Do rising rents lead to longer commutes?
A gravity model of commuting flows in Ireland

Abstract. The classical monocentric city model suggests that property prices decrease and transport cost rise with distance to the urban centre, implying that employees face a trade-off between long commutes and high housing costs when making location decisions. Accordingly, some commuters might be forced to take on longer commutes due to rising rents in central locations. In this study, we investigate empirically whether the rental differential between employment centres and residential areas predict changes in average commuting times. To this end, we consider a gravity model of commuting flows for Ireland over 2011-2016. We present results for Ireland and the metropolitan area of Dublin, which constitutes the largest commuting region in Ireland. The results imply that a 10% rise in rents in employment centres is associated with an up to 0.6 minute rise in one-way daily average commuting times nationally (about 2.2% of the average commute duration).

Keywords: Commuting, rental market, gravity model, Ireland.

Introduction

The monocentric city model predicts that unit housing costs decrease with distance from the city centre where most of the employment opportunities are located, whereas the costs of transport to the centre are higher for residents in the periphery (Muth, 1969; Alonso, 1964; Mills, 1967). This suggests that workers face a trade-off between low housing costs and long commutes when making location decisions. If property prices increase in employment centres relative to sub-urban areas, it might drive residents away from the centre and force them to accept longer commutes. To get a better understanding of the existence and magnitude of this displacement effect, the present study investigates the relationship between relative rental prices and commuting behaviour using a gravity model of bilateral commuting flows in Ireland.

Ireland is a particularly suitable place to examine this relationship. The period of recovery in the Irish housing market following the property price crash of 2009 allows us to study commuting behaviour and the housing market during a period of dramatic changes, with rental price increases exceeding 30% over 2011-2016 in some areas (RTB, 2019). The tightness of the Irish housing market has been highlighted by a recent survey which found that Irish renters are willing to extend the daily commute by 23 minutes on average in order to achieve home-ownership, pointing to a trade-off between desirable housing and commuting (Corrigan et al., 2019). In addition, the five-yearly Irish census contains spatial data on commuting journeys for the whole population, and it has proved possible to link this information to administrative data on rents at small area level.

A vast literature relates property prices to spatial structures. The basic prediction that property prices fall with distance to an exogenously defined city centre has been widely tested and generally confirmed, even though the relationship is often distorted by local amenities, infrastructure and geographical factors (Albouy and Lue, 2015). More recent empirical studies account for complex and polycentric urban structures by directly relating property prices to employment opportunities or accessibility measures (Osland and Thorsen, 2008; Ahlfeldt and Wendland, 2016). A distinct field of research analyses commuting behaviour, e.g. with a focus on excess commuting (Ma and Banister, 2006), mode of transport choices (Johansson et al., 2006) or the gender gap in commuting (Crane, 2007).

In comparison, less attention has been paid to the relationship between housing costs on commuting behaviour, even though existing evidence suggests that housing costs are an important determinant for commuting behaviour. Cervero and Wu (1997) relate commuting flows to house prices at the location of residence and workplace using a cross-sectional gravity model. They find that residential house prices are negatively associated with the number of commuters between two locations, implying that low house prices in peripheral locations act as a pull factor. So et al. (2001) distinguish between four location choices: living and working in a metropolitan area, living and working in a non-metropolitan area, or cross-commuting either from or to a metropolitan area. Their multinomial logit model suggests that a 10% increase in metropolitan housing costs reduce metropolitan residence by 3.4% and increases demand for non-metropolitan housing by 1.9%. Cheshire et al. (2018) offer a public policy perspective on the relationship between housing markets and commuting. Using election outcomes as instrumental variables, they show that planning restrictions lead to an increase in average commuting distances. O'Kelly et al. (2012) develop a calibrated spatial interaction model for Ireland based on 2006 commuting data from the Census-based source also used in the present paper. Though data on actual rents were not available to them, the authors infer from the spatial structure of commuting trips that there were higher rents in the "job-rich core" (Dublin) than in peripheral locations. However, we are not aware of an empirical analysis of the commuting-housing nexus in the context of dramatic housing market changes. This study attempts to fill this gap.

This research is motivated by the adverse effects of commuting. Aside from the monetary costs for commuters, passive commuting, which excludes walking and cycling, has been associated with negative effects on well-being and mental health (Stutzer and Frey, 2008; Sandow et al., 2014; Künn-Nelen, 2016). While the review of Saunders et al. (2013) concludes that there is some evidence that active commuting (i.e., walking or cycling) can be beneficial, the monetary costs and time spent commuting puts an additional burden on workers. Commuters have also been shown to be a risk group for exposure to air pollution (Zuurbier et al., 2010). On the other hand, commuting is an essential part of modern labour markets and restrictions to commuting impede labour market efficiency (Monte et al., 2018). Commuting is also related to urban form. Low density and dispersed urban structures are associated with higher commuting times (Antipova et al., 2011; Travisi et al., 2010). In that sense, demand for long-distance commuting combined with demand for housing in non-metropolitan areas may lead to low-density and dispersed urban structures, commonly referred to as sprawl.

In the first step of our empirical analysis, we develop a gravity model of commuting flows for Ireland in order to explore the link between commuting and rental prices, which we interpret as a general measure of housing user costs.[1] We link commuting data on small areas from the Irish Census, which includes the location of residence and workplace for each Irish citizens, with microdata on tenancy agreements from Ireland's Residential Tenancy Board. With regard to the estimation strategy, we build on existing gravity models of commuting that explore how the commuting intensity between two locations depends on transport costs, distance and other geographical factors (de Vries et al., 2009; McArthur et al., 2011b,a; Duran-Fernandez and Santos, 2014; Persyn and Torfs, 2016; Ahlfeldt and Wendland, 2016). The gravity models allow us to predict the effect of changes in the relative rental prices of urban centre to periphery on average journey times in the second step of the analysis.

We find a significant association between commuting behaviour and rental prices over the study period 2011-2016. The main result of this study is that a 10% rise in rents in employment centres is associated with up to 0.6 minute higher one-way average journey times nationally, which corresponds to 2.2% of the average commute duration. Our

[1] In line with the theory of rental equivalence we assume that the house price to rents ratio is stable over time and across space. Rental equivalence is commonly used to infer the user cost of owner-occupied housing (European Commission, 2017). While short-run deviations are shown to exist, these are unlikely to distort our estimations which focus on dynamics over a 5-year horizon (Borgersen and Sommervoll, 2012).

results indicate that the effect is generally larger for Dublin, the largest metropolitan region in Ireland. However, the effects appear moderate in scale, which seems to reflect a relatively slow response by commuters to changes in the spatial structure of housing costs. Nevertheless, the results provide some empirical support for the existence of a trade-off between commuting and housing costs. This has implications for urban planning, as the process of sprawl and dispersion is likely to continue if rents rise faster in the urban centre relative to the commuting belt.

Data sources and data exploration

Commuting data

We obtain commuting data from the Place of Work, School or College (POWSCAR) microdata file.[2] POWSCAR data is collected as part of the Irish Census, which is conducted by the Central Statistical Office (CSO). We utilise data for the census years 2011 and 2016. Each data point codes the location of residence and place of work for each resident in Ireland. For the analysis of bilateral commuting flows, we aggregate the data to the level of Electoral Divisions (EDs), a geographical unit of which there are 3,409 in Ireland.[3] The aggregation allows us to compute the number of commuters between each pair of EDs. Intra-ED commuters, home workers and mobile workers are excluded from

[2] Access to the POWSCAR dataset is restricted. To apply for data access, see https://www.cso.ie/en/census/census2016reports/powscar/ (last visited on July 1, 2019.)

[3] With an average population of 1,397 in 2016, Electoral Divisions are significantly smaller than, for example, US census tracts. The choice of the unit of analysis is primarily due to data considerations. EDs are the smallest division for which we could compile a dataset of rents and commuter data. We acknowledge that, as any statistical analysis using administrative boundaries, the results may suffer from biases associated with the Modifiable Area Unit Problem (Viegas et al., 2019).

the analysis. Figure 1 illustrates ED-to-ED commuting flows in Ireland by plotting direct lines between the centroids of origin and destination. Darker lines indicate a larger number of commuters. The metropolitan area of Dublin clearly stands out as the largest commuting region.

[Figure 1 about here]

The POWSCAR dataset includes information on self-reported one-way journey minutes and primary means of transportation for each commuter, which are summarised in Table 1 for Ireland and the metropolitan area of Dublin[4]. The average national journey time increased from 25.9 minutes per journey to 27.3 over the course of five years, implying a rise of up to 14 minutes on a weekly basis (i.e., when assuming ten journeys per week). With 30.5 and 32.2 minutes in 2011 and 2016, commuting times are above the national average in Dublin, which is consistent with congestion effects due to higher population and employment density.

[Table 1 about here]

Private motorised vehicles are the dominant form of transportation. In 2011, 77.2% of commuters either drive or are passenger in a car, van or motor cycle, although the share of motorised commuting dropped by more than 1 percentage point between 2011 and 2016. Public transport, on the other hand, increased from 9.4% to 10.4% over the same period. Compared to the national average, Dublin exhibits a higher level of public and

[4] For this analysis, we define the metropolitan area of Dublin as including the counties Dublin City, Kildare, Louth, Meath and Wicklow.

non-motorised commuting. The data for Dublin also indicates a shift towards active commuting and public transport, which both increased from 2011 to 2016.[5]

A decomposition of travel times

Two factors may help explain the rise in average journey times: first, changes in the time it takes to travel from location *i* to *j* due to congestion or infrastructure improvements, and secondly, changes in the origin-destination structure (which in turn is determined by commuters' residence-workplace location decisions). For exploratory purposes, we decompose the rise in commuting times from 25.9 to 27.3 minutes. To this end, we first consider a simple linear regression of journey times against a constant and a binary 2016 indicator:

$$\tau_{c,t} = \underset{(0.018)}{25.913} + \underset{(0.024)}{1.410} \times year2016_{c,t} + \hat{u}_{c,t}, \quad R^2 = 0.1\% \qquad (1)$$

Here, $\tau_{c,t}$ is the travel time of commuter $c = c(i, j)$ who commutes from i to j in year t. The year dummy equals 1 in year 2016, 0 otherwise. The resulting point estimate on the year dummy corresponds to the percentage-point increase in average commuting times. When adding origin-destination fixed effects,

$$\tau_{c,t} = \underset{(0.015)}{0.705} \times year2016_{c,t} + \hat{\mu}_{ij} + \hat{u}_{e,t}, \quad R^2 = 70\%, \qquad (2)$$

the point estimate falls to 0.71 percentage points and can be interpreted as the change in travel times due to congestion effects and changes in infrastructure, i.e., when holding the spatial structure of origin-destination pairs constant. The increase in the overall R^2 from 0.1% to 70.0% provides evidence that commuting times are predominantly driven by

[5] For a detailed analysis of the mode of transport for the Greater Dublin Area, we refer to Commins and Nolan (2011), who link the choice of mode of transport to socio-economic characteristics using data from 2006.

location choices rather than changes in travel time for given origin-destination pairs. The empirical analysis of this study thus focuses on using a gravity model to explain how commuters choose the location of residence and work.

Rent price data

Rental prices are taken from Ireland's Residential Tenancy Board (RTB), which provides information and dispute resolution services to tenants and landlords.[6] All tenancy agreements in Ireland are required to be registered with the RTB in accordance with the Residential Tenancies Act 2004. Landlords may face fines of up to €4,000 and/or 6 months imprisonment if they fail to register. In addition to the rent level, the data records property-level characteristics (e.g. number of rooms, type of house). More than 78% of observations have Eircodes (Irish postal codes) which permit the rental data to be matched with EDs.[7]

We have rental data available going back to 2007, Quarter 3. Since the commuting data is only available for two points in time (2011 and 2016), we calculate average rents for the years 2007-2011 and 2012-2016, respectively, which we relate to commuting in 2011 and 2016. This approach also accounts for persistence in commuting behaviour as commuting flows recorded in 2011 and 2016 are likely to be determined by conditions that manifest throughout the previous years. Thus, taking only current or lagged rents seems inappropriate. Furthermore, we discard EDs for which there are fewer than 30 rent

[6] Data on rental prices is confidential. It was obtained by request to the RTB (https://www.rtb.ie/, last visited on July 1, 2019).

[7] Observations without Eircodes could not be included in the analysis. However, we do not find any systematic differences between rental data with and without Eircodes.

data points. Sufficient rental price data is available for 1,970 out of 3,409 Irish Electoral Divisions. Summary statistics are provided in the Supplementary Material.

Figure 2 shows a time-series graph of average rents where EDs are split into quartiles based on the empirical employment density distribution. The rental price level is strictly ordered by density groups, with high-density EDs exhibiting higher rent levels across all years. The drop in rents after 2007 is striking. Rents in the second group (between first and second quartile) fell by 28.7% between the second half of 2007 and 2011. A prolonged recovery only started in 2013, but the speed of recovery varied across groups. Rental price growth has been more pronounced for above-median EDs and EDs above the 3rd quartile, with growth rates of 19.4% and 26.3% over 2011-2016. For comparison, the growth figures for the EDs below the 1st and 2nd quartile are 9.5 and 9.7%, respectively, suggesting a divergence in rental prices between areas with high and low employment density.

[Figure 2 about here]

A cross-section of Dublin

Given its relative size and importance, we discuss the Dublin metropolitan area separately. Figure 3 provides insights into the urban structure of Dublin, the largest commuting area in Ireland. Sub-figures (a) to (d) show average journey time (in minutes), the job density, monthly rent (in e) and population density on the vertical axis. The horizontal axis is the distance to the Dublin city centre, which we take to be The Spire of Dublin (a 120m high monument on O'Connell Street). While this is a somewhat arbitrary location, it is only used here for illustrative purposes. The points in Figure 3 are averages per ED and the lines are fitted values from linear regressions with higher-order polynomials. Note that sub-figures (b) to (d) use logarithmic scales for the vertical axis.

[Figure 3 about here]

The relationship between journey time and distance resembles an inverted *u*-shaped function. Journey times are between 20 and 30 minutes in direct proximity to the centre and increase up to a peak of 35min on average at a distance of around 35 to 40km. Above 40km from the centre, travel times decrease; presumably because many residents in these areas do not commute to the centre of Dublin, but travel to alternative employment centres around Dublin. Job density, monthly rents and population density are decreasing with distance, but level off above 40km. Rents exhibit a much wider spread around the centre, with rents in the range of €750 to €2,000. By comparing the job and population density, it can be seen that, as typical for urban structures, the centre of Dublin shows higher density of jobs than population, while the two regression curves seem to align as we move away from the centre.

Methodology

The empirical analysis is based on gravity models. An approach using journey times directly as the dependent variable would require us to take either the workplace or the place of residence as given, with the distance to the workplace or distance to the residence as the commuters' choice variable. However, residence-job decisions are often taken simultaneously. A gravity model on the other hand allows us to explain bilateral commuting flows through both origin and destination factors. Another approach allowing for simultaneous location choice is to use multinomial models (So et al., 2001; Vega and Reynolds-Feighan, 2008). These models however rely on *ad hoc* categorisation (e.g. urban versus non-urban) and impose a limit on the number of spatial units, whereas a gravity model allows us to explore commuting at a spatially disaggregate level.

A cross-sectional model of commuting

Ahlfeldt and Wendland (2016) consider the cross-section commuting model

$$\pi ij = \tau tij + oi + dj + uij. \qquad (3)$$

The dependent variable π_{ij} is the logarithm of the probability of commuting from residence i to place-of-work j, i.e., $\pi_{ij} = \ln C_{ij}/(P_i)$, where C_{ij} the number of commuters from i to j and P_i is the number of residents. t_{ij} is a measure of geographic distance or travel time between i and j. The parameters o_i and d_j are push and pull factors that capture the attractiveness of i and j as location of residence and workplace. For example, o_i may include proximity to natural sights and d_j could depend on the accessibility of location j.

The model (1) provides insights into the spatial decay of commuting probabilities, and has been used to study urban structures. There are, however, a few drawbacks to the model: First, the additive fixed effects o_i and d_j capture *global* push and pull factors. In other words, model (1) assumes that, for example, ED j is equally attractive as a location for work for all i. However, the attractiveness of ED j as a workplace is likely to vary across i, even when observable measures of distance and travel time are accounted for. Secondly, this cross-section model does not allow one to disentangle the effect of specific location factors, such as rental prices, from other local characteristics captured by the push and pull factors. Both issues can be addressed in a two-period panel framework, which can exploit changes in commuting behaviour over time.

A linear first-difference gravity model of commuting

We consider an extension of the above base specification:

$$\pi_{ij,t} = f(r_{i,t}, r_{j,t}) + \boldsymbol{x}'_{i,t}\boldsymbol{\theta} + \boldsymbol{x}'_{j,t}\boldsymbol{\delta} + \mu_{ij} + \varepsilon_{ij,t}. \tag{4}$$

Here, the dependent variable is defined as above, but we add the time index t. The vectors $\boldsymbol{x}_{i,t}$ and $\boldsymbol{x}_{j,t}$ are observable, time-varying characteristics of locations i and j. These include the number of jobs, the number of residents and socio-economic characteristics. The control variables include property characteristics from the RTB database as well as the number of residents, the number of jobs, other demographic factors and socio-economic variables which are taken from the CSO Census.[8]

The pair-wise fixed effects μ_{ij} captures the time-invariant attractiveness of commuting from residence location i to place-of-work location j. μ_{ij} depends on distance which is in principle observable (as Euclidean or road distance) and other factors that are not easily captured with readily available data. For example, the demand for commuting from i and j may be low if, for example, i has a high share of luxury apartments and j is dominated by low-skilled manual labour, implying that residents of i have a low propensity of commuting to j. To account for these unobserved factors, we estimate (4) in first differences:

$$\boxed{\Delta\pi_{ij,t} = \Delta f\left(r_{i,t}, r_{j,t}\right) + \Delta\boldsymbol{x}'_{i,t}\boldsymbol{\theta} + \Delta\boldsymbol{x}'_{j,t}\boldsymbol{\delta} + \Delta\varepsilon_{ij,t}}. \quad (5)$$

[8] RTB variables are: share of property type (apartment, detached, semi-detached, terrace, part house, other), number of bedrooms (1 to 5 or more), rent frequency (fortnightly, monthly, quarterly, weekly, annual), number of tenants (1 to 4 or more), tenancy length (1-6 months, 7-9 months, 10-12 months, 12 or more months), additional costs incurred by the tenant (TV license, waste, electricity, oil, gas, other), monthly rent in e, renewal of tenancy agreement, floor size in square feet.

Variables from the CSO Census (Small Area Populations Statistics): average age, age by age group, total population, share female, share foreign born, share married, age of housing stock by period built (8 time periods), type of heating in houses, household composition (single, married or unmarried, with or without children), accommodation type and number of rooms, education level (8 groups ranging from no formal education to PhD level), 8 socio-economic groups (e.g. low-skilled or high professional), broadband access, share of students and unemployment rate.

We refer to the Supplementary Material for more details and summary statistics.

The main interest lies in the role of r_i and r_j, which denote the rental price at location i and j in logarithmic terms. We consider two specifications for the link function $f(r_{it}, r_{jt})$:

$$\boxed{f(r_{it}, r_{jt}) = \alpha(r_{jt} - r_{it})} \quad \text{(rental differential)} \qquad (6)$$

$$\boxed{f(r_{it}, r_{jt}) = \beta_1 r_{it} + \beta_2 r_{jt}} \quad \text{(additive effect)} \qquad (7)$$

The aim is to estimate the effects α, β_1 and β_2. We refer to $r_{jt} - r_{it}$ as the rental differential. The rationale for considering the rental differential specification is that location decisions may be determined by relative prices between centre and periphery rather than the absolute levels only. The testable hypothesis is that, *ceteris paribus*, a larger rental price gap between destination and origin location makes commuting more worthwhile, thus increasing the commuting probability. For example, a positive coefficient on the rental differential, i.e., $\alpha > 0$, implies that the commuting probability is increasing in the rental differential. The additive model provides insights into whether location decisions are primarily driven by pull factors (low rents in the periphery) or by push factors (high rents in the centre). With regard to the additive model, we expect $\beta_1 < 0$ and $\beta_2 > 0$.

Post-double-selection lasso

Since gravity models are concerned with the relation between two units, i.e., origin and destination location, there is a need to adjust for confounding factors both at the origin and destination. Given the large set of putative controls, an empirical concern is to select the right set of control variables. The total number of variables included in $\boldsymbol{x}_{i,t}$ (residence-specific controls) and $\boldsymbol{x}_{j,t}$ (place-of-work controls) is 192, many of which are highly collinear. Omitting relevant control variables induces an omitted variable bias, whereas including too many leads to over-fitting and inefficient causal inference.

To appropriately account for confounding factors, we consider the post-double-selection strategy of Belloni et al. (2014), which provides a data-driven method for selecting controls that is rooted in the Machine Learning literature. The framework has been extended to the panel data setting with fixed effects in Belloni et al. (2016). The methodology relies on employing the Lasso estimator due to Tibshirani (1996). The Lasso is a linear regularisation method that, like OLS, minimises the squared error, but at the same time penalises the absolute size of coefficient estimates. Due to penalisation approach, the Lasso sets some coefficient estimates to exactly zero, and thus removes some variables from the regression model.

The double-selection technique allows to exploit the strength of the Lasso as a prediction technique for causal inference. Unlike standard approaches for variable selection, such as the general-to-specific approach, the method does not suffer from pre-testing bias issues. The double-selection algorithm proceeds as follows: (a) The dependent variable (here, π) is regressed against the set of controls (i.e., $\boldsymbol{x}_i$, $\boldsymbol{x}_j$); (b) the variables of interests, i.e., either r_i and r_j or $(r_j - r_i)$, are regressed against the controls; and (c) the final estimate is the OLS estimate of π against the variables of interest and the controls selected by the Lasso in Step (a) and (b). The advantage of the post-double-selection approach is improved and robust causal inference on the parameters of interested (β_1, β_2 and α in our case) without the need for manual and error-prone model selection. A drawback is that the approach cannot provide valid inference for coefficients on individual controls.

Over-dispersion of the dependent variable

Another concern for the estimation is due to the nature of the dependent variable. As common with count data, the number of commuters is highly over-dispersed. 51.4% have only one commuter and 90.2% have 10 or fewer commuters.

We consider two different approaches to address the issue. First, as in Ahlfeldt and Wendland (2016), we employ a linear model where the dependent variable is the logarithm of the probability of commuting from ED-to-ED rather than the number of commuters. This seems to address the issue of over-dispersion to some extent (see Figure

S1 in the Supplementary Material). In addition we also consider a fixed effects Poisson model with the count of commuters as the dependent variable, which is shown to be robust even in the presence of over-dispersion (Wooldridge, 1999). While the fixed effects negative binomial estimator is another popular choice in this setting, Guimarães (2008) emphasises that it only controls for fixed effects under a narrow set of assumptions.

Results

Rental prices and commuting flows

We first present results for the linearised gravity model in (5) with rental differential and additive rental effects as defined by equations (6) and (7). The model is estimated in first differences to eliminate the pairwise fixed effect. The estimation results are shown in Table 2. The first two models include bilateral commuting flows with at least one commuter, while the third and fourth model include flows with at least 5 commuters to verify the robustness of results. In each table, we present OLS results without additional controls and post-double-selection results, where the set of control variables is chosen by the Lasso estimator as proposed by Belloni et al. (2014). We confine the discussion and interpretation of the results to the rental variables.[9]

[Table 2 about here]

The OLS regression results in Panel A in Table 2 indicate that commuting probabilities are increasing in the rental differential when adjusting for origin-destination fixed effects. The post-double-selection methodology, which adds Lasso-selected controls to the estimation, confirms this insight. For example, the point estimates in Panel A, column (3) suggest that a 1% rise in the rental differential at the origin is associated

[9] The post-double-selection methodology was implemented in Stata using the *pdslasso* package (Ahrens et al., 2018, 2019). Full regression output can be found in the Supplementary Material.

with a 0.2% rise in commuting probability. We find the association to be significant at the 5% level in 5 out of 8 specifications. Panel B in the same table separates the rental differential into prices at the location of residence and workplace. The results reveal that the statistical association appears to be more robust for rental prices at the location of residence.

One concern is that the linear specification does not appropriately capture the relationship between rents and commuting. Table 3 considers the fixed effects Poisson estimator, both with rental differential and additive effects, while we include the same set of controls as in the linear specifications above. The effects are generally larger in magnitude compared to the linearised first-difference gravity model in Table 2. In particular, the association with workplace rents is statistically significant, with point estimates of 0.22 and 0.79 for the national and Dublin sample. The discrepancy in magnitude between the linearized specification and the Poisson model might be because the former is less robust to over-dispersion and also known to be biased in the presence of heteroskedasticity (Silva & Tenreyro, 2006).

[Table 3 about here]

We refrain from drawing causal inferences based upon the estimation results in the previous sections. Rents themselves are determined by the interaction of property demand and supply, which in turn are affected by past rents. However, the gravity model allows us to establish a statistical association that we can exploit for the second part of the analysis. The ultimate aim of the analysis is to predict the partial equilibrium effect of changes in the spatial structure of rents on commuting times.

Commuting times

The previous section has provided evidence for a statistical association between rental prices and commuting flows. We now predict the effect of changes in rental prices on commuting times. For this purpose, we induce a 10% shock in employment centres which we define as EDs for which the job density is above the 50th, 75^{th} and 90th percentile. The predicted changes in one-way journey times are shown in Table 4 and are based on the fixed effects Poisson models. For the calculation, we assume that bilateral journey times are fixed, i.e., we rule out changes in the journey duration from i to j due to, for example, changes in infrastructure. We obtain the expected change in total journey times by first predicting the change in the number of commuters between each origin and destination following the 10% shock in rents. We then multiply the predicted change in the number of commuters by the average journey time in 2016, which we hold constant.

[Table 4 about here]

Average predicted changes in journey minutes along with confidence intervals are presented in Table 4. Point estimates range between 0.08 and 0.39 on the national level and between 0.15 and 1.67 for Dublin. For example, the predicted change in journey minutes based on the differential model is 0.24 and 0.43 for Ireland and the Dublin region when relative rents in EDs with above-median employment density increase by 10%. Naturally, the effect size is smaller when only the top 25% or 10% of EDs are exposed to the shock. This finding is in line with the expectation that high rental costs in urban centres provide an incentive for commuting, while high costs in sub-urban areas discourage commuting.

Conclusion

A common narrative holds that high housing costs force people to commute longer distances. In this study, we investigate the statistical association between commuting patterns and housing costs, which we approximate using rental prices. We relate bilateral commuting flows to spatially disaggregated rent data utilising a panel gravity model that accounts for pairwise, i.e., origin-destination fixed effects. The results for Ireland are consistent with the notion that the demand for commuting is increasing in the rental differential between two locations. In other words, we find evidence that workers face a trade-off between high commuting costs and low housing costs when making location decisions. For example, a 10% rise in rents within the top quartile of employment centres is associated with daily one-way commutes being longer by around 0.1 to 0.3 minutes nationally and by around 0.2 to 1.2 minutes for the Dublin metropolitan area. While our method accounts for time-invariant factors affecting commuting and we apply data-driven methods to adjust for a range of observable confounding factors, future work is needed to establish if the associations we have reported are causal.

The developments in the Irish rental market described in this paper reflect a period of pronounced changes. Other places and times are likely to experience less extreme developments in price levels and relative prices. Nevertheless, our results underline the potential conflict between trends in local planning restrictions and broader environmental and social objectives such as climate policy or efforts to improve public health. It is well established that restrictive planning can raise house prices (Hilber and Vermeulen, 2016). Local pressure for restrictions is likely to be more pronounced where prices of existing properties are higher and local interest groups are longer-established and better resourced (Taylor, 2013; Taylor and Hurley, 2016). In a monocentric city these places would likely be closer to the city centre. This mechanism could provide an impetus for the spatial housing cost gradient to steepen over time, contributing to growing commuting distances.

If journey times for commuters continue to rise, this is likely to have negative monetary, health and environmental consequences. The costs of longer journeys will fall partly on individuals but also on government budgets as many countries or cities subsidise particular transport modes. The existing challenges of developing appropriate decarbonised transport systems will be compounded. Long commutes can harm well-being and mental health, and commuters may be exposed to additional air pollution. Our analysis also suggests that demand for housing in sub-urban areas rises with increasing rents in the city centre, which in turn may lead to sprawl: a dispersed low-density urban structure. Finally, there may be distributional consequences to added commuting as some socioeconomic groups bear more of the costs of adjustment than others.

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Means of transport in %	National 2011	National 2016	Dublin 2011	Dublin 2016
Active commuting	13.3	13.55	15.78	16.58
Foot	10.70	10.15	11.76	11.15
Bicycle	2.60	3.40	4.02	5.43
Public transport	9.44	10.36	17.45	18.77
Bus	5.87	6.48	10.28	11.06
Train	3.57	3.88	7.17	7.71
Private motorised transport	77.22	76.08	66.75	64.64
Motor bike	0.55	0.47	0.82	0.67
Drive car	67.70	66.86	59.22	57.57
Passenger in car	4.45	4.44	3.67	3.50
Van	4.52	4.31	3.04	2.90
Working from home	0.02	0.01	0.02	0.01
One-way journey to work in minutes	25.91	27.32	30.46	32.23

Table 1: Self-reported one-way journey time and means of travel in 2011 and 2016 by region.

	(1)	(2)	(3)	(4)
Dependent variable: $\Delta\pi_{ij,t}$				
Panel A: Rental differential				
OLS				
$\Delta(r_{jt} - r_{it})$	0.204***	0.224***	0.0879*	0.0921
	(0.0257)	(0.0345)	(0.0381)	(0.0524)
Post-double-selection				
$\Delta(r_{jt} - r_{it})$	0.0317	0.00373	0.234***	0.525***
	(0.0359)	(0.0601)	(0.0515)	(0.0924)
Panel B: Additive effect				
OLS				
Δr_{jt}	0.159***	0.176***	0.0598	-0.0835
	(0.0308)	(0.0509)	0.0419)	(0.0667)
Δr_{it}	-0.245***	-0.257***	-0.119**	-0.257***
	(0.0310)	(0.0431)	(0.0459)	(0.0684)
Post-double-selection				
Δr_{jt}	-0.0456	-0.0450	0.227***	0.891***
	(0.0483)	(0.101)	(0.0645)	(0.161)
Δr_{it}	-0.127**	-0.0102	-0.211**	-0.286**
	(0.0481)	(0.0733)	(0.0674)	(0.111)
Obs.	78620	58270	32471	23526

Region	National	Dublin	National	Dublin
Threshold	1	1	5	5

Note: Standard errors in parentheses are robust to arbitrary forms of heteroskedasticity.

∗ $p < 0.05$, ∗∗ $p < 0.01$, ∗∗∗ $p < 0.001$

Table 2: Commuting flows in Ireland and Dublin. Linear specification in first-differences.

	(1)	(2)

Dependent variable: C_{ij}

Panel A: Rental differential		
$(r_{jt} - r_{it})$	0.203***	0.354***
	(0.0359)	(0.0596)
Panel B: Additive effect		
r_{jt}	0.217***	0.787***
	(0.0436)	(0.108)
r_{it}	-0.0863	-0.0706
	(0.0472)	(0.0722)
Obs.	157240	116540
Region	National	Dublin

Note: Standard errors in parentheses are robust to both arbitrary heteroskedasticity and within-ED correlation. All models include time effects and ED-level fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Commuting flows in Ireland and Dublin. Fixed effects Poisson.

	National			Dublin		
	mean	low	high	mean	low	high

Difference						
50th percentile	0.244	0.115	0.374	0.431	0.214	0.649
75th percentile	0.176	0.087	0.265	0.310	0.161	0.460
90th percentile	0.083	0.043	0.123	0.146	0.079	0.213
Additive						
50th percentile	0.387	0.159	0.614	1.667	1.118	2.216
75th percentile	0.227	0.109	0.346	0.915	0.626	1.204
90th percentile	0.101	0.051	0.150	0.395	0.273	0.517

Note: 'mean' is the average rise in journey times. 'low' and 'high' are the averages of the 95% confidence interval.

Table 4: Predicted change in one-way journey minutes.

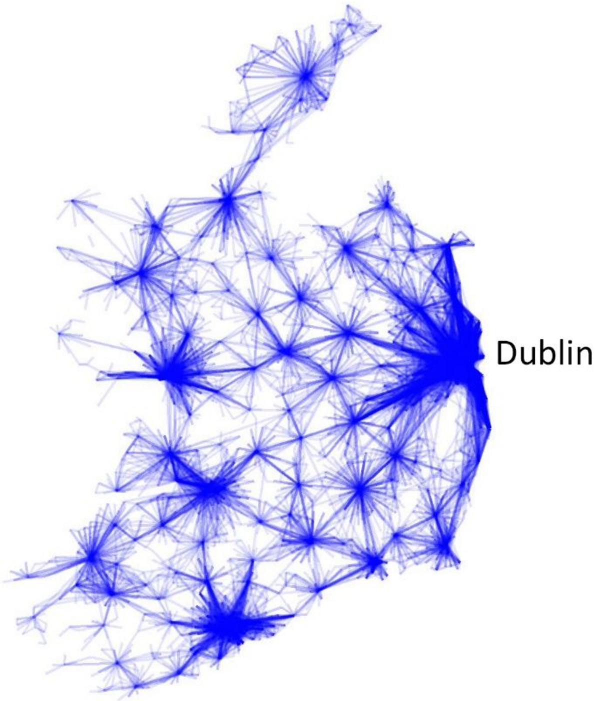


Figure 1: Map of bilateral commuting flows in Ireland in 2016

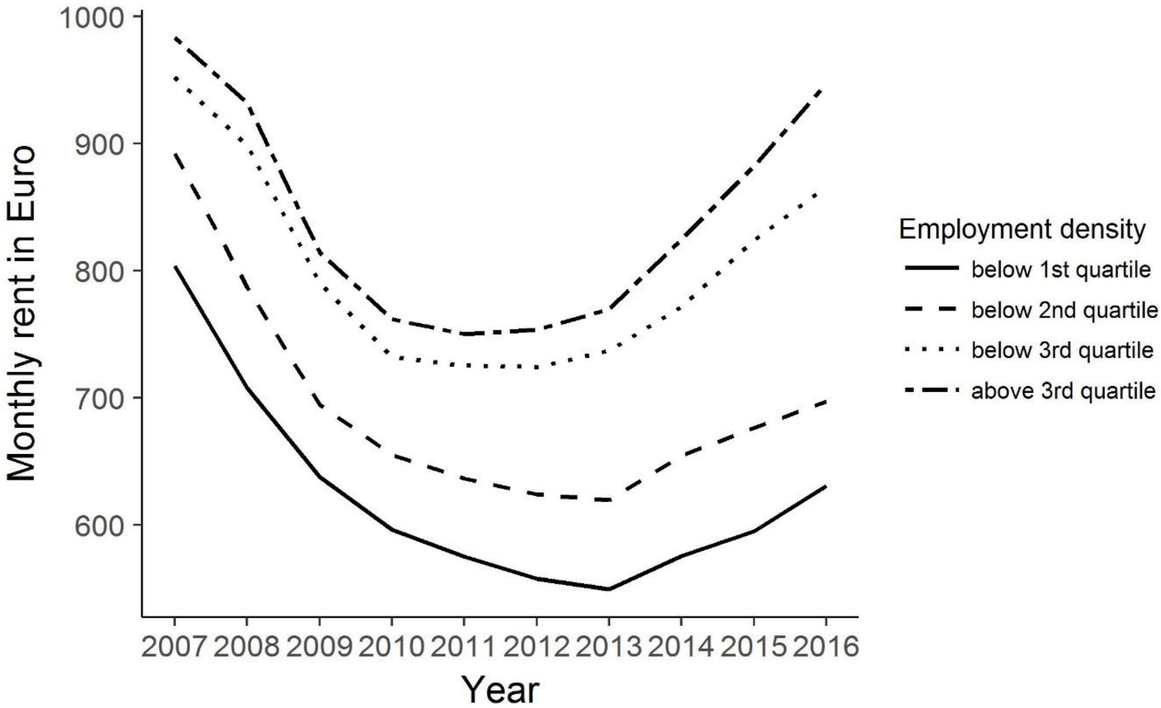
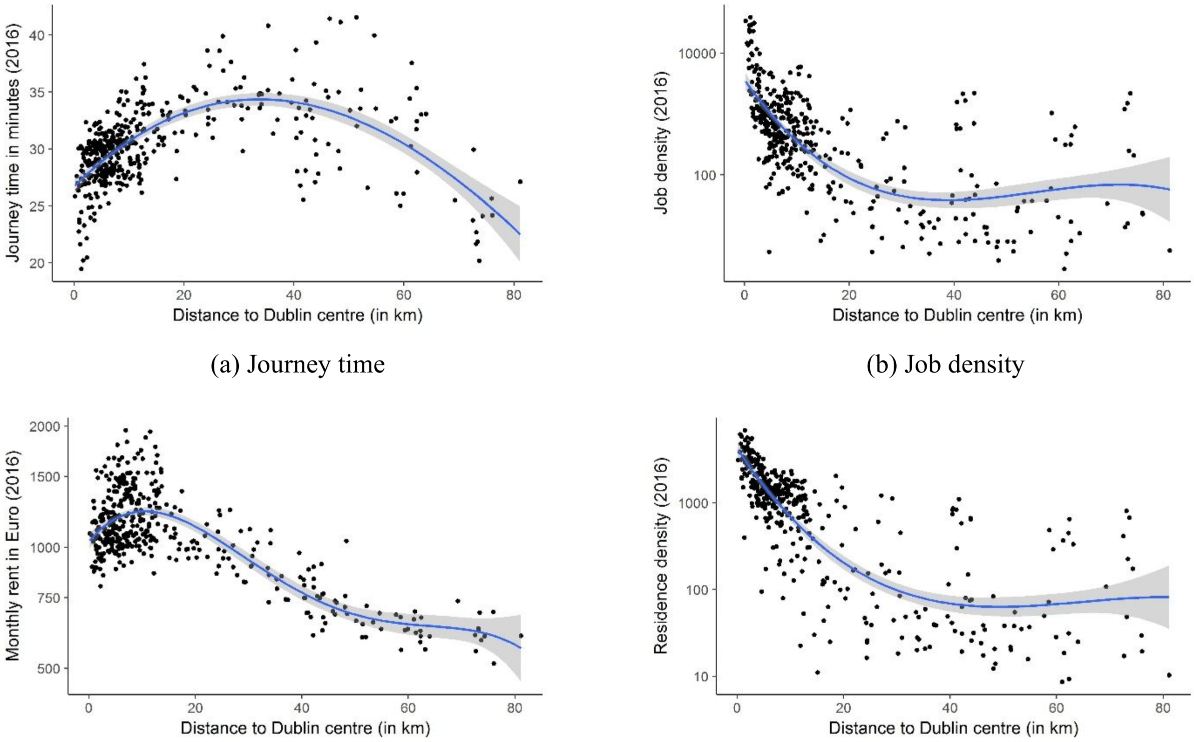


Figure 2: Time series graph of average rents grouped by employment density quartile



(a) Journey time (b) Job density

(c) Monthly rent (d) Population density

Figure 3: Dublin cross-section. Journey time (minutes), job density, monthly rent (in €) and population density as a function of distance to the centre of Dublin