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Local Labour Market Concentration and Wages in Ireland

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Abstract

Economic theory predicts that monopsonistic employers suppress wages below the marginal product of labour. We measure local labour market (LLM) concentration in Ireland from 2008 to 2019 using an employment share Herfindahl-Hirschmann Index (HHI), a proxy for monopsony power. LLM concentration in Ireland has followed a similar pattern to the US and UK since 2008, surging as firms closed during the financial crisis and falling throughout the recovery. There is substantial variation in HHI by region, with the Midlands having the highest average HHI in every year. As elsewhere, workers in concentrated LLMs earn less. To investigate causality we use a leave-one-out instrumental variable design that exploits national trends in firm numbers within industry to predict local HHI. Using this approach we find an elasticity of -0.27, meaning a 10% increase in the HHI reduces earnings by 2.7%.

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1 Introduction

Labor markets in which a small number of firms dominate employment are *concentrated*. Classical monopsony theory predicts that employers in concentrated labour markets hold wages below the marginal product of labour, and employ fewer workers than would be employed in a competitive market.[1] Long considered implausible in modern labour markets, recent evidence that concentration suppresses wages has revived interest in classical monopsony,[2] with implications for competition regulation, trade unionization, and minimum wage legislation.

We present the first evidence on local labour market (LLM) concentration in Ireland. We find substantial variation in concentration across both: industries and regions, with the Midlands sticking out as the most concentrated region in every year from 2008 to 2019, and Greater Dublin the least. Concentration surged during the financial crisis, but returned to pre-crisis levels by 2012, subsequently declining further until stabilising in 2016. Rinz (2020) and Abel et al. (2018) document similar patterns for the US and UK respectively.

Importantly, concentration is associated with lower earnings. This is consistent with employers in concentrated markets exploiting monopsony power to suppress wages. To investigate causality, we use the 'leave-one-out' instrumental variable method of Azar et al. (2020a) to show that national trends in firm count within an industry – presumably driven by underlying technological and national-level regulatory changes – predict lower earnings in a LLM. We estimate that a 10% increase in concentration reduces earnings by 2.7%. These findings suggest that pro-competitive regulatory policy and minimum wage hikes could both benefit workers and increase total economic output.

Consider a monopsonist employer – the only employer in a labour market. In order to attract marginal workers, who have relatively weak labour market attach-

[1] Robinson (1933).

[2] See Azar et al. (2020a), Benmelech et al. (2020), Hershbein et al. (2019), and Rinz (2020) for recent studies in the US, Bassanini et al. (2020) and Marinescu et al. (2021) for France, Abel et al. (2018) for the UK, Martins (2018) for Portugal, and Bassanini et al. (2023) for a study of Denmark, France, Germany, Italy, Portugal, and Spain.

ment (for example, those nearing retirement, or second earners), the monopsonist must offer higher wages. The monopsonist weighs the benefit of a larger workforce against the cost of matching the new, higher wage offer for its existing employees. In equilibrium the monopsonist hires fewer workers than would be hired in a competitive market, resulting in lower employment – and as it declines to bid wages up in order to attract them, wages are also lower than in a competitive market.[3] This argument extends to markets with few employers, or where one employer dominates. In contrast, employers in a competitive market do not hesitate to post higher wages in order to attract marginal workers because this cuts mostly into competitors' bottom lines.

Although there are many employers in Ireland, employment options for a particular worker may be limited by specialty and geography. In this case employers in concentrated markets may exploit monopsony power to suppress wages. We test this prediction of monopsony theory in Irish LLMs.[4] Following recent studies on the US and Europe, we define a LLM as an industry-region, with industry given at the two-digit NACE level, and region based on NUTS 3 designation used to allocate EU structural funds.[5] This approximates the employment options open to a worker, an approach that has been validated by a variety of alternative and/or more sophisticated definitions of employment options that are not possible with our data.[6]

[3]Perfectly price-discriminating monopsonists do no face this tradeoff, and so hire the socially efficient number of workers.

[4]In a companion paper we investigate the effect of concentration on employment, finding that minimum wage hikes increase employment and hours worked in concentrated LLMs (Devereux and Studnicka 2023).

[5]The two-digit NACE classification contains a similar number of industrial categories as the three-digit NAICS classification that has been used for the US. Although NUTS 3 regions are not explicitly designed to minimize cross-border commuting as are US commuting zones, they are similar in terms of geographic size and population, and exhibit little interregional commuting aside from Dublin and the Mideast, which we combine into the Greater Dublin region.

[6]Azar et al. (2020a) define a LLM as an occupation-region and finds similar results to Rinz (2020), who defines a LLM as we do. Arnold (2021) uses the same US dataset as Rinz (2020) and, augmented

To measure monopsony power, we calculate the employment-share Herfindahl-Hirschman Index (HHI) of each Irish LLM using the Business Register (BR). The HHI is the sum of squared employment shares across all employers within a LLM. For example, a monopsonist employs all workers in its LLM, and so has a share of one, and the market has a HHI of one. Two equally-sized competitors each employ half the market, which has a HHI of one-half. A perfectly competitive market – with an infinite number of employers, each having an infinitesimal employment share – has a HHI of zero. We find that Irish LLMs have HHIs ranging from 0.002 to one. The average HHI is 0.15, which is the US Federal Trade Commission's threshold for a moderately concentrated product market (although since HHIs are sensitive to the delineation of markets, this is not an apples-to-apples comparison). If LLMs approximate workers' employment options and firms exert monopsony power, then all else equal, earnings in concentrated LLMs should be lower.

Irish workers in concentrated LLMs earn less. We find an elasticity of -1% between HHI and average earnings as reported by the Irish Labour Force Survey (LFS). This holds with industry-by-region (that is, LLM) and region-by-time fixed effects, but is statistically insignificant in all specifications. This negative relationship is not causal. Even within market, different shocks may drive wages and the HHI in different directions. For example, suppose a small firm experiences a positive productivity shock. It hires more, driving market wages up, and offsets its larger competitor's employment share, driving HHI down. However, if instead the large firm receives the shock, it bids wages up in order to hire more, and in doing so also raises the market's HHI.[7]

To estimate the causal effect of monopsony power on earnings, we leverage national-level trends to explain local earnings, purging the portion of concentration that is determined locally. Following Azar et al. (2020a) we instrument local concentration using the leave-one-out average of log inverse firm count within industry, across region. Suppose the number of firms in a given industry in any

with cross-industry exposure, and finds again similar results.

[7]Miller et al. (2022) make an analogous argument for product markets.

region is given by N; then the leave-one-out average for a given region is the average of $\ln(1/N)$ across all other regions. Local productivity shocks are excluded, obviating the problem noted above.

We contribute to a growing recent literature on LLM concentration and earnings. Traditionally, empirical research on the relationship between the monopsony power and wages focuses on specific occupations. Example include bursing (Staiger et al. 2010, Matsudaira 2014), teaching (Landon and Baird 1971, Luizer and Thornton 1986 Falch 2010, Ransom and Sims 2010), and retail (Ransom and Oaxaca 2010, Dube et al. 2019). Recent evidence shows, however, that predictions of the monoposonistic model are supported in more general settings. In particular, papers by Qiu and Sojourner (2019); Azar et al. (2020b), Benmelech et al. (2020), Rinz (2020), Marinescu et al. (2021) examine the effects of concentration on wages and find that more concentrated local labour markets are characterised by lower wages. Despite different definitions of LLMs (for example using commuting zones as geographical division), different ways of calculating concentration (vacancy shares or employment shares within different occupations or industries), and different countries studied, the findings in these papers are consistent with the predictions of the monopsony model.

This paper is organised as follows. Section 2 describes our data and our definition of labour markets and concentration. Section 3 examines the evolution of concentration in Ireland over time and its determinants, as well as cross-sectional variation by region and industry. Section 4 presents our empirical model of concentration and earnings and section 5 the results. In section 6 we present robustness checks. The final section concludes.

2 Data

We use two data sets from the Central Statistics Office (CSO): the Irish Business Register (BR) and the Labour Force Survey (LFS). We use the BR to calculate employer concentration at the local labour market (LLM) level, which we match to worker-level earnings data from the LFS. In this section we first discuss our definition of the LLM in subsection 2.1. We then turn to our concentration measure in subsection 2.2. In the final subsection we describe the earnings data.

2.1 Defining the Local Labour Market

Following recent literature using US administrative data (Benmelech et al. 2020, Rinz 2020) we define a LLM as a given industry in a given geographic region. While using geography to approximate the effective market facing a worker is uncontroversial, different studies have taken various approaches to approximating what type of job is a relevant option. Studies that use occupations rather than industries (Azar et al. 2020b, Azar et al. 2020a, Marinescu et al. 2021) have found similar results to those using industry, suggesting a robust relationship between earnings and various approximations of relevant jobs. Furthermore, studies that allow for spillovers across industries (Arnold 2021) or occupations (Schubert et al. 2021) find that the earnings-concentration relationship estimated from simple measures is robust to more sophisticated measurement of a worker's outside options. On the other hand, Dodini et al. (2020) find that using a skill-based LLM definition yields lower concentration measures than those based on occupation or industry. However, they do find a similar negative relationship between concentration and earnings.

2.1.1 Industrial Classification

We classify industries as two-digit NACE categories, the finest industrial definition common to both data sources.[8] This gives us 88 categories, far fewer than the 1005 four-digit NAICS/SIC industrial categories used by US studies, but comparable in number to the 85 two-digit SIC industrial codes used in the study of concentration in the UK by Abel et al. (2020).[9] Using fewer categories

[8]Although the BR reports industry at the four-digit NACE Rev. 2 industrial code level, the LFS reports only the two-digit level.

[9]Abel et al. (2020) find a negative correlation between wages and concentration in the UK, but do not conduct an instrumental variables analysis to explore causality.

mechanically lowers concentration measures, as there are by definition (weakly) more firms operating within a broader industrial category in any given area. Our measurements should therefore be taken as a conservative benchmark compared to US studies, but are comparable to the aforementioned study of the UK.[10] Rinz (2020) observes that only a quarter of job-switchers remain within the same four-digit NAICS industry, suggesting our broader measure has the advantage of not artificially separating related industries.[11] Moreover, analyzing cross-industry job flows, Corella (2020) finds that LLMs can be well-approximated using as few as 60 industry clusters. Overall, our broad industrial definition accommodates cross-industry job-switching better than comparable US studies, at the expense of a potentially underestimating concentration. Classifying industry more broadly also reduces sample size, as there are fewer LLMs when industry is more broadly defined, hampering statistical power.

2.1.2 Geographical Classification

Studies of the US and France have used commuting zones to delineate LLMs geographically. In the US these are developed by the Department of Agriculture specifically to group together counties in a way that minimizes cross-border commuting.[12] Although no equivalent geographic unit is readily available for Ireland, the NUTS 3 regions designed to allocate EU structural funds are similar in population size and geographic area.

We use NUTS 3 regions as the geographic basis for our definition of a LLM.[13] As the LFS reports the region both of residence and employment for a worker,

[10] Marinescu and Wolthoff (2020) observes that the elasticity of applications to wage offers within a six-digit SOC occupational code is negative. Azar et al. (2020a) argue that this indicates the six-digit SOC, which they use to define a LLM, may itself be overly broad. There are 1,463 six-digit SOC codes, comparable to the number of four-digit NAICS codes.

[11] The LFS asks workers about the industry of their previous occupation, but this data is not made available to non-CSO researchers so we cannot construct a similar measurement for Ireland.

[12] See Azar et al. (2020a) for an discussion.

[13] Abel et al. (2020) uses NUTS 2 regions, each containing around one million jobs – substantially more than the average US commuting zone.

we observe that in most cases there is little cross-region commuting – only 11% of workers commute across NUTS 3 borders nationally – supporting this delineation. However, 35% of workers residing in the Mideast commute to Dublin. We therefore consider Dublin and the Mideast to be effectively a single commuting zone. We term this modified regional delineation as NUTS 3*. As a result we have a total of seven regions across Ireland consisting of roughly similar populations to US commuting zones.[14] To calculate concentration we assign firms to NUTS 3* groups based on the county of registration.

When defining the NUTS 3 region, we need to be aware of the fact that the definition of the NUTS 3 regions in Ireland was revised under the 2014 Local Government Act. The revision transferred South Tipperary from the Southeast into the Midwest NUTS 3 region, and Louth from the Border to the Mideast NUTS 3 region. Because the LFS reports NUTS 3 as the finest geographic unit – reporting pre-revision regions until 2011 and post-revision regions thereafter – we must change the geographic definitions slightly in the post-revision period. Luckily the revision does not constrain calculations based on the BR data, as the BR reports the county or sub-county in which a given firm is registered. We calculate the exact HHI corresponding to pre- and post-revision regions, which we then match to the corresponding units in the LFS.

In sum, we define LLMs according to the above categorisations of geography and industry, as well as by year. We define a market m as an industry-region; for example, financial service activities (NACE 64)-Midlands; and construction of buildings (NACE 41)-Southwest are two markets we observe when defining the LLM at the two-digit NACE-NUTS 3* level. With 88 two-digit NACE categories and seven NUTS 3* categories, there are a maximum of 88×7 markets each year, but there are fewer in practice because not all industries are active in every region in every year.

[14]These are: Border, Greater Dublin, Midlands, Midwest, Southeast, Southwest, and West. See appendix A for a discussion of interregional commuting.

2.2 Measuring Concentration

We measure labour market concentration using the Herfindahl-Hirschman Index (HHI) of employment. The HHI is widely used by researchers and policymakers, having theoretical justification[15] as well as several intuitive properties.

Consider a market m containing one or more firms. Each firm f employs a number of workers e_f. The total number of workers employed in the market is $E_m \equiv \sum_{f \in m} e_f$, and any firm f's employment share is $\frac{e_f}{E_m}$. The HHI is defined as the sum of squared employment shares:

$$HHI_m = \sum_{f \in m} \left(\frac{e_f}{E_m} \right)^2 \tag{1}$$

which ranges from just above zero to one. A monopsonist employer employs every worker in its labour market, having an employment share of one. The market then has a HHI of one, the highest possible level of concentration, whereas a labour market split evenly by two firms has a HHI of one-half. The US Department of Justice / Federal Trade Commission guidelines consider a HHI of 0.15-0.25 as moderately concentrated and above one-quarter to be highly concentrated, which corresponds to four equally-sized firms. As the number of firms in a market grows large and each possesses a small share of employment, the HHI trends towards zero.

The BR reports the number of workers employed by each active enterprise in Ireland at the annual frequency. Each enterprise is associated with a county and an industry, which we use to assign it to a LLM. We use these employee counts to calculate the employment shares of firms in a LLM, from which we calculate the HHI concentration index. The county depends on the address at which the enterprise is registered for revenue purposes, which may not correspond to the operating location. This introduces measurement error to our HHI calculation, which should be considered with this caveat.[16]

[15] A Cournot model of quantity competition in the labour market produces a wage markdown proportional to the HHI of that market.

[16] The full sample of the Earnings Analysis from Administrative Data Sources (EAADS) could be

The BR data is available for the period 2008-2019. We use the entire span in our descriptive analysis of market LLM concentration and calculate the HHI of each LLM in each year.

Some studies use job posting (Azar et al. 2020a) or hiring (Marinescu et al. 2021, Dodini et al. 2020) rather than employment to calculate market shares. These yield results quantitatively similar to studies using employment. Moreover, these studies find similar results using employment as a robustness check; additionally, Marinescu et al. (2021) reports that hiring and employment are highly colinear in France.

2.3 Earnings

The Labor Force Survey (LFS) is a nationally-representative survey of Irish households, reporting individual-level data employment status, industry, and region both of work and residence. One of the caveats for our analysis is that over our sample period, the survey does not contain precise information on income; rather, it groups individuals into income deciles based on income bands set by the CSO. We use the information on income deciles to calculate the midpoint income for each income band and calculate average and median midpoint income per worker at the LLM level.

The second caveat is the large number of missing information regarding the income decile. Since the information on income decile is available from 2009 on, we limit our analysis of concentration and earnings to the 2009-2019 period. We present the summary statistics of both variables of interest for the estimation sample in Table 1. At first glance we can see that the average midpoint income was around €486, while the average HHI was 0.15.[17]

used to construct HHI measurements based on the location at which the worker resides, but these data are not presently available to researchers outside the CSO.

[17]For comparison, Marinescu et al. (2021) find that the average LLM concentration in France is 0.17.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Average Midpoint Income	5,505	486.47	150.22	70.5	1364
HHI	5,505	0.15	0.2	0.002	1

A unit of observation is a LLM-year. A LLM is an industry-region, with industry defined at the two-digit NACE level and region at the NUTs 3* level.

3 Local Labour Market Concentration in Ireland

In this section we present results on labour market concentration Ireland over the period of 2008-2019. National concentration has followed the same trend as average concentration at the LLM level, peaking during the 2009 crash, and falling below 2008 levels by 2013. This is driven by firm exit, broadly distributed across the country. ¡mention decomposition¿

3.1 National Trends

Employment concentration within industries has varied substantially both at the local and national level over 2008-2019. Figure 1 presents time series of concentration using two alternative labour market definitions. Panel (a) presents average concentration by industry, classing all employment in that industry nationwide in a single labour market. There are 88 labour markets according to this definition: one for each two-digit NACE industry. Panel (b) uses our LLM definition of an industry-region, showing average concentration over every LLM. The former labour market definition mechanically produces smaller HHI measurements, as more firms are included in each market.

Both national and local concentration exhibit a surge during the post-2008 downturn. Concentration then steadily declines until stabilising in 2016. Qiu and Sojourner (2019) and Rinz (2020) find a similar pattern over the same time period for the US, as does Abel et al. (2020) for the UK.[18]

Figure 2 shows that the crisis-era concentration surge was driven by firm deaths, and the subsequent decline by firm births. Before the crisis, there were around 5200 firms in an average two-digit NACE sector at the national level, shown in panel (a). By 2010 this fell to around 4400. Starting in 2010 firm numbers gradually recovered, with the number of firms exceeding 5400 in 2019. At the LLM level, we see a similar drop in the number of firms (from around 1350 to around 1200 firms per LLM) with a steady recovery; the number of firms per LLM exceeded 1550 by 2019.

While national and local trends in concentration are similar over our sample period, these can diverge if large firms spread their operations across many regions, increasing concentration at the national level, but decreasing it in LLMs. Rinz (2020) and Hershbein et al. (2019) document such a divergence in the US over the period of 1976-2015, with national concentration in the US falling sharply in the 1980s and rising steadily until the financial crisis surge, while average local concentration fell from the 1980s to the 2000s (the latter finding being confirmed also by Lipsius 2018). Because LLM concentration has been falling in the US even as national concentration has increased, it has been rejected as a cause of declining real wages (Stansbury and Summers 2020, Rinz 2020, Lipsius 2018). Because the BR reports only county of registration rather than the county in which employees work, we would be unable to document such divergence even with a longer sample period: we must assign all employees of a given firm to the LLM in which the firm is registered.[19] Therefore the extent to which national and local trends differ is driven by the nonlinearity of the HHI; aggregating markets

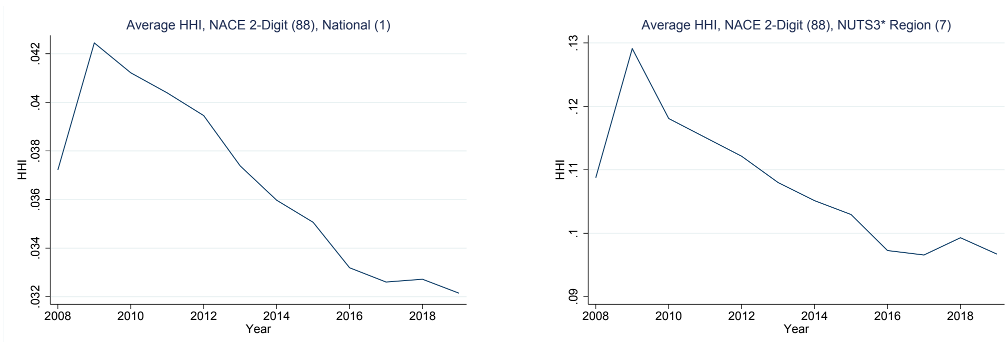
[18] Rinz (2020) shows that over this time period, US national and LLM-level concentration follow similar patterns, as they do in Ireland. However, during the 1990s to mid 2000s, national concentration in the US was increasing while local concentration decreased; Lipsius (2018) confirms this pattern. We are unable to investigate such a divergence in Ireland due to the unavailability of the BR prior to 2008.

[19] The full sample of the Earnings Analysis from Administrative Data Sources links employees to employers, and could reveal discrepancies between national and local trends as seen in the US. However, this dataset is only available to CSO researchers.

to the national level weights each LLM by its squared share of national employment, whereas taking the mean HHI over LLM weights each HHI by its share of employment. National level HHI therefore weights large markets relatively more than does mean HHI across markets.[20]

Figure 1: Average HHI by Year

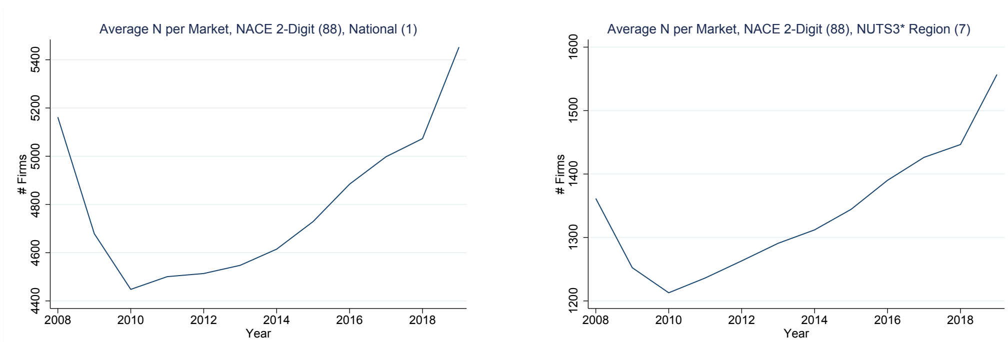
(a) (b)



This figure plots the HHI of concentration, defined in equation (1), for LLMs across Ireland. A LLM is an industry-region in a given year. Our NUTS 3* grouping follows the EU structural funds NUTS 3 regions, with Dublin and the Mideast combined into a single region.

Figure 2: Number of Firms Year

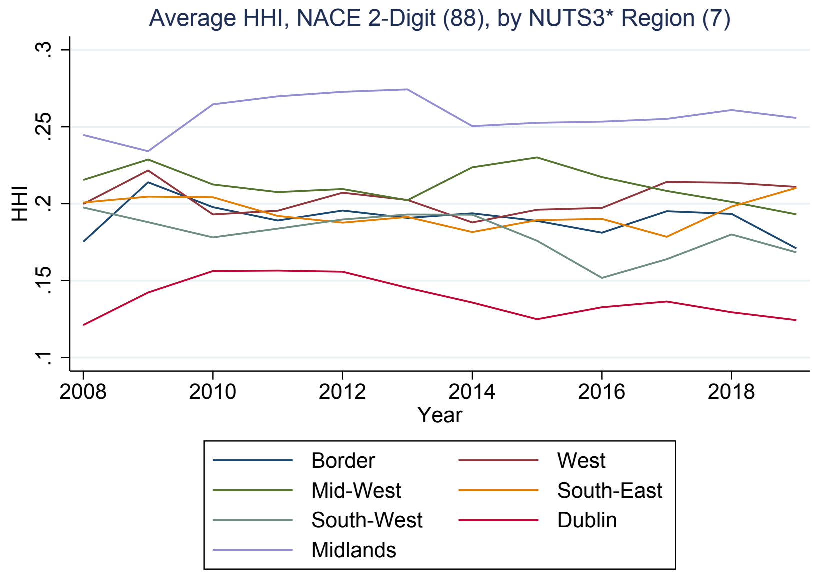
(a) (b)



This figure plots the number of firms in a local labour market (LLM) for a variety of LLM definitions. A LLM is an industry-region in a given year. Our NUTS 3* grouping follows the EU structural funds NUTS 3 regions, with Dublin and the Mideast combined into a single region.

[20]Consider two markets a and b, containing respectively E_a and E_b workers. The employment-weighted average HHI of the two markets is $\overline{HHI}_{a,b} = HHI_a \frac{E_a}{E_a+E_b} + HHI_b \frac{E_b}{E_a+E_b}$, whereas the HHI for the total market $a \cup b$ is $HHI_{a\cup b} = HHI_a \left(\frac{E_a}{E_a+E_b}\right)^2 + HHI_b \left(\frac{E_b}{E_a+E_b}\right)^2$.

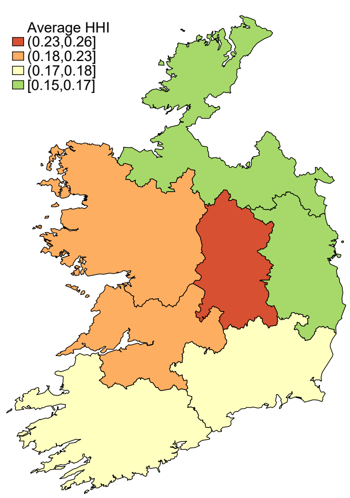
Figure 3: Average HHI by year



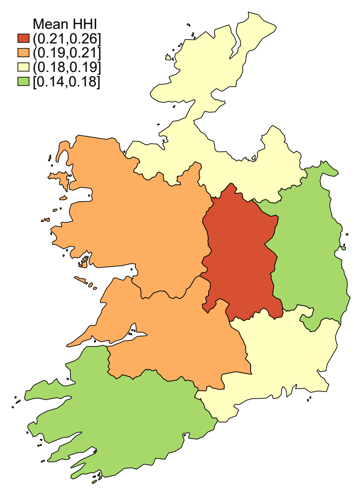
This figure plots the evolution of the average HHI by region. Our NUTS 3* grouping follows the EU structural funds NUTS 3 regions, with Dublin and the Mideast combined into a single region.

Figure 4: Average HHI, 2008-2019

(a) NUTS 3* Rev. 99

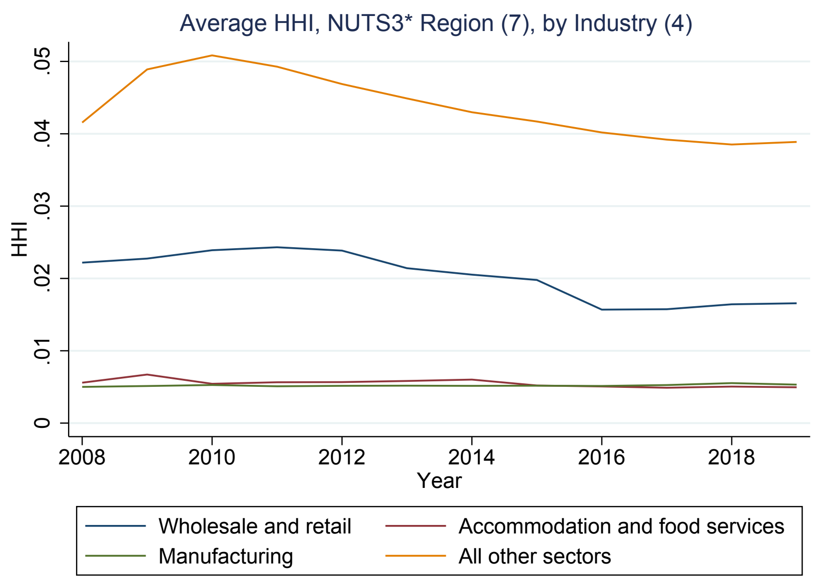


(b) NUTS 3* Rev. 2016



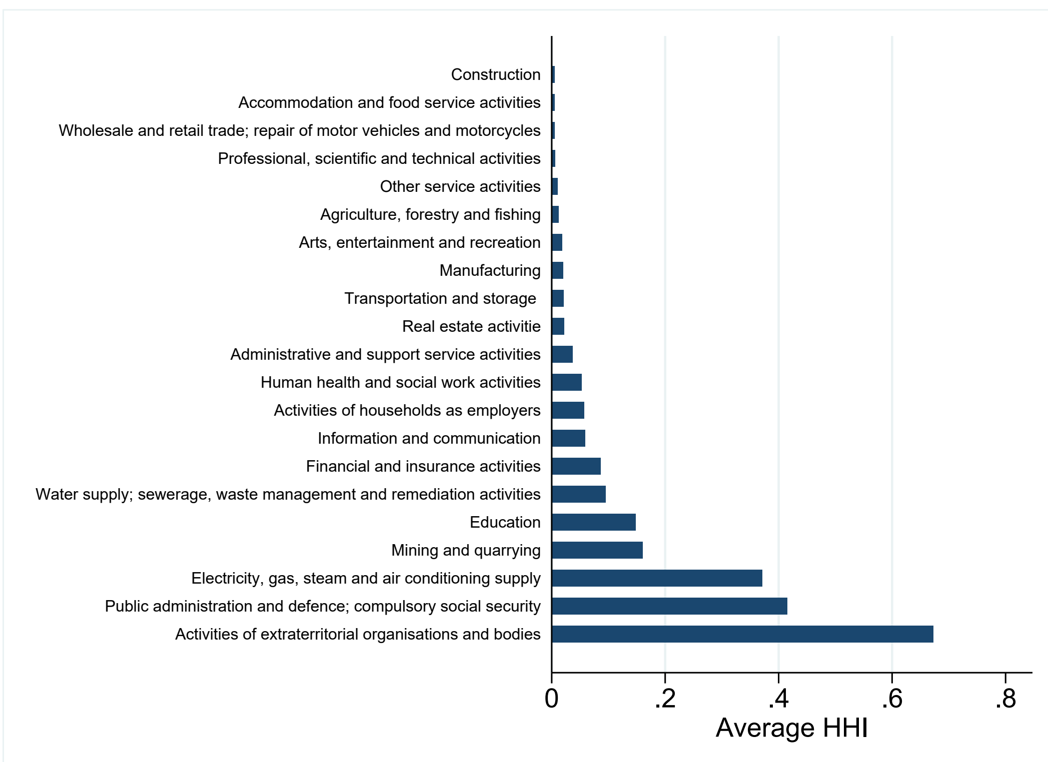
This figure plots the average HHI by region across all years. Our NUTS 3* grouping follows the EU structural funds NUTS 3 regions, with Dublin and the Mideast combined into a single region.

Figure 5: Average HHI by Industry



This figure plots the evolution of the average HHI by industry.

Figure 6: Average HHI by NACE 1-Digit Industry



This figure plots the average HHI by industry across all years.

3.2 Regional Analysis

Figure 3 shows average HHI at NACE 2-digit level in each NUTS 3* region from 2008 to 2019. The initial 2009 surge in concentration is driven by the Border, the Midwest, and West regions, but concentration reverts sharply to 2008 levels in 2010. High levels of concentration in the following crisis years are driven by the Midlands and Greater Dublin, wherein concentration remains high until 2014 and 2015 respectively. During this time the Midwest exhibits a second surge before declining again in 2016. Unlike other regions, the Southwest and Southeast do not show any apparent concentration response to the crisis; concentration in the Southeast stays relatively stable throughout the sample period, while concentration in the Southwest shows a modest decline.

Concentration was the highest in the Midlands and the lowest in Dublin in every year through 2019. Figure 4 shows the average HHI at NACE 2-digit level in each NUTS 3* region across all years for both revisions. These results rationalise the finding of McGuinness et al. (2019) that Dublin and the western regions – with generally low levels of concentration – show relatively large disemployment effects following the 2018 minimum wage increase; markets with low concentration should be closer to a competitive equilibrium, in which any binding minimum wage causes disemployment. In a companion paper we study the three national minimum wage increases from 2016-2019, explicitly allowing the employment response to minimum wage changes to vary by degree of concentration, confirming this intuition (Devereux and Studnicka 2023).

3.3 Sectoral Analysis

We present average HHI for select one-digit NACE industries at the NUTS 3* level in Figure 5. We focus on wholesale & retail, accommodation & food services, and manufacturing – the three sectors McGuinness et al. (2019) identify as having the highest concentration of minimum wage workers. We group together all other sectors. Concentration in the wholesale & retail sector increases slightly in 2009 and plateaus through 2012, when it starts to decline. Accommodation & food services shows an initial surge in 2009 before falling back down in 2010, holding steady, then declining further starting in 2015. The grouping of all other industries also shows a 2009 surge then declines steady starting in 2011. Concentration in manufacturing remains low and steady throughout the duration.

McGuinness et al. (2019) find disemployment effects of the 2018 minimum wage increase in the manufacturing sector. This is consistent with its low average level of concentration compared to the other sectors with high concentrations of minimum wage workers. Although concentration does not vary substantially over time manufacturing, we can make use of contemporaneous regional variation market concentration within industries order to identify the relationship between concentration and wages. For other sectors we can take advantage of both time-series and cross-sectional variation in concentration. In the Section 4 we take the first steps to establishing concentration's causal effect on wages.

Figure 6 shows time-averaged HHI for each of the 21 one-digit NACE industries. Outside of the publicly-dominated sectors, concentration is highest in electricity and mining, where average concentration across regions exceeds the FTC threshold for high concentration of 0.25. Education and water supply and waste management exceed the moderate concentration threshold of 0.15. Among sectors with high concentrations of minimum wage workers, concentration is among the lowest of any one-digit NACE sector for accommodation and food services and wholesale and retail trade, while it is in the low to mid range among sectors for manufacturing.

3.4 Counterfactual Decomposition

We now decompose the average HHI into different components in a series of counterfactual exercises, following Rinz (2020).

We start with the average national HHI at time t which can be written as:

$$\overline{HHI}_t = \sum_i Share_{it} * HHI_{it} \tag{2}$$

where $Share_{it}$ is the share of national employment of industry i at time t (industrial composition), and HHI_{it} is the HHI within this industry. We plot the actual national average HHI against two counterfactual trends: 1) keeping industry shares of employment constant at their 2008 levels and letting HHI_{it} vary over time; 2) and keeping the HHI_{it} constant, letting the industry shares vary (Figure 7, Panel (a)). The counterfactual trend where only the HHI_{it} varies over time is the one that follows closely the actual trend in average HHI. The industrial composition was, on the other hand more stable over time, suggesting that changes in HHI_{it} are driving changes in the national trend. Rinz (2020) find similar results for the US.

At the local level, we can write the average HHI of regions as:

$$\overline{HHI}_t^r = \sum_r \sum_i NUTS3 * Share_{rt} * LLMShare_{rit} * HHI_{rit} \tag{3}$$

where $LLMShare_{mt}$ is the local labour market employment share in national employment, $LLMIndShare_{rit}$ is the share of local labour market employment of industry i (industrial composition) and HHI_{rit} is its HHI.

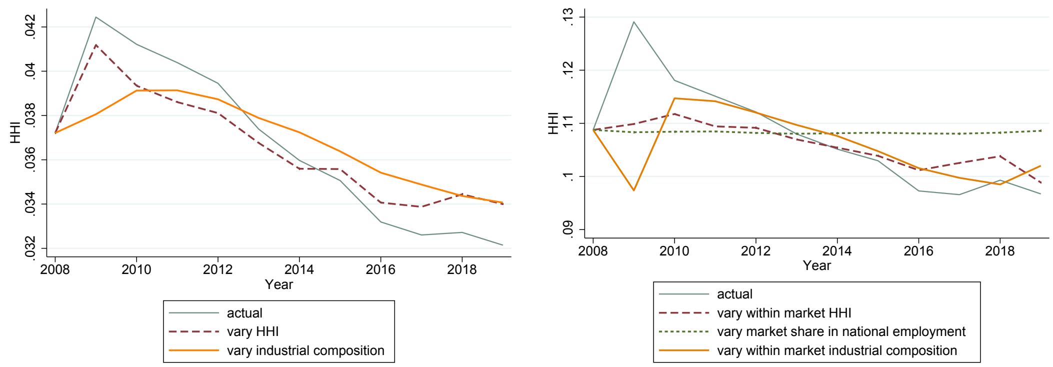
Figure 7 Panel (b) presents counterfactual trends that vary each of the three components of the local labour market HHI trend, keeping the two other terms constant.

Our findings show that changes in local labour market employment shares were stable, having little impact on the actual trend. Letting the within market industrial composition vary put a downward pressure on the actual HHI in 2008 and 2009. After those years it was roughly in line with the actual HHI, mostly above it from 2012 on. Within market HHI, was rather stable and evolved below the actual HHI until 2014.

Overall, our counterfactual exercise suggests that changes in the average national HHI were driven more by the evolution of the industry-specific and industry-LLM-specific HHIs, rather than by the evolution of the respective industrial compositions.

Figure 7: Decomposition

(a) National (b) NACE 2-Digit, NUTS 3*



Panel (a) plots the decomposition of the HHI, defined in equation (2). Panel (b) plots the decomposition of the HHI defined in equation (3).

4 Empirical Model

In this section we study the association between concentration and earnings, and take a first step towards investigating causality. To the latter end we employ an instrumental variables approach. This allows us to address the issue of omitted variable bias and simultaneous causality. These are caused by the fact that wages in any labour market result from an interaction of demand and supply factors that may also affect concentration. Moreover, prevailing wage rates certainly affect hiring and entry decisions by firms, which determine concentration.

We follow Azar et al. (2020a), Martins (2018), Qiu and Sojourner (2019), and instrument local HHI using the "leave-one-out" average $\ln(1/N)$ instrument, where N is the number of firms in other LLMs.[21] This is defined as follows. For any given LLM at time t – which we define as a two-digit NACE industry in a given NUTS 3* region in a given year – the "leave-one-out" instrument is the employment-weighted average of the natural logarithm of the inverse number of firms in all other NUTS 3* regions in the same NACE two-digit industry and

[21]In the robustness checks, we use the instrument proposed by Rinz (2020): "the leave-one-out" average of the HHI across other LLMs.

year. It is defined as follows.

$$IV_{irt} = \frac{\sum_{q \neq r} \ln\left(\frac{1}{N_{iqt}}\right) \times E_{iqt}}{\sum_{q \neq r} E_{iqt}}$$

In the above equation, the instrumental variable for a market m, which is defined as an industry i and region r pair, at time t, is the average of the log inverse number of firms in regions $q \neq r$ within the same industry, weighted by employment in those regions, which is given by E_{iqt}. This captures national-level business cycle trends that do not depend on local labour market factors. In this way we capture spillovers from other regions that affect a given region's concentration, without depending directly on conditions in the given region. For example, if the productivity of an industry falls in the Dublin area, this could have an effect on both wages (decrease) and concentration (increase). By instrumenting concentration with the number of firms in other regions in the same industry, we exclude a direct effect of productivity changes in Dublin on concentration. For brevity, we denote a market by $m = (i, r)$ hereafter, so that $IV_{irt} \equiv IV_{mt}$, and so on.

We estimate the following first-stage regression:

$$\ln HHI_{mt} = \alpha_0 + \alpha_1 IV_{mt} + \mu_{mt} + \epsilon_{mt} \tag{4}$$

where $HHI_{m,t}$ is the average HHI in local labour market m, at year t, IV_{mt} is the employment weighted average of the log of the inverse number of firms in all other LLMs in year t, and μ_{mt} is a set of fixed effects.[22]

The effect of concentration on earnings is:

$$\ln y_{mt} = \beta_0 + \beta_1 ln\widehat{HHI}_{mt} + fe_{mt} + \epsilon_{mt} \tag{5}$$

where y_{mt} is the average income for workers in market m at time t, $\widehat{HHI}_{mt}$ are the fitted values from the first stage regression and μ_{mt} are the fixed effects. In addition to the IV method, we estimate equation 5 using OLS to show the

[22]Note that for clarity reasons Equations 4 and 5 do not include the subscripts of all fixed effects used in our regressions. We consider both separate sets of fixed effects by industry, region, and time, as well as specifications with interacted industry by region effects – the latter being equivalent to market fixed effects.

unconditional correlation. In both models and all specifications we cluster the standard errors at the LLM level.

5 Concentration and Earnings

We begin our discussion by presenting the results of the first stage regressions in table 2. We consider a variety of fixed effects specifications, including: industry and region (column 1); industry, region, and year (column 2); industry×region and year (column 3); and industry×region and year×region (column 4).

The leave-one-out instrument is a strong predictor of concentration in a given market. The coefficients in the first two columns are negative but change signs when we include interacted fixed effects in columns (3) and (4). This finding shows the importance of focusing on within-market variation in estimating the effects of market concentration. In addition, the Kleibergen-Paap F-statistics in these two columns exceed the critical values, rejecting the null hypothesis of weak instruments. The results from the last two columns show that the when the number of firms in other LLMs within the same industry falls (ln(1/N) goes up – an increase in the leave-one-out instrument), concentration in the LLM increases. This suggests variation in concentration driven by common national factors, unrelated to local conditions. This result is in line with the findings by Azar et al. (2020a) and Rinz (2020) who also find a positive relationship between their respective instrumental variables and concentration when controlling for market-level fixed effects.

Next we study the association between concentration and earnings. We consider the unconditional correlation given by OLS regression – which makes no attempt to establish a causal relationship – as well as instrumental variable regression, which exploits the portion of concentration driven by common national factors within an industry to predict local earnings. Table 3, panel (a) shows the results from the baseline wage regressions estimated using OLS, Panel (b) shows the results form the second-stage IV regressions. The OLS associations are negative, but small in magnitude and statistically insignificant. This finding is in line

Table 2: First-Stage Instrumental Variable Regressions, Two-digit NACE, NUTS 3*

	(1)	(2)	(3)	(4)
Average Ln (1/N) in Other Markets	-0.282***	-0.316***	0.416***	0.416***
	(0.0897	(0.093)	(0.096)	(0.097)
Constant	-6.766***	-6.997***	-0.785	-0.808
	(0.667)	(0.710)	(0.648)	(0.653)
Observations	5,500	5,500	5,500	5,500
R-squared	0.786	0.787	0.967	0.967
FE industry	yes	yes	no	no
FE year	no	yes	yes	no
FE region	yes	yes	no	no
FE year-region	no	no	no	yes
FE industry-region (LLM)	no	no	yes	yes
Kleibergen-Paap F-stat	10.45	11.42	18.87	18.51

First-stage estimation results. Dependant variable :average HHI in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Second-Stage Instrumental Variable Regressions, Two-digit NACE, NUTS 3*

	(a): OLS				(b): IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Ln(HHI)	-0.010	-0.010	0.000	-0.001	-0.110*	-0.164**	-0.267**	-0.267**
	(0.006)	(0.006)	(0.015)	(0.015)	(0.061)	(0.066)	(0.112)	(0.113)
Constant	5.754***	5.765***	5.820***	5.833***	5.272***	5.026***	4.865***	4.870***
	(0.051)	(0.051)	(0.055)	(0.061)	(0.296)	(0.320)	(0.403)	(0.410)
Observations	5,500	5,500	5,500	5,500	5,500	5,500	5,500	5,500
R-squared	0.457	0.481	0.621	0.625	0.426	0.408	0.586	0.591
FE industry	yes	yes	no	no	yes	yes	no	no
FE year	no	yes	yes	no	no	yes	yes	no
FE region	yes	yes	no	no	yes	yes	no	no
FE year-region	no	no	no	yes	no	no	no	yes
FE industry-region (LLM)	no	no	yes	yes	no	no	yes	yes

Second-stage estimation results. Dependant variable: average midpoint income for each income decile in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** p<0.01, ** p<0.05, * p<0.1.

with Azar et al. (2020a). The coefficients in the IV regressions are negative and statistically significant, and larger in magnitude. Their magnitude increases further when we introduce industry-region fixed effects in columns (7) and (8). That suggests that some of the negative effect is driven by the within-market variation in wages. We consider these latter specifications to be the most reliable, both because they exploit within-market variation – in a context where across-market earnings can vary for a variety of reasons unrelated to concentration – and because their first-stage F-statistics reject the null hypothesis for weak instruments (see table 2). Columns (7) and (8) show the elasticity is around -0.27, meaning that a doubling in the HHI – for example, moving from an equally-split duopsony to a monopsony – decreases average income by 27%.

6 Robustness

In this section we test the robustness of our main results to various sample restrictions and IV specifications. Most results carry over, and those that do not illustrate the variation that drives the statistical power behind our results.

Table 4 shows that our results are not driven by outlier LLMs. Removing markets for which the HHI=1 produces economically and statistically significant results in line with the main sample. This is a relatively small number of LLMs; their exclusion demonstrates that it is not outlier observations in terms of concentration driving the main results.

Table 5 shows that our main results are also statistically-significantly robust the the exclusion of the Dublin plus Mideast region.[23] As Ireland's only major metropolitan area, the exclusion of this region removes both many LLMs, and important variation used to identify the effect of concentration on wages. Azar et al. (2020a) emphasize the divergence in concentration between urban and rural areas in the US. Our results, however, stay unchanged, showing that they are not driven only by these regions.

[23] Recall that figure 4 shows the Dublin plus Mideast region as the lowest concentration area both before and after the NUTS 3 revision.

Table 4: Excluding outliers (HHI=1), Two-digit NACE, NUTS 3*

	First-stage				Second-stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Ln(1/N) in Other Markets	-0.274***	-0.307***	0.398***	0.397***				
	(0.090)	(0.097)	(0.093)	(0.093)				
Average Ln(HHI)					-0.119*	-0.179**	-0.241**	-0.244**
					(0.065)	(0.072)	(0.116)	(0.117)
Constant	-6.716***	-6.939***	-0.906	-0.944	5.233***	4.956***	4.957***	4.955***
	(0.685)	(0.731)	(0.627)	(0.629)	(0.313)	(0.349)	(0.416)	(0.425)
Observations	5,456	5,456	5,456	5,456	5,456	5,456	5,456	5,456
R-squared	0.782	0.782	0.966	0.967	0.420	0.393	0.589	0.593
FE industry	yes	yes	no	no	yes	yes	no	no
FE year	no	yes	yes	no	no	yes	yes	no
FE region	yes	yes	no	no	yes	yes	no	no
FE year-region	no	no	no	yes	no	no	no	yes
FE industry-region	no	no	yes	yes	no	no	yes	yes
Kleibergen-Paap F-stat	9.30	10.10	18.50	18.16				

IV estimation results. First-stage dependant variable: average HHI in LLM (Two-digit NACE, NUTS 3*). Second-stage dependant variable: average midpoint income for each income decile in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Excluding greater Dublin, Two-digit NACE, NUTS 3*

	First-stage				Second-stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Ln(1/N) in Other Markets	-0.087	-0.166	0.428***	0.430***				
	(0.112)	(0.149)	(0.105)	(0.106)				
Average Ln(HHI)					0.818	0.216	-0.271***	-0.270**
					(1.114)	(0.308)	(0.124)	(0.124)
Constant	-5.430***	-5.958***	-0.703	-0.721	9.745*	6.849***	4.852***	4.863***
	(0.831)	(1.078)	(0.709)	(0.712)	(5.369)	(1.483)	(0.444)	(0.450)
Observations	4,612	4,612	4,612	4,612	4,612	4,612	4,612	4,612
R-squared	0.39	0.839	0.965	0.965	0.330	0.334	0.554	0.560
FE industry	yes	yes	no	no	yes	yes	no	no
FE year	no	yes	yes	no	no	yes	yes	no
FE region	yes	yes	no	no	yes	yes	no	no
FE year-region	no	no	no	yes	no	no	no	yes
FE industry-region	no	no	yes	yes	no	no	yes	yes
Kleibergen-Paap F-stat	0.60	1.23	16.70	16.56				

IV estimation results. First-stage dependant variable: average HHI in LLM (Two-digit NACE, NUTS 3*). Second-stage dependant variable: average midpoint income for each income decile in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Our third robustness check (Table 6), removes the top income decile from the regression analysis. Our results stay unchanged.

In our final robustness check we use an instrument based on that of Rinz (2020). It is a ‘leave-one-out’ instrument similar to that used in the main results, described in section 4. Rather than using the inverse firm count to predict concentration, it uses the HHI itself. Unlike Rinz, we take the log of HHI before taking the leave-one-out average, to make the calculation method consistent with Azar et al. (2020a)’s instrument that we use in the main results. The instrument is calculated as follows.

$$\overline{\ln(HHI)}_{irt} = \frac{\sum_{q \neq r} \ln(HHI_{iqt}) \times E_{iqt}}{\sum_{q \neq r} E_{iqt}}$$

Our first stage results in columns (3) and (4), show that this instrument performs less well in our preferred specifications. In addition, our second stage results are not statistically-significant. These results confirm that our initial instrument is a better choice for our analysis.

Table 6: Excluding top income decile, Two-digit NACE, NUTS 3*

	First-stage				Second-stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Ln(1/N) in Other Markets	-0.280***	-0.313***	0.436***	0.435***				
	(0.087)	(0.093)	(0.097)	(0.098)				
Average Ln(HHI)					-0.124**	-0.173**	-0.244**	-0.247**
					(0.063)	(0.068)	(0.105)	(0.106)
Constant	-7.025***	-7.112***	-1.008	-0.946	5.211***	4.985***	4.946***	4.945***
	(0.664)	(0.695)	(0.816)	(0.812)	(0.306)	(0.330)	(0.378)	(0.387)
Observations	5,450	5,450	5,450	5,450	5,450	5,450	5,450	5,450
R-squared	0.786	0.786	0.967	0.968	0.420	0.401	0.598	0.603
FE industry	yes	yes	no	no	yes	yes	no	no
FE year	no	yes	yes	no	no	yes	yes	no
FE region	yes	yes	no	no	yes	yes	no	no
FE year-region	no	no	no	yes	no	no	no	yes
FE industry-region	no	no	yes	yes	no	no	yes	yes
Kleibergen-Paap F-stat	10.30	11.22	20.01	19.56				

IV estimation results. First-stage dependant variable: average HHI in LLM (Two-digit NACE, NUTS 3*). Second-stage dependant variable: average midpoint income for each income decile in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Different instrument, Two-digit NACE, NUTS 3*

	First-stage				Second-stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average Ln(HHI) in Other Markets	-0.948***	-0.958***	0.121*	0.124*				
	(0.059)	(0.059)	(0.066)	(0.067)				
Average Ln(HHI)					-0.020	-0.016	-0.105	-0.104
					(0.014)	(0.014)	(0.233)	(0.227)
Constant	-9.222***	-9.253***	-3.030***	-3.043***	5.706***	5.737***	5.445***	5.462***
	(0.351)	(0.352)	(0.308)	(0.309)	(0.078)	(0.078)	(0.836)	(0.820)
Observations	5,500	5,500	5,500	5,500	5,500	5,500	5,500	5,500
R-squared	0.831	0.832	0.966	0.967	0.456	0.481	0.615	0.620
FE industry	yes	yes	no	no	yes	yes	no	no
FE year	no	yes	yes	no	no	yes	yes	no
FE region	yes	yes	no	no	yes	yes	no	no
FE year-region	no	no	no	yes	no	no	no	yes
FE industry-region	no	no	yes	yes	no	no	yes	yes
Kleibergen-Paap F-stat	256.75	266.35	3.35	3.44				

IV estimation results. First-stage dependant variable: average HHI in LLM (Two-digit NACE, NUTS 3*). Second-stage dependant variable: average midpoint income for each income decile in LLM (Two-digit NACE, NUTS 3*). Standard errors are clustered at the LLM level. *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusion

We provide the first evidence of local labour market (LLM) concentration in Ireland, and investigate the causal relationship between LLM concentration and earnings. In doing so we test the predictions of monopsony theory on Irish LLMs.

LLM concentration in Ireland surged during the financial crisis, before falling to pre-crisis levels by 2012. It declined further until 2016, when it stabilised. This trend mirrors the experience of the US and UK over the same time period. In Ireland, the surge and subsequent decline were driven by the number of active firms, rather than disproportionate employment share increases by some competitors. Concentration surged as many firms shut down during the crisis, and fell as new firms opened up during the recovery.

There is substantial variation in average LLM concentration across regions. The Midlands has the highest average concentration in every year from 2008 to 2019, and Greater Dublin (consisting of Dublin and the Mideast) the lowest. There is also large sectoral variation, with the typically low-wage sectors of *manufacturing* and *accommodation and food services* having low levels of concentration, and *manufacturing* having concentration around the middle of the range. Other sectors have a higher level of concentration on average.

Classical monopsony theory predicts that employers in concetrated markets suppress wages. We find that workers in concentrated LLMs earn slightly less on average. However, because both earnings and concentration are equilibrium outcomes of LLMs, this alone does not constitute a test of the theory. Leveraging national trends in concentration, while purging the share of local concentration due to local demand and supply shocks, we find that concentration causes a large and statistically significant reduction in earnings. A 10% increase in concentration reduces earnings by 2.7%. A 100% increase in concentration – equivalent to a shift from two equally-sized competitors to a single monopsonist – would reduce earnings by 27%. This effect is about twice the magnitude seen in US studies.

These results have implications for competition regulation and minimum wage legislation. Given that concentration allows employers to suppress labour market earnings, regulators should be cognisant of the effects of mergers on labour markets – not just product markets. This evidence also suggests the viability of minimum wages to increase workers' earnings without substantial employment losses, and with potential gains to employment. We present evidence to this effect in a companion paper (Devereux and Studnicka 2023).

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A Commuting Patterns

In this appendix we present commuting patterns across NUTS 3 regions in order to justify our grouping together of Dublin and the Mideast into the Greater Dublin region for our preferred NUTS 3* classification. All other regions remain unchanged. Data come from the Labour Force Survey (LFS), which reports the region both of work and residence. Figures are averages over all years using the 2016 revision of NUTS 3 that reallocated Louth from the Border to the Mideast, and South Tipperary from the Southeast into the Midwest.

Figure 8 shows the percentage of workers working in a destination NUTS 3 region who commute from any other region. This indicates how large a share outside-region commuters play as a share of the destination region. The largest flow is from the Mideast to Dublin, with 14% of Dublin's workforce commuting from the Mideast. The second highest flow is the reverse, with 8% of the Mideast's workforce commuting from Dublin. Flows consisting of less than 2% of the destination's workforce are not pictured.

Figure 9 shows the percentage of workers in an origin region who commute into the destination region. This indicates how important the destination region is to the origin as a source of work. The largest flow again is the Mideast to Dublin, with 35% of workers residing in the Mideast commuting into Dublin. The second highest flow is from the Midlands into Dublin, at 9%.

These patterns show the integration of the Mideast and Dublin as a commuting zone – particularly the dependence on the former on the latter as a place of work, but also the Dublin's dependence on the Mideast as a source of labour. For this reason we group the two regions together in our NUTS 3* classification.

Figure 8: Percent Workers in Destination Commuting from Region

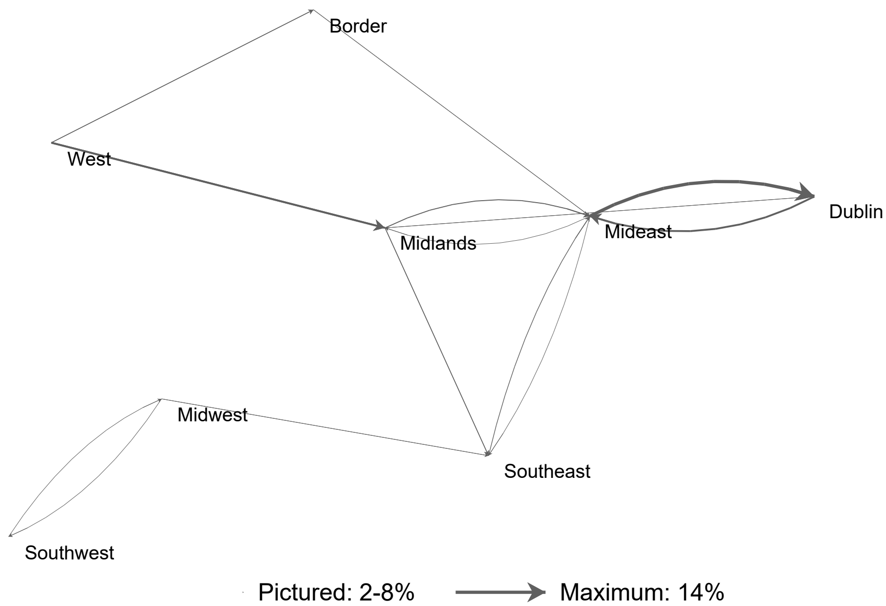
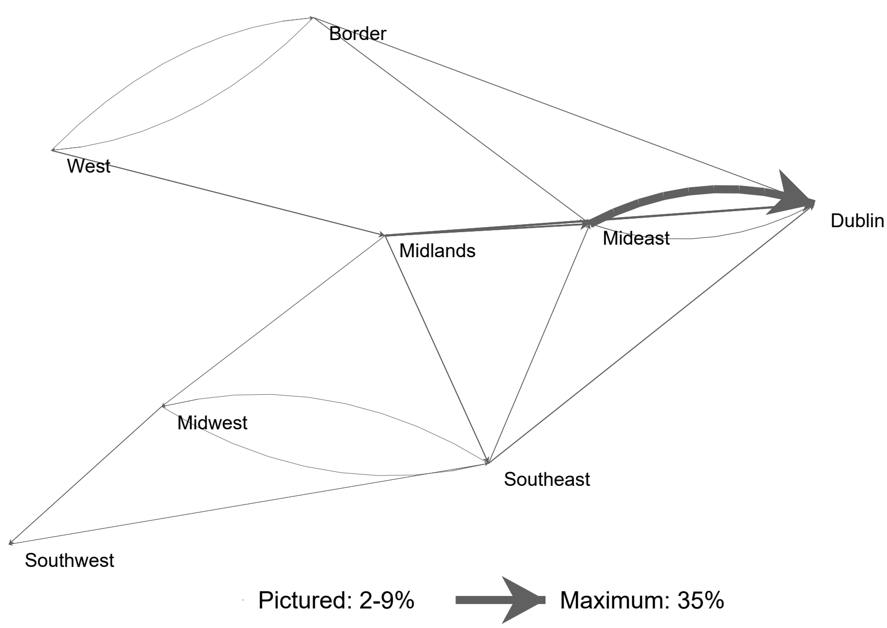


Figure 9: Percent Residents Commuting to Destination Region



The top panel shows the percentage of workers in a destination NUTS 3 region who commute from another region; for example, 14% of workers employed in Dublin commute from the Mideast. The bottom panel shows the percentage of working residents from a region who commute to the destination; for example, 35% of workers living in the Mideast commute to Dublin. Percentages below 1% are suppressed.

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