing, the yearly transaction datasets, encompassing both leasehold and freehold residential property transactions in England and Wales spanning from 1995 to 2018, is employed, with the intervention year set as 1999. The synthetic control results shed light on the effects across different property characteristics, as detailed below:

Figure A3.1: Overall property transactions and its gap between the actual Doncaster and the synthetic Doncaster

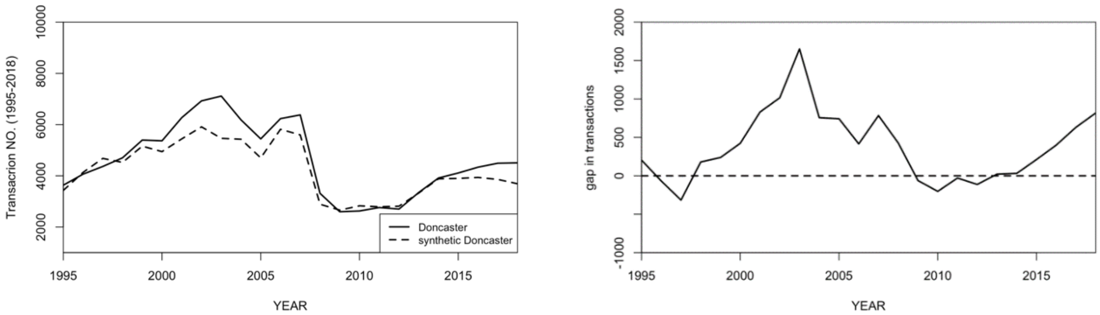

Figure A3.2: Overall Detached property transactions and its gap between the actual Doncaster and the synthetic Doncaster

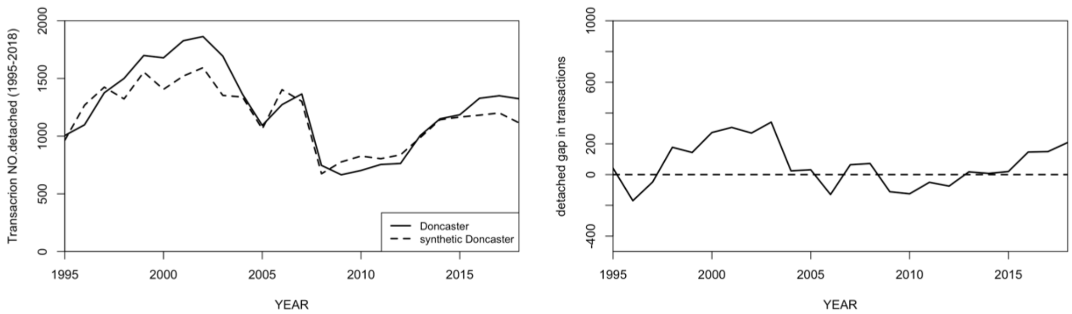

Figure A3.3: Semi-detached property transactions and its gap between the actual Doncaster and the synthetic Doncaster

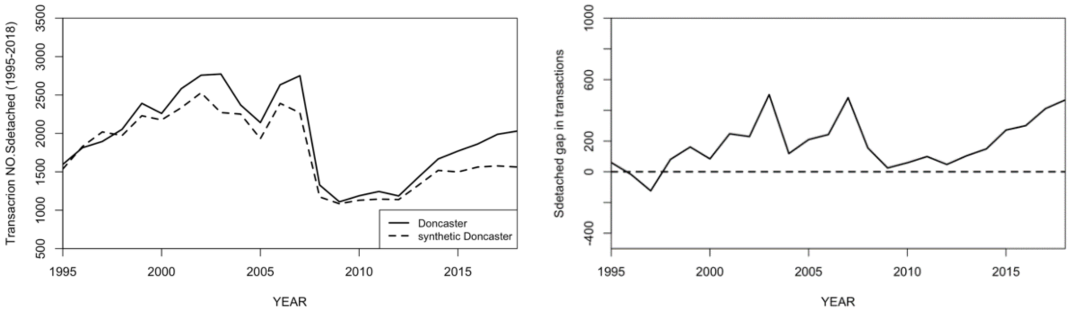

Figure A3.4: Terraced property transactions and its gap between the actual Doncaster and the synthetic Doncaster

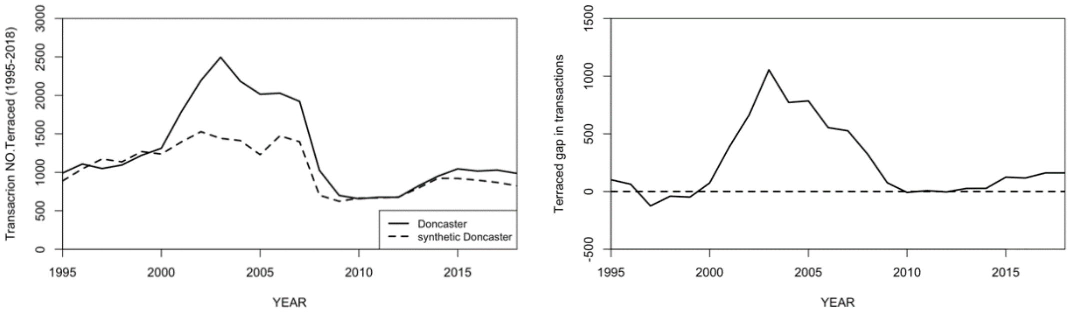

Figure A3.5: Flat/Apartment transactions and its gap between the actual Doncaster and the synthetic Doncaster

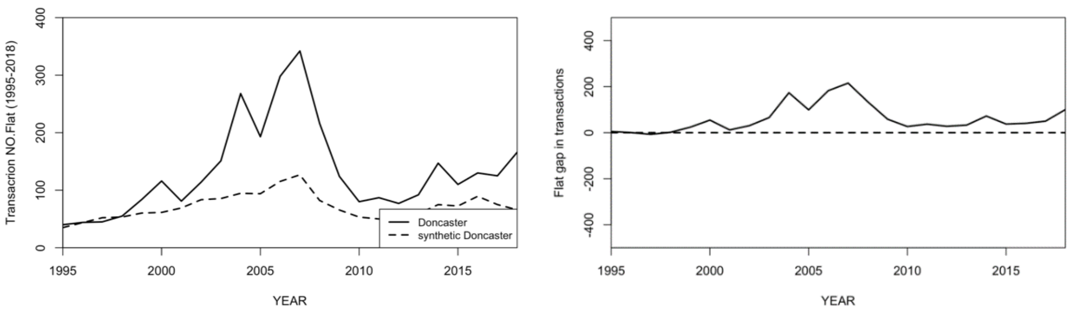

Figure A3.6: Transactions of properties built between 1999-2005 and its gap between the actual Doncaster and the synthetic Doncaster

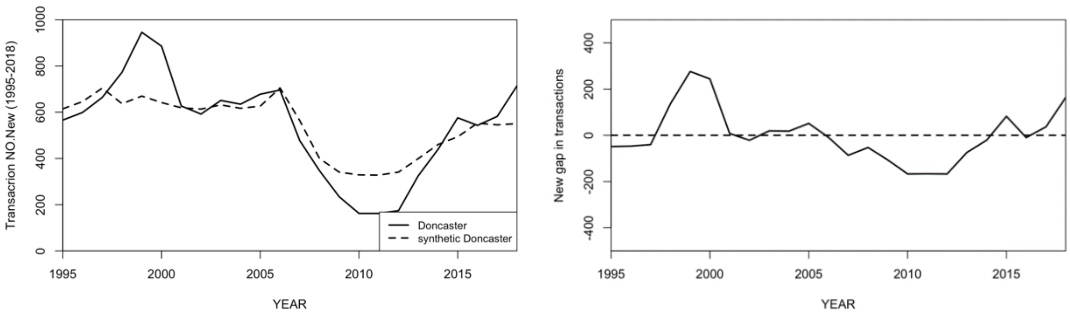

Figure A3.7: Transactions of existing properties in 1999 and its gap between the actual Doncaster and the synthetic Doncaster