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Clicks and jobs: measuring labour market tightness using online data

Pawel Adrjan and Reamonn Lydon
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Clicks and jobs: measuring labour market tightness using online data

Pawel Adrjan and Reamonn Lydon***

Record employment levels in Ireland in 2019 are putting upward pressure on wages and salaries as labour demand rises relative to supply. Analysis of online data reveals the skills employers look for, the jobs workers search for and the salaries for different roles – all at a highly granular level. A new measure of labour market tightness using the number of clicks on a job posting shows that advertised salaries are significantly higher in jobs where the supply of potential workers is low relative to demand.

Introduction

Online job search plays a central role in matching workers to jobs. The spectacular growth and scale of online job postings and website traffic, which we summarise below, is evidence that the internet is now the primary platform for hiring and job search.

This *Economic Letter* uses online job postings and job search data from [Indeed's](#) Irish website to analyse the relationship between labour market tightness and salaries. 'Tightness' here means the relative balance between employer demand for workers and the supply of workers. We use online data to construct a new measure of tightness based on the number of clicks on each job posting.

The idea that bargaining power shifts from employers to employees in a tighter market, leading to wage increases, is central to economic models of the labour market. In most empirical studies, unemployment is a proxy for tightness. The Phillips curve is one example. Studies on wage flexibility also show how the pay of newly hired workers moves in line with changes in regional unemployment; see, for example, [Lydon and Lozej \(2018\)](#).

The key additional contribution we make in this *Letter* is the granularity of the tightness measure – i.e. at the level of the job posting. We show that clicks can explain more of the variation in salaries than regional unemployment alone. The granular data also allows us to see where labour shortages might be most acute – whether that is at the level of regions/counties, sectors or occupations.

The basic idea – online job postings and job search data shed new light on the labour market

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Online data is not perfect: like other ‘non-traditional’ data, it does not always lend itself easily to economic analysis and interpretation. There are important questions around measurement, comparisons with existing official labour market data, separating trends from the effects of growing market size, and addressing the concerns of the corporate data owners.¹ Therefore, in the first half of the *Letter*, we test the reliability and representativeness of the online data used in this study across several dimensions. We find that the data are broadly comparable to Central Statistics Office (CSO) labour market data. However, online data is more than just a parallel indicator. We also examine some of the real-time advantages, for the first time allowing timely analyses of job vacancies and job search at the occupation, job-type and county level. The final section looks at the relationship between labour market tightness and posted salaries – an especially important issue today given where we are in the economic cycle.

The data: Irish job postings on Indeed

Indeed is the largest job site worldwide², with a presence in 60 countries and 250 million unique visitors per month³. Indeed has been in Ireland since 2009 and is now the most-visited job site in the country, with 3.9 million monthly visits.⁴ On average, over 30,000 new job postings are added each month. For comparison, the CSO vacancy series reported 19,000 vacancies on the last day of each quarter in 2018.

Online job search data has both advantages and disadvantages over other data sources, as summarised in Table 1. The fact that is usually available at shorter time lags and higher frequency means that it can provide timely updates on the state of the labour market.

Granular online data can also provide fresh insights into the job search and hiring process – what economists call the ‘matching function’. Several recent studies have used online data to analyse job search and matching. [Faberman and Kudlyak \(2016\)](#) show that job search effort is stronger for workers with weaker prospects – counter to standard assumptions in the literature. [Kuhn and Mansour \(2014\)](#) show that online job search helps unemployed people find jobs more quickly – improving matching *efficiency*. [Brown and Matsa \(2016\)](#) show that, during the financial crisis, jobseekers were more likely to apply to more financially sound firms, highlighting the importance of job security to applicants. [Marinescu and Wolthoff \(2016\)](#) use the job description in online postings to show that job characteristics can explain up to 90% of the variance in wages – far higher than previous estimates of around 50%.

*Indeed is in
Ireland since
2009*

*3.9 million
visits per month*

*30,000 new
jobs added per
month*

¹ These themes and others were explored at a recent Brookings event on “Can big data improve economic measurement?” Presentations are available on [Brookings.edu](https://www.brookings.edu)

² comScore, Total Visits, March 2018

³ Google Analytics, Unique Visitors, September 2018

⁴ SimilarWeb, Total Visits, January 2019

For policy use, representativeness is a key factor. Whilst there are no published Irish data on the extent of online job search, [Sinclair and Mamertino \(2018\)](#) show that 78% of new hires in a set of advanced countries (UK, Germany, France and the Netherlands) reported using online resources in their job search. As a further test of its representativeness, in the following sections we compare our online data with CSO data on vacancies, employment growth by county and the occupations and salaries of new hires.

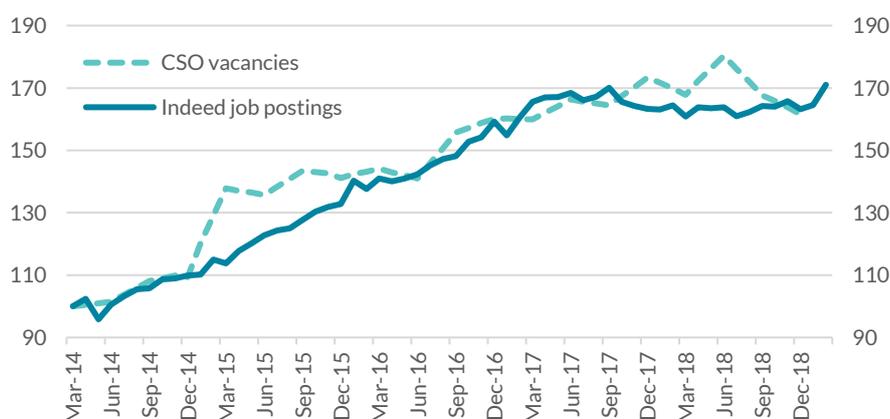
Table 1 | Advantages and disadvantages of online data relative to survey sources

Advantages	Disadvantages
Shorter lags in data delivery	Limited historical data
Higher granularity	Proprietary taxonomies
Information on labour demand & supply	May not be representative of population
Global reach	Limited demographic information

Trends in job postings versus job vacancies

Figure 1 shows that trends in monthly job postings closely track trends in official job vacancies series. The correlation in levels (differences) is 0.96 (0.60). The job postings data, shown to end-February 2019, suggest that growth in job openings in Ireland levelled off in 2018, although they remained high relative to recent historical patterns. The slowdown in vacancy growth is consistent with the slowdown in employment growth in Q4 2018 to 2.2% on an annual basis from 3.2% in each of the preceding four years.

Figure 1 | Job postings vs. CSO vacancies
Index, March 2014 = 100



Online job postings track CSO vacancy trends, with higher frequency data available

Source: Indeed monthly data to end-Feb 2019. CSO vacancies to Q4 2018 from EHECs. Both series seasonally adjusted.

Comparing the mix of job postings and new hires

Table 2 lists the ten job titles with the most postings on Indeed in 2018 alongside the top-ten new hires by four-digit occupation code from the Labour Force Survey. Because job postings primarily reflect gross labour demand (i.e. both growth and turnover) and new hires reflect the intersection of both demand and supply, we do not expect the two lists to be identical. Nonetheless, there is a high degree of overlap between the two lists, with several job titles/occupations appearing in both. Furthermore, several of the job titles in the job postings list that do not appear in the new hires list are only just outside the top ten. For example, accountants are 12th and nurses 16th in the ranking of new hires. Similarly, almost all jobs in the new hires top ten that do not appear in the job postings top ten appear just outside the top ten.

There are two other notable patterns in Table 2. First, sector and skill coverage is broad, which suggests that online job postings are not especially concentrated in a select number of jobs. Second, the share of the top-ten online job postings among all postings in 2018 (9.2%) is only a fraction of the share of top-ten new hires (32.6%) based on occupation codes. This illustrates the granularity of the online data. Standard occupational classifications, such as those used in surveys, cannot replicate this level of granularity, even at the lowest (four-digit) level.

Table 2 | Top-10 online job postings (Indeed) and new hires (CSO, LFS)

Top 10 job titles by number of postings 2018 ⁺	LFS top 10 occupations by number of new hires 2018 ⁺⁺
Customer service representatives	Sales and retail assistants
Chefs	Waiters and waitresses
Cleaners	Other administrative occupations
Registered nurses	Kitchen and catering assistants
Quantity surveyors	Bar staff
Sales representatives	Cleaners and domestics
Administrators	Elementary construction occupations
Accountants	Chefs
Sales assistants	Childminders & related occupations
Project managers	Elementary storage occupations
Share of top ten = 9.2%	Share of top ten = 32.6%

Source: (+) Indeed and (++) CSO Labour Force Survey. LFS occupations are four-digit UK SOC codes (the lowest classification level).

There is substantial overlap between the most popular job postings on Indeed and the most common occupations of new hires in the Labour Force Survey

Job postings versus employment growth, by county

To assess geographic coverage, we compare county shares of job postings with net employment growth from 2014 through 2016, the latest available year of CSO county-level employment data. Job postings and employment growth should be positively correlated provided that some of the job postings constitute growth hiring rather than replacement hiring. Job postings represent gross flows, whereas employment growth is a net change – that is, the sum of jobs gained minus jobs lost (there is no county-level information available on new hires). We therefore do not expect an exact match in levels. Instead, the key thing to look for is similar levels of geographic coverage, which is what we find.

Figure 2 illustrates the degree to which Dublin dominates the Irish labour market. Some 45% of net employment growth is in Dublin, according to CSO data, and Indeed data show that Dublin had 60% of job postings, followed by Cork at 10% and Galway at 8%. Relative to net employment growth, online job postings are over-represented in the larger population areas. That said, we do observe some posting activity in smaller counties. The correlation between job posting and employment growth shares by county is 0.99. Removing the three largest counties – which could sway the correlation upwards – it remains high, at 0.77.

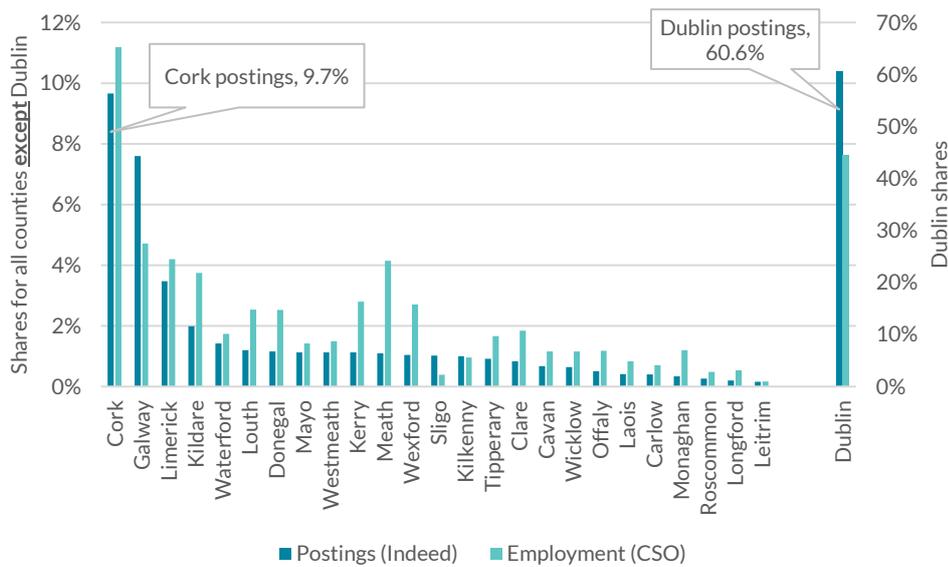
One of the advantages of the Indeed online data is that county-level job postings are available after the CSO employment series ends in 2016. The number of postings remained high in 2017/18, with Dublin (59%), Cork (11.5%) and Galway (5.7%) still accounting for the largest shares.

Why does Dublin have a higher share of gross postings compared with net employment growth?⁵ One explanation is that there is a greater concentration of workers in sectors with higher turnover in Dublin. Information Technology (Nace Rev2 sector J) is one example. IT workers have higher rates of job turnover, as illustrated by the fact that they have 30 months *less* average time on the job (average job tenure) relative to other workers (controlling for age). In 2018, 7% of employees in Dublin worked in IT, compared with 2% in the rest of the country.

Workers in the “Professional, Scientific and Technical Activities” sector (Nace Rev2 M) also tend to change jobs at a higher rate than average. Workers in this sector accounted for 7% of Dublin employees, compared with 4% in the rest of the country. These factors contributed to a higher rate of job switching more generally in Dublin. In 2018, job churn, as measured by the quarterly job switching rate in [Staunton and Lydon \(2018\)](#), was a full percentage point higher for jobs in Dublin (3.9%) than in the rest of the country (2.9%).

⁵ We have replicated the analysis at the NUTS III level (8 regions). Cork and Galway’s higher share of gross postings relative to net employment growth washes out when we aggregate to regions (South-West and West respectively). Dublin – being a NUTS region on its own – still has a higher share of gross job postings compared with net employment growth.

Figure 2 | County shares of employment growth and job postings 2014-2016



During 2014-16, Dublin accounted for the bulk of job postings (60%), followed by Cork (10%) and Galway (8%)

Source: Indeed and CSO business demography (Table BRA08, persons engaged by county, excluding public sector and self-employed). Note: The larger Dublin share can make it hard to see other counties clearly. We therefore represent it on its own right-hand side axis.

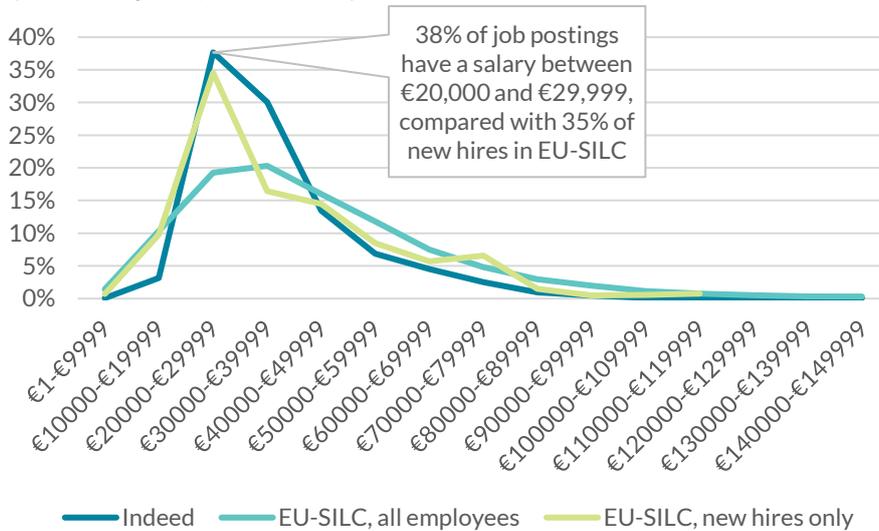
Salaries in job postings versus new hires' salaries

What does Indeed data tell us about pay? It is important to note that not all job postings include salary or wage information. In 2018 around one in seven of Indeed's Irish postings included salary or wage information. This raises the question of whether only certain types of jobs (or employers) post salaries. However, we find that the distribution of salaries is very similar to that in EU-SILC, the official source for data on incomes (Figure 3). The mean advertised salary in the Indeed Ireland job posting data is €36,700, compared with €38,800 for new hires in EU-SILC.⁶

The distribution of posted hourly wages (Figure 4) bunches around the minimum wage – €9.25 per hour in 2017, with an average of €11.30. This is not representative of the average hourly wage in the population, which was just over €21 in 2017/18, according to the CSO (there is no individual hourly wage data to compare distributions). This might be because higher-paying jobs tend to post an annual salary rather than an hourly wage. Bunching of the posted hourly wage might also explain why support is weaker in the Indeed data for annual salaries at the lower end of the distribution (up to €19,000). As few jobs post both annual and hourly pay, future work could combine the two series. Here we concentrate on annual salaries.

⁶ We use the 2017 data to calculate the salary distribution, the latest available from EU-SILC. [Lydon and Lozej \(2018\)](#) show that the salary distribution for new hires is very different from that of incumbent workers, hence our focus on new hires.

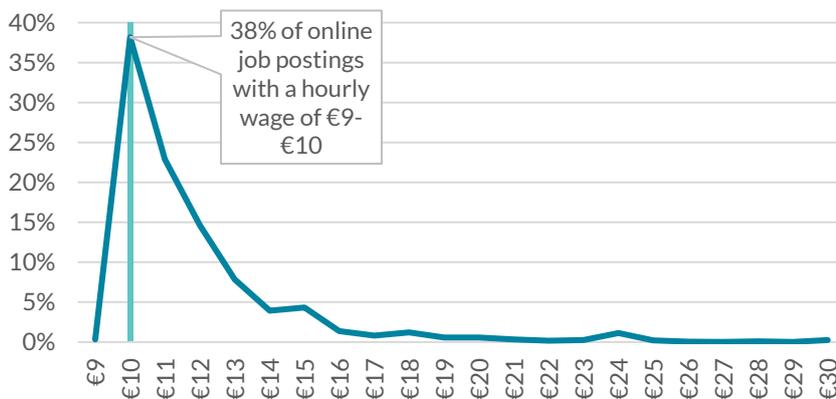
Figure 3 | Distribution of salaries in online job postings 2017
(% share by €10,000 bracket)



The average salary in the Indeed data in 2017 was €36,700. In EU-SILC, the average salary of all new hires was €38,800.

Source: Indeed 2017 and EU SILC 2017 (latest available SILC data, conditional on full-time, full-year workers).

Figure 4 | Distribution of hourly wage in job postings
(% share by €1 bracket)



Job postings that report hourly pay tend to be lower paid

The broad comparability of the Indeed and EU-SILC annual salaries is important for several reasons. First, it suggests that even though we observed salaries for only a subset of postings, those appear to be broadly representative. This contradicts the evidence provided by [Brenčič \(2015\)](#), who finds that employers are reluctant to post salaries when looking for skilled workers.⁷ Second, it gives us confidence that econometric analysis of the Indeed data – for example, looking at the relationship between tightness and wages – can inform our understanding of how the labour market works more generally.

⁷ [Brenčič \(2015\)](#) uses data for the US, UK and Slovenia. Only the US data comes from online job postings. The UK and Slovenian data are from public employment agencies. Results therefore may not be directly comparable with the exercise here.

Labour market tightness and salaries

Labour market tightness refers to the balance of demand and supply in the labour market. The more demand for workers rises relative to the available supply, the tighter the market. Tightness plays a key role in determining wage levels in search and matching models of the labour market, where firms and workers bargain over wages.⁸ Tightness tends to increase with productivity, as higher productivity implies that the total gain from the match is higher and firms can hire more workers. As the available worker pool shrinks, wages tend to rise, partly because of a shift in bargaining power from employers to employees.

Understanding the relationship between tightness and wages is important for policymakers. One reason is that wages are a key source of income for households, so understanding how wages are determined provides insights on can help understand household spending trends. Tightness is also highly relevant to employers, who need to adjust wage offers to take into account current hiring conditions.

The wage bargaining framework in search and matching models motivates our analysis. This framework defines labour market tightness as the ratio of vacancies to unemployment. The evidence in Figure 1 indicates that online job postings are a substitute for the official vacancies series. In the standard model, the inclusion of unemployment in the denominator captures how much job search is happening at any one time. However, job search is actually the product of two factors: the *number* of people searching and the *degree* of search effort. Unemployment only imperfectly captures the first element and, arguably, does not capture search effort well at all.⁹ We use Indeed data on *clicks* to capture job search directly.

Clicks capture the number of user clicks on job postings. When a jobseeker clicks on a posting in either the mobile or web format of the Indeed site, a description of the position appears.¹⁰ It is important to point out that we do not capture the number of users doing the clicking.¹¹ Using clicks or cookies to track economic behaviour is how targeted online advertising works. Economists have used clicks to measure product demand. For example, [Gorodnichenko et al. \(2018\)](#) use data from an online shopping platform to build a demand curve by matching clicks (as a proxy for sales) to price quotes. In our case, clicks capture the degree of search (both search numbers and search effort) for a given job or

⁸ See Chapter 9 in “Labor economics”, by Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg (MIT press, 2014) for a derivation of a wage curve linking wages and labour market tightness through the wage bargaining process. [Hornstein et al \(2005\)](#) also explain the theoretical framework linking wages to tightness (unemployment in their case).

⁹ This is one of the contributions of [Faberman and Kudlyak \(2016\)](#), who use online job search data to measure search effort directly.

¹⁰ We exclude activity carried out through the Application Programming Interface, or API, which captures activities of customers or internal programmers.

¹¹ Whilst only using cookies or registered user data is possible, these remain imperfect ways to identify unique users. In any case, it is difficult to see how using the number of clicks could bias our measure across time and/or between jobs. It is reasonable to assume that the same jobseeker clicking on the same job multiple times is not something that varies systematically across jobs or time.

occupation. If clicks are high, we interpret this as implying the supply of workers is ample. We assume that employers can observe supply in advance and adjust wages in job postings to reflect the state of the labour market.

Table 3 shows the results of a regression where the dependent variable is the log of the salary in the job posting, using data from January 2016 to December 2018. As we are interested in whether salaries and tightness are positively correlated *after* including other metrics to capture the state of the labour market, such as regional unemployment, we build the specifications adding key variables incrementally.

In the first column, the sole explanatory variable is regional unemployment (eight NUTS3 regions), measured monthly in percentage points. The coefficient (0.98) is a semi-elasticity, which means that a 1-percentage point decrease in the unemployment rate is associated with a 0.98% increase in wages. This result is in line with the results in [Lydon and Lozej \(2018\)](#), yet unemployment alone explains only a fraction of the variation in salaries in the data (R-squared of 0.001).

Column (2) includes the online tightness measure, the log of postings/clicks, as the only explanatory variable. As we want to compare it with the unemployment coefficient, we aggregate postings and clicks to the same region-month level in this specification. The coefficient (0.13) is statistically significant and very large – a doubling in tightness implies a 13% increase in wages. The R-squared, while still low (0.017), is nonetheless an improvement on column (1).

Column (3) adds back the unemployment rate. The coefficient and statistical significance of log (postings/clicks) are almost unchanged from column (2). This suggests that tightness measures from the online data are informative for salaries over and above traditional measures such as unemployment. Column (4) disaggregates log (postings/clicks) to the three-digit occupation level. The R-squared improves significantly (to 0.048) because the lower level of aggregation explains more of the cross-sectional variation in the dependent variable.

Column (5) includes the online tightness measure at the most granular level, log(1/clicks) for each posting. The coefficient is smaller again (0.062), but still significant. The R-squared increases to 0.06. Columns (6) and (7) add in a range of fixed effects – first, job characteristics such as seniority/experience, education requirements, full-/part-time jobs, contract type (permanent/temporary), apprenticeship/internship; then, county, time and occupation fixed effects. The combination of job characteristics and fixed effects improves the fit considerably, with an R-squared of 0.41 in the final regression.

To assess the economic significance of the coefficients in column (7), we look at the implication of a one-standard-deviation change in the explanatory variables. Table A1 shows the summary statistics, including standard deviations, for the online tightness measures and unemployment. The average number of clicks per job posting is 19, although the range is large, from just one click on a job posting to

over 14,000. In addition, a one standard deviation fall in the unemployment rate (1.19) is associated with a 1% increase in posted salaries (1.19×-0.85), whereas a one standard deviation increase in tightness is associated with an 2.7% rise in salaries (1.495×0.019).

Table 3 | Regression to explain log (salaries) in job postings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemployment (t-3) <i>region-month</i>	-0.98*** (0.14)		-1.45*** (0.14)	-1.86*** (0.13)	-1.24*** (0.13)	-1.21*** (0.13)	-0.85*** (0.29)
Log (postings/clicks) <i>region-month</i>		0.13*** (0.005)	0.14*** (0.005)				
Log (postings/clicks) <i>region-occupation-month</i>				0.10*** (0.002)			
Log (1/clicks) <i>job posting level</i>					0.062*** (0.001)	0.044*** (0.001)	0.019*** (0.001)
Job characteristics	No	No	No	No	No	Yes	Yes
Month-year fixed effects	No	No	No	No	No	No	Yes
Occupation fixed effects	No	No	No	No	No	No	Yes
County fixed effects	No	No	No	No	No	No	Yes
R-squared	0.001	0.015	0.017	0.048	0.061	0.181	0.410
Observations	52,197	52,196	52,196	52,079	50,941	50,941	50,941

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is log of salary in the job posting. Unemployment is measured quarterly at the NUTS3 region level in percentage points, lagged three months. Job postings January 2016-December 2018. Occupation dummies are at the three-digit US SOC level. The final specification includes county dummies, controls for contract type (permanent, temporary, fixed-term, etc), part-time/full-time, apprenticeship/internship, educational requirements (none, bachelor, masters, doctoral) and job grade (manager, associate or other). Specification including log (postings/clicks) as the three-digit US SOC level clusters standard errors at that level. A small number of postings (669) have zero clicks and have been excluded. Results in levels, which include these observations, are almost identical.

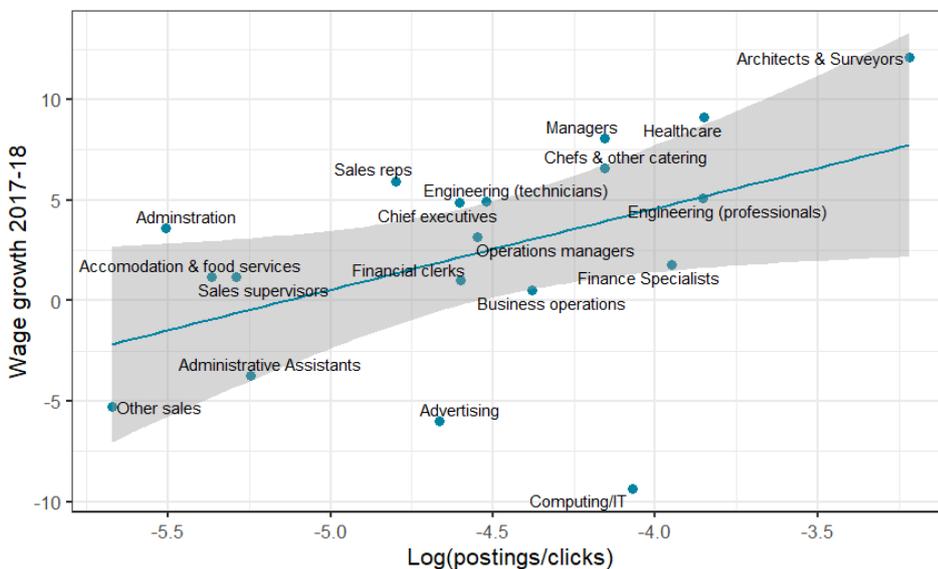
Online job search data and the Phillips Curve

The link between wage levels and tightness emerges from the wage bargaining process in search and matching models of the labour market. One question is whether tightness is also informative for wage *growth* when we group together many jobs, as posited in the wage-Phillips curve – a macroeconomic relationship that typically relates wage growth in the aggregate economy (or within an occupation or region) to the unemployment rate or other measures of ‘slack’. This question is also interesting for monetary policymakers, given the link between wage and price inflation. Recent analysis at the Central Bank of Ireland shows

that aggregate wage growth tends to pick up when unemployment is low and job-switching rates are high (see [Linehan et al. \(2017\)](#) and [Byrne and Zekaite \(2018\)](#) for Phillips curve analysis and [Staunton and Lydon \(2018\)](#) on job switching).

In Figure 5, we aggregate jobs to the level of occupations and plot the relationship between year-on-year wage growth (2017-18) and tightness, measured by the log of postings-per-click.¹² To be able to calculate wage growth in a robust way, we focus on jobs with *at least* 200 postings each year. Because of this restriction, the chart is based on approximately 17,000 job postings each year, with an average of 900 job postings per three-digit occupation. The chart shows that occupations with higher levels of tightness tend to experience higher wage growth. While this chart is based on a relatively small number of occupations, it illustrates the type of relationship we might expect from a Phillips Curve-type framework: that *different* jobs with different levels of tightness tend to experience different wage growth. *Computing Occupations* (US SOC 15-1) are an outlier in the chart in that wage growth in 2018 was negative but tightness was in the middle-to-higher end of the range. When we decompose the wage changes, we find 92% of them can be attributed to reallocation *across*, as opposed to *within*, job titles. For example, the proportion of job postings with the word ‘Support’ in the job title increases from 15% to 24%, whilst the proportion of jobs with ‘Senior’ in the title falls from 10% to 9%.

Figure 5 | Wage growth and online measure of tightness (US SOC occupations)



Source: Indeed job postings Jan 2017-December 2018.

¹² Figure A1 at the end of this Letter shows the distribution of wage changes within occupations. The average pay growth is around 3%, similar to figures from the CSO. However, certain occupations experience negative average wage growth, in line with the evidence in [Doris et al. \(2015\)](#), who find that individual-level pay often declines from one year to the next when considering continuing job-worker matches.

Which jobs currently have the tightest labour market?

We can use the online data to look across all jobs and skills, even those without advertised salaries, to see where demand for workers is particularly strong or weak relative to supply. Table 4 ranks detailed job titles by postings-per-click, that is, the jobs where online data indicate an under-supply of candidates relative to demand from employers. There is clearly a tight labour market for a number of high-skilled roles in healthcare, finance and engineering. Therefore, we might expect salary levels and growth in those roles to be higher than average. Table 5, on the other hand, shows the bottom 20 jobs using the same measure. These are the jobs with the greatest supply of online jobseekers relative to job postings. They tend to be lower-skilled – and lower paid – roles in retail, transportation, construction and childcare.

Conclusion

With nearly 2.3 million people in work in Ireland, employment levels have surpassed those seen over a decade previously in 2007. Key indicators, such as job vacancies and strengthening real wage growth, all point to a tighter labour market. This *Economic Letter* introduces a new measure of labour market tightness based on the number of clicks on online job postings. We show that this measure can explain the salaries in online job postings even after controlling for regional unemployment rates and a wide range of job and occupation characteristics.

We use the measure of tightness based on clicks to identify jobs in Ireland with the highest and lowest levels of tightness. This information is highly relevant to employers, policymakers and jobseekers. Future research directions include developing an indicator of the state of the labour market from postings and clicks data. This indicator could be used alongside other indicators, such as unemployment and vacancies, with the added benefit of greater timeliness, availability at a higher frequency and more granularity.

Looking beyond tightness, the Indeed online data offer a number of interesting avenues of research. For example, job search geographic information could provide fresh insights into migration patterns and potential labour supply in Ireland and other open economies. This is particularly relevant for our analysis of clicks. Unlike unemployment as a measure of slack, clicks encompass the potential supply of migrant labour. Identifying the specific jobs and sectors where migrant labour supply will be significant in the future is important for understanding potential employment growth. This is particularly the case for small regional labour markets in the EU, such as Ireland's.

Table 4 | Top 20 job titles by postings per click

Job postings per click - <u>top</u> 20+
Senior Fund Accountant
Gastroenterologist
Senior Mechanical Designer
Tax Senior
Dermatologist
Senior Agency Manager
Tax Director
Regulatory Reporting Manger
Corporate Lawyer
Senior Quality Engineer
Senior Design Engineer
Learning Disability Nurse
Accounting Supervisor
Senior Process Engineer
Senior Auditor
Senior Staff Nurse
Radiologist
Senior .Net Developer
Commercial Lawyer
Registered Nurse - Medical / Surgical

Source: Indeed. In ascending order by (postings / clicks). Job titles with a minimum of 100 postings in 2018.

Table 5 | Bottom 20 job titles by postings per click

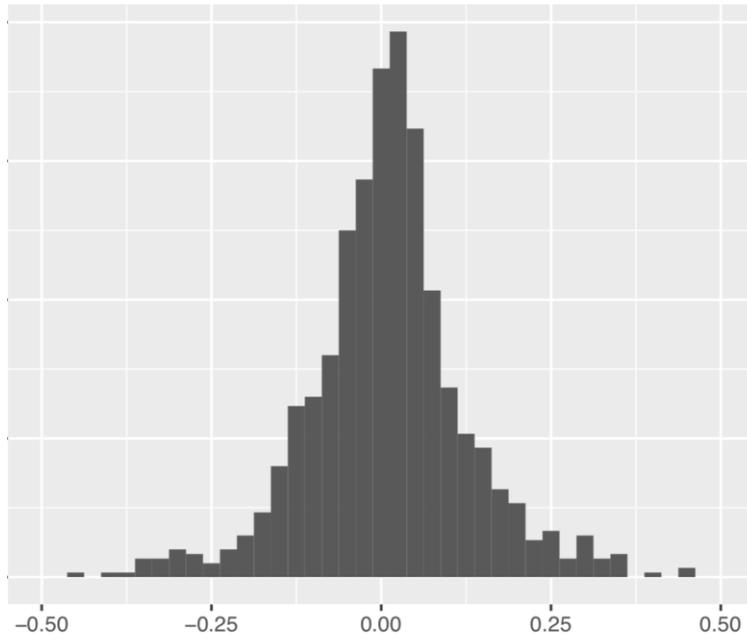
Job postings per click - <u>bottom</u> 20+
Babysitter/Nanny
Van Driver
Floor Staff
Shop Assistant
House Cleaner
Packer
Office Assistant
Factory Worker
Sales Assistant
Handy Man
General Assistant
Production Operator
Customer Assistant
Stocking Associate
Apprentice Electrician
Pharmacy Assistant
Labourer
Medical Secretary
Office Administrator
Retail Sales Associate

Source: Indeed. In ascending order by (postings / clicks). Job titles with a minimum of 100 postings in 2018.

Table A1 | Summary statistics

	N	Mean	Std. Dev.	Min	Max
Log (wage)	52,066	10.49	0.38	9.21	13.12
<i>Tightness</i>					
Unemployment	52,066	6.29	1.19	3.80	14.60
Posting-per-click (US SOC 3-digit)	52,066	0.014	0.009	0.002	0.074
Log (posting-per-click, US SOC 3-digit)	51,116	-4.468	0.635	-6.112	-2.598
1/clicks (individual job posting level)	50,941	0.054	0.124	0.00007	1
Log (1/clicks, individual job posting level)	50,941	-4.066	1.495	-9.528	0

Figure A1 | Distribution of average wage growth within jobs (2017/18)



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