



Job Employment Intensity, Matching, and Earnings 1999–2005

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The tables in this paper contain information about groups of people so that the confidentiality of individuals is protected. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person or firm. The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. These tax data must be used only for statistical purposes, and no individual information is published or disclosed in any other form, or provided back to Inland Revenue for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the LEED for statistical purposes, and is not related to the ability of the data to support Inland Revenue's core operational requirements. Careful consideration has been given to the privacy, security and confidentiality issues associated with using tax data in this project. Any person who had access to the unit-record data has certified that they have been shown, have read and have understood section 87 of the Tax Administration Act 1994, which relates to privacy and confidentiality. A full discussion can be found in the LEED Project Privacy Impact Assessment paper (Statistics NZ, 2003).

Abstract

In this paper, we exploit the worker-firm “link” information in the Linked Employer-Employee Database (LEED) to describe the patterns of employment intensity in jobs, matching between workers and firms, and the effect on job-level employment and earnings. First, we characterise workers’ annual employment experiences by their full-time (within month) and full-year (across months) dimensions, and firms’ mix of full-time and full-year jobs, and describe the extent of matching along these dimensions. We identify substantial cross-sectional variation in average employment intensity separately for workers and for firms, and some evidence that high-intensity workers are disproportionately employed in high-intensity firms. We then examine the relationship between jobs’ employment intensity and their earnings rates. Although there is a strong positive correlation between employment intensity and earnings that is largely associated with the full-time dimension, after controlling for other worker and firm factors, we find that there is only a modest direct impact of intensity on earnings. We conclude that the earnings premium associated with the full-time employment intensity is relatively small, and there is a premium for part-year work. The full-time employment intensity premium consists of both a continuous gradient across part-time levels and a discrete premium associated with full-time work.

Job Employment Intensity, Matching, and Earnings 1999–2005

Acknowledgements	1
1. Introduction	4
2. Background Literature.....	4
3. Data Description.....	6
4. Characterising the Annual Employment Experiences of Workers and Firms.....	8
5. Analysis of Job Earnings Rates	12
6. Concluding Discussion.....	14
References	16
Appendix 1. FTE Calculation and Comparison with Household Labour Force Survey	17

1. Introduction

Part-time jobs are often viewed as poor jobs with low pay or career prospects, and international studies find a part-time wage penalty (for example see cites in Booth and Wood, 2004). For example, the average wage of part-time jobs is about 75 percent of that of full-time jobs.¹ However, recent analysis by Hirsch (2005) for the US, and Rodgers (2004) and Booth and Wood (2004) for Australia find little or no evidence of a part-time wage penalty after controlling for observed and unobserved worker differences.

In this paper we use data from Statistics New Zealand's Linked Employer-Employee Database (LEED) to investigate two related issues. First, we characterise workers' annual employment experiences by their full-time (*within* month) and full-year (*across* months) dimensions, and firms' mix of full-time and full-year jobs, and describe the extent of matching along these dimensions. Although the LEED data does not contain information on hours worked to identify part-time work directly, we are able to construct measures of workers' and jobs' employment intensities and earnings rates. Using these measures of employment intensity, we investigate the incidence and concentration of employment across workers and firms, and the extent to which employment intensity observed separately for workers or for firms provides an adequate picture of job intensity patterns. We also describe how the intensity of the employment relationships is related to other worker and firm characteristics.

Second, we examine to what extent a job's employment intensity directly affects its earnings rate, or whether the earnings differential represents differences in workers and/or firms that are found in low-employment intensity jobs. Using our construct of employment intensity, the full-time equivalent (FTE) annual earnings rate of part-time workers is 69 percent that of full-time workers.² We then analyse the relationship between the job earnings premium associated with a job's employment intensity, controlling for the worker's and firm's employment intensity, and other observed worker and firm characteristics. We also control for either two-way worker and firm fixed effects, or for job fixed effects, to allow for unobserved earnings-related characteristics of workers and firms, or jobs. In these fixed effects specifications, the estimated earnings impact of intensity is identified from workers and firms that experience changes in intensity, or from jobs (worker-firm pairs) that have different intensities in different years.

The paper is organised as follows. The next section contains a brief overview of recent relevant literature on non-standard and precarious work and on part-time wages. In section 3, we describe the LEED data, provide a brief discussion of the algorithm we adopt to estimate the employment intensity associated with each job, and how we aggregate the monthly LEED data up to the annual level. Section 4 describes the characterisation of workers' and firms' annual employment experiences along the full-time and full-year dimensions, and then analyses the interaction patterns over the period. In section 5 we analyse the relationship between the annualised earnings rate associated with a job and the characterisation of worker and firm employment experiences. The paper concludes with a discussion and summary of the main findings.

2. Background Literature

The focus of our analysis in this paper is the composition of (total) employment observed across both the extensive (or full-year) margin and the intensive (or full-time) margin, and the relationship between the size of a job, as measured along these two margins, and its earnings rate. The analysis touches on two strands of literature: the first is literature around *non-standard* and *precarious* work, and the second is literature on part-time wage gaps.

¹ Authors' calculations based on the Household Labour Force Survey, Income Supplement (HLFS-IS) for the period 1999–2005.

² This is an annual-based measure of full-time workers that requires a worker to be full-time throughout the year (strictly whenever they are employed during the year). As a result, the sample of full-time workers is arguably more selective than that based on a point-in-time measure in the HLFS-IS, and thus generates a lower ratio of part-time to full-time average earnings rate in LEED.

Tucker (2002), Web Research (2004), and McLaren et al (2004) provide reviews and analysis of precarious work and non-standard employment, where *non-standard* employment is defined as employment that is not full-time and permanent, and *precarious* employment is defined as low-quality, with high health and safety and/or poverty risks associated with it.³ One conclusion from this literature is that, while there is an association between non-standard and precarious work, there is neither a definitive nor causal link between them. For example, many non-standard jobs with “good” working conditions and prospects are attractive both to firms and workers because of the employment flexibility they offer, and, conversely, many standard employment jobs may be precarious. Furthermore, although there are some objective measures of precarious work, such as poor employment and/or health and safety protection, limited non-wage employment benefits (such as leave entitlements), little scope for training or skill development, irregular and/or uncertain hours, low wages and little prospect for wage growth, not all workers in such work may perceive it as precarious.

In the LEED data, we can observe the interactions between workers and firms, and are able to make a reasonable inference about whether or not a job is non-standard based on the dynamic employment patterns and earnings associated with jobs.⁴ In particular, we focus on the full-time and full-year dimensions of a job to characterise whether or not it is a non-standard job. In contrast, the LEED data do not provide any qualitative measures to gauge the precariousness or otherwise of a job, other than an estimate of the (FTE annual) earnings rate associated with each job. To the extent that our estimated earnings rate is correlated with other dimensions of precariousness, this should provide a reasonable proxy measure for analysis.

The full coverage of wage and salary employment in LEED, together with the longitudinal nature of the data and the link between workers and firms, facilitates analysis of whether any relationship between non-standard employment and earnings may be due to the job per se, or whether it is associated with the worker in the job, or the firm in which the job resides. If the non-standard or precarious nature of a job is mainly associated with the worker in the job, then we would expect to see most jobs held by such workers characterised as non-standard or precarious. Similarly, if the characteristic is mainly associated with the firm, then we would expect to see that a disproportionate number of workers and jobs in such firms are non-standard or precarious. Alternatively, if the relevant characteristic of the job is idiosyncratic to that job, then we would expect to see a wide distribution of non-standard or precarious jobs across workers and firms.

Although part-time jobs are widely observed to pay lower wages rates than full-time jobs, the international evidence on whether this differential reflects a part-time penalty is at best mixed. Blank (1990) presents a variety of estimates of the effect of part-time work using alternative techniques based on cross-sectional data for the US. Using standard regression analysis, she finds a large penalty associated with part-time work (a coefficient of -0.19 on a part-time dummy variable in a log wage regression for women, and -0.26 for men). She then uses both instrumental variables (IV) and selection model methods to control for the non-random selection of workers into part-time jobs, and the resulting estimates from these approaches vary wildly. In particular, the IV based estimates are -0.6 for women and +0.8 for men, while the selection model estimates are a +0.17 log-point part-time premium for women and a -0.18 log-point penalty for men. Lettau (1997) estimates a log wage penalty part-time penalty of -0.16, and log total compensation penalty of -0.23, using underlying data from the US Employment Cost Index to compare the wage rates of part-time and full-time jobs within establishments and (3-digit) occupation, but he is not able to control for differences in individual level socio-demographic and human capital.

More recently, Hirsch (2005) uses US panel data to control for observed socio-demographic and human capital differences of workers and unobserved differences that are uncorrelated with job

³ See, for example, Tucker (2002).

⁴ However, it should be noted that our measure of a (non-)standard job is based on the ex-post realisation of how long the job exists, rather than an objective measure of permanence. In addition, while we can infer something about the “size” of a job from its earnings, we have no direct measure of the number of hours worked nor (for example) the time of day worked, etc.

changes in which workers employment status changes between part-time and full-time. The raw part-time log wage effect is -0.22 for women and -0.46 for men, and -0.09 and -0.19 when controlling for observed worker and job differences. Using a fixed effects specification to control for correlated unobserved factors, Hirsch then estimates marginally positive part-time effects of about 0.02 for both women and men, and concludes that much of the wage difference between part- and full-time work can be explained by observed and unobserved differences in workers and jobs.

Rodgers (2004) and Booth and Wood (2004) also analyse part-time wage effects in Australia using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. Using a selection model to control for non-random differences in the allocation of workers to part-time jobs, Rodgers estimates part-time log wage premia to women and men of 0.09 and 0.03, compared to raw differences of -0.07 and -0.21, respectively. Using a fixed effects specification to control for unobserved differences, Booth and Wood also estimate positive and quite large part-time effects on the order of 13–15 percent for women and men. The fixed effects specification estimates the part-time penalties for workers who switch between part-time and full-time status. The extent to which the subset of ‘status-changers’ is representative of all workers will determine whether such estimates are reliable measures of the ‘causal’ effect of part-time work on wages.

Dixon (2000) provides a series of estimates of the part-time wage gap for women in New Zealand using cross-sectional data from the Household Labour Force Survey, Income Supplement (HLFS-IS), controlling for observable demographic and human capital differences. While the point estimates are (almost) always negative, after controlling for alternative measures of experience the individual estimates are not statistically significant and, in these specification, the estimated part-time log(wage) gap is typically on the order of -0.01 to -0.05.

3. Data Description

The analysis in this paper uses Statistics New Zealand’s Linked Employer-Employee Database (LEED). The LEED uses information from tax and statistical sources to construct a record of paid jobs.⁵ Since April 1999, all employers in New Zealand are required to file Employer Monthly Schedules (EMS) with Inland Revenue (IRD), which lists all their paid employees during the month, the earnings they received and the amount of tax that was deducted at source. Two types of recipients are covered by EMS: those who have pay-as-you-earn (PAYE) tax deducted, who are employees; and those who pay withholding tax, who are a subset of the self-employed. Because the selection and coverage of which self-employed workers have tax withheld is unknown, we use only information on PAYE-deducted (employee) jobs.

Firms (employers) and workers (employees) are identified by unique confidentialised identifiers based on their respective IRD tax numbers. For workers, this represents a single identifier over time, enabling workers to be tracked longitudinally and across the firms that they work for. In the IRD data, employers are identified as the legal or administrative unit to which the EMS return relates, and do not equate to any consistent conception of a firm. That is, legal and/or other administrative changes can trigger a change in an employer’s IRD identifier, with no effective change in the economic structure of the firm. For this reason, we use a version of the LEED that has allocated EMS returns to geographic units, identified by a unique identifier known as the permanent business number (PBN) in Statistics New Zealand’s Longitudinal Business Frame (LBF) (Seyb, 2003), and adopt such geographic units as our concept of firms.⁶

In addition to regular firm-worker employment jobs being identified in the LEED, several other relationships involving PAYE tax deductions can be identified by particular “employer” identifiers.

⁵ See Statistics New Zealand (2003), Kelly (2003), and Crichton, Stillman and Hyslop (2005) for more detailed discussions of the LEED.

⁶ Note that the algorithms used in identifying PBNs in the LBF don’t correct for all false births and deaths. Also, allocation procedures will tend to generate some false job changes between geographic units within multi-unit enterprises.

These are taxable working-age social welfare benefits;⁷ earnings-related accident compensation payments from the Accident Compensation Corporation (ACC), student allowance payments, paid parental leave payments, and New Zealand Superannuation retirement pensions. In what follows, we make a distinction between LEED *earnings* from employment-jobs and other LEED *income* from these other (non-employment) sources.

Conceptually, the LEED covers the universe of PAYE employment relationships and earnings in New Zealand over the period. In addition, there is limited information on the characteristics of workers and firms: age, sex, and location of workers; and industry and location of firms. However, there are some significant weaknesses with the LEED. Perhaps the main weakness of the LEED for the current analysis is that it contains no information on hours worked. The EMS returns report only monthly earnings for each employee. As a result, we cannot accurately distinguish low hourly *wage* rates from low monthly *employment intensity*. Similarly, high earnings may result from either a high wage rate or high employment intensity. We must therefore derive a proxy measure of employment intensity.

In what follows, we use the subscript *i* to index workers, *j* to index firms, and *m* (months) or *t* (years) to index time. We define a job (*ij*) as an employment pair between worker (*i*) and firm (*j*), and the basic unit of observation for our analysis will be a job-year (*ijt*) observation. When the data are aggregated across jobs to the worker or firm level, the relevant worker-year or firm-year index will be (*it*) or (*jt*). To proceed from the monthly-observed data to annual unit of observation, we develop an algorithm to allocate workers' effort or relative *employment intensity* across multiple jobs, both within a month and across months in a year. This provides a partial adjustment for the lack of hours information, and takes into account the worker's LEED earnings from employment and any earnings-tested income they receive from other sources.

We first assume that each worker can have up to one unit of employment intensity in any month, and that their employment is zero in any month that they have no LEED earnings. A worker's total monthly employment intensity is reduced either if their total monthly earnings are less than full-time minimum wage earnings, and/or if they receive any earnings-tested LEED 'non-work payments' income.⁸ In the case of low earnings, we estimate an individual's employment intensity as the ratio of their actual to full-time minimum wage monthly earnings;⁹ while, in the presence of 'non-work payments', we estimate the employment intensity as the fraction of earnings to total LEED income (that is earnings plus non-work payments). Specifically, we estimate individual-*i*'s employment intensity in month-*m* of year-*t*, e_{imt} , as

$$e_{imt} = \min \left\{ 1, \frac{earn_{imt}}{(earn_{imt} + non_earn_{imt})}, \frac{earn_{imt}}{FT_mw_earn_{imt}} \right\} \quad (1)$$

where $earn_{imt}$ is *i*'s total LEED employment earnings in month-*m* of year-*t*, non_earn_{imt} is their total (earnings-tested) non-work income, and $FT_mw_earn_{imt}$ is the full-time minimum wage earnings level applicable to them in that month. As hourly wages generally exceed both minimum wages and non-work income rates, these adjustments likely overstate the employment intensity of part-time workers and those receiving non-work payments relative to full-time workers.

In order to give a sense of the reliability and possible bias in this measure, we have compared the estimated average employment intensity and the fraction estimated to be full-time with analogous estimates using Household Labour Force Survey (HLFS) data for workers over the sample period. The

⁷ The major working-age benefits are the unemployment, domestic purposes, sickness and invalids benefits. Although receipt of a taxable working-age benefit is identified, the specific benefit-type is not separately identifiable from the LEED data.

⁸ That is, if a person receives any (working-age) non-work payments (that is working-age benefit, ACC, student allowance or paid parental leave payments), we infer that they were not-working for at least part of the month. We do not include New Zealand Superannuation income as a non-work payment, as its eligibility does not depend on employment status.

⁹ We assume 40 hours per week, 4.35 weeks/month, and apply the relevant minimum wage based on age and period – for example full-time minimum wage earnings for adults in 2002/03 were \$1392 = \$8/hour * 40 hours/week * 4.35 weeks/month.

results are discussed in appendix 1 and summarised in appendix table A1. In summary, we believe the results provide some assurance that, first, the LEED employment intensity construct has similar properties to analogous survey estimates and, second, in the absence of any direct hours measure, it provides a useful first-order adjustment for estimating differing levels of employment intensity across workers.

For workers with multiple jobs, each worker's total monthly employment intensity (or 'effective employment') is allocated across the jobs they held in that month in proportion to the earnings from each job, to give their effective monthly employment in those jobs. We define a *job* as a unique firm-worker (that is PBN-employee) combination, and a *job-month* as a unique firm-worker-month combination. That is, worker-*i*'s effective employment in firm-*j* (job-*ij*) in month-*m* of year-*t* is

$$e_{ijmt} = \frac{earn_{ijmt}}{earn_{int}} * e_{int} \quad (2)$$

where $earn_{ijmt}$ is worker-*i*'s LEED earnings from firm-*j* in month-*m* of year-*t*. Aggregating the job-level effective employment of each worker within a firm-*j*, gives the firm's total effective monthly employment

$$e_{jmt} = \sum_{i=1}^{N_{jmt}} e_{ijmt}. \quad (3)$$

Also, summing either a worker's, job's or firm's monthly effective employment across months in a year provides our estimate of the annual effective employment of the worker, job or firm, which we express in annual terms (that is a full-time, full-year worker has annual effective employment of 1, etc.). For example, summing a worker's monthly employment intensity across the 12 months in year-*t*, gives their annual effective employment in year-*t*

$$e_{it} = \sum_{m=1}^{12} \frac{e_{int}}{12}. \quad (4)$$

Finally, based on these estimates of worker, job and/or firm annual effective employment, we estimate the corresponding full-time-equivalent (FTE) annual earnings rate as the relevant annual earnings divided by estimated annual effective employment. For example, the FTE annual earnings rate of job-*ij* in year-*t*, is

$$Y_{ijt} = \frac{earn_{ijt}}{e_{ijt}} \quad (5)$$

where $earn_{ijt}$ is job-*ij*'s total LEED earnings in year-*t*.

4. Characterising the Annual Employment Experiences of Workers and Firms

In this section we describe the LEED annual employment experiences of workers and firms over the sample period, and the interactions at the job-level between these. As described above, we capture two dimensions of a job's employment status over the course of a year: the number of months it exists (that is, it has LEED earnings) during the year (the full-year dimension), and the employment intensity during months worked (the full-time dimension). Using these dimensions, we characterise a job as full-year (FY) if it exists in each of the 12 months during the year, and as part-year (PY) otherwise. Similarly, using the employment intensity measure that we construct from the monthly LEED data, we characterise a job as full-time (FT) during the year if its monthly employment intensity is *always* 1 during months that the job exists during the year, and part-time (PT) otherwise. Note, that the requirement that the job has employment intensity of 1 in each month to be classed as FT is quite strict. For example, it rules out any ostensibly full-time jobs associated with workers who may have secondary jobs, income from a benefit or ACC income in any month, as well as jobs associated with workers who have earnings from two jobs in a month due to a (full-time) job change – each of these jobs will be classified as part-time for the year. As a result, this measure will tend to underestimate the level of full-time jobs.

Analogously, we characterise workers according to their total employment across all jobs held in a year, as full-year (FY) if they work during each month of the year, and as full-time (FT) if they work full-time during each of the months that they are employed. This means that workers who either receive working-age means tested income support and/or have low (that is, less than full-time minimum wage) earnings during any month will be classified as a part-time worker. Also, although any worker associated with a FY (or FT) job is necessarily a FY (or FT) worker, the converse is not true: that is, it is possible for workers to be FY (or FT) without having a FY (or FT) job. For example, full-time workers with more than 1 job during a month, because of either a secondary job holding or a full-time job change, will be (correctly) classified as full-time. Similarly, workers who experience a job change during the year will be full-year workers so long as they have earnings in each month.

In contrast to the characterisation of workers employment, we characterise a firm's employment by the mix of jobs held in it during the year, as summarised by the average full-year and full-time content of jobs.¹⁰ In particular, we characterise a firm's job mix as predominantly full-year (FY) during a year if, on average, its jobs last for at least 0.75 of the year (that is, 9 months), and as predominantly full-time (FT) if its average job employment intensity is at least 0.95 during months the jobs exist.¹¹ One advantage of characterising firms' job mix by the average job rather than aggregated jobs, is that it controls for the scale effects associated with firm 'size', such as the number of jobs a firm has at a point in time.

In the analysis that follows, we choose to weight job-year observations by the FTE employment of that observation. This choice is partly driven by the existence of multiple job holdings by workers, and a desire not to give undue importance to such workers. One interpretation of the choice is that analysis weights each unit of employment equally, with the implication being that part-time and part-year jobs and workers will contribute less weight to the analysis than full-time and full-year jobs and workers. For example, although job-year observations associated with full-time, full-year workers account for less than one-third of all job-year observations, and such worker-year observations account for less than 40 percent of all worker-year observations, they account for 57 percent of total effective employment.

Table 1 summarises the annual job, worker and firm-level characteristics, employment and earnings over the 6-year period of LEED. The first column describes the mean characteristics of the full sample of job-year observations across all years pooled. There were a total of 18.7 million job-year observations, 11.7 million worker-year observations, and 1.2 million firm-year observations during the 6-year sample period, averaging 3.1 million jobs, 1.95 million workers, and 200,000 firms annually. These annual observations were generated by 9.7 million distinct jobs held by 2.8 million distinct workers in 320,000 distinct firms over the period. On average jobs appear in 3.8 years, workers in 5.5 years, and firms in 5.7 years. Of the job-year observations, the weighted average annual FTE employment was 0.78, 55 percent were full-time jobs, 62 percent were full-year, 43 percent were both full-year and full-time, and the average FTE annual earnings rate of jobs was \$44,100 (expressed in constant, December 2005, \$-values, adjusted using the consumers price index).

The FTE-employment weighted average age of workers is 38.0 years and 46 percent are female. On average, workers appear in LEED for over 95 percent of the year, they have employment earnings for 94 percent of the year, and their annual FTE employment is 0.88 from 1.6 jobs. Furthermore, 62 percent of workers work full-time (when employed), 79 percent work full-year, and 57 percent work

¹⁰ There are alternative ways to characterise a firm's employment patterns which are, arguably, less dependent on the worker intensity, such as by seasonal fluctuations in the number of jobs at the firm. One consideration with such alternatives is how to identify part-time work, which is handled in a conceptually consistent way in the approach adopted here.

¹¹ To take account of firms entering or exiting LEED partway through a year, we have scaled the number of jobs at each firm by the fraction of the year the firm appears in LEED. So this measure should be interpreted as conditional on the firm existing for the full-year, and may bias upwards the estimate of full-year status for truly part-year firms engaged in, for example, seasonal employment. About 70 percent of firms have stable FT, 50 percent stable FY, and 43 percent stable FT,FY employment mix over the period. Also, "between" firm variation accounts for 98.9 percent of the total variation in firms log(Employment Intensity); 91.1 percent of firms that exist in all six years.

full-time for the full-year. In addition to employment, 12 percent of workers on average receive some non-earnings working-age income support during the year, and such support is received for 6 percent of the year.¹² At the firm-level, the FTE-weighted average number of jobs in a firm during a year is 300, and the average annual FTE-employment is 163.¹³

In the next four columns of table 1, the overall sample has been stratified by workers (that is, full-year and full-time) annual employment status. Column (2) shows that nearly 40 percent of worker-year observations are classified as full-time, full-year, covering about one-third of all jobs and 57 percent of effective employment. These workers are, on average, older (1.9 years), more likely to be male (6 percentage points), and have higher FTE annual earnings rates (20 percent), than the overall sample average. In addition, these workers work in larger firms (10–20 percent higher number of jobs and FTE employment), whose job-average FTE earnings is 10 percent higher than the overall average.

Column (3) summarises the characteristics associated with full-time, part-year workers. This sample covers 7 percent of worker-year observations, and 6 percent of all job-year observations and effective employment. The workers average annual FTE employment is 0.7 (about 8.4 months), and they are about 1 year younger, and 6 percentage points more likely to be male (about the same as full-time, full-year workers), than average. Interestingly, the FTE earnings rate of these workers is over 30 percent higher than average, and even higher than that of full-time, full-year workers.¹⁴

The samples of part-time workers are described in column (4) (full-year) and column (5) (part-year). While the characteristics of these sub-samples are by no means identical, they do share broad similarities. Combined they account for about 55 percent of worker-year observations, 60 percent of job-year observations, but only 38 percent of effective employment. Part-time workers tend to be younger and are more likely to be female, work in smaller firms, and earn substantially (about one-third) lower FTE annual earnings rates, than average.

In columns 5–9, we similarly stratify the sample by firms annual job mix of full-year and full-time annual employment. The patterns of characteristics across the different firm employment status categories are roughly similar to those across analogous worker categories. Although more than half of effective employment is accounted by full-time, full-year workers, most firm-year observations are classified as part-time, part-year. This covers about one-half of firm-year observations, about three-quarters of the job-year observations, and 60 percent of effective employment. Another one-quarter of firm-year observations are part-time, full-year, associated with 10 percent of job-year observations and 13 percent of effective employment. Workers in part-time firms are more likely to be female, while those in part-year firms tend to be younger than average. As with workers, the FTE annual earnings rates are substantially higher in full-time than part-time firms, and these rates differ relatively less across full-year versus part-year firms.

Appendix table A2 summarises the distributions of firm employment mix and worker employment status across each 1-digit industry. The patterns of allocation across industries largely accord with common priors. For example, workers in Mining, Manufacturing, Electricity, Gas and Water, and Government Administration industries are more likely full-time workers than average, and firms in those industries also have more predominantly full-time jobs; while the reverse is true for the Agriculture, Fisheries and Forestry, and Accommodation, Cafes and Restaurants industries. The distribution of firms' job mix in Education appears unusual, and deserves some comment. In particular, about 95 percent of firms in the Education sector are classified as having predominantly part-time and part-year jobs, while less than 1 percent have mainly full-time, full-year jobs. (In

¹² This includes working-age taxable social welfare benefits, ACC earnings compensation, student allowance, and paid parental leave.

¹³ In contrast, note that the average firm has 15.4 jobs during a year, and annual FTE-employment of 6.6 workers. The reconciliation of these large differences comes from the fact that most firms are small, but most employment is in large firms.

¹⁴ This could either be due to a real earnings premium for this group, or perhaps timing issues in the payment of part-year earnings in LEED, for example job-end lump-sum payments.

contrast, the distribution of workers' employment status in Education is roughly average although, for part-time workers, a greater proportion are part-year than for all industries.) The part-year characterisation is largely due to the seasonal nature of the education jobs on a calendar basis, together with (possibly) the asynchronisation with our tax-year based observations. For example, about 60 percent of the annual jobs in Education last for 9 months or less.¹⁵ In addition, the median average monthly earnings of jobs in Education is on the order of full-time minimum wage earnings, which suggests there is a high fraction of part-time jobs.

We next consider the interaction between the workers' and firms' annual employment along the part-time dimension. Figure 1 presents a detailed description of this interaction, again weighted by the FTE associated with each worker-firm job-year observation. This graphs workers' employment intensity conditional on being employed against firms' conditional employment intensity, where each measure has been rounded to the nearest 0.025. The figure shows a strong concentration of workers employed full-time together with a strong concentration of firms close to full-time (mean = 0.82). Although there doesn't appear to be a strong relationship between worker and firm employment experiences, this may be due to the skewed distribution of workers' employment: the correlation coefficient between worker and firm conditional employment intensity is 0.45.

Table 2 summarises the interactions between the characterisations of workers' and firms' annual employment experiences over the period, using the full-time, and full-year constructs described above. First, over 70 percent of effective employment occurs within 4 cells in table 2: about 30 percent is FT, FY workers employed in PT, PY firms; 16 percent is PT, FY workers in PT, PY firms; 13 percent is PT, PY workers in PT, PY firms; and 12 percent is FT, FY workers in FT, FY firms. Much of the observed allocation in table 2 is driven by the simple characterisations of workers' and the firms' employment – that is, the respective marginal distributions.

Second, in order to provide a sense of how much 'matching' occurs between workers and firms on the basis of the employment dimensions over and above what would be expected just from the marginal distributions, the parenthetical entries in the table are the expected fractions assuming independence between the worker and firm marginal distributions. The actual fractions on the diagonal are each greater than the fractions in parentheses, suggesting that positive matching between workers and firms along the full-time, full-year dimensions does occur. For example, although 57 percent of workers work full-time, full-year, more than 75 percent of these workers work in firms with mainly full-time, full-year employment. Similarly, 21 percent of part-time, part-year workers work in firms with mainly part-time, part-year employment, compared to there being only 16 percent of such workers. Although the off-diagonal fractions are not all less than the predicted fractions in parentheses (9 of 12 are lower), the fractions in the 2 extreme corners are both significantly lower than the predicted fractions, which is also consistent with non-random matching. That is, only 48 percent of full-time, full-year employment is employed in PT, PY firms (compared to there being 57 percent of such employment), and only 5 percent of part-time part-year employment works in FT, FY firms (compared to 16 percent of such workers).¹⁶

The interaction between workers' employment and firms' job mix differs in predictable ways along several dimensions, as suggested by table 1. For example, females and younger workers are more likely to work part-time than males and/or prime-aged workers, and also to work in firms whose job mix consists predominantly of part-time, part-year jobs. Among workers who are not employed full-time, full-year, those who receive work-tested non-employment income (mainly working age benefits)

¹⁵ There are about 30 percent fewer jobs in Education in January, and about 10 percent fewer in February, than during other months. Also, across all jobs (worker-firm pairs) that we observed over the period, the rate at which the last month a job appears is December is 3-4 times the rate of other months, and the rate at which the first month a job appears is February or March is much higher than other months. There may also be some reallocation of jobs across schools ("firms") in the LBF that contributes to the apparent seasonality, however we believe that most of the timing and magnitude of the observed changes is genuine.

¹⁶ Given the huge sample size, it is not surprising that a Pearson χ^2 test easily rejects the independence between workers and firms intensity characterisation: $\chi^2 = 602,131$ ($p < 0.0001$).

are far more likely to be both part-year and part-time workers (over 50 percent compared to 30 percent for the remainder of this subgroup). These workers are also more likely to work in firms whose job mix is mainly part-time, part-year jobs.

Similarly, firms with a predominance of part-time and/or part-year jobs tend to be in agriculture; accommodation, cafes and restaurants; retail trade; and services industries.¹⁷ These industries are broadly in line with industries where precarious jobs have been identified to exist (for example, see Tucker (2002) for a summary). In contrast, firms with a large incidence of full-time and/or full-year jobs are dominate manufacturing, government administration, and transport and storage industries. This simple characterisation accords with common priors on the industries the contain firms with predominant part-time versus full-time employment.

5. Analysis of Job Earnings Rates

In this section, we turn our attention to the relationship between the employment intensity of a job and its FTE annual earnings rate. Our focus is particularly on whether the positive correlation between FTE annual earnings and employment intensity may reflect a direct relationship, or whether it may be due to the sorting of workers across firms. Before presenting the formal analysis, we first describe the relationship between job earnings and employment intensity along two important dimensions: across workers life cycle age profiles, and across firm industries.

Figure 2 describes the average job FTE annual employment intensity (solid line), the average worker FTE annual employment intensity (dotted line) and the average job FTE annual earnings rate (dashed line) by worker age.¹⁸ The figure shows there are systematic life cycle patterns in both workers' annual and job-specific employment intensities and in their earnings rates which are likely to confound the estimated relationship between a job's employment intensity and its earnings rate. Each of the lines exhibits an inverted-U shape over the lifecycle. The average worker's and the average job's FTE employment intensities follow a very similar profile, although the difference between these declines from about 14 percentage points for teenagers to around 5 for the over 60, reflecting the greater turnover and job holdings of younger workers.¹⁹ The average FTE annual earnings rate rises steeply to a peak of about \$50,000 for workers in their late 30s to early 50s, and then drops off.

Similarly, in figure 3 we plot the average job employment intensity (solid diamond), together with the full-time (hollow square) and full-year (x) intensity components, and the average job FTE earnings rate (solid circle) by 3-digit ANZSIC96 industry. The industries have been arranged in increasing order of employment intensity. This figure shows the positive correlation between the average job employment intensity and average job earnings rate in an industry, which will confound the estimated (direct) impact of a job's employment intensity on its earnings rate. For example, the average FTE annual earnings in low FTE industries (those with average job FTE employment less than 0.7) is \$32,510, compared with the overall average of \$53,175. In contrast, the average FTE annual earnings in particularly high FTE industries (those with average job FTE greater than 0.9) is \$53,522.

To analyse the relationship between jobs' employment intensity and their earnings rates, we adopt regression models of the following form:

$$Y_{ijt} = \gamma E_{ijt} + \gamma_w E_{it} + \gamma_f E_{jt} + X_{ijt}'\beta + \varepsilon_{ijt} \quad (6)$$

where Y_{ijt} is the log(FTE annual earnings) of job-ij in year-t; E_{ijt} , E_{it} and E_{jt} are, respectively, the log(employment intensity) of job-ij, worker-i and firm-j in year-t; X_{ijt} is a vector of control variables

¹⁷ For example, these industries dominate across firms with average job FTE employment less than 0.7.

¹⁸ We have censored age below at 15 and above at 70, so that the averages at these extremes are across these respective groups.

¹⁹ Age profiles for Males and Females separately have remarkably similar shapes, with the average Male employment intensity about 6-7 percent higher than Female's.

associated either with worker-*i*, firm-*j* and/or job-*ij* in year-*t*; ε_{ijt} captures other unobserved factors; and γ , γ_w , γ_f , and β are parameters. Table 3 contains the results of this analysis based on all jobs.²⁰

First, the results in column (1) are for the simple regression of the job's log(FTE annual earnings) on its log(employment intensity). The coefficient of 0.263 implies that a 10 percent increase in employment intensity is associated with a 2.6 percent increase in the FTE earnings rates across jobs. We next split the total employment intensity effect into its 'full-time' (that is, the average intensity across the months the job exists) and 'full-year' (that is, the fraction of the year the job exists for) components. In line with the patterns observed in table 1, the results in column (2) imply the employment intensity premium is dominated by the full-time margin: a 10 percent increase in employment intensity within a month is associated with a 5.9% increase in the earnings rate across jobs, compared to 0.8% from an increase in job months.

In the specification in column (3), we add the worker's and firm's log(employment intensities), and the interaction between these variables, to the regression. Including these variables reduces the measured job full-time effect by about one-third, turns the implied full-year effect negative, suggesting that much of the observed simple relationship between a job's employment intensity and its earnings rate is due to the relative employment intensity of either the worker or, to a lesser extent, the firm. For example, a 10 percent increase in worker's employment intensity is associated with a 2.5 percent increase in the job earnings rate. Including worker demographic (age and sex), time (year dummies), and firm industry controls, reduces the estimated coefficients on all the employment intensity variables, as shown in column (4), which implies that much of the co-variation between job earnings rates and job employment intensity is associated with these controls rather than employment intensity per se.

Columns (5) and (6) provide alternative controls for unobserved worker and firm heterogeneity. In column (5), we present estimates from a joint two-way worker and firm fixed effects model (see Maré and Hyslop, 2006) – that is, we specify $\varepsilon_{ijt} = \alpha_i + \theta_j + u_{ijt}$ where α_i is a fixed effect for worker-*i*, θ_j is a fixed effect for firm-*j*, and u_{ijt} is a residual job-year effect. Including the two-way fixed effects causes a reduction in each of the estimated coefficients on the (job and worker and firm) employment intensity variables.²¹ The estimated direct effect of a job's FT employment on its earnings rate is 0.10, a drop of 60 percent from that in column (4), while the negative effect of a job's FY dimension also falls by over 50 percent to -0.02. In addition, the estimated coefficients on workers' and firms' employment intensities dropped by about one-third and two-thirds respectively.

In column (6), we estimate a standard one-way fixed effects model to control for unobserved individual job effects – that is, we specify $\varepsilon_{ijt} = \omega_{ij} + u_{ijt}$ where ω_{ij} is a fixed effect for job-*ij*, and u_{ijt} is an idiosyncratic job-year effect. Note that this specification absorbs the two-way worker and firm fixed effects in column (5) (as well as time invariant variables such as sex and industry). In this specification, the coefficient on employment intensity can be interpreted as the effect of a *change* in employment intensity on the job earnings rate after controlling for permanent unobserved job-level factors.²² Except for the estimated FY intensity coefficient, which is similar to that presented in column (4), the estimated employment intensity effects on earnings are either similar to, or smaller than, those in column (5). In particular, the estimated job full-time earnings elasticity is now about 0.06, and about the same magnitude as the worker FTE employment elasticity, while the estimated firm average job employment intensity effect is 0.015.

²⁰ Although much of the international literature on part-time wage effects finds results differ for males and females, our results are generally very similar – see Appendix Table A3.

²¹ Linear age, year and worker fixed effects are not jointly identified in this specification. As a result, we adopt a two-step estimation approach (see Maré and Hyslop, 2006), and estimate unrestricted gender age profiles for each year in the first stage, and treat the residuals from this as the dependent variable in the second stage regression.

²² The job employment intensity effects in this specification are identified by jobs that change intensity over the period. Roughly speaking, this excludes jobs that are full-time, full-year in all years they exist (10.4 percent of effective employment over the period), and jobs that exist in only one year (an additional 10.4 percent).

In other words, these results imply there is a relatively weak relationship between the time variation in employment intensity and earnings of jobs, at least among the subset of jobs whose employment intensity changes over time. This may not seem surprising if there are ‘good’ and ‘bad’ jobs independent of employment intensity, however the regression results without controls for job fixed effects for this group and the full sample are similar.

An implication from the pair of fixed effects regressions in columns (5) and (6) is that much of the variation in the job, worker and firm employment intensity variables over the sample is cross-sectional in nature. For example, the job fixed effects account for over 50 percent of the total variation in job-year FTE earnings over the period. A consequence of this is that it is difficult to identify the direct impact of employment intensity on a job’s FTE earnings rate separately from other persistent effects associated with workers, firms and/or jobs. Although most part-time jobs are short term in nature (the average part-time job is observed for about three quarters of a year during the sample period, compared to about 2 years for full-time jobs), many of the workers who fill these jobs also have other part-time jobs and, similarly, there is a concentration of part-time jobs in some firms.

To further explore this, table 4 presents the simple, marginal and partial R²s associated with the contributions of alternative sets of variables on log(job FTE earnings).²³ Although the simple R²s in the first column show that each of these sets of variables are reasonably correlated with job FTE earnings, the job fixed effects completely dominate and account for 95 percent of the variation. The marginal and partial R²s in the next two columns confirm this – that is, conditional on job FEs being controlled for the contributions of the other variables are generally negligible. The only exception being that worker demographic and time effects continue to make a noticeable contribution (marginal and partial R²s of 0.008 and 16 percent, respectively).

Finally, as a check of the robustness of the specification in column (6) of Table 3, we include a dummy variable for whether the job is full-time in each month it exists during the year. This allows a separation of the earnings premium associated with full-time employment intensity into a continuous component across levels of part-time work, and a discrete component associated with the full-time work. The results, presented in column (7), show a further reduction in the gradient along the full-time intensity continuum to 0.038, together with a positive premium of 0.033 (3.3 percent) associated with discrete full-time employment. Also, the premium associated with the discrete margin appears to be relatively larger for females than males (see Appendix Table A3). For example, the discrete full-time work earnings premium is 4.6 percent for females compared to 2.2 percent for males; while 10 percent higher part-time employment is associated with 0.3 percent higher earnings for females and 0.5 percent higher earnings for males.

6. Concluding Discussion

This study had two main objectives. The first was to describe and analyse the employment interactions between workers and firms using the job link information in the LEED data. For this purpose, we characterised workers according to the level of their FTE annual employment, which involves variation at both the across-month extensive (that is ‘full-year’) margin, and also the within-month intensive (that is ‘full-time’) margin. Analogously, we characterised firms by their mix of full-time and/or full-year jobs. Using these characterisations of workers’ and firms’ annual employment, we described and analysed their interactions at the job-level, and found that part-time workers tend to work in firms with a lot of part-time work, which implies part-time work is concentrated among certain workers and firms.

²³ Each simple R² is the R² from the regression of log(Job FTE earnings) on that set of variables; the marginal R² is the change in R² between the regression in column (6) of table 3 (the “full” regression), and the regression which drops this set of variables; and the partial R² is equal to the marginal R² divided by 1 – the R² from this latter regression – that is the partial R² is the fraction of the remaining variation explained by adding the set of variables to the full regression.

Job Employment Intensity, Matching, and Earnings 1999–2005

Second, we examined the relationship between jobs annual employment intensities and their full-time equivalent annual earnings rate. There is a strong correlation between a job's employment intensity, particularly along the full-time margin, and its earnings rate: a 10 percent increase in the full-time employment intensity is associated with a 5.9 percent increase in earnings, while a 10 percent increase in the full-year intensity is associated with a 0.8 percent increase in earnings. However, after controlling for observable worker demographics, worker and firm total employment intensities, and unobservable fixed effects associated with either workers and firms or with their job interactions, the estimated elasticity of earnings with respect to full-time employment intensity is only 0.06, while the full-year elasticity is -0.03. Furthermore, the full-time employment intensity premium consists of both a continuous gradient across part-time employment levels and a discrete premium associated with full-time work: for example, increasing part-time employment by 10 percent is associated with a 0.4 percent increase in earnings, with an additional premium of 3 percent for full-time work.

We estimate a similar magnitude of effect of workers' total employment intensity on job earnings rate, and a smaller effect of firms' average job intensity (0.015). These results highlight the difficulty in measuring the direct impact, if any, of a job's employment intensity on its earnings rate separate from these other time-constant worker, firm and/or job characteristics that are associated with much of the variation in earnings.

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Appendix 1. FTE Calculation and Comparison with Household Labour Force Survey

In order to give a sense of the reliability and possible bias in our employment intensity measure, we have compared the estimated average employment intensity and the fraction estimated to be full-time with analogous estimates using Household Labour Force Survey (HLFS) data for workers over the sample period. The results are summarised in appendix table A1.

First, we estimated an analogous employment intensity measure for wage and salary workers from the June Quarter HLFS Income Supplement (HLFS-IS) over the sample period, using reported weekly earnings and non-employment incomes together with the relevant minimum wage rate.²⁴ Both the average employment intensity and the fraction employed full-time estimated in the LEED are 2–3 percent lower than their HLFS-IS counterparts: average employment intensity is 0.87 compared with 0.89, and the fraction estimated to be full-time is 0.73 compared with 0.76. Average employment intensity for males is about 10 percent higher than for females (0.91 versus 0.82 in the LEED), while the fraction employed full-time is roughly 20 percent higher (0.82 versus 0.64 in the LEED).

Second, we compare these earnings-based measures of employment intensity, with a direct hours-based measure of employment intensity using reported hours worked in the main HLFS quarterly surveys. Using workers' (usual) weekly hours worked, we first censored hours above at 40 hours, and constructed their employment intensity as the ratio of hours-worked to 40, and a full-time indicator for those working at least 40 hours. The estimated average employment intensity is 0.85 (0.92 for males and 0.77 for females), and the fraction working full-time is 0.66 (0.83 for males and 0.48 for females). The estimates for males are reasonably close to their LEED and HLFS-IS earnings-based counterparts, but the estimates for females are both somewhat lower (particularly the fraction employed full-time). Next, we repeated this exercise using 30 hours as the full-time threshold, which is the standard survey definition of full-time work. The results from this exercise are remarkably similar to the HLFS-IS earnings-based estimates, especially for females: average employment intensity is 0.89 (0.94 for males, 0.84 for females), and the fraction working full-time is 0.78 (0.89 for males, 0.66 for females). In comparison with our LEED estimates, the 40-hours based measure appears a better match for males, while the 30-hours based measure is closer for females.

In summary, we believe these results provide some assurance that, first, the LEED employment intensity construct has similar properties to analogous survey estimates and, second, in the absence of any direct hours measure, it provides a useful first-order adjustment for estimating differing levels of employment intensity across workers. Furthermore, a closer look at the reported hours distribution in the HLFS shows that as well as there being a substantial fraction of part-time employment, a large fraction of workers also work more than the standard full-time level. In fact, about one-third of workers report usual hours of less than 40 hours per week, one-third report 40 hours, and one-third report more than 40 hours in the HLFS over the sample period. Thus, using a single level of full-time employment will also bias downwards the employment level of those working long hours, and bias upwards their (hourly) earnings rate.

²⁴ The HLFS-IS reference period varies by income source and, for wage and salary earners, by payment type (hourly wage versus salary), and is reported on a weekly basis in the data extract.

Table 1

Characteristics of Jobs, Workers and Firms in LEED, 1999–2005

	All Job-Year Obs (1)	Worker Employment Status				Firm Job Mix			
		Full Time		Part Time		Full Time		Part Time	
		Full Year (2)	Part Year (3)	Full Year (4)	Part Year (5)	Full Year (6)	Part Year (7)	Full Year (8)	Part Year (9)
Annual Job Characteristics									
No. Obs	18,676,324	6,016,515	1,115,879	4,332,277	7,211,653	1,517,025	1,321,089	1,897,874	13,940,336
FTE Employment	8,018,349	4,544,086	446,374	1,764,507	1,263,381	1,189,180	802,722	1,059,222	4,967,224
Job FTE Emp	0.782	0.928	0.612	0.710	0.416	0.918	0.834	0.831	0.730
Fraction FT	0.549	0.849	0.877	0.035	0.074	0.788	0.752	0.547	0.460
Fraction FY	0.624	0.839	0	0.675	0	0.797	0.621	0.756	0.555
Fraction FT,FY	0.430	0.759	0	0	0	0.674	0.532	0.475	0.345
Earnings	\$36,501	\$49,362	\$34,962	\$20,965	\$12,486	\$52,531	\$49,113	\$36,053	\$30,721
FTE earnings	\$44,077	\$53,175	\$58,485	\$28,589	\$27,891	\$56,947	\$58,470	\$41,684	\$39,179
Annual Worker Characteristics									
No. Obs	11,716,402	4,544,086	850,338	2,303,008	4,018,970
Age	38.0	39.9	37.2	36.7	33.4	39.3	37.4	40.3	37.3
Female	0.462	0.400	0.394	0.594	0.523	0.314	0.327	0.523	0.506
Rec'd Benefits	0.123	0	0.088	0.241	0.413	0.050	0.073	0.093	0.155
Rec'd NZS	0.015	0.009	0.020	0.023	0.023	0.011	0.008	0.024	0.016
Fraction of Year:									
Employed	0.936	1	0.698	1	0.700	0.972	0.947	0.962	0.920
Rec'd Benefits	0.055	0	0.022	0.099	0.204	0.014	0.023	0.042	0.073
Rec'd NZS	0.013	0.008	0.016	0.021	0.021	0.009	0.007	0.021	0.014
In LEED	0.954	1	0.727	1	0.802	0.977	0.958	0.972	0.943
FTE Employed	0.878	1	0.698	0.851	0.537	0.962	0.934	0.901	0.843
Fraction FT	0.622	1	1	0	0	0.843	0.813	0.629	0.537
Fraction FY	0.787	1	0	1	0	0.898	0.825	0.862	0.738
Fraction FT,FY	0.567	1	0	0	0	0.789	0.723	0.592	0.483
No. Jobs	1.57	1.32	1.42	1.90	2.06	1.25	1.45	1.40	1.70
Total Earnings	\$40,455	\$53,175	\$40,009	\$25,252	\$16,091	\$54,885	\$54,557	\$39,027	\$35,025
FTE earnings	\$44,077	\$53,175	\$58,485	\$28,589	\$27,891	\$56,864	\$58,116	\$41,737	\$39,245
Annual Firm Characteristics									
No. Obs	1,211,200	186,981	79,050	323,638	621,531
Fraction of Year	0.984	0.992	0.959	0.986	0.960	0.983	0.992	0.964	0.987
No. Jobs	300.4	335.5	295.8	229.4	274.9	209.8	156.1	364.1	331.8
No. FYE Jobs	188.8	221.2	183.3	138.0	145.5	172.3	100.7	284.7	186.6
Average Age	36.3	37.1	36.1	35.6	34.5	38.5	36.2	39.2	35.2
No. Females	165.4	185.3	160.4	130.9	144.0	71.0	58.4	256.9	185.8
No. FTE Jobs	162.6	194.7	160.8	112.6	117.5	167.9	97.3	261.4	150.8
Avg Earnings/job	\$25,607	\$30,478	\$27,531	\$18,910	\$16,765	\$46,191	\$36,914	\$28,776	\$18,177
FTE Earnings/job	\$44,077	\$48,620	\$49,551	\$36,182	\$36,828	\$56,947	\$58,470	\$41,684	\$39,179

Notes: There are a total of 9,729,904 jobs, 2,776,361 workers and 322,713 firms observed in LEED over the sample period. Years are tax years (ie April–March). Means are weighted by job annual FTE employment. All earnings are calculated conditional on positive values, and expressed in constant (December-quarter 2005) \$-values, adjusted using the CPI. 'Full Year' firms have actual number of worker-months of at least 75 percent of potential worker-months (Number of workers * Number of months firm observed); 'Full Time' firms have FTE of at least 95 percent of number of worker-months.

Symbol: ... not applicable

Job Employment Intensity, Matching, and Earnings 1999–2005

Table 2

Employment Interactions, 1999–2005

Worker Employment Status:	Firm Job Mix				
	Full Time		Part Time		Total
	Full Year	Part Year	Full Year	Part Year	
Full Time, Full Year	11.70 (8.40)	7.24 (5.67)	7.81 (7.49)	29.91 (35.11)	56.67
Full Time, Part Year	0.80 (0.83)	0.90 (0.56)	0.50 (0.74)	3.37 (3.45)	5.57
Part Time, Full Year	1.61 (3.26)	1.02 (2.20)	3.58 (2.91)	15.79 (13.64)	22.01
Part Time, Part Year	0.71 (2.34)	0.85 (1.58)	1.32 (2.08)	12.88 (9.76)	15.76
Total	14.83	10.01	13.21	61.95	100.00

Notes: Entries in parentheses are the expected cell percentages assuming independence between the firm and worker marginal distributions.

Job Employment Intensity, Matching, and Earnings 1999–2005

Table 3

Regressions of log(Job FTE Annual-Earnings Rate)

	Regression Specification						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Job FTE employment)	0.263 (0.0002)
log(Job FTE / Job months)	...	0.587 (0.0003)	0.378 (0.0004)	0.235 (0.0003)	0.103 (0.)	0.058 (0.0004)	0.038 (0.0004)
log(Job months)	...	0.080 (0.0002)	-0.046 (0.0003)	-0.042 (0.0002)	-0.017 (0.)	-0.031 (0.0002)	-0.032 (0.0002)
Full-time Job	0.033 (0.0001)
log(Worker FTE employment)	0.183 (0.0005)	0.111 (0.0004)	0.074 (0.)	0.060 (0.0003)	0.062 (0.0003)
log(Firm FTE employment)	0.059 (0.0001)	0.050 (0.0001)	0.015 (0.)	0.015 (0.0002)	0.015 (0.0002)
log(Worker FTE)*log(Firm FTE)	0.037 (0.0001)	0.030 (0.0001)	0.007 (0.)	0.002 (0.0001)	0.001 (0.0001)
Worker demographics	x	x	x	x
Firm 3-digit ANZSIC	x
Worker & Firm Two-way FE	x
Job Fixed Effects	x	x
R-squared	0.120	0.172	0.239	0.457	0.909	0.959	0.959

Notes: The number of job-year observations used is 18,676,324, accounting for 8,018,349 FTE employment; all regressions are weighted by job-year FTE employment; worker demographics include separate quartic age profiles, and year-specific intercepts, for males and females. Due to computational constraints, we have not estimated standard errors for the two-way fixed effects specification in column (5); we expect these should be bounded by the estimated standard errors in columns (4) and (6).

Symbol: ... not applicable

Job Employment Intensity, Matching, and Earnings 1999–2005

Table 4

Simple, Marginal and Partial R-squareds of Contributions to log(FTE Earnings)			
Contribution	Simple R ²	Marginal R ²	Partial R ²
1. log(Job FTE / Job months) and log(Job months)	0.172	0.0003	0.007
2. log(Worker FTE employment)	0.156	0.0002	0.004
3. log(Firm FTE employment)	0.061	0.0000	0.001
4. Worker demographics and time effects	0.262	0.0079	0.160
5. Firm 3-digit ANZSIC	0.199
6. Job Fixed Effects	0.950	0.535	0.928

Notes: For each contribution (row), the simple R² is the R² from the simple regression of log(job FTE Earnings) on that contribution; the marginal R² is the change in the R² between the specification in column (6) of table 3 and the regression that omits that contribution; and the partial R² is the marginal R² divided by (1 - R² from the regression that omits that contribution). The firm industry dummies are absorbed by job fixed effects.

Symbol: ... not applicable

Job Employment Intensity, Matching, and Earnings 1999–2005

Figure 1

Joint Distribution of Firm and Worker FTE to Notional Employment Ratios

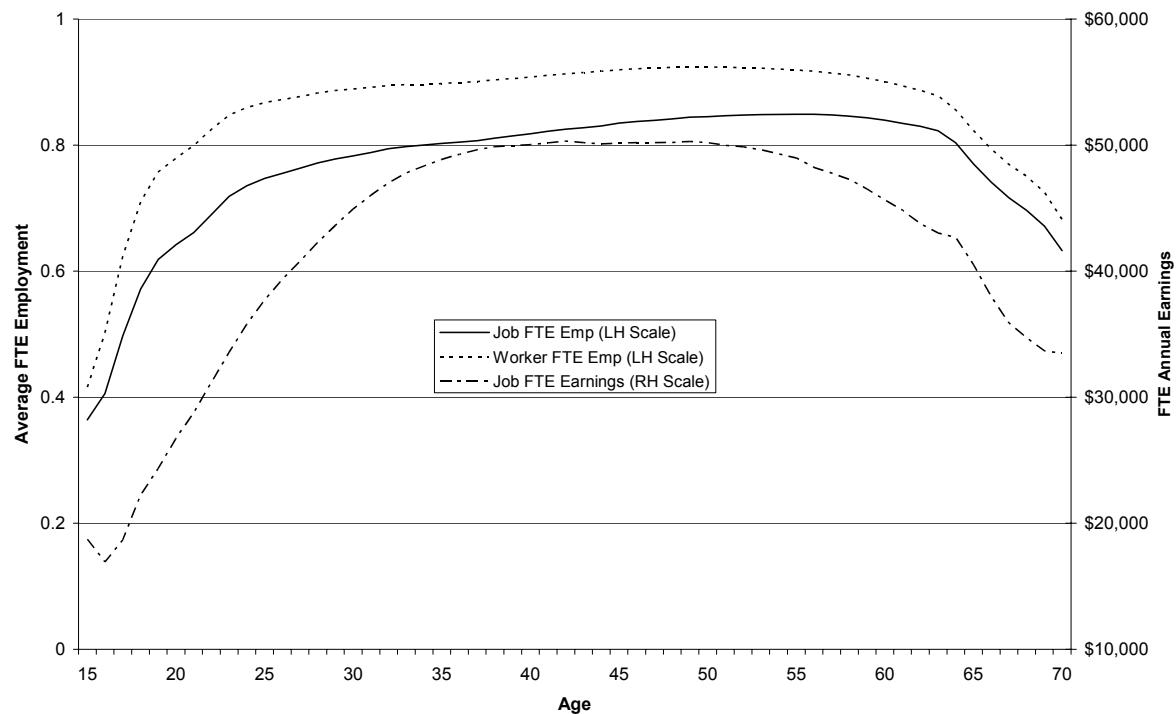


Notes: The FTE to notional employment ratios for firms, (FTE employment / total number of worker-months); and for workers, (FTE employed / number of months employed).

Job Employment Intensity, Matching, and Earnings 1999–2005

Figure 2

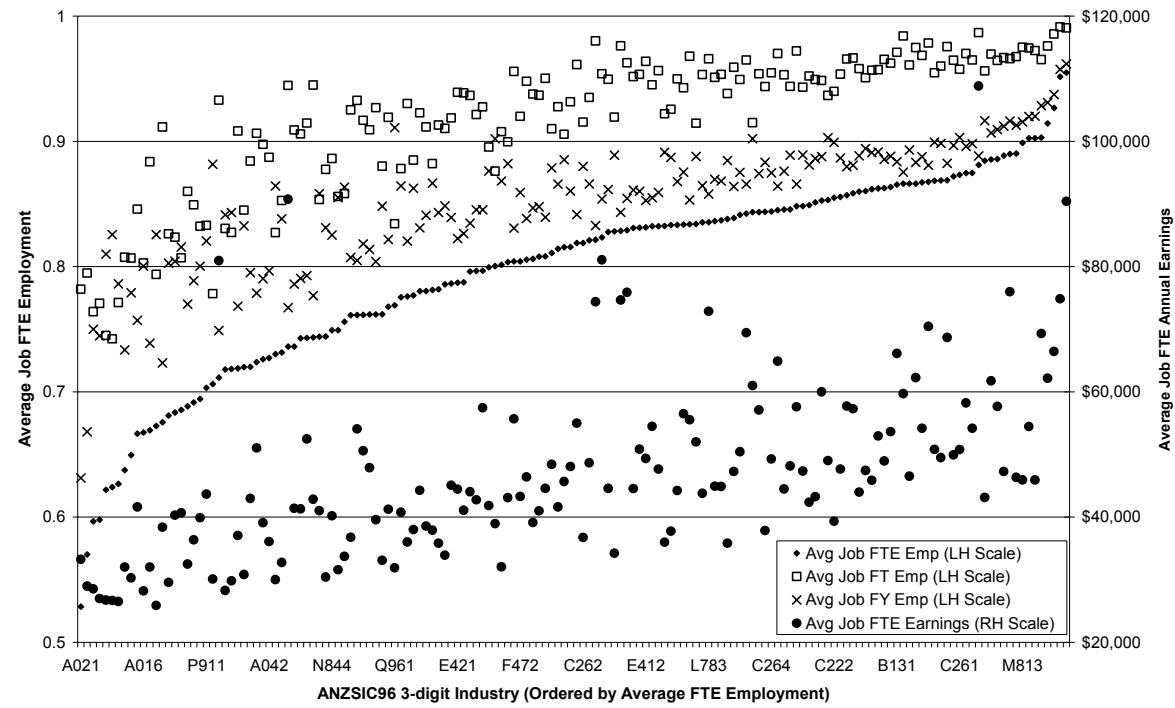
Job and Worker FTE Employment, and Job FTE Annual Earnings, by Age



Job Employment Intensity, Matching, and Earnings 1999–2005

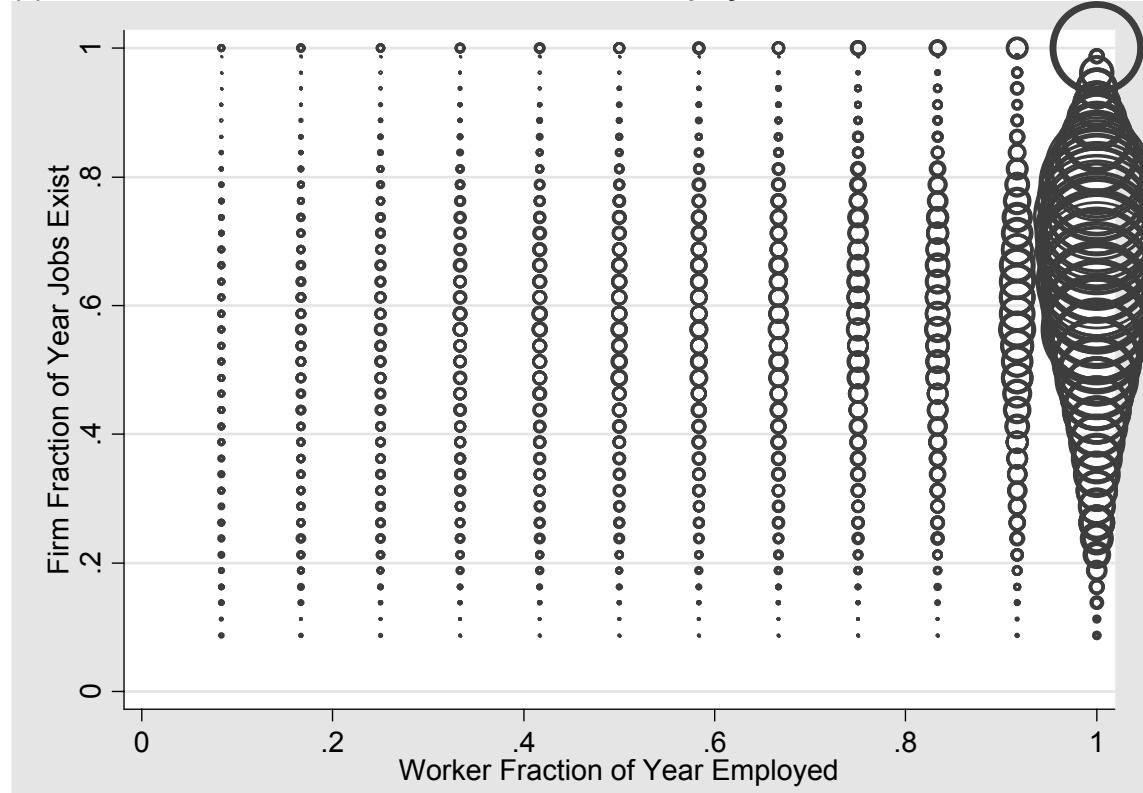
Figure 3

Average Job FTE, FT and FY Employment, and FTE Annual Earnings, by Industry



Appendix figure 1

(a) Joint Distribution of Firm and Worker Notional Employment Ratios



Notes: The notional employment ratios for firms, the (total job-months / 12*number of jobs); and for workers, the fraction of the year employed.

(b) Joint Distribution of Firm and Worker FTE Employment Ratios



Notes: The FTE employment ratios for firms, (total FTE employment / number of workers); and for workers, (FTE employment / 12).

Job Employment Intensity, Matching, and Earnings 1999–2005

Appendix table A1

	All	Males	Females
Average Monthly Employment Intensity			
LEED (Earnings)	0.865	0.909	0.818
HLFS-IS (Earnings)	0.888	0.936	0.839
HLFS (40 hours)	0.845	0.921	0.766
HLFS (30 hours)	0.890	0.942	0.837
Fraction Employed Full-time			
LEED (Earnings)	0.733	0.819	0.643
HLFS-IS (Earnings)	0.764	0.868	0.656
HLFS (40 hours)	0.660	0.829	0.484
HLFS (30 hours)	0.778	0.894	0.658

Notes: All estimates are based on workers aged 15 and over. The LEED estimates are based on PAYE employees, and the HLFS and HLFS-IS are based on wage and salary workers. The LEED and HLFS-IS employment intensity is measured as the lesser ratio of employment earnings to total income or full-time (40 hours per week) minimum wage earnings. The HLFS employment intensity is measured as reported 'usual hours' worked, censored at 40 (or 30) hours, as a fraction of 40 (or 30).

Job Employment Intensity, Matching, and Earnings 1999–2005

Appendix table A2

Distributions of Firm and Worker Employment by Industry

	Full Time		Part Time		FTE Employment Share
	Full Year	Part Year	Full Year	Part Year	
Firm Employment Mix					
A: Ag, Fish, Forestry	5.63	5.12	7.51	81.74	5.23
B: Mining	35.50	19.28	8.72	36.50	0.25
C: Manufacturing	25.89	11.58	12.70	49.82	16.41
D: Elect, Gas, Water	40.49	28.08	8.01	23.42	0.43
E: Construction	18.56	21.11	11.75	48.58	5.58
F: Wholesale Trade	21.66	16.58	13.97	47.79	6.94
G: Retail Trade	6.70	4.50	13.76	75.03	11.17
H: Accom, Cafes, Restaurants	0.56	0.31	4.67	94.46	4.49
I: Transport, Storage	21.65	13.10	11.45	53.80	4.33
J: Communication	13.63	27.79	8.36	50.22	1.44
K: Finance, Insurance	31.79	25.02	12.78	30.41	2.90
L: Property, Business Services	18.02	15.59	12.37	54.01	13.02
M: Govt Admin	23.50	15.98	11.37	49.16	3.98
N: Education	0.80	0.67	4.05	94.48	8.79
O: Health & Community Services	1.93	0.92	31.95	65.20	9.17
P: Cultural & Recreation Services	5.32	5.35	11.18	78.15	2.27
Q: Personal & Other Services	27.71	5.84	19.19	47.26	3.50
Unspecified	35.50	2.84	40.33	21.32	0.11
Total	14.83	10.01	13.21	61.95	100
Worker Employment Status (Main-job Industry)					
A: Ag, Fish, Forestry	35.82	5.97	25.33	32.88	5.23
B: Mining	72.43	6.32	11.74	9.50	0.25
C: Manufacturing	60.19	5.28	21.64	12.89	16.41
D: Elect, Gas, Water	79.99	5.29	8.55	6.18	0.43
E: Construction	58.08	7.28	19.19	15.45	5.58
F: Wholesale Trade	68.23	6.14	15.34	10.29	6.94
G: Retail Trade	45.13	3.98	32.29	18.60	11.17
H: Accom, Cafes, Restaurants	28.58	4.48	37.33	29.61	4.49
I: Transport, Storage	65.03	5.30	16.90	12.77	4.33
J: Communication	65.94	5.63	17.69	10.74	1.44
K: Finance, Insurance	73.77	6.79	11.59	7.84	2.90
L: Property, Business Services	58.89	7.48	18.62	15.01	13.02
M: Govt Admin	77.94	4.76	10.02	7.29	3.98
N: Education	58.27	5.52	16.61	19.59	8.79
O: Health & Community Services	53.70	4.58	29.65	12.07	9.17
P: Cultural & Recreation Services	53.57	5.90	22.84	17.70	2.27
Q: Personal & Other Services	60.82	4.36	22.00	12.81	3.50
Unspecified	33.64	8.44	30.93	26.99	0.11
Total	56.67	5.57	22.01	15.76	100.00

Notes: For workers with multiple jobs, industry is assigned on the basis of their main (highest earning) job during the year.

Job Employment Intensity, Matching, and Earnings 1999–2005

Appendix table A3a

Regressions of log(Job FTE Annual-Earnings Rate) – Males

	Regression Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Job FTE employment)	0.274 (0.0003)
log(Job FTE / Job months)	...	0.620 (0.001)	0.426 (0.001)	0.260 (0.001)	0.052 (0.0004)	0.047 (0.0006)
log(Job months)	...	0.124 (0.0003)	-0.012 (0.0004)	-0.025 (0.0003)	-0.032 (0.0002)	-0.032 (0.0002)
Full-time Job	0.022 (0.0002)
log(Worker FTE employment)	0.183 (0.0007)	0.121 (0.0006)	0.056 (0.0005)	0.065 (0.0005)
log(Firm FTE employment)	0.070 (0.0001)	0.055 (0.0001)	0.011 (0.0003)	0.017 (0.0003)
log(Worker FTE)*log(Firm FTE)	0.041 (0.0002)	0.026 (0.0002)	0.005 (0.0001)	-0.002 (0.0001)
Worker demographics	x	x	x	x
Firm 3-digit ANZSIC	x
Worker & Firm Two-way FE
Job Fixed Effects	x	x
R-squared	0.112	0.149	0.226	0.440	0.950	0.959

Notes: The number of male job-year observations used is 9,325,464, accounting for 4,315,349 FTE employment; all regressions are weighted by job-year FTE employment; worker demographics include separate quartic age profiles, and year-specific intercepts. Due to computational constraints, we haven't estimated standard errors for the two-way fixed effects specification in column (5); we expect these should be bounded by the estimated standard errors in columns (4) and (6).

Symbol: ... not applicable

Job Employment Intensity, Matching, and Earnings 1999–2005

Appendix table A3b

Regressions of log(Job FTE Annual-Earnings Rate) – Females

	Regression Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Job FTE employment)	0.228 (0.0002)
log(Job FTE / Job months)	...	0.492 (0.0004)	0.290 (0.0004)	0.223 (0.0004)	0.052 (0.0004)	0.030 (0.0005)
log(Job months)0.044 (0.0003)	-0.071 (0.0003)	-0.068 (0.0003)	-0.032 (0.0002)	-0.033 (0.0002)
Full-time Job	0.046 (0.0002)
log(Worker FTE employment)	0.170 (0.001)	0.111 (0.001)	0.057 (0.0004)	0.060 (0.0004)
log(Firm FTE employment)	0.054 (0.0001)	0.044 (0.0001)	0.011 (0.0003)	0.011 (0.0003)
log(Worker FTE)*log(Firm FTE)	0.033 (0.0001)	0.032 (0.0001)	0.005 (0.0001)	0.004 (0.0001)
Worker demographics	x	x	x	x
Firm 3-digit ANZSIC	x
Worker & Firm Two-way FE
Job Fixed Effects	x	x
R-squared	0.125	0.188	0.263	0.400	0.950	0.951

Notes: The number of female job-year observations used is 9,350,860, accounting for 3,703,000 FTE employment; all regressions are weighted by job-year FTE employment; worker demographics include separate quartic age profiles, and year-specific intercepts. Due to computational constraints, we haven't estimated standard errors for the two-way fixed effects specification in column (5); we expect these should be bounded by the estimated standard errors in columns (4) and (6).

Symbol: ... not applicable