From Working from Home to Living in the Office?

The Economic Implications of Remote Working on the Commercial Office Market in Dublin.

MSc Spatial, Transport, Environmental Economics (STREEM)

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Abstract

The surge in remote working, prompted by the COVID-19 pandemic, has disrupted commercial office markets in major cities worldwide, with vacancy rates reaching unprecedented highs. By utilising lease data, we quantify the impact of teleworking on Dublin's commercial office market and evaluate the implications of our findings for the widely discussed concept of adaptive reuse. Our findings show an increase in leases moving toward peripheral locations, potentially to accommodate commuters from farther afield, and influenced by declining relative rental rates. We found that decade-high vacancy rates have not negatively impacted office yields in central areas, nor do we observe evidence of shortening lease lengths attributable to market instability.

“Time makes the high building costs of one generation the bargains of the future generation...time makes certain structures obsolete for some enterprises and they become available for others”.

Jane Jacobs, (1993)

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1. Introduction

The COVID-19 pandemic has fundamentally shifted the way in which individuals work, rearranging the long-term spatial relationship between place of residence and place of work. The shock of the pandemic which led to the widespread adoption of teleworking, initially as an emergency preventative measure, has subsequently rewritten the norms for corporate workplaces across the globe. Typically, with an economic shock, like that of COVID-19, one would expect a widespread drop in demand for all property types, as markets suffer across the board from deteriorating economic conditions. The pandemic shock, however, has prevailed as a unique scenario where demand for a specific strand of property, in this case commercial offices, is said to have been greatly impacted, whereas residential property has seemingly emerged relatively unscathed.

Publicly, much has been made of the rise in office vacancies over the past four years or so. Office vacancy rates currently stand at 36.7% in San Francisco and 22% in Beijing, with availability rates of 27.5% in Houston and 20% in Manhattan (CBRE, 2024a; 2024b; 2024c; 2024d). Closer to home a similar trend prevails. In Dublin over the past 24 months office vacancy has risen faster than in all but one of the 39 European office markets, now standing at 17.5% (McCartney, 2023; CBRE, 2024e). Dublin's vacancy rate has been exacerbated by the innate inflexibility of the construction industry, as developers completed almost 84,000 sqm of office space in Dublin over the first three months of this year, in addition to the 200,000 sqm delivered in 2022 and 80,000 sqm delivered in 2023 (McCartney, 2023; 2024a; 2024b). This comes at a time when Dublin is suffering through a devastating housing crisis, with a 1% vacancy rate amongst its residential housing supply (GeoDirectory, 2024).

Given the recent trends witnessed in both residential and commercial property, one narrative that naturally arises time and time again is "why are vacant offices not converted into homes?". This concept is called *adaptive reuse*, which is being increasingly implemented in cities across the world as a housing solution that provides a sustainable approach to the construction of new homes by preserving the embodied carbon within structures. While adaptive reuse may simultaneously solve two integral issues in the Dublin property market, there has been no research as of the present from an Irish context which points toward its viability. This study aims to address the viability of these schemes under current market conditions. By assessing this topic, we aim to simultaneously address key unanswered questions circulating in the public realm regarding the condition of the commercial property market in Dublin since the onset of the pandemic. To achieve this, we will analyse data trends of Dublin office leases, placing a specific emphasis on the following three key areas: locational demand changes, price changes and changes to lease lengths. We will then subsequently address what implications these trends may have on a larger scale by incorporating socioeconomic factors such as agglomeration and by assessing the associated implications of housing supply.

The study will be structured as follows; Section 2 will determine the current research frontier that addresses post-COVID changes to commercial office markets. Here, we specifically explore shifts in office space demand, alterations in bid-rent gradients, and the evolving influence of agglomeration economies on urban societies. After establishing a clear understanding of the current academic landscape, we introduce our hypotheses at the end of Section 2, which we aim to investigate throughout the paper. In Section 3 we outline the source of our data, our collection methodology, the filtration process implemented, our descriptive statistics and outline our regression set-up. In Section 4 we present our findings that address the changes to intensive and extensive demand in the commercial property market. Section 5 presents a thorough discussion of our findings, evaluating the conditions necessary for implementing adaptive reuse programs and analysing the outlook of the commercial property market in Dublin. Section 6 covers the limitations of the study and suggests areas for further research, which is followed by our concluding remarks in Section 7.

2. Literature Review

Our literature review will prioritise findings in relation to the post-COVID office market, as we try to gauge the limit of the current research frontier, while also providing some background into foundational urban economic models. The evolving nature of the pandemic and the limited number of data years available since the pandemic has resulted in a heavier reliance being placed on more recent academic findings that most accurately document the current situation. In Section 2.1 we investigate the academic sentiment regarding the current changes in demand for office space since the onset of the pandemic. Section 2.2 addresses Alonso’s bid-rent model and explores changes found in the post-COVID office rental gradient. Section 2.3 focuses on how changes in demand impact agglomeration economies. Finally, our hypotheses are formed in Section 2.4, which are based on the cumulative influence of empirical and theoretical research done by the authors cited below.

2.1 Declining Demand for Office Space

The consensus among academic sources, which is not overly surprising, is that the future prosperity of the commercial office market looks bleak. Employees' newfound flexibility to work from home (WFH) ultimately means the demand for commercial office space is not equivalent to the levels seen pre-pandemic. Firms are reassessing the long-standing trade-off between diminishing agglomerative benefits and city centre rent premiums. Firms have identified that some collaborative, innovative work is best done in the office, while other actions which benefit less from agglomeration can be performed at home.

Delventhal et al. (2022) found a direct link between WFH prominence and land prices, saying that if the fraction of teleworkers rose to 33%, the income of commercial office landowners would fall by 8%. They attributed this to residents reallocating themselves to less expensive suburban locations due to their newfound ability to WFH. Therefore, the demand for land in urban areas decreased, firms had an increased number of telecommuters and subsequently firms required less office space. In a similar vein, research done by Oladiran et al. (2022) showed that WFH experience and sentiment was a key determinant of future demand for office space. They found that firms reporting a positive WFH experience have a 35% higher probability of reducing their office space within the next three years, and those with a neutral experience have a 29% higher probability of reducing their space sizes over the next three years.

As previously alluded to, the implication of downsizing is beginning to be reflected in the market as vacancy rates are soaring in New York and San Francisco, with the quantity of square feet under tenancy falling by 10.93% from December 2019 to December 2022 across 90 US markets (Gupta et al., 2023a). Gupta et al. (2023a) also have included projections in their research that suggest that NYC office valuations in 2029 will be on average 49.2% below their 2019 valuation in a low WFH economy, and 61.9% below their 2019 valuation in a high WFH economy. Employee occupancy reportedly standing at 50% is a key driving force behind the rational to downsize office space, with more tech-oriented employment cities, such as San Francisco, experiencing higher vacancy rates compared to less WFH compatible cities (Ghosh et al., 2022). Ghosh et al. (2022) also estimate that urban office square footage demands fell by almost 5%, and suburban office square footage demands decreased by 15.5% from pre to post-COVID transactions.

Surprisingly, there is not widespread agreement among academics on whether the anticipated decrease in office demand is reflected in real-world observations. According to Harley (2022), major Australian commercial property advisers have helped 60 businesses relocate or renegotiate office leases with none of them seeking to cut their space requirements. It was even stated that strong employment demands, particularly in the tech sector, are increasing office demand. This is reflected in the data as every Australian city saw declining CBD (Central Business District) office vacancy rates from July 2021 to January 2022 apart from Melbourne and Brisbane (Harley, 2022). Glaeser (2022) noted that during 2020, Amazon, Apple, Facebook, and Google all expanded their footprint in New York City, anticipating a continued demand for office space. Finally, Ghosh et al. (2022) found results contrasting to that of Delventhal et al. (2022) and Gupta et al. (2023a) in relation to transaction value, stating that the average transaction price per square foot of office space increased from pre to post-COVID by $0.91 in urban areas and $22.17 in suburban areas for US cities.

2.2 The Monocentric City Model and the Bid-Rent Curve

The seminal paper by Alonso (1964) builds upon the Ricardian theory of land rent, which emphasises the economic advantage of location in determining land use, by adapting these foundational ideas specifically for urban economics. Alonso is accredited with developing the bid-rent model, as seen in Appendix A, which outlines how different types of land users (commercial, residential, and industrial) compete for land. This model shows that the willingness to pay for land decreases with an increasing distance from the city centre, reflecting higher land prices and greater demand in more central areas.

More recent applications of Alonso's model are seen in Rosenthal et al. (2022), Ghosh et al. (2022) and Duranton and Handbury (2023), who all allude to a flattening bid-rent curve arising from the impacts of a hybrid working model in the US. Rosenthal et al. (2022) found that for each mile from the city centre, the post-COVID rent gradient of offices in the US declined 0.6% less relative to a pre-COVID base of 5.7%. The reasons for increased demand in suburban areas are multifaceted, but the key contributors are decreased agglomerative forces in urban areas and decreased commuting (Delventhal et al., 2022; Duranton and Handbury, 2023), coupled with cheaper suburban prices (Ghosh et al., 2022).

Decreasing urban demand gives rise to a potential urban doom loop, or donut effect, as cited by Glaeser (2022), Ou et al. (2023), Duranton and Handbury (2023) and Gupta et al. (2023b). The prevailing concept is that rising commercial vacancies lead to a decrease in pedestrian traffic at urban restaurants, gyms, and cafes, resulting in further vacancies and negative externalities in commercial neighbourhoods. This contributes to increased crime and public disorder, increasingly lowering retail property values and lowering retail property tax revenues (Gupta et al., 2023b). This can further spiral as lower income tax returns can result in less expenditure on amenities, which leads to increased out-migration, further decreasing demand for property and quality of life for remaining residents.

In contrast the above findings, Ou et al. (2023) originally did find a flattened bid rent curve during the lockdown, but state that by extending the study period to the post-vaccine era they found a steepened bid-rent curve due to the introduction of vaccines, reflecting people's growing confidence in the recovery of real estate markets. Gupta et al. (2023a) also discovered that when accounting for office quality and age, they found an increasing commercial bid-rent gradient, even steeper than pre-COVID times, signalling a "flight to quality" effect. Ou et al. (2023) saw that changes to the bid-rent curve varied based on property type, as the density price gradient increased by approximately 10% for commercial units after Wuhan's lockdown, in contrast to a 3% decrease for residential units during the same period. This phenomenon highlights the stark differences in post-COVID impacts between the bid-rent functions of the various property sectors.

Finally, Glaeser (2022) challenges the notion of an 'urban doom loop' scenario, stating that predictions about the demise of the office market ignore the ability of office rents to adjust downward and attract new tenants. He does however outline that lowering rents is more viable in markets like New York and San Francisco where a larger rent premium is charged, in comparison to markets such as Cleveland and Detroit, where rents are much closer to the landlord's operating costs.

2.3 Changing Agglomerative Economies

Ever since Alfred Marshall's seminal contributions to the concept of agglomeration, there have been few instances in history where the long-term viability of agglomeration economies was seriously questioned, and this may well be the first. With increased sprawl and decreased density in major urban areas, one would expect that agglomerative forces would be severely tarnished in the hybrid era. Duranton and Handbury (2023) estimate that the productive advantage of knowledge spillovers could be majorly reduced with a lower downtown density. They do however note that the agglomeration forces in relation to the thickness of local labour markets and the network of input-output transactions are less susceptible to the impacts of WFH. Rosenthal et al. (2022) discovered that in the post-COVID era, the elasticity of rent in relation to density is approximately 2% lower compared to the pre-COVID era. This finding suggests a diminished appeal of city centres and a decreased value placed on density, noting however that both city centres and density continue to retain relative attractiveness despite these changes.

Delventhal et al. (2023) on the other hand found that the effect of companies reallocating to more productive, central locations, that benefit from agglomeration externalities almost perfectly offsets a larger fraction of the workforce not contributing to these externalities. In total they concluded that a rise in telecommuting to 33% accounted for a 0.3% increase in average wages overall. Duranton and Handbury (2023) also mention an interesting possibility that industries, such as entertainment, medical services, and education, that were previously outbid for downtown space, might relocate closer to city centres as rents decline. This element of economic and cultural diversity in urban settings might foster resilience, innovation, and further harness the forces of agglomeration, à la Jacobs.

2.4 Hypotheses

Based on the academic literature and empirical studies discussed earlier in this chapter, several hypotheses are constructed. Initially we observe how the demand for commercial office space may have changed in Dublin since the pandemic. Delventhal et al. (2022), Ghosh et al. (2022) and Gupta et al. (2023a) all found a declining demand for land in US urban cores due to lower employee occupancy and the increasing prominence of WFH. This questions the diminishing agglomerative benefits, as urban and suburban areas may have witnessed varying post-COVID outcomes, as is noted by Ghosh et al. (2022), Duranton and Handbury (2023) and Delventhal et al. (2022). To resolve this question, we will investigate the extensive demand, which refers to the locational concentration of new leases and changes to broader market size, to assess the potential diminishing importance of agglomerative benefits. Therefore, the first hypothesis is:

Hypothesis 1: The extensive demand for office space has changed in Dublin from pre to post-COVID.

Following the above, we wish to explore the change in intensive demand for office space in Dublin between the same two periods. Intensive demand refers to changing lease terms such as price per square meter (PPSQM) and lease length due to decreasing demand or changing market sentiment. Rosenthal et al. (2022), Oladiran et al. (2022) and Duranton and Handbury (2023) all state that falling demand and a change of organisational strategy have impacted lease prices and lengths.

The second hypothesis also explores changes to Alonso's (1964) commercial bid-rent gradient, which assesses changes to the PPSQM at a given the distance to the CBD. Our second hypothesis is as follows:

Hypothesis 2: The intensive demand for office space has changed in Dublin from pre to post-COVID.

3. Data and Methodology

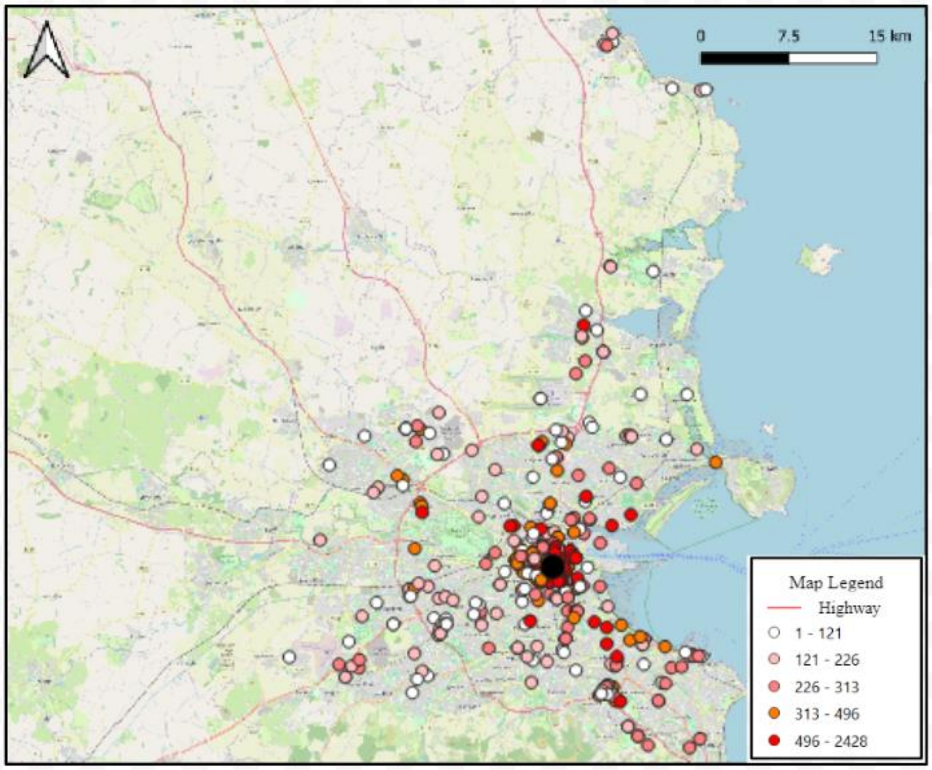
This chapter discusses the data which has shaped our research and delves into the methodology used to evaluate and answer the previously identified hypotheses. Section 3.1 explains our data collection, which will be followed by Section 3.2, where the data cleaning process is described. Section 3.3 covers the use of spatial variables; Section 3.4 conveys the descriptive statistics behind the data and Section 3.5 addresses our regression set-up used in our empirical section.

3.1 Data Description

To comprehensively answer the hypotheses provided, we have integrated a variety of data inputs from various sources. The main data source used was the Commercial Leases Register from the Property Services Regulatory Authority of Ireland[1]. From this source we obtained all commercial leases in Dublin from 2019 and 2023, which consists of 555 leases in 2019 and 461 leases in 2023 after cleaning the data. The data was cleaned using in-data filters to retain only office leases, removing leases that may have been part office and part retail/industrial and additionally duplicate entries were removed. After this, the data was subject to an additional cleaning process which we will discuss in Section 3.2. The data provides lease commencement dates, lease lengths, building addresses and the annual lease amount. We were then assigned the daunting task of manually entering the square footage information for each lease, a detail only included in the physical lease submissions to the Property Services Regulatory Authority of Ireland but absent as a data column in the mass download of lease information. This tedious task was crucial to establish a comparative benchmark over time, which was essential to accurately reflect the evolving demand for office space between the time periods through PPSQM calculations. A colour coded map has been compiled below in Figure 3.1 and 3.2, illustrating the PPSQM and locational concentration of our leases across both 2019 and 2023. As we can see 2019 appears to be more densely concentrated within the CBD. Further detailed maps of the two years combined can be found in Appendix B and C.

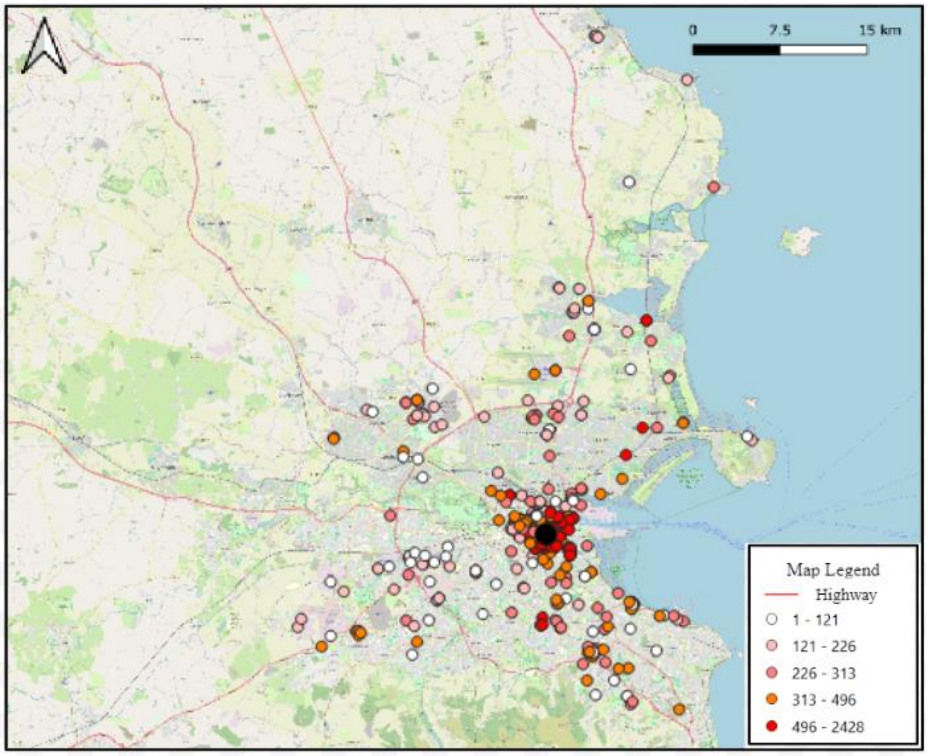
[1] https://www.psr.ie/

Fig. 3.1: Dublin Leases 2019



Note: The black dot represents our CBD Point. The scale represents PPSQM and is denoted in euro.

Fig. 3.2: Dublin Leases 2023



Note: The black dot represents our CBD Point. The scale represents PPSQM and is denoted in euro.

We decided on 2019 and 2023 as our pre- and post-COVID years as we wanted the research to be as relevant as possible from a recency perspective, while also maintaining integrity in the underlying data. 2019 was chosen as a pre-COVID control as we wanted the most recent year possible to best reflect the commercial office market in Dublin that was unaffected by the virus. The virus originated in Wuhan, China, in December 2019 and was identified as SARS-CoV-2 on 12 January 2020 by Chinese authorities, which subsequently reached Irish shores on the 28th of February 2020 (Spiteri et al., 2020; RTE, 2020). Given these dates, we are confident that all commercial office leases for 2019, which are likely negotiated a month or two in advance of the commencement of the lease, are unaffected by the arrival of the virus. 2023 was chosen as our post-COVID year of references as it is the most recent year with a sufficiently large dataset available.

3.2 Data Cleaning

To best reflect the current Dublin commercial lease market, our data needed to be cleaned to exclude invalid entries. To ensure best practices, inspiration was taken from Boeing and Waddell (2017) who have researched effective data cleaning for leases from public and commercial databases. As identified by the authors, the first step in an effective data cleaning process is the removal of duplicates. This was done by concatenating key lease elements such as commencement date, lease amount and square footage of the lease. A COUNTIF function was then used to count how many times the concatenated term appeared and if the number was greater than one, a physical inspection was done on the duplicates and removed where necessary. This process was followed by a conditional formatting test in excel and a further physical inspection was done on all highlighted duplicate values. The second step taken was the removal of any leases where square footage details were omitted in the dataset as we cannot make any comparative inferences about the lease without this pivotal information.

The remaining dataset was then filtered to retain only those listings that had reasonable values for square meterage and rent per square meter. These two elements are key as an inflated square meterage may mean that an industrial space was miscategorised as an office and irregular rent per square meter values will account for typos and any suspicious, non-market transactions that may distort the analysis. To account for this within the data a similar approach was taken to that of Boeing and Waddell (2017), who define a "reasonable" range by taking the values at the 0.2 percentile and the 99.8 percentile nationwide for each of these two fields as a minimum and maximum to minimise truncation and provide sensible ranges. This was altered to 0.25 percentile on each end as a 0.2 percentile was not compatible given the size of the data set, thus, a reasonable value is one in the middle 99.5 percent of each variable's distribution. The datasets of 2019 and 2023 were combined to calculate this range as the ranges must be comparable across the two years. Minimum square footage values were then manually readjusted from 6.56 sqm to 6 sqm as it felt it was unnecessary to exclude what are deemed to be valid leases, especially with a relatively small dataset.

Fig. 3.3: Reasonable Value Filter Cut-Offs

	Reasonable Values	
	p0.25	p99.75
Rent PSM	0.138	2442
SQM	6.000	101127.08

Note: Rent PSQM refers to annual rent per square meter. This is calculated by dividing the annual rent by the square meters of office space. SQM solely refers to the square meters of office space for a given office.

3.3 Spatial Variables

Given that our Commercial Leases Register database is somewhat limited in terms of variables, to better explain the variation of rental prices from one year to another, spatial variables were used. The spatial variables will play a key role in our fixed effects model, as we control for the impact that common characteristics have on PPSQM. According to Fuerst (2007) physical controls such as building age and amenity controls like transport accessibility and waterfront locations, can often provide explanatory power on the variability in lease prices. Unfortunately, due to data access restrictions we were unable to account for building age, which we will further discuss at a later stage. Subsequently, the common characteristics that have been identified are proximity to bus stops, proximity to a LUAS[2] platform, proximity to a railway platform, proximity to a highway, distance to the CBD point, proximity to the coastline and proximity to a waterway.

These variables were constructed using QGIS (Quantum Geographical Information System), and data was obtained through a multiple-step process. Firstly, all leases which met the eligibility criteria from the data cleaning process for a single year were loaded into the software according to their address. Geo coordinates were obtained from a Google Maps Geocoding API through a Python programme for those that ran successfully, and the remainder were manually inputted based on Google Maps coordinates. These geographical points were transformed into the projected CSR (Dublin - ED50 / UTM zone 29N (EPSG: 23029) to ensure the accurate projection of coordinates based on their global location. Once the leases were loaded, a rectangular grid was created with 100-meter x 100-meter internal squares that spanned a size to cover all lease locations

[2] LUAS refers to the tram system in Dublin.

(see Appendix D). The grid allowed us to analyse which square each lease fell into and assign a grid ID number for each lease. By inserting a centroid in each grid square we were able to calculate the distance from the middle of each square to the closest point of each of our previously identified spatial variables. In total we had a grid with 108942 squares, that was approximately 45 km in length and 28 km in width. Our spatial variables and background map were added through the Open Street Maps, Travel Time, and Quick Map Services plugins.

3.4 Descriptive Statistics

The description of our original variables before cleaning compared to our cleaned variables is shown below in Figure 3.4. Here we attempt to outline the impacts the data filtering process had on the dataset. Mean and median values are reported on the following metrics: total lease amount (rent), square meterage, rent per square meter and lease lengths. As seen below the impact of our data filtering process reduced the original data set from 566 leases to 555 leases in 2019 and from 475 leases to 466 leases in 2023. Based on the median, mean and length of leases we can conclude that the data remains generally consistent after being subject to the data filtration process.

Fig. 3.4: Summary Statistics of Lease Contracts

	2019	2023	2019	2023
Descriptive Statistics	Original Data Set		Final Data Set	
Count of Listings	566	475	555	461
Median Rent	42,267.50	40,000.00	43,200.00	40,000.00
Mean Rent	148,101.63	147,083.16	150,143.22	146,388.04
Median SQM	-	-	200.00	200.00
Mean SQM	-	-	932.30	859.40
Median Rent/SQM	-	-	269.10	294.87
Mean Rent/SQM	-	-	322.50	326.20
Median Lease Length	5 Years	5 Years	5 Years	5 Years
Mean Lease Length	7.4 Years	7.08 Years	7.4 Years	7.03 Years

Note: The original dataset contained listings that were missing SQM (square meter) values, hence the blanks seen in this section as it is not an accurate comparison. The original data set also contains leases before being deemed to have “unrealistic values”.

The description of non-spatial variables used in our study is shown below in Figure 3.5. We have included a yearly breakdown of our non-spatial variables in Appendix E and Appendix F, showing individual information for 2019 and 2023 respectively. The mean, standard deviation, minimum and maximum values are reported after values have gone through the data cleaning process. The data in this table is based on the dataset compiled through the Commercial Leases Register.

Fig. 3.5: Summary Statistics of Non-Spatial Variables in 2019 & 2023

Non-Spatial Variables 2019 & 2023					
	Count	Mean	SD	Min	Max
PPSQM	1016	324.16	259.96	0.17	2,427.75
SQM	1016	900.67	4,529.18	6	98,693.00
Lease Length	1016	2,640.15	1,804.80	30.44	12,783.75
Observations	1016				

Note: PPSQM refers to Price Per Square Meter of Office Space. Similarly, SQM refers to Square Meters of Office Space. Lease Length is observed in days. Variables relate to leases after the data cleaning process. Observations is the sum of leases in 2019 and 2023 (555+461=1016).

The description of spatial variables used in our study is shown below in Figure 3.6. We have included a yearly breakdown of our spatial variables in Appendix G and Appendix H, showing individual information for 2019 and 2023 respectively. The mean, standard deviation, minimum and maximum values are reported after values have gone through the data cleaning process. The data in this table is based on the datasets compiled through Open Street Maps, Travel Time, and Quick Map Services GIS plugins.

Fig. 3.6: Summary Statistics of Spatial Variables in 2019 & 2023

Spatial Variables 2019 & 2023					
	Count	Mean	SD	Min	Max
Distance to Luas	1016	2,065.70	3,763.49	24.52	26,838.93
Distance to Train Station	1016	1,623.85	1,448.53	86.9	7,951.04
Distance to Waterway	1016	395.42	339.64	2.86	2,359.81
Distance to Coastline	1016	3,764.09	3,226.87	23.57	17,537.00
Distance to Bus Stop	1016	131.09	121.56	2.99	1,277.41
Travel Time (s)	1016	1,837.86	1,224.95	83	5,880.00
Distance to CBD Point	1016	5,413.12	5,778.67	0	29,566.57
Distance to Highway	1016	2,021.32	1,278.97	4.22	10,506.27
Observations	1016				

Note: All values are measured in meters, apart from Travel Time which is measured in seconds. Values refer to the distance of an office lease to the nearest spatial variable. Luas refers to the tram system in Dublin. Waterways refers to the distance to a river or tributary. Variables relate to leases after the data cleaning process. SD refers to standard deviation.

In Figure 3.7 below, we have developed a correlation matrix to test the correlation between variables included in our study. When analysing the graph, we see that there is a negative correlation between PPSQM and our spatial variables such as proximity to public transport, waterfront property and travel time/distance to the CBD. These results signal that as the distance to these desirable amenities increases, we see a decrease in the PPSQM of leases. It should be noted however, that the correlation coefficients, especially for the transportation and waterfront variables, are not economically significant, with coefficients of between -0.09 and -0.22. Travel Time and Distance to CBD have higher correlation coefficients at -0.35 and -0.32 respectively. We also see a positive correlation between PPSQM and Lease Length. This may indicate that prime real estate owners and tenants are more likely to enter into longer rental agreements. Lastly, we see a positive correlation between the Highway variable and PPSQM. This can largely be explained by the highway's peripheral location and a downward sloping rental gradient rather than any negative connotations of being located near the highway itself, as shown in Figure 3.1.

Fig. 3.7: Variable Correlation Matrix

Variables	PPSQM	SQM	Lease Length	Luas	Train	Waterways	Coastline	Bus	Travel Time	Distance to CBD	Highway
PPSQM	1										
SQM	-0.12***	1									
Lease Length	0.11***	0.10**	1								
Luas	-0.19***	-0.02	-0.01	1							
Train	-0.21***	-0.02	0.03	0.40***	1						
Waterways	-0.09**	-0.05	0.01	0.22***	0.27***	1					
Coastline	-0.22***	-0.05	-0.03	0	0.35***	0.13***	1				
Bus	-0.14***	0.01	0.01	0.32***	0.37***	0.15***	0.29***	1			
Travel Time	-0.35***	0	0	0.60***	0.66***	0.23***	0.57***	0.45***	1		
Distance to CBD	-0.32***	-0.02	0	0.73***	0.55***	0.22***	0.52***	0.38***	0.89***	1	
Highway	0.11***	-0.06	-0.06*	0.01	-0.34***	0.03	-0.24***	-0.19***	-0.34***	-0.28***	1

$^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$

Note: As above, our non-spatial variables are unchanged. Our spatial variables again all refer to distance to Luas (tram), Train station, etc. Travel Time is again in seconds. A negative sign refers to negative relationship, meaning an increase in one variable sees a decrease in the other.

3.5 Regression Set-Up

For our OLS and fixed effects regressions in Section 4 we use a specific grouping set-up to compensate for our relatively small sample size. If we were to split data across 30 different 1 km groups our sample sizes would be extremely unreliable. We therefore group data in bins, which have been established at a 3 km distance apart to incorporate a larger sample size for each distance bin and to improve the reliability of our results. Leases are split into different bins based on their distance from the CBD point, rounding to their nearest multiple of 3, as can be seen in Figure 3.8 below. This method is used throughout our empirical results section.

Fig. 3.8: Summary of Bin Category Ranges

Bin Category	Range Covered by Bin	Count 2019	Count 2023
0 km	0 km - 1.5 km	213	158
3 km	1.5 km - 4.5 km	136	108
6 km	4.5km - 7.5km	51	43
9 km	7.5 km - 10.5 km	55	43
12 km	10.5km - 13.5km	53	50
15 km	13.5 km - 16.5 km	25	37
18 km	16.5km - 19.5km	9	7
21 km	19.5 km - 22.5 km	5	8
24 km	22.5km - 25.5km	1	2
27 km	25.5 km - 28.5 km	1	1
30 km	28.5km - 31.5km	6	4

Note: Bin distance refers to the category established in our study. Count refers to the number of leases that fall into the respective bin category.

4. Empirical Results

This chapter will investigate the results of our study in accordance with the hypotheses constructed earlier in the paper. Starting with Hypothesis 1 in Section 4.1, we explore if the extensive demand for office space has changed in Dublin from pre to post-COVID using a straightforward OLS regression. In this section we aim to examine behavioural changes in the commercial office rental market, potentially stemming from the shift to teleworking and the impacts of the COVID-19 pandemic. In Section 4.2 we begin to explore our findings which relate to our second hypothesis, the intensive demand for office space. This section investigates how the PPSQM for office space in Dublin varies with the office's distance to the CBD from pre to post-COVID, using a fixed effects regression model. Additionally, we observe changes to the rental gradient and examine if changes have been witnessed in lease lengths.

4.1 Changes to Extensive Demand

Hypothesis 1, which relates to changes in the extensive demand, explores the locational concentration of new leases and changes to broader market size. The overall goal is to assess the potential diminishing importance of agglomerative benefits, by exploring if behavioural changes have been witnessed in the commercial office market.

To assess if any behavioural change has taken place, we first sort leases by their 100 m^2 grid and count the number of times a lease appears in that grid in 2019 and in 2023. We also categorise these leases into locational bins based on their proximity to the CBD, as detailed in Section 3.5. For each bin, we then conduct an OLS regression to determine how the number of leases per bin deviates from changes observed in our baseline variable category. In this model, the dependent variable is the count of leases, while the independent variables include the distance to the CBD rounded to the nearest 3 km and a binary year variable (2019 or 2023) that serves as a control. Our baseline variable in this case is the CBD category, which refers to leases located at distances of $<$ 1.5 km from our CBD point.

According to Figure 4.1, the first coefficient we see that is statistically significant (p-value < 0.1, as indicated by a single asterisk) is at 6km. At this location, (4.5 km - 7.5 km from the CBD), the number of leases has grown positively more than within the CBD, with on average 0.460 more leases being accounted for. We found a similar result at 24 km, where the number of leases has grown positively more than within the CBD, with on average 1.11 more leases being accounted for. This is a more economically significant result which was found at a 99% confidence interval level. We do, however, suffer from a small sample problem at this distance, with only 1 lease in this distance in 2019 and 2 in 2023, hence this finding can be effectively disregarded. A full robustness check can be found in Appendix I which shows the continued statistical significance of our 6 km finding when using a variety of different distance ranges as omitted variables. Our regressions were calculated using robust standard errors to account for the presence of heteroskedasticity in our error terms. In Figure 4.2 we have included a coefficient plot with error bars representing a 90% confidence interval, to provide a better visual representation of our findings. As a general market overview, we see the number of leases before the filtration process declining from 566 in 2019 to 475 in 2023, indicating a 16.1% decline on a year over year comparison.

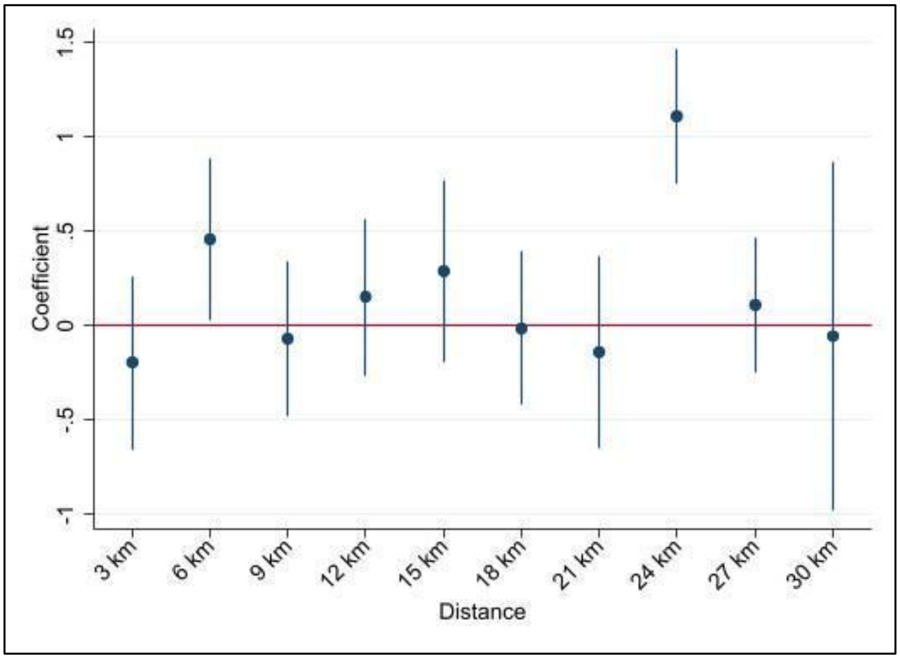
Fig. 4.1: OLS Extensive Demand Regression

Change in Leases Per Location Compared to CBD	
	(1)
	OLS
3 Km	-0.193
	(-0.69)
6 Km	0.460*
	(1.76)
9 Km	-0.0675
	(-0.27)
12 Km	0.154
	(0.61)
15 Km	0.292
	(1.00)
18 Km	-0.0132
	(-0.05)
21 Km	-0.138
	(-0.45)
24 Km	1.112***
	(5.15)
27 Km	0.112
	(0.52)
30 Km	-0.0548
	(-0.10)
Constant	1.775***
	(11.97)
Observations	706

p-value in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The coefficients describe how the number of leases from that distance category have changed with respect to the change witnessed in our omitted 0 km category (within the CBD), from 2019 to 2023.

Fig. 4.2: Coefficient Plot for H1 Regression Findings



Note: This is a graphical representation of our results from regression table Fig. 4.1 above. The error bars represent a 90% confidence interval.

The results indicate that there is a statistically significant increase in lease growth around the 6 km area, relative to the growth witnessed in the CBD. This ultimately means there may be validity in the point that was made by both Duranton and Handbury (2023) and Rosenthal et al. (2022) that the perceived productive advantage of knowledge spillovers is in decline, with an increase in demand in areas away from the city centre. For transparency a map of Dublin with the 6 km bin and the 24 km bin can be seen in Appendix J and K respectively. The most notable observation for the 6 km bin is that its range aligns almost perfectly within the M50[3] ring, which suggests a strategic relocation of offices to areas adjacent to the highway, potentially facilitating easier commutes for employees travelling from further afield. This is compatible with the findings of Delventhal et al. (2022) who found that residents relocate themselves to less expensive, distant, suburban locations due to their newfound ability to WFH. Descriptive statistics of the distribution of leases in each bin can be found in Appendix L.

[3]M50 refers to the highway that encircles Dublin city.

4.2 Changes to Intensive Demand - Price Per Square Meter

To investigate Hypothesis 2, which addresses intensive urban demand, we explore the change in market conditions through lease terms, such as PPSQM and lease length. We seek to assess if the implications of COVID-19 have materially impacted the underlying demand in the commercial office market. Initially, we will discuss PPSQM changes given an office's distance from the CBD point, followed by analysing the evolution of our rental gradient, and finally investigating changes to lease lengths.

By implementing a similar approach to Hypothesis 1, we once again divide our leases into 3 km bins based on their distance from the CBD, using the 0 km group as our omitted variable. However, there are two key differences in our approach compared to Hypothesis 1. Firstly, we investigate PPSQM as our dependent variable, as opposed to the number of leases. Secondly, we have included grid-level fixed effects in the form of Grid ID to control for all unobservable heterogeneity that could bias our results. We chose Grid ID as our control as it will account for any difference in intrinsic characteristics between grids that might influence PPSQM, such as neighbourhood quality or proximity to amenities.

Our results, as shown in Figure 4.3, indicate statistically significant negative coefficients for both our 3 km group and our 6 km group at a 90% level. These results can be interpreted as leases in the 3 km / 6 km bin have changed €111.8 / €170.2 less, relative to the change witnessed in the PPSQM change of our omitted 0 km category from 2019 to 2023. This means that the relative attractiveness of CBD locations from a PPSQM perspective has increased in comparison to our 3 km bin and 6 km bin from pre to post-COVID. In Figure 4.4 we have included a coefficient plot with error bars representing a 90% confidence interval, to provide a better visual representation of our findings. We have included our findings when using the >12.5 km group as the omitted variable in Appendix M and N, but results have returned statistically insignificant at all distances, likely due to the simultaneous increase in suburban rents. Additionally, we have added in a descriptive graph of the average PPSQM in each of our bins, as seen in Figure 4.5 below. We largely see increases in average PPSQM for all our bin distances, except for 3 km, 6 km, and 12 km bins. Finally, for completeness, in Figure 4.6 we have included a regression table outlining the expected change in the PPSQM for a one-unit change in a respective variable, holding all other variables constant. We see that the most statistically and economically significant driver that influences PPSQM is the Distance to CBD variable, with every one-kilometre increase from the CBD resulting in a €13.56 decrease in PPSQM.

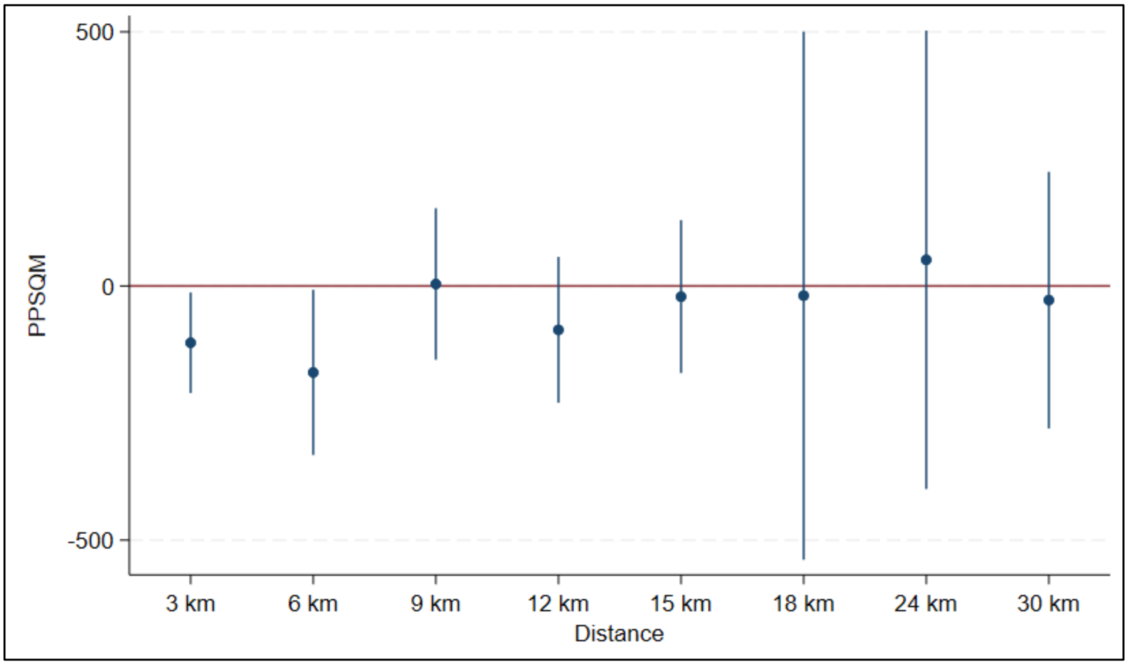
Fig. 4.3: OLS Intensive Demand Regression - PPSQM

Change in PPSQM Per Location		
	(1)	(2)
	OLS	FE
3 km	-28.61	-111.8*
	(0.485)	(0.063)
6 km	-55.46	-170.2*
	(0.331)	(0.085)
9 km	33.77	3.817
	(0.55)	(0.966)
12 km	-71.46	-86.33
	(0.193)	(0.322)
15 km	-1.598	-21.1
	(0.981)	(0.817)
Constant	416.2***	252.9664*
	(0.000)	(0.055)
Grid-Level Fixed Effects	No	Yes
Observations	1012	623
R-squared	0.129	0.513

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

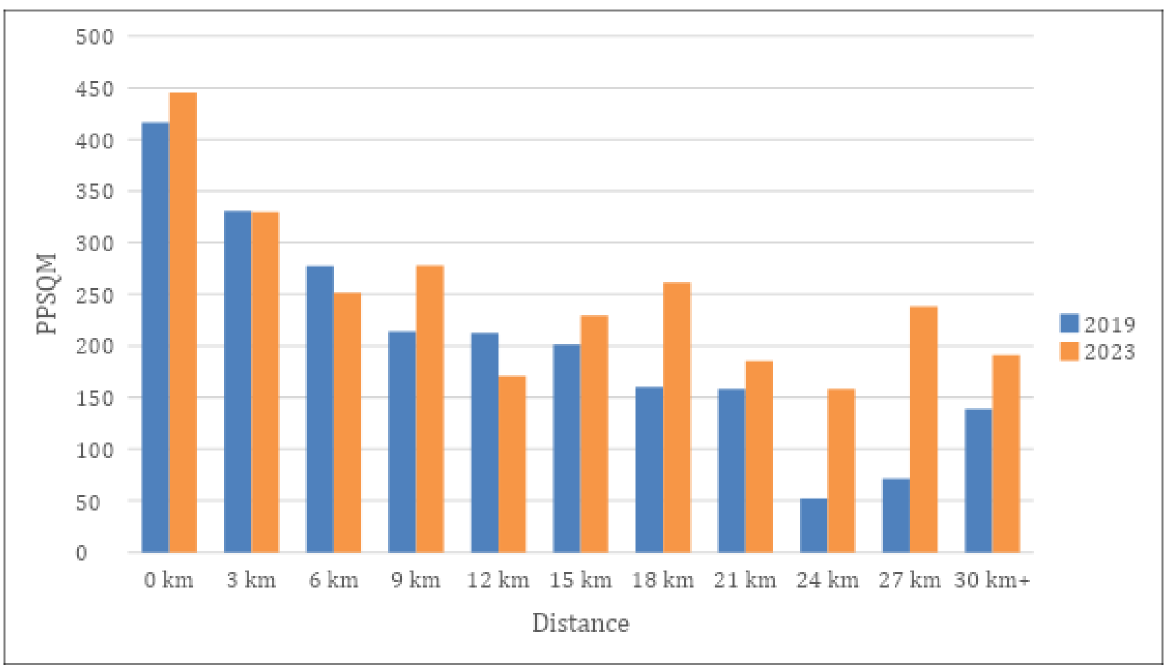
Note: The coefficients describe how the PPSQM of leases from that distance category have changed relative to the change witnessed in our omitted 0 km category, from 2019 to 2023. Our OLS regression is displayed in the first column with our grid-level fixed effects model being shown in the second column. Distances above 12 km have not been included but results were not statistically significant, as can be seen in Fig. 4.4 below. The number of observations dropped when implementing Grid-Level Fixed Effects is due to a small sample size and collinearity between leases in the same grid.

Fig. 4.4: Coefficient Plot for H2 Regression Findings



Note: This is a graphical representation of our results from regression table Fig. 4.3 above. The error bars represent a 90% confidence interval.

Fig. 4.5: Average PPSQM Bin Distances



Note: This graph shows the average PPSQM value of leases in each of our distance bins from both 2019 and 2023.

Fig. 4.6: PPSQM Spatial Variable Regression

Impact of Spatial Variables on PPSQM	
	(1)
	OLS
Bus	-0.0163
	(0.822)
Luas	0.00340
	(0.433)
Train	-0.00906
	(0.190)
Coastline	-0.00366
	(0.344)
Waterways	-0.00860
	(0.721)
Highway	-0.000928
	(0.896)
Distance to CBD	-13.46***
	(0.000)
Control	13.97
	(0.370)
Constant	419.6***
	(0.000)
Observations	1016
R-squared	0.108
p-values in parentheses	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$	

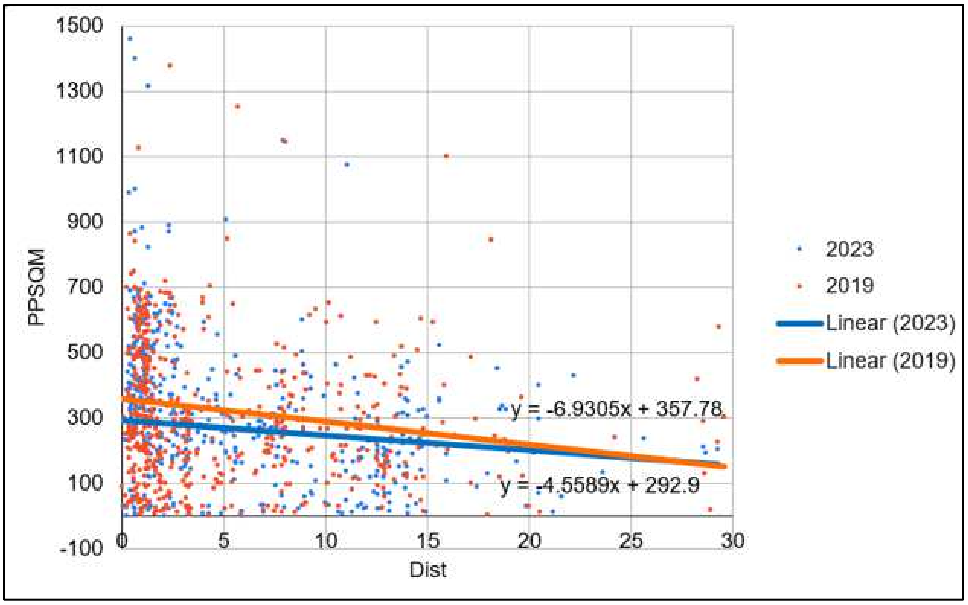
Note: The above OLS regression outlines the impact of various spatial variables on PPSQM.

We can therefore conclude that our findings are in line with Ghosh et al. (2022) who also found an increasing average PPSQM for office space from pre to post-COVID, finding a larger average increase in suburban regions than in urban regions, as we see in Figure 4.5. However, unlike Ghosh et al. (2022), who saw suburban prices increasing more significantly relative to central urban areas, we identify a concurrent rise in CBD prices and suburban prices during these years. These findings are more in line with those of Ou et al. (2023) who found a rebounding demand for central locations in the post-COVID era. Interestingly, the 6 km, subcentral area where we see a statistically significant relative decrease in PPSQM, is the area where we saw an increasing number of leases, relative to the CBD, in our Hypothesis 1 investigation.

There are however potentially confounding factors that need to be addressed. The first factor of note is that inflation reduced the real value of 2019 rents by approximately 16.9% from 2019 to 2023, which should have put an upward pressure on 2023 rents (McDonnell, 2024). The knock-on implications of rising inflation are the interest rate hikes that followed for office owners, and the increased construction costs of new offices, both of which should additionally inflate rental prices. The second factor that should be considered is office vacancy in Dublin increased from 5.5% in Q1 2019 to 16.7% in Q4 2023. This is likely to have been the counterbalancing downward pressure that was the attributable factor for relative price declines over the period, as seen in our 3 km bin and 6 km bin.

The second part of our analysis delves into the changes in the rental gradient from 2019 to 2023. The rental gradient, or the bid-rent curve as discussed in Section 2, estimates the willingness to pay for land at a given distance from the city centre. Rosenthal et al. (2022), Ghosh et al. (2022) and Duranton and Handbury (2023), all allude to a flattening bid-rent curve arising from the impacts of a hybrid working model in the US. We find a similar trend in relation to the Irish office market, with the average rents decreasing compared to 2019 as seen in Figure 4.7, resulting in a flattening rental gradient slope. Truthfully, the rental gradient more closely resembles an exponential decay shape, but for the purposes of calculating a linear slope we see the below results. This is consistent with our PPSQM findings above, as higher suburban values and lower subcentral (3-6 km) values will result in a declining slope.

Fig. 4.7: 2019 vs 2023 Rental Gradient



Note: The rental gradient shown above, with distance on the x-axis and PPSQM on the y-axis, shows the declining rental gradient from 2019 to 2023.

4.3 Changes to Intensive Demand - Lease Length

The final lease characteristic we seek to explore, which concludes our analysis of the second hypothesis, is lease length. Changing lease lengths for commercial offices gives an insight into the psyche of market participants, with longer lease lengths potentially exhibiting more confidence and stability in market conditions. On average lease lengths in Dublin have fallen from 90.1 months to 85.5 months from 2019 to 2023, which is in line with the findings of Rosenthal et al. (2022) who also found decreasing lease lengths in US cities.

Despite this finding, we feel there is a further, more in-depth analysis that can be done to extrapolate a greater understanding of the behaviour of market participants from the data. In Figure 4.8 below we have again divided our data into 3 km bins to estimate findings across comparable sub-groups. It should be noted that we do not expect distance from CBD to majorly influence lease length, it is merely structured in this manner to maintain consistency. Our findings show a variety of results, with no real findings of note in either a positive or a negative direction. The same can be said of Figure 4.9, where a regression plot is presented, with distance from the CBD on the x-axis and lease length in days on the y-axis. The shaded area represents a 90% confidence interval.

Given the overlap of the confidence intervals of 2019 and 2023 throughout, we cannot say with any statistical significance that the lease lengths have decreased from 2019 to 2023. We therefore conclude that our findings were not necessarily consistent with those of Rosenthal et al. (2022). For the purposes of validating our models' assumptions and ensuring robustness, Appendix O includes a histogram of the residuals, showing they are mostly centred around zero, indicative of unbiased predictions.

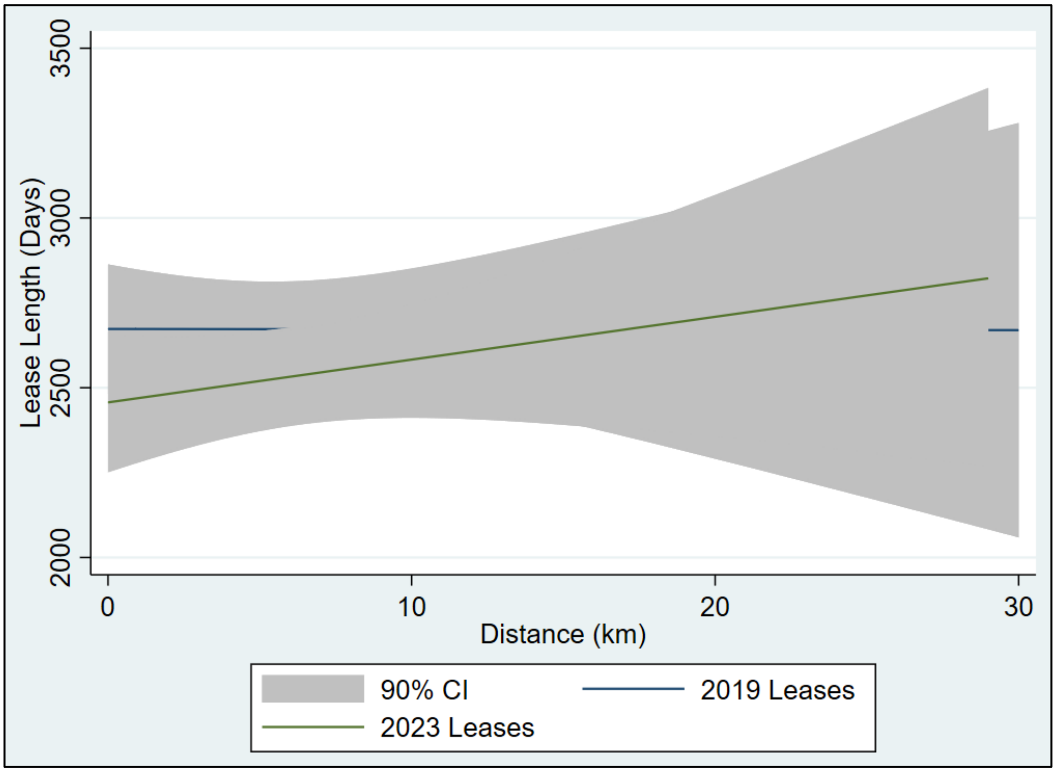
Fig. 4.8: OLS Intensive Demand Regression - Lease Length

Change in Lease Length Per Location		
	(1) OLS	(2) FE
3 km	82.66	-158.0
	(0.799)	(0.747)
6 km	-476.7	446.3
	(0.202)	(0.254)
9 km	342.5	872.9
	(0.461)	(0.172)
12 km	-590.6	-348.5
	(0.211)	(0.475)
15 km	-173.0	-689.6
	(0.749)	(0.277)
18 km	1789.8**	72.59
	(0.014)	(0.763)
24 km	221.7	513.9**
	(0.271)	(0.034)
Constant	2686.0***	4379.8***
	(0.000)	(0.000)
Grid-Level Fixed Effects	No	Yes
Observations	881	465
R-squared	0.035	0.554

p-values in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: The coefficients describe how the change in lease lengths from 2019 to 2023 varies across different distances from the CBD. Our OLS regression is displayed in the first column with our grid-level fixed effects model being shown in the second column. The number of observations dropped when implementing Grid-Level Fixed Effects is due to a small sample size and collinearity between leases in the same grid.

Fig. 4.9: Lease Length Regression Plot with 90% CI



Note: This is a graphical representation of our results from regression table Fig. 4.8 above. The shaded area represents a 90% confidence interval. The green line (to the front) represents 2023 lease lengths, and the blue line (to the back) represents 2019 lease lengths.

5. Discussion

We will now examine our findings, interpreting them within the context of the viability of adaptive reuse schemes in Dublin in Section 5.1, which will be followed by an analysis of the outlook of the commercial office market in Section 5.2.

5.1 Adaptive Reuse

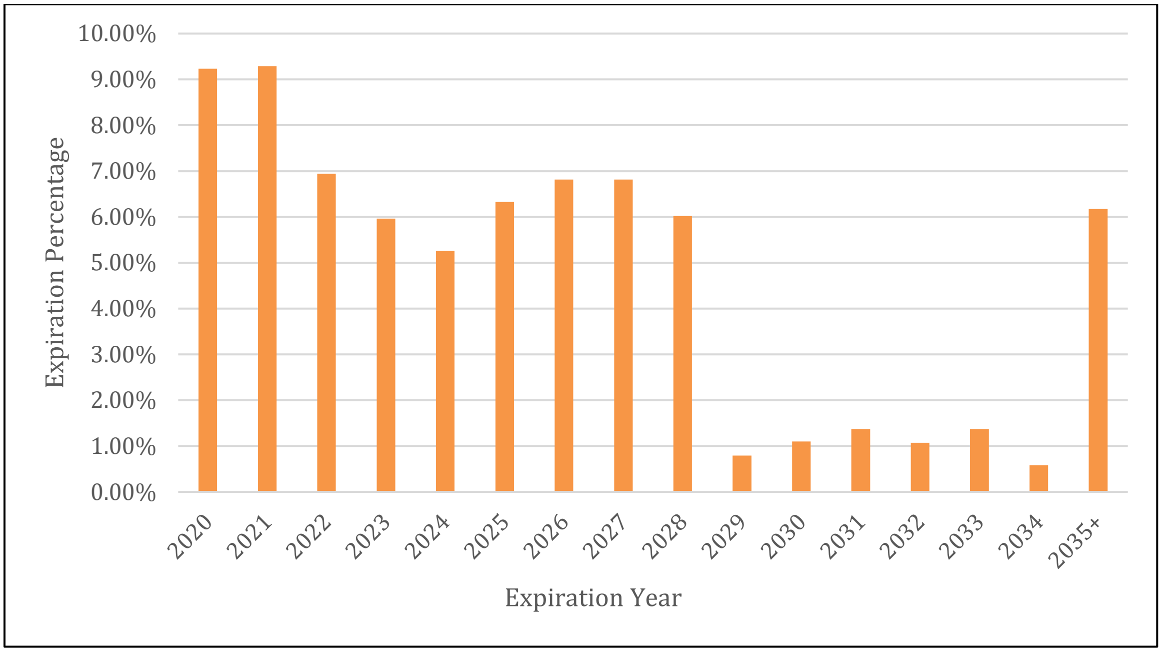
Through conversations with Nellie Reid, Managing Director of sustainable construction consultancy firm Meehan Green, and Fiona Craven, Programme Manager for Adaptive Reuse in Dublin City Council (DCC), both outlined the two-pronged necessary conditions for the viability of adaptive reuse programs. Firstly, viability must exist from a general locational and (lack of) demand perspective. To align this concept with our hypotheses, the extensive demand forces need to undergo deteriorating market conditions to stimulate such changes. Our data portrayed an increasing number of leases moving away from CBD locations to more accessible premises for those working from remote locations. Coupling these findings with Dublin's fast rising vacancy rate of 17.5% implies that the extensive demand conditions for adaptive reuse may exist in the city.

The second imperative hurdle for adaptive reuse projects, which was cited by both Nellie and Fiona, is financial viability. This pertains to the intensive demand section of our study, specifically addressing PPSQM studies. The viability of projects hinges on the current yields of offices and their subsequently derived valuations. While DCC receives a funding allowance from the Irish government for adaptive reuse schemes, which reaches *"up to €520,000 for the creation of a 2-bed unit and €460,000 for a one-bed unit"*, according to Fiona the issue of financial viability is said to remain. Landowners are refusing to budge on vacant property prices as they remain at a standoff with prospective tenants resulting in few leases across the board. Duranton and Handbury (2023) provide an insight into the psyche of both landlords and organisations claiming that landlords prefer to wait for rents to recover rather than being stuck with a long term low paying tenant, which in turn maintains an artificially high level of vacancies. This behaviour is consistent with Kahneman and Tversky's prospect theory (1979), as landlords favour short term inaction for the prospect of future gains. This further relates to the purchase price anchoring of real estate owners who are subject to losses, as described by Genesove and Mayer (2001). We find indications that the above situation is currently unravelling, as commercial property yields remain in line or greater than those from 2019 in CBD regions. Despite witnessing the highest vacancy rates in a decade, we are seeing no downward movement in rents in central locations. The behavioural fallacies of landowners in central locations raise questions about the efficiency of the free market for commercial property and ultimately renders adaptive reuse programs largely unviable here. We do however see signs of price movements in our 6 km range, which indicates that landlords may be downwardly adjusting their rents. This has resulted in a positive demand response in the area, which reflects a sustained interest in reasonably priced leases, a trend that does not necessarily bode well for the conversion of office spaces. Given the high level of vacancy, it may be important for landlords in less desirable locations to gain a first mover advantage, and lock in tenants before rates decrease in more desirable, central locations.

5.2 Future Outlook

Lease terms are typically an effective vehicle through which current market sentiment can be reflected upon and can offer valuable insights into the timing of if/when changes in the office market will fully manifest. The persistence of leases must be considered when estimating the outlook of the commercial office market. As we attempt to decipher future trends, we have compiled the expiration year of all office leases in Dublin that were signed from 2014 until the end of 2019. Assuming all leases run their full course, 43.7% of leases signed since 2014 have yet to expire. This highlights the longevity of the issue at hand, as vacancy rates look all but guaranteed to further rise in years to come, as firms look to downsize on space given new hybrid approaches to working. A reduction in the total square footage demanded should subsequently put downward pressure on rents.

Fig. 5.1: Lease Expiration Schedule of Pre-Covid Leases



Note: Pre-COVID leases only account for leases signed from 2014 onwards due to data restrictions. Percentage refers to the percentage of all leases signed between 2014 and 2019 and their expiry year.

Another future perspective that must be considered is oncoming environmental regulation. As of January 2024, EU public interest entities with more than 500 employees are in scope for Corporate Sustainability Reporting Directive (CSRD). Dublin-based firms have until June 2024 to be compliant with new regulation, which expands to companies of over 250 employees in January 2025 and to SMEs from January 2026 (Department of Enterprise, Trade and Employment, 2024). As per the CSRD, companies must report on their environmental impact, including detailed information on greenhouse gas emissions (European Union, 2022). This materially impacts firms' demands for energy efficient office space as the CSDR encompasses Scope 1 (direct emissions from owned or controlled sources) and Scope 2 emissions (indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company). The challenge with the implementation of such a directive lies in the increased demand for energy-efficient office spaces, as firms strive to reduce their emissions. However, in a relatively small office market, the supply of energy-efficient buildings remains limited. This is especially true given the prominence of Dublin's Georgian office buildings, which were largely built in the 1700s. Given the limited supply for "green offices", newer buildings are likely commanding rents above or consistent with pre-COVID rates, which may provide some explanatory power behind our increased PPSQM findings.

6. Limitations and Future Research

In this section we will discuss limitations in our study, and address areas that present opportunities for further research. Section 6.1 will touch on the topic of “Flight to Quality” in the commercial office market, which will be followed by Section 6.2 which discusses potential limitations that arise from the definition of our CBD Point. We will conclude with Section 6.3 which addresses issues arising with our sample size.

6.1 Flight to Quality

When conducting a similar vein of research in New York, Gupta et al. (2023a) discovered that when accounting for office quality and age, they found an increasing commercial bid-rent gradient, even steeper than pre-COVID times, signalling a “flight to quality” effect. Unfortunately, it was not possible to replicate such an investigation due to the non-existence of construction year data or energy efficiency data for our leases. There is a consensus among research houses and Ireland’s largest property developers, Pat Crean and Johnny Ronan, that a “flight to quality” has been witnessed with rising vacancies (Daly, 2023). The flight to quality is said to have been propelled by the sustainability agenda as occupiers seek to meet their internal ESG objectives (JLL, 2023). This would be a very topical area for further research in Dublin by examining trends when accounting for office energy labels and age.

6.2 Arbitrary CBD Location

In our study, a specific CBD point was chosen to most accurately reflect the influence of price and locational changes based on their relative distance to this point. Dublin, unlike many other cities, does not have a distinctive and obvious CBD, and consequently this specific point has been estimated based on an approximate central area. This may lead to a small degree of variation in the results, but given the relatively small size of the city, results should be reasonably consistent. Additionally, another issue arises with the CBD point due to Ireland’s small size. Leases have been exclusively filtered for the county “Dublin". This was done to eliminate the possibility of a distortion of results from smaller business districts in neighbouring counties, for example from Bray to the south or Celbridge to the west. The issue that subsequently arises is that the Dublin border stops at ~18 km to the south and ~16 km to the west, meaning that all results from beyond these distances are solely reflecting the north side of the county. A full map of the county has been included in the Appendix P for transparency. This may distort the analysis of bid-rent gradients, which do not neatly conform to administrative limits. Additionally, the data's limitation to the northern part of the county may introduce a north-side bias, potentially skewing conclusions to disproportionately reflect northern dynamics. Given these limitations we therefore suggest that findings should be interpreted cautiously, with potential gaps in the external validity of findings.

6.3 Sample Size Limitations

Lastly a potential issue arises in our research which relates to the relatively small sample size in use. Our sample contains approximately 500 leases for both 2019 and 2023, of which ~90% of leases in both years are concentrated within 12 km of our CBD point. This leaves a lot to be desired when extracting findings from our sample, especially at distances over 12 km. Not only does a smaller sample size hamper the statistical significance of our findings but it also limits the external validity of our results. With a large concentration of leases within 12 km of the CBD, our ability to draw reliable conclusions about the market dynamics at greater distances is significantly weakened. Furthermore, the smaller number of observations at these larger distances could lead to overfitting and increased variability in our regression results, thus affecting the reliability of our conclusions. To address these issues, future research should aim to include a more balanced distribution of leases across various distances from the CBD, ideally with a larger dataset throughout to improve the statistical significance of the analysis.

7. Conclusion

In our study we have identified the novel trend of an increase of commercial offices relocating to subcentral areas next to highways, potentially to accommodate longer distance commuters and/or due to lowering relative rents. Despite this shift, the benefits of knowledge spillovers within agglomeration economies appear to be preserved, as central areas retain relative attractiveness, with increased average rental prices in central regions from pre to post-COVID periods. Furthermore, we found that, in contrast to academic sentiment, office lease lengths remained stable, reflecting confidence in the commercial lease market.

Our findings suggest that on paper the commercial office market seems relatively healthy, but the persistent issue of rising vacancies remains. According to McCartney (2023), office vacancy has risen more rapidly in Dublin than in almost any other European location, however, the pricing of Dublin office investments has adjusted by less than the European average. This, in my view, perfectly encapsulates the current standing of the commercial office market in Dublin. In an efficient free market, when vacancy rates rise above the natural rate, rents will fall below their equilibrium level; development will stop until demand growth sees rental and vacancy rates return to their initial levels (Hendershott et al., 2002). Our research indicates that we are currently enduring this cycle, where rents may be starting to fall in less attractive locations. In central areas rents remain stubbornly high due to opportunistic landlords and a scarce supply of "green offices" which, due to looming environmental regulatory pressures, is accelerating the flight to quality effect.

The Irish Central Bank has listed the illiquidity of commercial real estate assets as their financial regulatory risk priority for 2024 and we estimate this to be the natural next step in the cycle for Irish commercial property (Central Bank of Ireland, 2024). To rebalance the market equilibrium and to reduce vacancy rates there are three possible outcomes. 1) Vacant offices are refurbished, making them suitable for modern client's requirements, 2) Office landowners succumb to the current conditions and adjust their rental rates downwards or 3) Offices are withdrawn from the market and repurposed for alternative uses. The Irish government find themselves in a dilemma as they are presented with an opportunity that perfectly conforms with their mandate to deliver urgently needed, large-scale housing, that adheres to the green agenda. However, proceeding may precipitate unwanted public backlash in an election year for bailing out commercial developers, an accusation that has tainted governments in the not-too-distant past.

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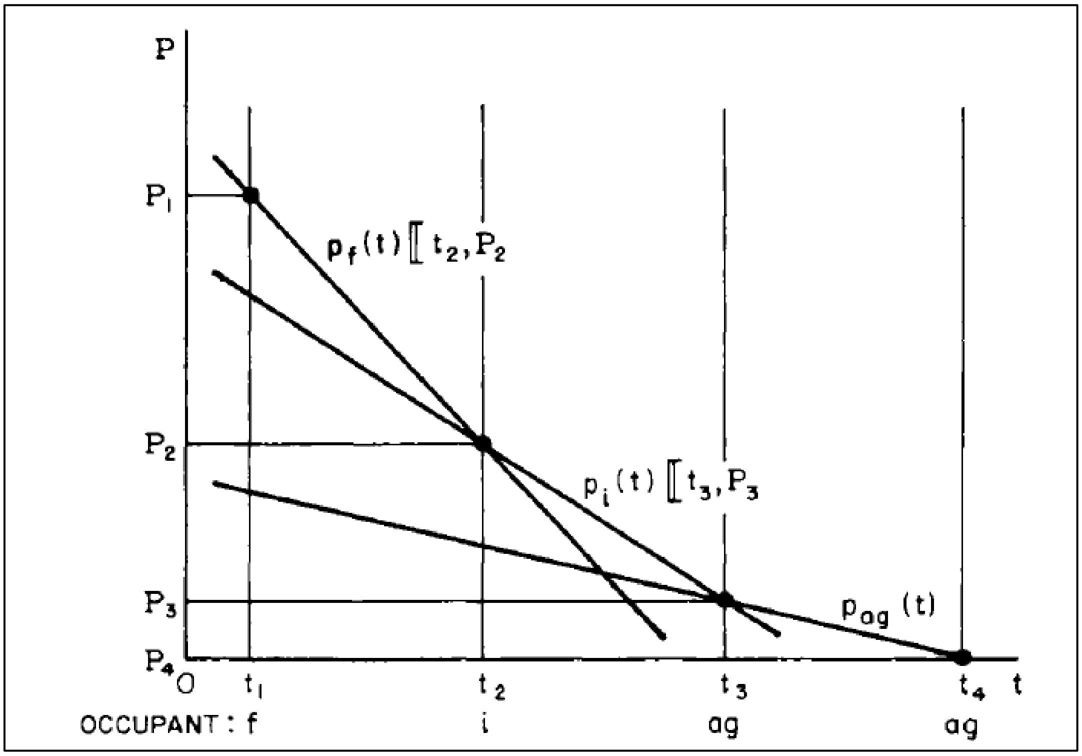
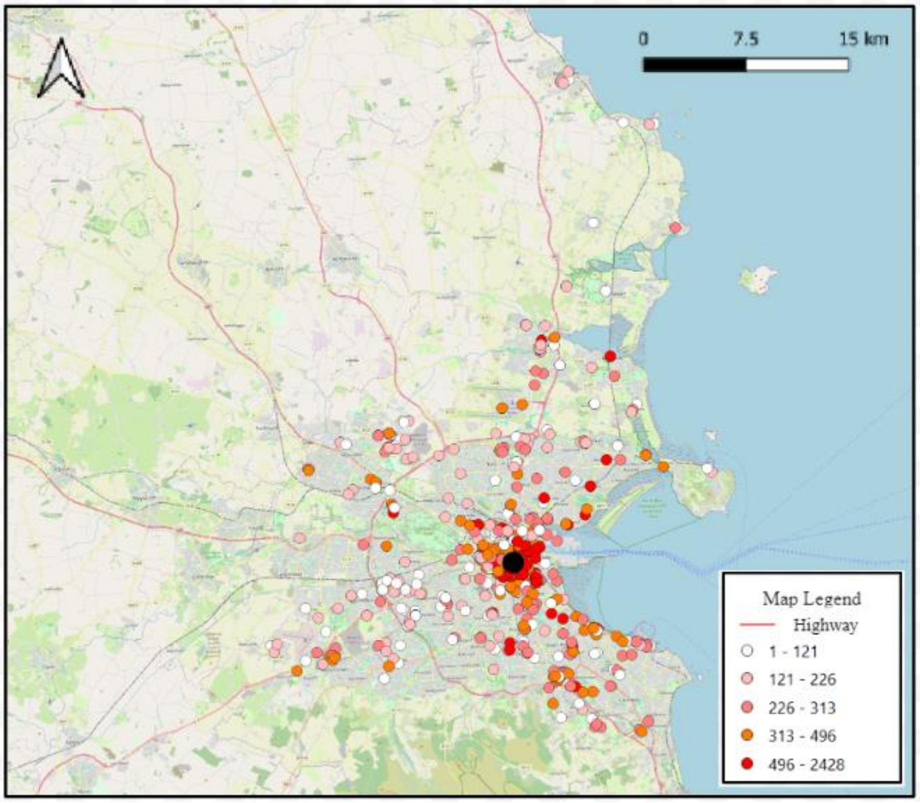
Appendix:

Appendix A: Foundational Bid-Rent Curve (cf. Fig. 27, Alonso, 1964)



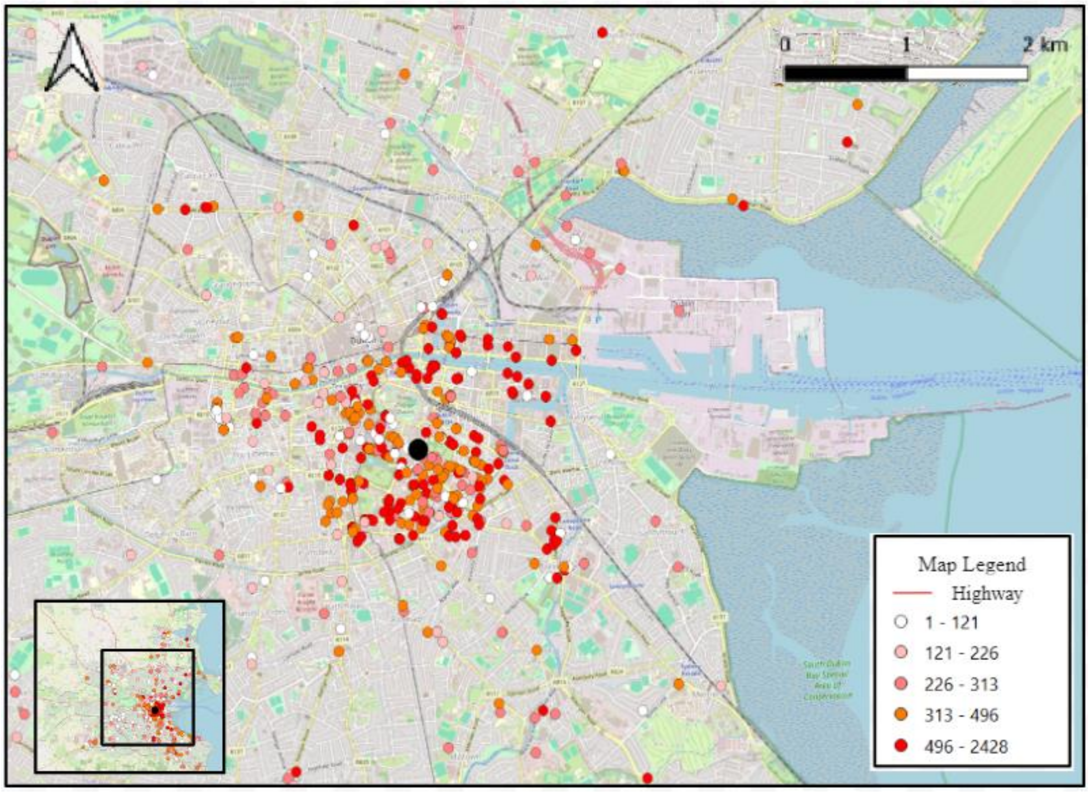
Note: The steepest line that intersects points P1 and P2 represents commercial offices/retail, the line between P2 and P3 represents manufacturing, and the final line represents residential space.

Appendix B: Dublin Leases 2019 & 2023



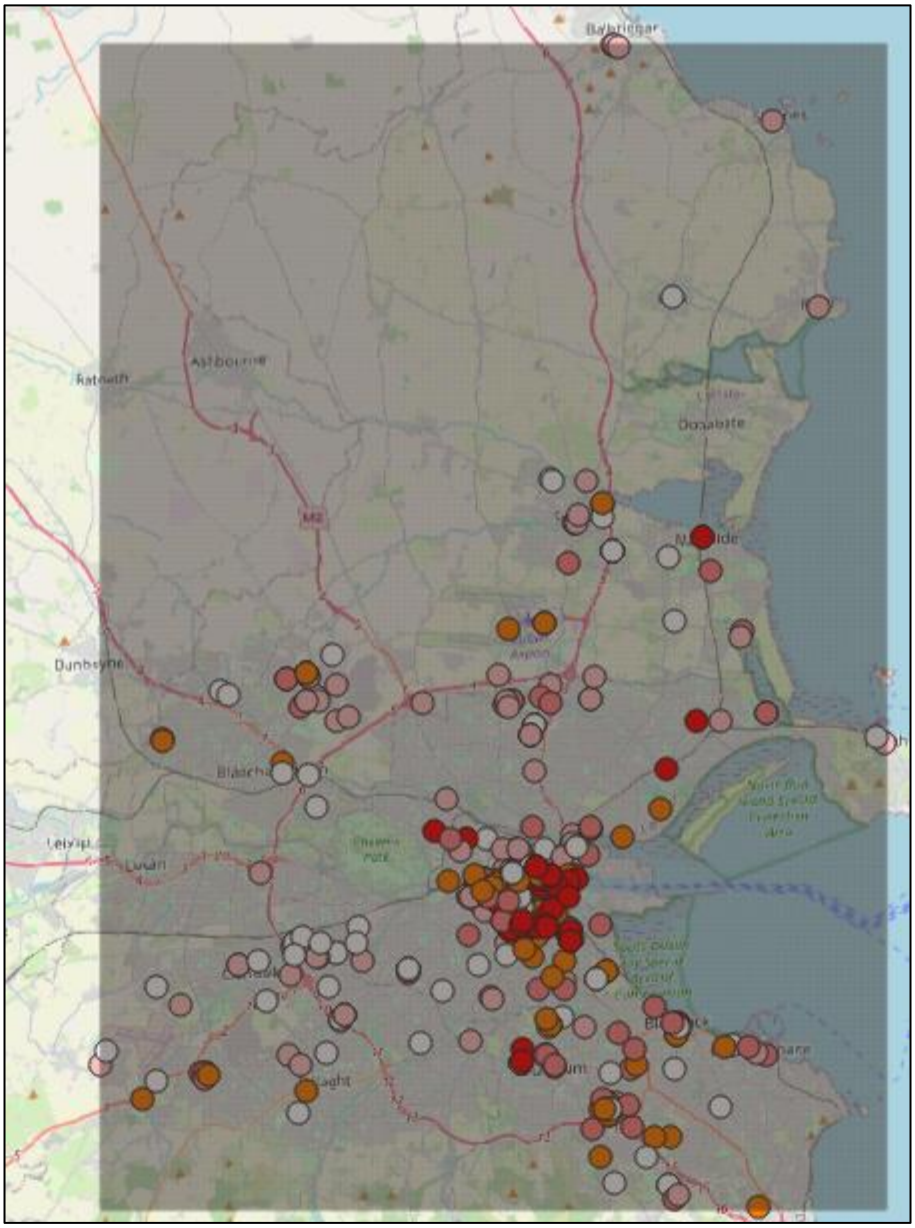
Note: The black dot represents our CBD Point. The scale represents PPSQM and is denoted in euro.

Appendix C: Dublin CBD Leases 2019 & 2023



Note: The black dot represents our CBD Point. The scale represents PPSQM and is denoted in euro.

Appendix D: GIS Constructed 100 m x 100 m Spatial Grid



Note: This shows the outline of our grid layer (grey) that was constructed to calculate the distance of centroid of the specific grid cells to our spatial variables.

Appendix E: Summary Statistics of Non-Spatial Variables in 2019

Non-Spatial Variables 2019					
	Count	Mean	SD	Min	Max
PPSQM	555	322.46	268.18	0.63	2,427.75
SQM	555	932.30	5,153.63	6.00	98,693.00
Lease Length	555	2,701.67	1,863.32	30.44	9,131.25
Observations	555				

Note: PPSQM refers to Price Per Square Meter of Office Space. Similarly, SQM refers to Square Meters of Office Space. Lease Length is observed in days. SD refers to standard deviation.

Appendix F: Summary Statistics of Non-Spatial Variables in 2023

Non-Spatial Variables 2023					
	Count	Mean	SD	Min	Max
PPSQM	461	326.2	249.99	0.17	2,348.58
SQM	461	862.59	3,643.28	6	50,146.00
Lease Length	461	2,566.08	1,730.83	182.63	12,783.75
Observations	461				

Note: PPSQM refers to Price Per Square Meter of Office Space. Similarly, SQM refers to Square Meters of Office Space. Lease Length is observed in days. SD refers to standard deviation.

Appendix G: Summary Statistics of Spatial Variables in 2019

Spatial Variables 2019

	Count	Mean	SD	Min	Max
Luas	555	1,903.82	3,672.09	24.52	26,838.93
Train	555	1,545.75	1,338.81	86.90	7,150.20
Waterways	555	392.02	309.12	3.92	1,929.14
Coastline	555	3,697.48	3,019.99	39.40	17,537.00
Bus	555	132.31	121.94	4.05	1,277.41
Travel Time	555	1,740.90	1,178.63	83.00	5,880.00
Distance to CBD	555	5,095.58	5,627.43	-	29,556.57
Highway	555	2,064.51	1,230.57	11.54	7,500.60
Observations	555				

Note: All values are measured in meters, apart from Travel Time which is measured in seconds. Values refer to the distance of an office lease to the nearest Luas stop, bus stop, train station etc. SD refers to standard deviation.

Appendix H: Summary Statistics of Spatial Variables in 2023

Spatial Variables 2023					
	Count	Mean	SD	Min	Max
Luas	461	2,260.59	3,865.68	41.14	26,838.93
Train	461	1,717.89	1,566.82	105.22	7,951.04
Waterways	461	399.53	373.39	2.86	2,359.81
Coastline	461	3,844.28	3,461.22	23.57	17,537.00
Bus	461	129.63	121.22	2.99	1,129.61
Travel Time	461	1,954.60	1,269.98	122	5,868.00
Distance to CBD	461	5,795.42	5,939.27	55.89	29,294.96
Highway	461	1,969.33	1,334.41	4.22	10,506.27
Observations	461				

Note: All values are measured in meters, apart from Travel Time which is measured in seconds. Values refer to the distance of an office lease to the nearest Luas stop, bus stop, train station etc. SD refers to standard deviation.

Appendix I: Robustness check for 6 km locational finding with a variety of omitted distance variables

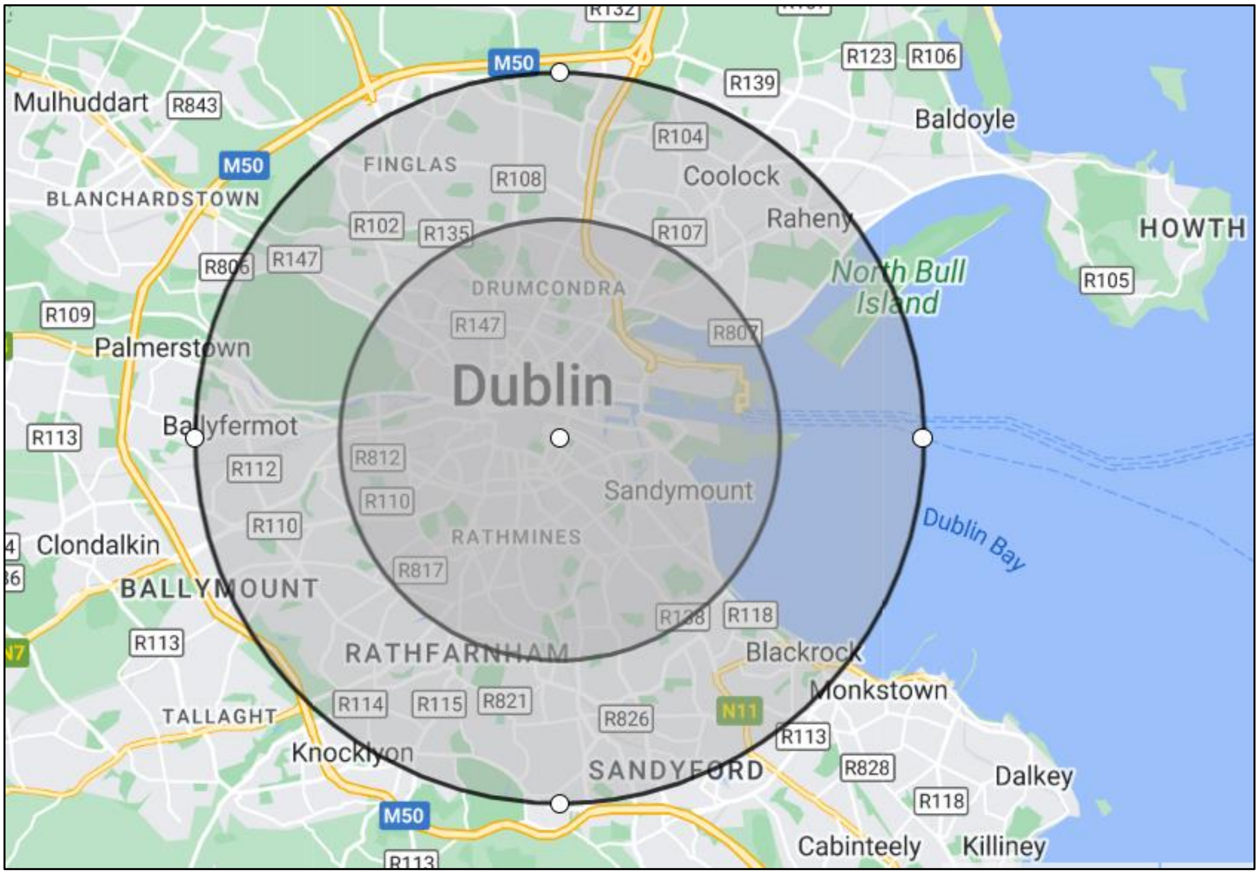
Robustness Check for H1 - Locational Changes

VARIABLES	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
0 km	0.178	-0.365*	0.106	-0.0794	-0.0839	-0.0411	-0.0411	-0.0411	-0.0411	-0.0795
	(0.343)	(0.037)	(0.502)	(0.650)	(0.706)	(0.736)	(0.736)	(0.736)	(0.736)	(0.532)
3 km		-0.543**	-0.0721	-0.258	-0.262	-0.220	-0.220	-0.220	-0.220	-0.258
		(0.004)	(0.682)	(0.177)	(0.264)	(0.126)	(0.126)	(0.126)	(0.126)	(0.081)
6 km	0.543**		0.471**	0.285	0.281	0.324**	0.324**	0.324**	0.324**	0.285*
	(0.004)		(0.004)	(0.108)	(0.210)	(0.010)	(0.010)	(0.010)	(0.010)	(0.029)
9 km	0.0721	-0.471**		-0.186	-0.190	-0.147	-0.147	-0.147	-0.147	-0.186
	(0.682)	(0.004)		(0.250)	(0.369)	(0.146)	(0.146)	(0.146)	(0.146)	(0.085)
12 km	0.258	-0.285	0.186		0.00455	-0.0383	-0.0383	-0.0383	-0.0383	-0.000159
	(0.177)	(0.108)	(0.250)		(0.984)	(0.761)	(0.761)	(0.761)	(0.761)	(0.999)
15 km	0.262	-0.281	0.190	-0.281		0.0429	0.0429	0.0429	0.0429	-0.0934
	(0.264)	(0.210)	(0.369)	(0.210)		(0.818)	(0.818)	(0.818)	(0.818)	(0.711)
18 km	0.220	-0.324**	0.147	-0.324**	-0.0429		-6.93e-14	-3.49e-13	-3.48e-13	
	(0.126)	(0.010)	(0.146)	(0.010)	(0.818)		(1.000)	(.)	(.)	
24 km	0.220	-0.324**	0.147	-0.324**	-0.0429	-3.88e-14	-6.94e-14		-3.48e-13	
	(0.126)	(0.010)	(0.146)	(0.010)	(0.818)	(.)	(1.000)		(.)	
Constant	1.447***	1.020***	1.250***	1.020***	1.190***	1.000	1.000***	1.000	1.000***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	825	825	825	825	825	825	825	825	825	825
Omitted Variable	3 km	6 km	9 km	12 km	15 km	18 km	21 km	24 km	27 km	15 - 30 km
R-squared	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.019

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

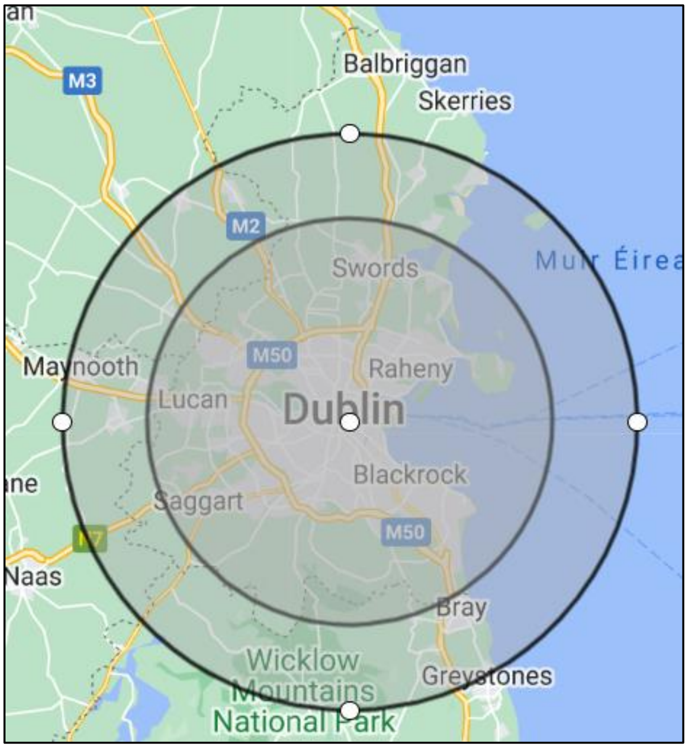
Note: The variables 21 km, 27 km and 30 km have been excluded due to the small sample size. A different omitted variable has been used in each to ensure our finding of an increase in leases at the 6 km bin was valid. We see a statistically significant result at all omitted variable levels bar 12 km and 15 km, potentially attributable due to small sample sizes.

Appendix J: 6km Bin Category (4.5 km - 7.5 km) Fitted to Dublin Map



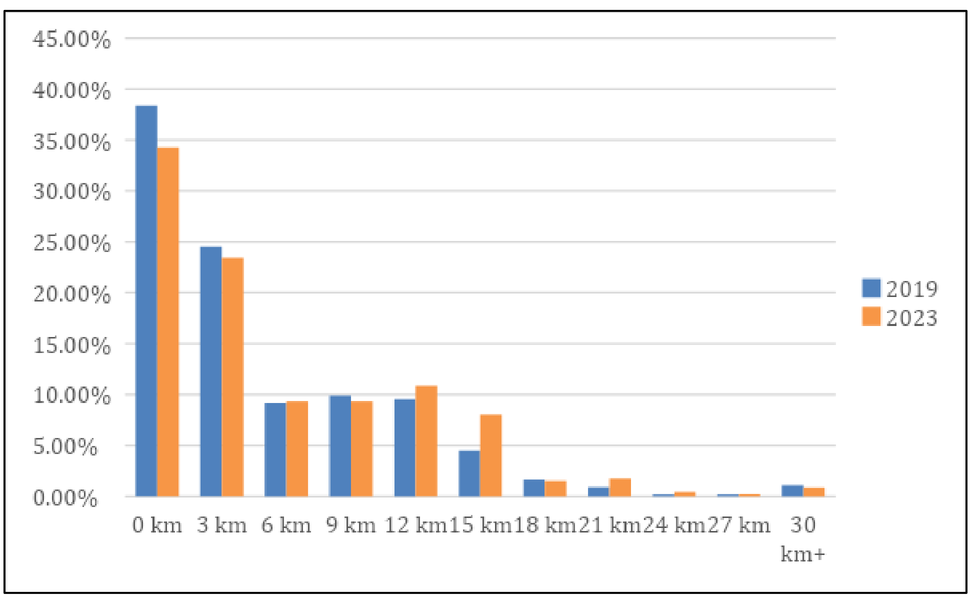
Note: The area outside of our inner circle and within our outermost circle is the area we are seeing a proportionately higher growth of new leases.

Appendix K: 24km Bin Category (22.5 km - 25.5 km) Fitted to Dublin Map



Note: The area outside of our inner circle and within our outermost circle is the area we are seeing a proportionately higher growth of new leases. The results however are dubious due to a small sample size.

Appendix L: Lease Locational Distribution Percentage



Note: Here we see the percentage of leases in both 2019 and 2023 based on their distance bins. We find an increasing percentage of leases at 6 km, 12 km, 15 km, 21 km and 24 km.

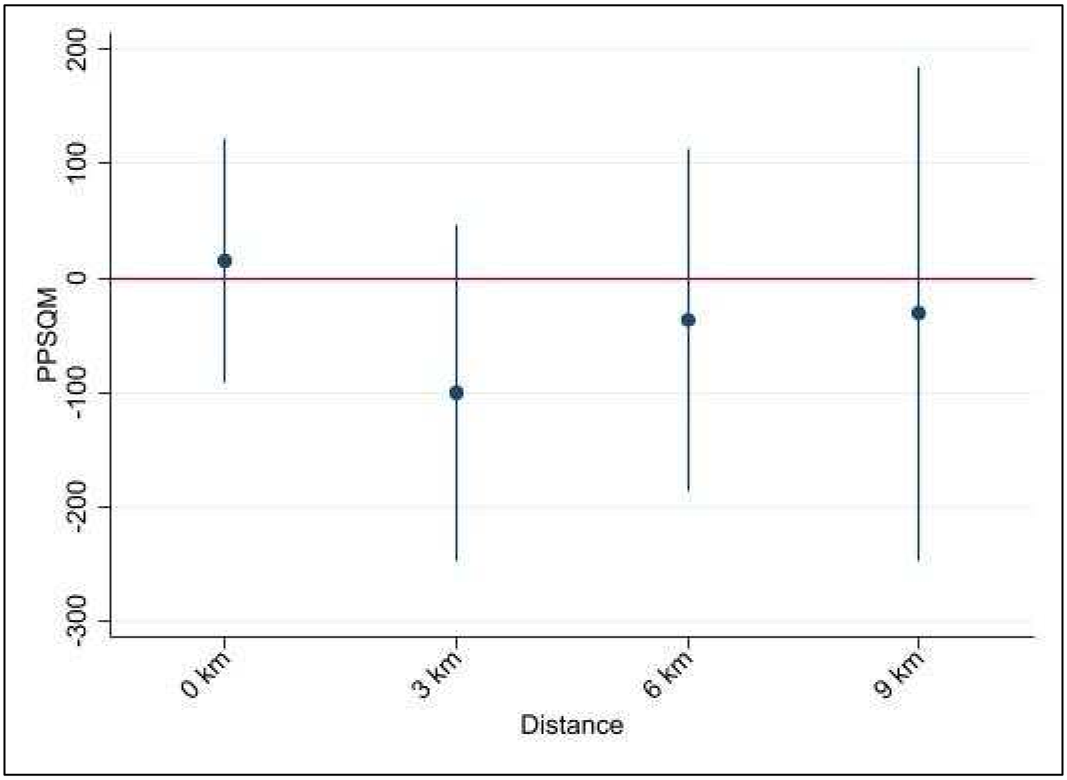
Appendix M: Intensive Demand PPSQM with >12.5km as Omitted Variable

	Change in PPSQM Per Location	
	(1)	(2)
	OLS	FE
0 km	3.160	15.13
	(0.944)	(0.814)
3 km	-62.76	-100.2
	(0.278)	(0.260)
6 km	2.307	-36.75
	(0.970)	(0.686)
9 km	-32.66	-31.07
	(0.645)	(0.812)
Constant	175.5***	322.4***
	(0.000)	(0.000)
Grid-Level Fixed Effects	No	Yes
Observations	1012	623
R-squared	0.129	0.508

p-values in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

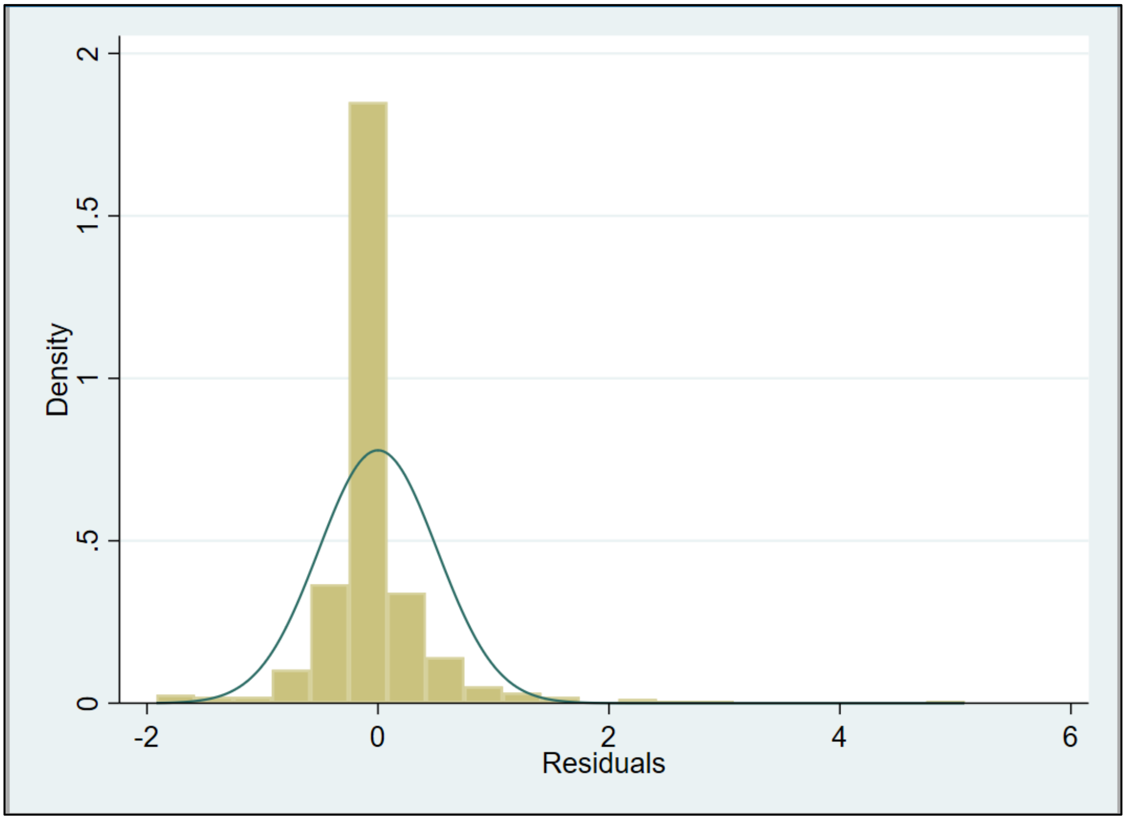
Note: The coefficients describe how the PPSQM of leases from that distance category have changed relative to the change witnessed in our omitted >12.5 km category, from 2019 to 2023. Our OLS regression is displayed in the first column with our grid-level fixed effects model being shown in the second column.

Appendix N: Coefficient Plot for H2 Regression Findings with >12.5km as Omitted Variable



Note: This is a graphical representation of our results from regression table Appendix M above. The error bars represent a 90% confidence interval.

Appendix O: Residual Robustness H2 Lease Length



Note: In the above we see a histogram of the residuals, given that they are mostly centred around zero, indicative of unbiased predictions.

Appendix P: Dublin County Map

Note: In the above we see the Dublin border stops at ∼18 km to the south and ∼16 km to the west, meaning that all results from beyond these distances are solely reflecting the north side of the county

Appendix Q: Lease Length Spatial Variable Regression

	Lease Length
PPSQM	0.853***
	(0.000)
Bus	0.0799
	(0.880)
Luas	-0.0281
	(0.374)
Train	0.0482
	(0.337)
Coastline	-0.0399
	(0.156)
Waterways	0.0781
	(0.656)
Highway	-0.0843
	(0.103)
Adjusted Distance	24.11
	(0.314)
Control	-156.5
	(0.168)
_cons	2562.8***
	(0.000)
N	1016
R-sq	0.023

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The OLS Regression shows which of our variables influences lease length. The only statistically significant finding is a relationship between a higher PPSQM and longer lease length.