

Labour market tightness and wages: evidence from online job postings

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The use of online job search has grown hugely over the last decade. Using data from *Indeed*, this article asks whether ‘big data’ can shed new light on how labour markets work. Comparisons with official data show that online job postings closely track vacancy data from firm-level surveys. They also have the distinct advantage of being timelier than data collected via survey methods. Another advantage of online data is its *granularity* – knowing what jobs employees search for, what skills employers want and what roles attract higher or lower wages. We combine information on job postings and clicks per posting to construct a measure of tightness for hundreds of job titles over several years. After controlling for observable job characteristics and traditional tightness measures, such as regional unemployment, we find that the number of clicks on a posting is a strong predictor of wages posted in job vacancies.

Key words: Internet, job search, wages, bargaining

JEL Classification: J64, E24, J30

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1. Introduction

Despite being a relatively recent development, online job search now plays a central role in matching employees to jobs. Once primarily the preserve of newspaper ads and notice boards, the presence of job advertisements in print is in steady decline. The spectacular growth and scale of online job postings and website traffic, which we summarise below, suggests that the internet is now the primary platform for hiring and job search. In the era of big data, information gleaned from online job search has the potential to improve our understanding of the labour market.

With a view to understanding how useful this data is for labour market research, this paper analyses online job postings and job search data from [Indeed's](#) Irish website. Ireland is an interesting case study as it is a labour market characterised by significant variation across time, geography and occupations, while its small size relative to other markets allows us to explore the data in substantial detail.

Indeed's data are attractive for several reasons. One attraction is that, unlike survey-based labour market statistics, there is a significantly shorter time lag with the online data. This means that up-to-date information on what skills employers are looking for, what jobs employees search for and how many jobs have been posted is readily available. However, such 'non-traditional' data, does not always lend itself easily to economic analysis and interpretation. There are important questions to be answered around measurement, comparisons with existing 'official' sources, separating trends from growing market size effects, and dealing with the concerns of the corporate data owners.¹ This means that when we use the data for economic analysis, it is vital to first assess the reliability and representativeness of the data.

Notwithstanding some of these concerns, for labour economists, the granularity of online data has significant potential. This is because it can provide fresh insights into the job search and hiring process – i.e. the 'matching function'. Several recent studies have used online data on job postings and search to research these questions. Faberman and Kudlyak (2016) show that job search effort is stronger for people 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. This means that online job search can improve matching *efficiency*. Brown and Matsa (2016) use online data to analyse job search during the financial crisis. They show that jobseekers are more likely to apply to more financially sound firms, highlighting the importance of job security

¹ These themes and others were explored in a recent Brookings event on "Can big data improve economic measurement?" Presentations from the event are available at <https://www.brookings.edu/events/can-big-data-improve-economic-measurement>.

to applicants. Brenčič (2015) investigates the measurement issues that arise when using job postings to analyse wages and salaries. They find that employers are less likely to post a wage in adverts for skilled workers. Previewing some of our own analysis, we find that despite only a sub-sample of postings including wage or salary information – around one one-in-seven postings include this information – comparisons with official survey data shows that the distribution of salaries (but not wages) is very similar to the national pattern.

The paper by Marinescu and Wolthoff (2016) is relevant for our own study. They use the role description in online job postings to show that job titles can explain up to 90% of the variance in wages. Previously, only around half of the cross-sectional variance in wages could be explained by worker and job characteristics (i.e. four-digit occupation codes). This effectively ascribed a large chunk of wage differences in the population to ‘luck’. Marinescu and Wolthoff’s important contribution is to show that luck has almost no role to play. Using OJS textual data from the role description, they show that fully controlling for the wide-ranging task and skill content in jobs explains almost all of the differences in wages we observe in the population. This paper is an important precedent for our own work in two ways. First, we also estimate wage regressions from the online job postings on Indeed. Second, we also use the text in the job title and job ad to extract observable job characteristics relating to geography, seniority/experience, education and job-type (permanent, contract, part-time, full-time, etc).

Our paper adds to a growing literature using online data in economic research. Our main research question is whether measures of labour market tightness derived from online job postings are informative for wages, *over and above* traditional tightness measures, such as unemployment, and after controlling for job characteristics. Before we get into this, however, the first part of the paper delves into some of the common measurement concerns about using online data. We do this by comparing the Indeed data with official labour market statistics in several dimensions. First, we show that job-posting trends closely track vacancies published by the Irish Central Statistics Office (‘CSO’). Next, we compare the geographic dispersion of postings with employment growth at the *county* level. Finally, we show that the distribution of salaries (but not wages) in the Indeed job postings data are very similar to distributions from the main household income survey carried out annually by the CSO.

The second part of the paper presents our analysis of wages and tightness. We show which jobs attract the highest posted salaries. We then show how the data can be used to construct a measure of labour market tightness, which can then be related to wages. Our analysis builds on the work of Lydon and Lozej (2018), who show the positive link

between new hires' pay and labour market tightness, as measured using unemployment at the *regional* level. Our contribution here is threefold: (1) construction of a measure of tightness from Indeed data; (2) more granular tightness measure (at the level of jobs); and (3) a more timely tightness measure.

2. The data – job postings on Indeed

Indeed is the No. 1 job site worldwide², with a presence in 60 countries. It provides details of job advertisements, both by aggregating other Internet sources, including companies' own career sites, and by employers posting jobs directly to the site. Globally, it has 250 million unique visitors per month³, 150 million CVs, and 600 million salary data points. Indeed is present in Ireland since 2009. It is the most-visited job site in the country, with 3.9 million monthly visits.⁴ On average, over 30,000 new job postings in Ireland are added each month. The typical duration of a job posting is just over one month.

For Labour research, Indeed's data has both advantages and disadvantages over other data sources, as summarised in Table 1. For policy use, representativeness is a key factor. Although, as more and more job search moves on-line representativeness becomes much less of a concern. Whilst we are unable to find Irish data on the extent of online job search, Sinclair and Mamertino (2018) report that according to a Harris Poll survey in 2015, 78% of new hires in a set of advanced countries (UK, Germany, France and the Netherlands) reported using online resources in their job search. Statistical agencies, like the CSO, use census weights to ensure that survey responses are representative of the population. In this paper, we do not attempt to re-weight the Indeed data. However, the sheer number of observations – on average 30,000 new job postings per month – means that we are able to make comparisons with official survey data across several dimensions.

In the following sections, we compare the online data across time, geographies, job mix and salaries. Whilst there are some differences between the sources – partly driven by differences in measurement concepts – the discrepancies are not so large as to lead us to conclude that this data are not representative of the labour market for new hires.

² comScore, Total Visits, March 2018

³ Google Analytics, Unique Visitors, September 2018

⁴ SimilarWeb, Total Visits, January 2019

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

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

2.1 Trends in job postings versus job vacancies

The most comparable official series for job postings is CSO vacancy data, collected in the quarterly Earnings, Hours and Employment Costs Survey (EHECS). Figure 1 shows that trends in monthly job postings on Indeed closely track trends in official job vacancies series. The job postings data, which we show to end-February 2019, suggest that growth in job openings in Ireland has levelled off in 2018, although they remain high relative to recent historical patterns. The fact that job postings have continued at a high level through to end-Feb 2019 suggests that the fall-off in the official vacancies series in December 2018 – vacancies were 10% lower than in June 2018 – is not the start of a downward trend.

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



Source: Indeed monthly data to end-Feb 2019. CSO vacancies to Q4 2018. Both series seasonally adjusted using X-13ARIMA-SEATS.

2.2 Cross-sectional coverage – mix of jobs, geography and salaries

The time-series coverage of the Indeed data is very good, albeit relatively short. It is also important to point out that, as a market, online job search is still growing. To be confident about using Indeed data to assess the state of the labour market, it is also important to verify its cross-sectional coverage. Here, we compare the mix of jobs, geographic coverage and salaries with published official statistics.

Indeed groups job postings under hundreds of granular, and proprietary, ‘job titles’. This is one of the common draw backs of using non-traditional data – direct comparisons with existing taxonomies – such as Standard Occupational Codes (SOC) – is not straightforward.⁵ Nonetheless, looking at the top-ten postings (Indeed) and new hires (LFS), it is possible to pick out commonalities in the jobs and roles (Table 2). Table 2 shows the top ten job titles in Indeed data for 2018 alongside the top-ten new hires by *four-digit occupation code* (UK SOC) 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. There is, however, a high degree of overlap between the two lists, with several job titles/occupations appearing in both lists. 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 nurses (16th in the ranking of new hires) and accountants (12th). 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.

⁵ The Indeed database does include a cross-walk of Irish job postings to US SOC occupation codes. We use this aggregation below to include occupation fixed effects in the wage regression because we do not have sufficiently large cell sizes at the Indeed job title level. However, this is not useful for comparisons with the Irish Labour Force Survey, which uses UK SOC codes. We have commenced a project using a UK-US SOC cross-walk, which is a work in progress.

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

Top 10 job titles on Indeed 2019 ⁺	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%

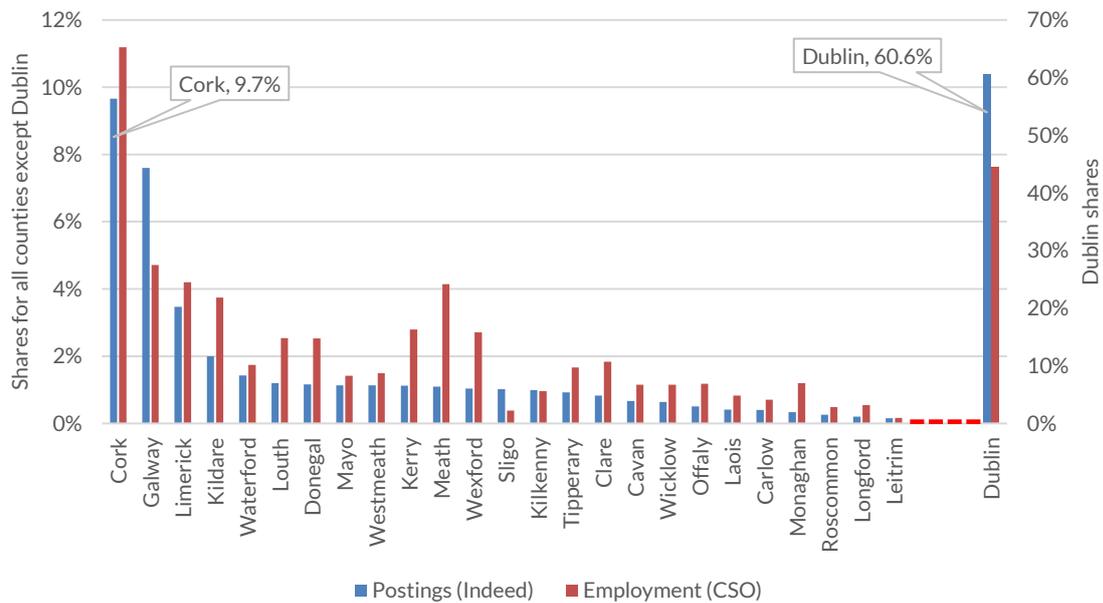
Source: (+) Indeed and (++) CSO Labour Force Survey (LFS). A new hire is defined as an employee who started a new job (from any of employment, unemployment or inactivity) during 2017Q3 – 2018Q3. LFS occupations are four-digit UKSOC codes (the lowest classification level).

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

To assess geographic coverage, we compare the county shares of job postings with (net) employment growth over the period 2014-16 (the latest available year of CSO county-level employment data). This is the only official county-level labour market data available. Job postings and net employment growth should be positively correlated, as long as some of the job postings relate to growth hiring, rather than just to replacing departing employees. As job postings are a gross flow and employment changes are a net flow – 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. Rather, the key thing we look for here is a similar level of geographic coverage, which is exactly what we find.

Almost half of net employment growth is in Dublin (45% in the CSO data). This is also where the majority of job postings are (60% of jobs posted), followed by Cork (10%) and Galway (8%), as Figure 2 shows.

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



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 difficult to see other counties clearly. We therefore represent it on its own right-hand side axis.

Relative to net employment growth, online job postings are slightly over-represented in the larger population areas (the earlier comment on gross versus net flows might also be relevant here). However, it is clearly not the case that smaller counties/rural areas are not represented at all. In fact, 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 very high, at 0.77.⁶ One of the advantages of the Indeed data is that county-level job postings are available long after the current CSO series ends in 2016. Postings have continued to grow strongly in 2017/18, with Dublin (59%), Cork (11.5%) and Galway (5.7%) still accounting for the largest share.

Why does Dublin have a higher share of gross postings compared to net employment growth?⁷ One explanation is that there is a greater concentration of workers in sectors with higher turnover in Dublin. Information Technology (IT, Nace Rev2 J) is one example. IT workers have higher rates of job turnover, as illustrated by the fact that

⁶ An alternative would be to use a weighted correlation. We did this using the inverse of employment shares by county from 2014-16 as analytic weights. The weighted correlation in this case is 0.92 (p-value=0.000). Excluding Dublin, it is 0.82.

⁷ 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 to net employment growth.

they have 30 months *less* average time on the job (average job tenure) relative to other workers (controlling for age).⁸ In 2018, 7% of employees in Dublin work in the IT sector, compared with 2% for the rest of the country. Similarly, workers in “Professional, Scientific and Technical Activities” (Nace Rev2 M), have 14 months less time on the job on average compared to other workers. Workers in this sector account for 7% of Dublin employees, compared with 4% in the rest of the country. These factors contribute to a higher rate of job churn 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%) versus the rest of the country (2.9%).

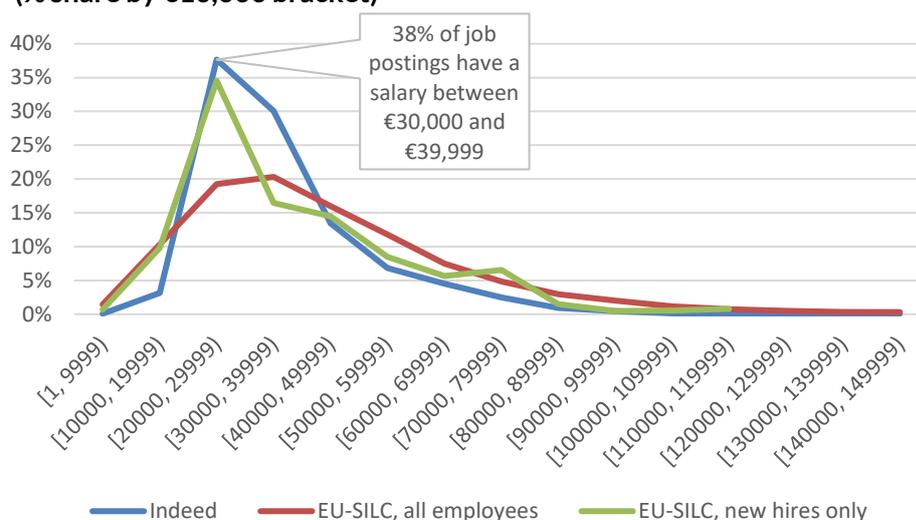
As summarised in Brenčič (2015), typically only a subset of job vacancy postings include salary or wage information. This is certainly the case with the Indeed Ireland, where only 14% of postings in 2018 included either salary or wage information. There could be several reasons for this, such as negotiable packages, or concerns about attracting (or deterring) applications from a certain pool of applicants. For example, employers sometimes point out that it can reduce the number of applications for a position, particularly for skilled jobs.

Despite only a fraction of job postings having salary or wage information, with over 360,000 new postings per year, we are not concerned about sample size, even at the job title level. Rather, the main concern is sample selection, and whether certain jobs or skills under-represented in the salary or wage distribution. We test this by comparing the distribution in Indeed data with nationally representative survey data (the EU Survey on Income and Living Conditions, EU-SILC). Figure 3 plots the two salary distributions for 2017, the last available year of EU-SILC micro data. It is important to point out that we restrict ourselves to salaries of *new hires* in the survey data. The two distributions are very similar. The mean salary in the Indeed Ireland job posting data is €36,700, compared with €38,800 for new hires in EU-SILC.⁹

⁸ Results from a regression of job tenure on a sector dummy (Nace Rev 2 J) and age, using the LFS microdata.

⁹ We use the 2017 data to calculate the salary distribution, as this is the latest available EU-SILC release. [Lydon and Lozej \(2018\)](#) show that the salary distribution for new hires is very different to that for incumbent workers, hence our focus on new hires.

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



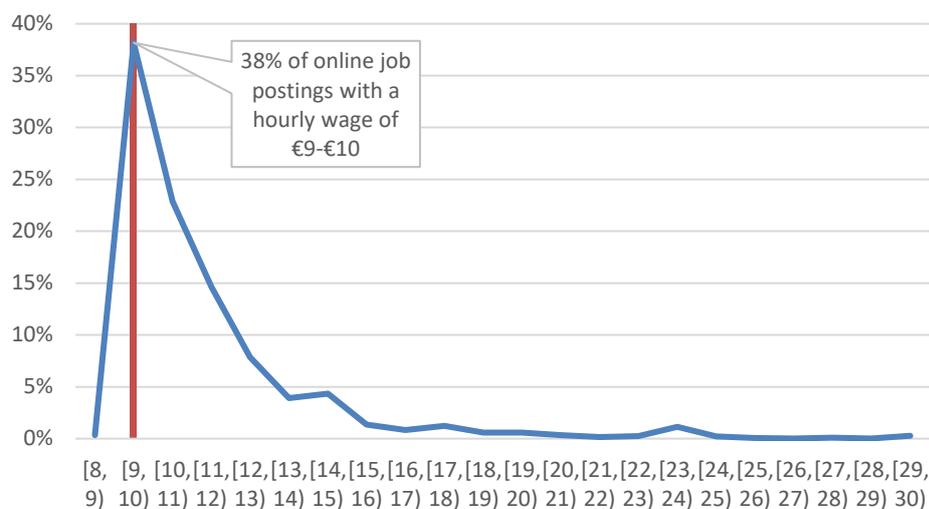
Source: Indeed 2017 and EU SILC 2017 (conditional on full-time, full-year workers).

The distribution of posted hourly wages (Figure 4) is bunched 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, according to the CSO was just over €21 in 2017/18 (there is no individual data on hourly wages to compare distributions). One reason for this might be that higher-paying jobs tend to post an annual salary, rather than an hourly wage. Bunching in the posted hourly wage might also explain why there is weaker support in the Indeed data for annual salaries at the lower end of the distribution (around €19,000). As few jobs post both annual and hourly pay, future work could combine the two series. For now, we concentrate on annual salaries in our analysis below.

The broad comparability of the Indeed and EU-SILC annual salaries is an important result for several reasons. First, it suggests that, despite only observing salaries for a subset of postings, they appear to be broadly representative. This contradicts the evidence in Brenčič (2015), who finds that employers are reluctant to post salaries when looking for skilled workers.¹⁰ Second, it gives us confidence that econometric analysis of the Indeed data – for example, to look at the relationship between tightness and wages – can inform our understanding of how the labour market works more generally.

¹⁰ Brenčič (2015) uses data from employment agencies for some countries, not online postings, which we expect is an important difference.

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



Salary *level* is obviously an important consideration for job seekers. This in turn can affect individuals’ decisions about migration, education and training, including choice of degree subject. While salary is not the *only* thing that matters, it is important, as the large literature on the signalling content of salary in occupation and degree choice shows (see Lydon (1999) for a discussion). Jobseekers also pay close attention to factors such as job security, location and other non-pecuniary aspects of the job. Table 3 lists the top job titles by average salary in 2018. For robustness, we focus on jobs with *at least* 50 salary observations. Recalling the granularity of the job title information, this means there are many individual jobs posted with higher salaries but with fewer total observations.

In Figure 5, we show a word cloud of all job titles in the *top half* of the annual salary distribution. The difference here versus the information in the table is we look at *all* job postings with salary information, with no restriction on numbers. In terms of a pattern, grade or experience is obviously a factor, with ‘manager’ or ‘senior’ standing out as commonly used words in job titles. Technical skills in IT, Engineering and Finance all attract top salaries. The word cloud presents a similar picture, with some additional information. For example, sales-related jobs and jobs located in Dublin are common in the top half of the salary distribution.¹¹ Jobs with finance skills, described by words like ‘accountant’ or ‘financial’ are also prominent, as are jobs related to engineering and construction. In the next section, we carry out a more formal analysis of wage determination, including controls for labour market tightness at the occupation level derived from the online data.

¹¹ Location might appear if an employer includes an expression like “Senior engineer – Dublin based” in the title.

3. Labour market tightness and wages

Labour market tightness refers to the balance of demand and supply in the labour market. The smaller the gap between the number of workers employers demand and the available supply of workers, the tighter the market. The wage bargaining setup in search and matching models allows the wage to increase with tightness as bargaining power shifts from employers to employees; see, for example, Cahuc et al (2014, Chapter 9) or Hornstein et al (2005) for an exposition of the framework. For policy makers, understanding tightness and how it affects wage growth is important for at least two reasons. First, higher wages mean higher costs for firms, which could feed through to inflation. Second, as earnings from employment are the main source of income for households, wage developments influence savings and spending decisions, contributing significantly to domestic demand.¹² Recent Central Bank research has looked at the relationship between wages and tightness using a Philips curve – which suggests that wage growth tends to pick up when unemployment is low – and job switching rates – which show that periods when job switching is high tend to be followed by higher wage growth.¹³

The basic search and matching framework defines labour market tightness as the ratio of vacancies (V) to unemployment (U). As Pissarides (2009) shows, however, the wage that matters for job creation is that of new hires, and not aggregate or average wages. This is one of the attractions of job posting data: by definition, all the information on (offered) wages and salaries is for new hires. Using a decade of wage data derived from administrative tax returns, and occupation/regional unemployment rates to proxy tightness, Lydon and Lozej (2018) show that new hires' pay is more than twice as sensitive to changes in the unemployment rate as incumbent workers' pay. In essence, our aim in this paper is to update the Lydon and Lozej (2018) evidence using a measure of tightness derived from Indeed's online job postings.

The evidence in Figure 1 indicates that online job postings are a close substitute for vacancies. In the standard model, the inclusion of unemployment in the denominator aims to capture, in a very broad sense, how much job search is happening at any one time. However, the extent of 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

¹² In 2018, personal consumption expenditure accounted for around half of total domestic demand in Ireland.

¹³ One of the draw-backs of the job switching metric for Ireland is that it cannot differentiate between voluntary and involuntary layoffs; see [Staunton and Lydon \(2018\)](#). This makes it all the more important to look at alternative measures of tightness. On Phillips curves, see [Linehan et al. \(2017\)](#) and [Byrne and Zekaitė \(2018\)](#). Of course, aggregate wage growth can also be impacted by other factors, such as firm dynamics, see [Adrian \(2018\)](#).

very well at all.¹⁴ We use Indeed data on the number of clicks on job postings to capture search effort directly. Our tightness measure is postings divided by clicks.

Clicks capture the number of user clicks on job postings, which open a description of the role in both the mobile and web formats of the Indeed site.¹⁵ It is important to point out that we do not capture the *number of users* doing the clicking. Whilst using cookies or registered user data could address this, these remain imperfect ways to identify unique users. They also introduce different problems, namely selection of registered 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 job seeker clicking on the same job multiple times is not something that varies systematically across jobs or time.

As well as capturing search effort directly, the granularity of the Indeed clicks and postings data offers other advantages. Studies that use micro data on wages, such as Stüber (2016), Haefke and Van Rens (2013) and Gertler et al (2016), typically relate *individual* wages to aggregate measures of unemployment and vacancies, for example at a regional or one-digit occupation level. In this paper, we construct a measure of tightness (postings/clicks) at the *three-digit* occupation level, almost 600 occupations in the data. This significantly reduces measurement error, and therefore removes a key downward bias from our estimates of the relationship between tightness and pay. With more data, we can also explore the functional form of the pay-tightness relationship. Specifically, we can test for threshold effects. The literature on non-linear Phillips curve (e.g. Albuquerque (2016)) finds that wages and inflation respond non-linearly to changes in slack, with larger jumps evident above certain threshold levels.

Using clicks to track behaviour, whilst relatively novel in economic research, is fundamental to the commerciality of online services. Clicks are one way in which the owners of the online content or technology monetise the interaction, either through advertising revenue or other forms of direct targeted sales. Clicks have also been used by economists to measure demand. A recent example is the paper by Gorodnichenko et al. (2018) uses data from an online shopping platform to build a demand curve, including 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 occupation. If clicks are high, we interpret this as implying there is

¹⁴ This is one of the contributions of [Faberman and Kudlyak \(2016\)](#), who use OJS data to measure search effort directly.

¹⁵ We exclude activity carried out through the Application Programming Interface, or API, which captures activities of customers or internal programmers.

ample supply of workers. We assume that employers can observe supply ex-ante, and post wages in job adverts to reflect the relative demand for and supply of employees.

Specification and Results

We use a wage regression to relate posted salaries (in logs) to job characteristics, a time-trend and tightness (postings/clicks in logs).¹⁶ We use data on job postings with salary information for the period January 2016 to December 2018, giving us a sample of around 52,000 jobs. Whilst Indeed has been posting jobs in Ireland since 2009, the initial years of operation are characterised by very high rates of growth, both as the online job posting market grew and as Indeed's penetration of that market increased. We therefore focus on the more recent years to minimise any bias arising from growth in market size/penetration. We also include month-year dummies for the date of initial posting. As we are specifically interested in whether the Indeed data contain any incremental information *over and above* what we can learn from existing public data sources, we also include regional unemployment (8 NUTS III regions) to capture local labour market conditions.

We consider both the cross-sectional and time-series dimension of clicks. Whilst clicks are observed at the level of the individual job posting, they can also be aggregated, for example up to Standard Occupational Codes (or SOC) using the indeed cross-walk from job titles to US SOC. Aggregation is potentially attractive for two reasons. First, if we have concerns about small cell-size or noise at the job posting level that could distort the results; and second, US SOC dummy variables are available at the same level of aggregation (3-digit). When we use postings/clicks at the US SOC 3-digit level, we use annual averages.

The job postings themselves contain a wealth of information on job and (desired) candidate characteristics. Indeed combines both postings published through its own platform and postings collated from across the internet, including from companies' own websites. This means that there is no job-posting template, resulting in a considerable amount of work to mine the information from the job ads.¹⁷ From this exercise, we extract information on experience, education, job type, contract type, full-/part-time and job location (26 counties). Summary statistics are shown in Table A1 in the appendix.

¹⁶ 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 the wage 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).

¹⁷ [Einav et al. \(2015\)](#) and [Marinescu and Wolthoff \(2016\)](#) carry out a similar exercise for ebay adverts and online job postings respectively.

Table 3 shows the regression results. The dependent variable is the log of the posted wage.¹⁸ The unemployment rate is available for eight NUTS III regions and is included at a three-month lag, to allow wages adjust to conditions. All specifications include month-year controls, and we incrementally add occupation fixed effects and/or the Indeed postings/clicks tightness measure.

The unemployment rate is significant in the specification with occupation fixed effects (column (2)). As unemployment is measured in percentage points, the coefficient can be interpreted as a semi-elasticity. The coefficient (-0.80) means that a 1% decrease in the unemployment rate is associated with a 0.8% increase in wages. This result is very much in line with the results in Lydon and Lozej (2018), Stüber (2016), Haefke and Van Rens (2013) and Gertler et al (2016).

The other factors that are correlated with higher wages tally with the unconditional picture from the word cloud (Figure 5). Posted wages are higher for jobs located in Dublin (over 8% higher on average). This can be interpreted as pure Dublin wage premium, as the regression includes many other controls, including occupation fixed effects. Not surprisingly, jobs with higher educational requirements tend to have higher posted wages. For example, jobs requiring a college degree have a 15 to 20% pay premium. Higher grade/experience jobs also pay more, with managerial jobs registering a premium of 21%. Posted wages for apprenticeships and internships are 30% lower. Jobs that involve part-time work also carry a large wage penalty, with wages 25% lower on average.

In column (3), we add the tightness measure (postings/clicks), initially at the US SOC 3-digit level. Tightness is positively correlated with wages and statistically significant, even when unemployment is not (when we exclude occupation fixed effects), with a coefficient of 0.18. Compared to specification (1), the R² is significantly larger including the tightness measure, increasing from 0.18 to 0.26. To interpret the 0.18 coefficient on tightness economically, it implies that a one standard deviation increase in tightness (0.64) increases wages by 11%. This seems implausibly high, and it seems likely that the measure is, in part picking up occupation fixed effects – given that we measure postings/clicks at the US-SOC 3 digit level. In specification (4), therefore, we add occupation fixed effects. The coefficient on tightness is reduced, but remains (just) statistically significant. As before, increases in the unemployment rate reduce posted wages (-0.747). Comparing the two effects, a one standard deviation fall in unemployment (1.19) is associated with a 0.88% increase in wages (-1.19*0.747); whereas a one standard deviation increase in tightness (0.64) is associated with a 3.7%

¹⁸ As inflation was almost zero during this period, hence we use nominal wages.

increase in wages (0.058×0.64). These effects, whilst still large and significant, are more plausible than the specification excluding occupation fixed effects.

In the final specification (5) in Table 3, we measure clicks at the *lowest* level of aggregation, the individual posting level. This also allows for full time variation in clicks. The average number of clicks at the job posting level is 19 (see Table A1 in the appendix), and the minimum is, obviously, one (we exclude a small number of postings with zero clicks, 669 observations). At this most granular, the standard deviation of the tightness measure is higher, increasing from 0.624 at the US SOC 3-digit level to 1.495 at this level. The coefficient on our tightness measure remains positive, although it falls from 0.058 to 0.018. That precision of the estimate is, however, far greater, as illustrated by the fall in the standard error compared with specification (4). In economic terms, the coefficient of 0.018 implies that a one-standard deviation increase in tightness (1.495) increases wages by 2.7%.

Allowing for threshold effects in tightness

The regression results suggest that wages are increasing in tightness, even after controlling for local unemployment, job/worker characteristics *and* occupation fixed effects. In the raw data, the wages-tightness relationship appears to move through several thresholds, as shown in Figure 6. There is little or no difference in wages at low levels of tightness (bottom third of the distribution), a large increase at the middle of the distribution, before flattening again, and, finally, one more large increase at very high levels of tightness (the top two deciles of the distribution).

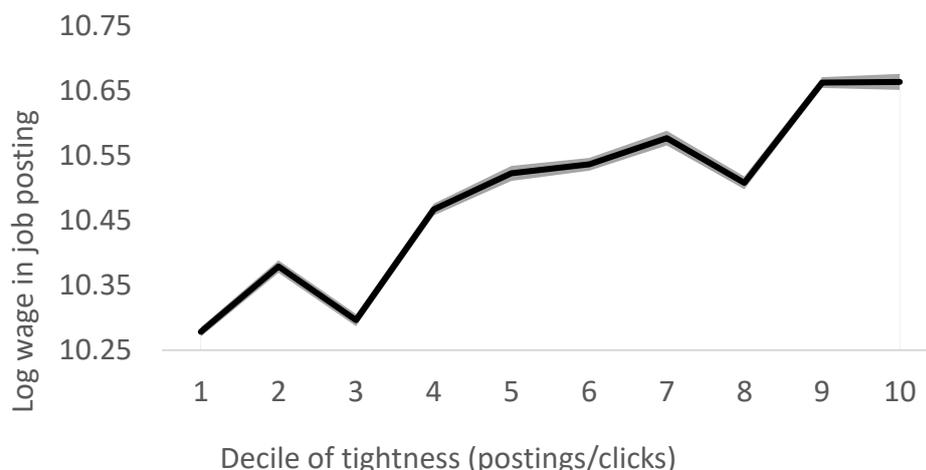
To test for threshold effects, we re-estimate specifications 4 and 5, with dummy variables for deciles of the tightness distribution. The results are shown in Table 4. The coefficients show that wage effects of tightness has several thresholds, more-or-less in-line with the pattern in Figure 6. At very low levels of labour market tightness, there is little or no wage boost from increasing tightness. Wages jump up considerably, by between 4 and 8%, in the middle of the distribution. Finally, in the top-two deciles, wages are around 10% higher. As with the linear results, the coefficients on $\log(1/\text{clicks})$ are measured with far greater precision. These results also suggest just one threshold in the tightness relationship with wages, at the 7th decile, after which the wage premium largely levels-off. It is important to emphasise that these effects are present even after controlling for a very wide range of job/application characteristics – many of which are positively correlated with pay – *and* after controlling for occupation fixed effects.

Table 3 | Wage regression results – (postings/clicks at US SOC 3-digit level)

	(1)		(2)		(3)		(4)		(5)	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Unemployment rate	0.100	(0.335)	-0.805***	(0.283)	0.102	(0.586)	-0.747***	(0.347)	-0.854***	(0.286)
Log (postings/clicks) ⁺					0.181***	(0.022)	0.058*	(0.033)		
Log (1/clicks) ⁺⁺					0.181***	(0.022)	0.058*	(0.033)	0.018***	(0.001)
Manager	0.199	(0.004)	0.209	(0.004)	0.188	(0.033)	0.211	(0.033)	0.203	(0.004)
Associate	0.120	(0.019)	0.071	(0.017)	0.061	(0.044)	0.070	(0.033)	0.062	(0.017)
Education < degree	[omit]		[omit]		[omit]		[omit]			
Bachelor	0.296	(0.007)	0.150	(0.007)	0.213	(0.018)	0.145	(0.013)	0.144	(0.007)
Master	0.305	(0.017)	0.197	(0.015)	0.267	(0.032)	0.197	(0.029)	0.199	(0.015)
Doctoral	0.303	(0.068)	0.181	(0.066)	0.274	(0.086)	0.177	(0.073)	0.187	(0.065)
Full-time	[omit]		[omit]		[omit]		[omit]		[omit]	
Part-time	-0.255	(0.012)	-0.249	(0.011)	-0.248	(0.041)	-0.248	(0.031)	-0.235	(0.011)
Permanent	0.084	(0.003)	0.049	(0.003)	0.071	(0.013)	0.048	(0.008)	0.041	(0.003)
Apprenticeship	-0.287	(0.051)	-0.310	(0.053)	-0.238	(0.054)	-0.318	(0.056)	-0.295	(0.053)
Internship	-0.265	(0.081)	-0.291	(0.086)	-0.280	(0.101)	-0.288	(0.095)	-0.273	(0.087)
Contract	0.026	(0.006)	0.033	(0.006)	0.028	(0.019)	0.032	(0.013)	0.030	(0.006)
<i>County</i>										
Dublin	[omit]		[omit]		[omit]		[omit]		[omit]	
Cork	-0.081	(0.005)	-0.075	(0.005)	-0.102	(0.031)	-0.077	(0.021)	-0.071	(0.005)
Clare	-0.122	(0.018)	-0.092	(0.015)	-0.124	(0.022)	-0.098	(0.017)	-0.081	(0.015)
Cavan	0.000	(0.022)	-0.034	(0.018)	-0.032	(0.031)	-0.035	(0.024)	-0.023	(0.018)
Carlow	-0.161	(0.021)	-0.141	(0.018)	-0.172	(0.036)	-0.144	(0.032)	-0.129	(0.018)
Donegal	-0.098	(0.022)	-0.122	(0.018)	-0.120	(0.031)	-0.123	(0.023)	-0.108	(0.018)
Galway	-0.084	(0.010)	-0.052	(0.009)	-0.087	(0.019)	-0.053	(0.015)	-0.039	(0.009)
Kildare	-0.075	(0.009)	-0.060	(0.008)	-0.072	(0.017)	-0.060	(0.011)	-0.052	(0.008)
Kilkenny	-0.119	(0.021)	-0.092	(0.016)	-0.119	(0.031)	-0.093	(0.021)	-0.077	(0.016)
Kerry	-0.151	(0.017)	-0.104	(0.015)	-0.156	(0.036)	-0.105	(0.025)	-0.095	(0.016)
Longford	-0.092	(0.035)	-0.081	(0.027)	-0.092	(0.064)	-0.083	(0.036)	-0.064	(0.027)
Louth	-0.121	(0.012)	-0.093	(0.01)	-0.106	(0.026)	-0.095	(0.020)	-0.081	(0.01)
Limerick	-0.095	(0.010)	-0.071	(0.008)	-0.091	(0.019)	-0.073	(0.012)	-0.060	(0.008)
Leitrim	-0.159	(0.036)	-0.087	(0.030)	-0.169	(0.044)	-0.087	(0.036)	-0.079	(0.029)
Laois	-0.118	(0.031)	-0.071	(0.026)	-0.099	(0.038)	-0.071	(0.026)	-0.052	(0.026)
Meath	-0.113	(0.013)	-0.083	(0.012)	-0.093	(0.023)	-0.084	(0.019)	-0.070	(0.012)
Monaghan	-0.092	(0.015)	-0.120	(0.015)	-0.091	(0.044)	-0.120	(0.031)	-0.112	(0.014)
Mayo	-0.075	(0.020)	-0.043	(0.017)	-0.089	(0.028)	-0.052	(0.019)	-0.029	(0.017)
Offaly	-0.156	(0.031)	-0.093	(0.027)	-0.136	(0.030)	-0.094	(0.021)	-0.069	(0.028)
Roscommon	-0.139	(0.023)	-0.108	(0.018)	-0.135	(0.027)	-0.110	(0.015)	-0.101	(0.018)
Sligo	-0.122	(0.021)	-0.095	(0.019)	-0.131	(0.025)	-0.096	(0.031)	-0.080	(0.019)
Tipperary	-0.091	(0.017)	-0.069	(0.013)	-0.086	(0.028)	-0.065	(0.011)	-0.064	(0.014)
Waterford	-0.074	(0.016)	-0.058	(0.013)	-0.079	(0.027)	-0.062	(0.013)	-0.050	(0.013)
Westmeath	-0.138	(0.019)	-0.090	(0.016)	-0.137	(0.035)	-0.094	(0.019)	-0.075	(0.016)
Wicklow	-0.134	(0.011)	-0.089	(0.009)	-0.122	(0.031)	-0.090	(0.025)	-0.083	(0.01)
Wexford	-0.026	(0.019)	-0.030	(0.015)	-0.044	(0.041)	-0.030	(0.030)	-0.014	(0.015)
Year-month FE	Yes		Yes		Yes		Yes		Yes	
Occupation FE	No		Yes		No		Yes		Yes	
N, R2	52,066	0.18	52,066	0.41	51,116	0.26	51,116	0.41	50,941	0.41

Notes: Data are Indeed Irish job postings with salary data posted between January 2016 and December 2018. Occupation fixed effects are at the US SOC 3-digit level. Dependent variable is the log of salary in job posting. Standard errors clustered at occupation level in specifications (2), (4) and (5). Standard errors in parentheses. Variation in sample size arises from a small number of postings with zero clicks. (+) Postings/clicks = sum of job postings at the US SOC 3-Digit level/sum clicks on these postings. (++) 1/clicks on each individual job posting.

Figure 6 | Mean of log wages by decile of tightness (postings/clicks, US SOC 3 digit)



Notes: Data are Indeed Irish job postings with salary data posted between January 2016 and December 2018. Shaded area is the 95% confidence interval.

Table 4 | Wage regression results, non-linear tightness

	Log(postings/clicks) ⁺		Log(1/clicks) ⁺⁺	
	Coeff.	Std. err.	Coeff.	Std. err.
Unemployment rate	-0.798***	(0.343)	-0.880***	(0.285)
Tightness decile				
1	[omit]		[omit]	
2	-0.009	(0.013)	0.017***	(0.006)
3	0.020**	(0.009)	0.045***	(0.006)
4	0.035*	(0.019)	0.053***	(0.006)
5	0.061**	(0.027)	0.064***	(0.006)
6	0.079**	(0.030)	0.079***	(0.006)
7	0.051*	(0.031)	0.093***	(0.006)
8	0.063**	(0.030)	0.094***	(0.006)
9	0.110***	(0.029)	0.096***	(0.007)
10	0.101***	(0.030)	0.086***	(0.007)
Manager	0.211	(0.033)	0.203	(0.004)
Associate	0.069	(0.033)	0.062	(0.017)
Education < degree level	[Omit]		[Omit]	
Bachelor	0.145	(0.013)	0.142	(0.007)
Master	0.196	(0.029)	0.198	(0.015)
Doctoral	0.177	(0.073)	0.190	(0.065)
Full-time	[Omit]		[Omit]	
Part-time	-0.250	(0.030)	-0.230	(0.011)
Permanent	0.048	(0.008)	0.040	(0.003)
Apprenticeship	-0.315	(0.056)	-0.289	(0.053)
Internship	-0.289	(0.094)	-0.270	(0.086)
Contract	0.033	(0.013)	0.028	(0.006)
Year-month dummies	Yes		Yes	
US-SOC 3D dummies	Yes		Yes	
N	51,116		50,941	
R2	0.41		0.41	

Notes: See notes for Table 3. (+) measured at the US SOC 3-digit level. (++) Measured at the level of the job posting

4. Conclusion

This paper shows how data on online job postings and job search behaviour can shed new light on labour market trends – and do so in a timely, highly granular manner. Using data from Indeed, we construct a measure of labour market tightness (postings/clicks) which summarises the balance of supply and demand in the labour market. We show that jobs where demand for employees is strong relative to supply have significantly higher wages, even after controlling for occupation fixed effects and other job and applicant characteristics. This result contributes to a growing body of research that quantifies the sensitivity of new hires' pay to changes in labour market conditions.

The tightness measure we construct is also useful for employers and policy makers. We illustrate this in Tables 4 and 5, by ranking the twenty 'most-tight' and 'least tight' jobs. A clear picture emerges of the relative demand for skills, with skilled and experienced jobs in engineering, finance and health dominating the list of most tight jobs. In contrast, the twenty least tight jobs tend not to be concentrated in any one sector, but are generally lower skilled or elementary roles.

Future research directions for this work include assessing how labour supply and demand respond to shocks, as well as extending the regression analysis to include job postings with hourly posted wages. Using geographic information in job search could also 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 does not ignore potential migrant labour supply. Identifying the specific jobs and sectors where migrant labour supply will be important in the future is important for understanding potential employment growth.

Table 4 | Top-20 job titles by postings per click / postings per CV

Job postings per click - top-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/ postings per CV

Job postings per click - bottom-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.

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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
Postings per click (US SOC 3-digit)	52,066	0.015	0.009	0.002	0.053
Log (postings per click, US SOC 3-digit)	51,116	-4.425	0.624	-6.012	-2.983
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
<i>Experience/grade</i>					
Manager	52,066	27.2%	44.5%	0	1
Associate	52,066	0.6%	7.8%	0	1
<i>Education</i>					
Bachelor	52,066	16.1%	0.367559	0	1
Master	52,066	1.4%	0.115493	0	1
Doctoral	52,066	0.2%	0.039654	0	1
Secondary	52,066	4.7%	0.212702	0	1
<i>Job/contract type</i>					
Permanent	52,066	46.3%	49.9%	0	1
Temporary	52,066	2.7%	16.3%	0	1
Apprenticeship	52,066	0.2%	3.9%	0	1
Internship	52,066	0.1%	2.6%	0	1
Contract	52,066	7.6%	26.5%	0	1
<i>Full-/part-time</i>					
Full-time	52,066	66.9%	47.1%	0	1
Part-time	52,066	2.7%	16.2%	0	1
<i>County</i>					
Cork	52,066	9.3%	29.1%	0	1
Clare	52,066	0.7%	8.1%	0	1
Cavan	52,066	0.4%	6.5%	0	1
Carlow	52,066	0.4%	6.6%	0	1
Dublin	52,066	68.3%	46.5%	0	1
Donegal	52,066	0.5%	7.4%	0	1
Galway	52,066	2.8%	16.5%	0	1
Kildare	52,066	2.5%	15.5%	0	1
Kilkenny	52,066	0.6%	7.8%	0	1
Kerry	52,066	0.7%	8.3%	0	1
Longford	52,066	0.2%	4.8%	0	1
Louth	52,066	1.7%	13.0%	0	1
Limerick	52,066	2.5%	15.6%	0	1
Leitrim	52,066	0.1%	3.8%	0	1
Laois	52,066	0.3%	5.1%	0	1
Meath	52,066	1.1%	10.2%	0	1
Monaghan	52,066	0.7%	8.1%	0	1
Mayo	52,066	0.6%	7.6%	0	1
Offaly	52,066	0.2%	4.8%	0	1
Roscommon	52,066	0.4%	5.9%	0	1
Sligo	52,066	0.5%	7.3%	0	1
Tipperary	52,066	0.8%	9.2%	0	1
Waterford	52,066	1.0%	9.7%	0	1
Westmeath	52,066	0.8%	9.1%	0	1
Wicklow	52,066	1.6%	12.6%	0	1
Wexford	52,066	0.8%	8.7%	0	1