“The Responsiveness of Industry Wages to Low-frequency Shocks in Canada: Differences Between Movers and Stayers”

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I. Introduction

Economists have studied the topic of wage rigidity in the labour market over the course of the business cycle ever since the appearance of Keynes' *General Theory*. Some of the empirical research has been within a macroeconomic framework for which the scope is the aggregate labour market, and composite real wages are linked to the global unemployment rate. Empirical studies based on this approach, such as Geary and Kennan (1982), have typically found weak correlations between real wages and the stage of the business cycle. More recent studies by Bils (1985), Shin (1994), and Solon et al. (1994) examine the cyclicality of real wages employing disaggregated micro data on wages, and arrive at the contrasting conclusion that real wages do tend to be strongly pro-cyclical.

There is another strand of literature in labour economics that investigates the relationship between wage changes and labour market slackness in a partial equilibrium framework at a less aggregated level, such as by skill or education level. While sharing a common theme with the real wage cyclicality literature, namely the responsiveness of real wages to employment conditions, in this literature the nature of the shocks to labour demand and supply is not high frequency innovations associated with the business cycle. Instead, it focuses on lower frequency shocks associated with an array of structural factors that are thought to gradually influence the structure of labour demand and hence ultimately the structure of wages.[1]

While a good part of the literature dealing with the changing structure of labour demand is based on the returns to skill, education, or work experience, an alternative dimension of analysis is the *industrial sector*. The central topic of the sub-strand treating wage changes by

[1] For instance, it is often asserted in the growing literature on wage inequality that technological change is skill-biased, as it raises the absolute and relative return to skill. The chapter authored by Katz and Autor in the *Handbook of Labor Economics* is an authoritative survey. For a recent, alternative view to the skill-biased technological change proposition, see Beaudry and Green (2005).

industry, of which Weinberg (2001) and Helwege (1992) are noteworthy articles based on US data, is the manner in which wages respond in industries that are in long-term decline or ascent. In these studies variation in the evolution of employment across industries is used as a proxy for shocks to labour demand, and is linked to variation in the average wage levels across industries. Given an upward sloping and a relatively stable long-run supply curve of labour facing an industry in a relatively efficient labour market, one would expect there to be a positive empirical association between those two variables, as positive (negative) shocks to labour demand generate increases (decreases) in both average wages and employment levels. On the other hand, if the empirical evidence suggests that sectoral wages are unresponsive to low-frequency shocks, one interpretation is that the long-term elasticity of labour supply is quite high. In light of the existence of evidence, however, that industry-specific skills are an important feature of the labour market, there should exist barriers to inter-industry mobility which militate toward an upward sloping labour supply curve. Therefore, a more likely explanation for an observation of unresponsive wages would be real wage rigidity rather than an elastic labour supply.

There are two primary objectives for this paper. The first is to examine the empirical relationship between low-frequency shocks to labour demand and average wages on an industrial basis using a Canadian data set. While Devereux (2005) and Weinberg (2001) achieve this goal using US data, to our knowledge there is no counterpart in the literature based on Canadian data. Any estimation of this empirical relationship should take account of the evolution of the characteristics of labour forces of the industries over the time interval during which the labour market is adjusting to shocks. In analyzing wage changes over time, Solon *et al.* (1994) and Bils (1985) pointed out the importance of ensuring a 'composition-constant' labour force that accounts for shifting characteristics of the labour forces over the medium range as labour is reallocated across firms and industries. In a similar vein, Devereux (2005) asserts that there are two complications involved in this task that some of the preceding literature did not fully treat, namely adjusting for changes in unobservable attributes as well as the observable ones. These econometric challenges can be mitigated by the use of panel data at the level of the individual worker such that one can control for fixed effects associated with unobservable attributes as well as for the observable attributes such as formal educational attainment. That is the approach that is adopted in this paper, which is based on Canada's primary longitudinal data set for workers' earnings and employment patterns, the *Survey of Labor Income Dynamics* (SLID).

The second major objective of this paper is to extend the existing industry-based literature on wage flexibility by estimating a specification including fixed effects for each worker-job match. Using the US *Panel Study of Income Dynamics* (PSID), Devereux (2005) estimates a model with a fixed effect for each worker-industry match based on the observation of workers switching reported industries. These estimates reflect the effects of industry-specific human capital, the composition of which changes in response to shocks to labour demand and the subsequent re-allocation of labour from contracting industries to growing ones. The SLID data set, however, contains a unique identifier for each position that an individual worker has held, allowing one to track *job* changes as well as *industry* changes. Estimating a specification accounting for fixed effects for worker-job matches allows for an empirical comparison of wage responsiveness of within-firm stayers to between-firm movers. In this respect, it applies one objective of the literature on real-wage cyclicality to a framework based on industries. That latter literature, while employing micro data, differs from this paper in that it is couched within the framework of the aggregate labour market.[2]

In general, the findings indicate that, consistent with the results from the US literature, average wages by industry tend to respond positively to low frequency changes in employment, and that there is a fairly high degree of unobservable heterogeneity in the composition of labour forces by industry. Failing to control for that effect tends to impart a negative bias on the statistical correlation between changes in average wages by industry and changes in employment levels. We also find evidence to support the conjecture that there is some degree of wage flexibility within-firm worker matches as well as between-firm switches, which militates against the prevalence of internal labour markets.

II. Survey of the Literature

To my knowledge there are few articles in the Canadian literature that deal with the empirical relationship between wages changes and employment changes on an industrial basis. An early Canadian reference dealing with the industrial structure of wages is Gera and Grenier (1994). Although their analysis is drawn from a longitudinal data set that is the pre-cursor to the SLID file, namely the *Labour Market Activity Survey* (LMAS), their goal is to explain wage differentials across industries rather than to link changes in average wages to changes in labour market slackness, and the scope of their paper is only cross-sectional.

Much of the existing empirical literature on wages by industry indicates that wages tend to be rigid in response to changes in industry demand. There are several articles in the US literature that are based on micro data at the level of the individual worker. Helewege (1992)

[2] For some well-known articles in this literature, see Devereux (2001), Devereux and Hart (2005), Bils (1985), Solon (1994) *et al.*, and Shin (1994). All of those studies deal with the within-match/between-match dichotomy for

finds that the inter-industry wage structure is stable over time despite a high degree of variation in growth rates in employment across these industries. Based on the cross-sectional data contained in the US Current Population Survey, Weinberg (2001) finds that there is no significant relationship between industry wages and industry employment levels over the 1970s or over the 1980s.

Based on the well-known longitudinal data set *The Panel Study of Income Dynamics*, however, Devereux (2005) refutes Weinberg's proposition. The lack of an empirical correlation could be attributed to either real wage rigidity or to very elastic long run labour supply functions. Heuristically, Devereux rules out the latter factor citing empirical literature stating the existence of specific human capital, which in turn renders that condition implausible (Neal (1995), Parent (2000)). In order to measure real wage flexibility, however, it is necessary to address composition bias, which affects empirical results derived from cross-sectional data. Since the composition of the labour force whose average wages are being compared at two points in time is not constant over that interval, wage changes reflect changes in the price of labour confounded with changes in its quality.

There are two channels through which changes in the composition of the labour force as labour is re-allocated across industries might arise: the selection effect tied to unobserved productivity-enhancing characteristics, and the loss of industry-specific skills and productive firm-worker matches. The former point is raised in McLaughlin and Bils (2001), who demonstrate using US data that inter-industry mobility over the business cycle tends to be characterized by positive selection that could be based on totally unobservable traits, such as a worker's inherent ability and motivation. Typically the least productive workers in declining industries are those who exit and are subsequently hired as the least productive workers in

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broad segments of the labour force, and employ broad statistics for measuring the business cycle.

growing industries, causing the average quality of workers to rise over time in declining industries but to fall over time in growing industries. The second point pertains to losses in industry-specific human capital and skills occasioned by the reallocation of labour between industries, in turn affecting the average productivity levels of industries – raising them in declining industries and lowering them in growing ones (as the new recruits have lost specific skills). To the extent that factors that gave rise to productive matches are not remunerated at the new jobs, average wages by industry will be affected. Failing to take account for either or both of the sources of changes in the composition of labour forces leads to estimated responses of average wages by industry to labour demand shocks that are biased downward, misleadingly suggesting the absence of a positive statistical relationship.

Exploiting the longitudinal aspect of the PSID file, Devereux addresses both of these potential sources compositional change. While including the observable characteristics of education and work experience, he accounts for changes in unobserved individual traits by estimating a fixed-effects equation. In another specification he accounts for changes in unobserved industry-specific human capital by the inclusion of fixed effects for any match between an individual and an industry. His empirical results indicate that after addressing the issue of endogeneity stemming from supply-side shocks, there does exist a positive relationship between demand side shocks and wage changes. All in all he concludes that the average real wages by sector are fairly flexible in the face of low-frequency labour demand shocks in the positive direction predicted by theory.   He also finds evidence, based particularly on his findings for the female sample, of the presence of industry-specific skills, which implies the existence of barriers to inter-industry mobility and hence upward sloping labour supply curves, dovetailing with his empirical finding of a positive relationship between wage changes and employment changes.

As it is based on the PSID file, Devereux's (2005) study has the advantage of spanning a 30-year period, which he divides into three different 10-year intervals (1971-1981, 1981-1991, 1991-2001). This time frame is quite suitable for assessing the impact of low-frequency shocks on wage changes, as the windows over which they are calculated are long. By contrast, the SLID data set employed in this study contains a maximum of six consecutive annual observations for any individual, rendering the estimation of fixed effects less precise. Nevertheless, the SLID file has at least one advantage over the PSID, namely that the sample size is considerably larger: each panel commences with approximately 30,000 observations at the individual level as opposed to 5,000 observations with the PSID. As a result, the cell sizes (categorized by industry and year) that are used in the primary equation of the empirical analysis are usually quite adequate, bolstering the precision of the estimates of average wages by sector-year.

The SLID file also contains an exact identifier for each job held by an individual, allowing one to observe job changes rather than industry changes. That information is exploited in order to examine the degree of real wage flexibility among existing job-worker matches. This information can shed light on two somewhat competing views regarding how wages adjust to labour demand shocks. In the framework of an internal labour market, wages tend to be sticky within firm-worker matches; the employment variable assumes most of the adjustment stemming from an employment shock. Under this scenario, most of any wage adjustment that might be captured in the wage equation would result from re-allocation of labour on the external (or spot) job market, with new hires accounting for most of any wage changes that are empirically observed. Wages could deviate from marginal productivity, and remain sticky in the face of shocks, for any number of reasons.[3] By contrast, if wages are flexible within firm-worker matches, any wage adjustment that might be captured empirically could be attributed to wage changes for incumbent workers as well as job movers on the external job market.

In regards to the existing empirical evidence on this question, Devereux and Hart (2005) employ UK data and find that within-firm stayers do exhibit some degree of wage flexibility, although much less than is the case for job movers. This empirical pattern is stronger (unsurprisingly) in the private sector and among workers not covered by collective agreements. Employing US data drawn from the PSID, Devereux (2001) finds pro-cyclical estimates for real average hourly earnings even among job stayers, with significant differences according to the mode of remuneration, e.g. incentive pay and overtime.[4] Based on US data drawn from the NLS, Bils (1985) and Shin (1994) both find that real wages are more pro-cyclical for job movers, although they are still slightly pro-cyclical for stayers. Solon *et al.*'s (1994) PSID-based study finds real-wage pro-cyclicality even among stayers.

III. Statistical Analysis Using Aggregated Data

Before turning to the analysis using micro data, I present some preliminary analysis based on aggregated data. This consists of an examination of the statistical relationship at the industry level between shocks to labour demand and wage changes using data that does not follow individuals over time, and thus does not take account of any intertemporal changes in the composition of the labour force. The measure of long-run labour demand shocks is the log change in the employment level by sector. The data are drawn from the firm-based *Survey of*

[3] These factors include the existence of implicit contracts that share risk of unemployment, bonding mechanisms designed to facilitate investments in human capital, and collective agreements covering wages.
[4] Unlike the data set that we use in this study, the PSID does not contain an exact identifier for the job. Job changes must be inferred by algorithm via reported start dates and end dates for jobs.

Employment, Payrolls and Hours (SEPH), which is Canada's only data source containing the number of paid employees, wages, and hours worked at detailed industry, provincial and territorial levels.[5] The sampling period for the SEPH data runs from 1991 to 2000 at an annual frequency. Employment data are disaggregated by industry using the North American Industry Classification System (NAICS) at the 3-digit level, generating 70 industry groups and thus 70 observations. This level of aggregation by industry is lower than the level utilised in any of the US or Canadian studies that are based on micro-data. The employment data does not categorize by gender, so the values reflect total employment in the industry.

The SEPH data distinguish between average *weekly* earnings and average *hourly* earnings, as well as between salaried workers and hourly workers and between overtime hours and standard hours. The series for average hourly earnings is calculated by dividing the average weekly earnings by the average weekly hours. It represents the gross dollar value before deductions for income taxes, social insurance contributions, etc, and it includes regular pay, overtime pay, and a portion of bonuses, commissions, and other type of special payments. The nominal wages that are reported are deflated by the consumer price index, for which the base year is 1992. The values for the changes in wages and the corresponding changes in employment are listed in the appendix Table, for which the type of employee is salaried employees who are paid a fixed wage or salary.

Figures 1-3 consist of detailed scatter plots of the data points that are listed in Table 1, which may give some visual perspective of a statistical relationship between changes in industry employment and changes in industry wages. Figure 1 displays the data points for the interval 1991-2000. Since all of these values points are based on calculations that are sensitive to the two

[5] The employment data are located in CANSIM Table 281-0024, while the wage data are located in CANSIM Table 281-0036.

end-points, we also show scatter plots for sub-intervals: the time-period 1991-1995 appears in Figure 2, and time period 1996-2000 appears in Figure 3. The numbers that are assigned to each industry serve as labels for the industries in the diagrams. The units for all of the figures are log changes, which are approximately equal to percent changes for relatively small values.

Visual inspection of Figure 1 suggests the existence of a positive relationship between changes in industry-level employment and real wages during the 1990s. The industries that registered shrinking employment over that decade include hospitals (# 59), gasoline stations (# 37), oil and gas extraction (# 2), construction of buildings (# 5), trunk transportation (# 42), and social assistance (# 61). Oil and gas extraction experienced a very large decrease in employment (-43.9 %), but nevertheless its real wage level is almost unaffected (-0.9 %). The industry that experienced the largest contraction in employment was retail gasoline, whose wage level and employment level fell by 13.6 % and 72.6 %, respectively.

The industries that registered growing employment levels include support activities for mining and oil and gas extraction (# 4), printing and related support activities (# 15), professional, scientific and technical services (# 56), and administrative and support services (# 57). The service sectors experienced a greater increase in employment than the goods sectors, especially in the administrative, professional, scientific, and technical services sector, which coincided with the development and implementation of new information technology. Certain industries are characterized by an increase in real hourly wages coupled with a small decrease in employment. One example is pipeline transportation (# 44), where employment has slowly decreased since 1990, but nonetheless employees enjoyed a substantial increase in average hourly wages (38 %).

The positive relationship observed in Figure 1 is less evident during the sub-periods 1991-1995 and 1996-2000. Figure 2 shows that during the period 1991-1995, which coincides with a harsh recession. Most industries are characterized by an *increase* in real wages – despite the adverse employment conditions - and a decrease in employment. In Figure 3, for the period 1996-2000, during which the Canadian labour market was in recovery phase, the positive relationship cannot be observed either.

The statistical relationship between changes in wages and changes in employment is investigated by estimating a very simple cross-sectional regression expressed in first differences:

$$w_{i,t_1} - w_{i,t_0} = \beta_0 + \beta_1 * \Delta E_{i,t_1-t_0} + \varepsilon_{it}$$

The dependent variable represents the log change in real wages in industry i between t_1 and t_0. The independent variable denotes log change in employment in industry i between t_1 and t_0. The ordinary least squares (OLS) method is applied to that equation,[6] which is estimated for seven different samples.[7] Note that since this specification does not take into account the simultaneity that would result from supply-side shocks to employment, the estimates can only be interpreted as a statistical association.[8]

The estimated coefficients for the 5-year time intervals (not shown) do not support the conjectured positive relationship between industry employment changes and industry wages, as none of the estimated coefficients are significantly different from zero. Table 1 reports the

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[6] The equation presented above is estimated using White's procedure for adjusting the estimated standard errors for heteroskedasticity of an unknown form, and the results (not shown) are robust to that issue

[7] There are salaried versus hourly workers, average hourly earnings versus average weekly earnings, and earnings including and excluding overtime. These distinctions give rise to 8 categories with one exception. In the case of salaried workers, any overtime hours are not remunerated, and so the distinction between overtime compensation and regular compensation does not apply. The SEPH data report average hourly earnings as all weekly compensation divided by average weekly hours.

[8] For this regression equation, the potential candidates for instrumental variables are shipments or indicators for production, which are fairly good proxies for demand shocks. They would be correlated with employment changes and perhaps uncorrelated with the disturbance term in the basic equation, as they would be

estimates of the equation above over the full 10-year interval. Most of the estimated coefficients over the seven specifications for the interval 1991-2000 are positive and significant. In the case of average weekly earnings for the salaried workers, the point estimates are approximately 0.125, while the estimate for hourly workers is slightly lower at 0.095. Taking overtime hours and pay into consideration makes almost no difference for the results. For the specifications involving average hourly earnings, there is no significant relationship. This may be in part a result of measurement error for that wage variable that would generate attenuation bias. Overall, the results from this statistical analysis militate toward the proposition that real wages are slightly responsive to changes in employment.

IV. Regression Models

IV.a Estimating Equations

The econometric methodology follows the approach of Devereux (2005) fairly closely, and it involves two sequential steps. The first step involves the micro data drawn from the SLID file. The objective is to estimate sector-specific wage effects. To this end an equation resembling an earnings function, including observable characteristics of education and experience, is estimated within a panel framework. Note that in the SLID file, there is a direct measure for work experience, so we do not utilize the commonly used proxy of age minus education minus 6. In order to control for composition bias, two types of fixed effects are included in separate regressions: an indicator specific to each individual for the selection effect, and an indicator specific to each individual-job. The latter capture effects specific to a particular employment bond, be it due to firm-specific skills, rents, or a suitable match. This specification

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independent of any supply shocks. Unfortunately, the data of shipments or production based on the same industrial classification scheme are not available.

differs somewhat from its counterpart in Devereux (2005), who includes a fixed effect for each person-*industry* as opposed to each person-*job*.

Separate equations are estimated for men and women. The estimating equation for stage one has the following form:

$$W_{ijt} = \beta_1 + \beta_2 X_{it} + \sum_j \sum_t \phi_{jt} D_{jt} + f_i + \varepsilon_{ijt} \qquad (1)$$

The dependent variable is the log real wage of worker i in sector j during year t. Two series are available: the hourly wage at the reference job, and the composite wage (contained in the SLID file based on a weighted average) for that worker across all jobs that he/she held over the reference year.[9] All wages are expressed in constant 1992 dollars.[10] These two wage measures are very highly correlated, with a Pearson coefficient of 0.97. The exogenous variables contained in the X matrix are comprised of the observable human capital characteristics of worker i at year t, namely formal education and work experience. The disturbance term includes a fixed effect for worker i (or for worker-job i) in order to capture time-invariant unobservable influences. The key variable of interest is the component of wages that is net of all of those observable and fixed effects. Each year-sector has its own data cell that corresponds to a binary variable D_{jt} and its own estimated parameter (the phi term), which reflects the adjusted average wage for sector j at year t. The estimated coefficients of the industry-year dummies D_{jt} are stored and then inputted into the second stage regressions. They can be interpreted as the average log real wage for the industry-year cell holding constant the influences of educational attainment, experience, and individual-fixed effects. The variant specification of equation (1) is

[9] For the fixed-effect model based on the individual, this wage refers to the primary job held during the reference year.
[10] The deflator is the CPI based on the 2001 market basket of goods and services.

also estimated that replaces the individual specification fixed effect with one specific for each job that an individual held over the interval of observation.

The SLID file currently contains two panels that are suitable for the estimation of a fixed effect model. Panel 1(2) was selected in December of 1992 (1995), is representative of the Canadian working age population at that point in time, and data are recorded annually from 1993 until 1998 (1996 until 2001). As the SLID was first created in 1992, no data are available for earlier periods. Although there are three years of overlap between the two panels, they share no common subjects. Each panel contains its own longitudinal weights in order to render the sample representative of the target population at the beginning of the panel, and to adjust for non-response and attrition thereafter. Because of the discrepancies in the sample selection process and in the weights, Statistics Canada recommends that the two panels be treated as independent samples. We therefore do not pool the two panels into a single data file. Throughout this paper, all equations are estimated separately across the intervals of 1993-1998 and 1996-2001, and the results are subsequently compared across these two time-periods.

For the econometric analysis at the second stage, the unit of observation is aggregated up to the level of the sector-year. The starting point for these estimating equations is the point estimate of the average adjusted wage (the theta_{jt} term obtained in step 1) by sector-year, which serves as the dependent variable. This sector-year variable is matched with the corresponding employment level data drawn from LFS in order to focus on the relationship between changes in wages and changes in employment levels. Under the hypotheses of exogenous and low-frequency, persistent shocks to labour demand (i.e. those associated with trends of ascending or declining industries) and weak endogenous responses to labour supply (i.e. relatively stable labour supply functions), one expects to observe a positive relationship.

Three different specifications are estimated at the second stage. First, there is the long-difference estimator, which consists of regressing the point-to-point (1993-1998 and 1996-2001) difference in the wage variable on the corresponding difference in the employment variable. The difference operation serves to net out permanent differences in wages and employment across industries; thus the parameters of equation (2) are identified solely by between-sector variation. For this specification the unit of observation is the sector (as opposed to the sector-year), so there are only as many observations as industries (21 in this case). The estimating equation has the following form, where E_{jt} refers to log industry employment at time t, and u_{jt} is the disturbance term.

$$\hat{\phi}_{jt+1} - \hat{\phi}_{jt} = \delta_1 + \delta_2 (E_{jt+1} - E_{jt}) + \mu_{jt} \quad (2)$$

Each observation is weighted by the average number of individuals in the industry over the two end years. While this approach has the advantage of capturing trend changes in employment and wages rather than short-term shocks (i.e. high-frequency changes), it employs only information from the end-points of the interval, which lowers the precision of the estimates. Furthermore the results are potentially sensitive to the selection of the end-points; it is quite possible that trends operating over the interlude are not captured.

The second specification consists of a fixed effect estimator for which the dependent variable is the adjusted log-wage level, and the independent variable is the log-employment level.[11] The frequency is annual, however, so the unit of observation is the sector-year, and specific effects are included for each year and each sector. The estimating equation has the following form:

$$\hat{\phi}_{jt} = \delta_1 + \delta_2 E_{jt} + \delta_3 YEAR_t + \delta_4 IND_j + \upsilon_{jt} \quad (3)$$

where $YEAR_t$ represents the year-specific binary variables, and IND_j reflects the set of industry-specific binary variables. Note that in contrast to equation (2), this equation is expressed in levels rather than in first differences. The weighting process assigns a weight of the number of individual observations in that industry year.

The focus for all of the empirical analysis is on the estimated coefficient of the employment variable in equations (2) and (3). To the extent that it is positive and statistically significant, there is evidence that wage responsiveness to low frequency shocks exists. Two empirical patterns are of interest.

- Does the magnitude of this estimate tend to increase when fixed effects are included, which would be consistent with the presence of composition bias?
- Does a positive and significant effect remain after the inclusion of job-specific effects? If so, there evidence of wage flexibility amongst job stayers.

There are a few other empirical issues that should be addressed. The annual frequency of the fixed-effect equations is obviously less than ideal for capturing low-frequency shocks to employment, as the annual variation will reflect both persistent shocks, which are relevant for the empirical task at hand, as well as transitory (but not seasonal) shocks. To address the issue, following Devereux (2005), I apply a smoothing technique to the employment series. In an auxiliary regression, the log of employment is regressed on a time trend for each industry over the six-year interval. The fitted value for log employment is then used as a proxy measure for the log of employment net of transitory fluctuations, which constitutes the third and final specification for the second stage of the estimation process.

[11] Note that the fixed-effect for equation (3) represents a sector. By contrast, the fixed effects specified in equation (1) in the first stage of the regression analysis (i.e. the earnings functions) are specific to individuals.

It should be noted that the fixed-effects estimator is likely to be affected by auto-correlation. Although it would be desirable to include a first-order auto-correlative process into the estimating equation in order to apply GLS, the six time periods that exist for this specification do not allow for the precise estimation of an autocorrelation parameter for each industry. Therefore, no correction for this issue is applied.

IV.b Data Details

As mentioned above, the earnings-type equations for stage one are estimated separately for each six-year panel contained in the SLID file. Following the sample selection criteria that are commonly employed in the literature, all self-employed individuals are omitted for those years in which they did not report paid employment. The same applies to part-time workers. We also omit those individuals with a low degree of labour force attachment during the reference year. The SLID file actually reports not-in-the-labour-force (NLF) status, and any subject with more than 26 weeks of NLF status is excluded for the reference year. The age range for inclusion is 21 through 65 years, and only workers reporting more than 5 years of FT work experience are included, which implies that many workers in their early twenties will drop out of the sample. Finally, because we only include the longitudinal subjects in our working sample, the ‘co-habitants’, defined as those who are surveyed if they happen to reside in the same household as the ‘longitudinal subject’ at the survey date, are not included. Such individuals are typically in a panel for about 2-3 years.

The weighting variable consists of the internal longitudinal weight for each of the two panels, which are designed to reflect the initial population. As is recommended for panel data estimation, all observations are weighted according to the individual’s value for the final year of the panel (1998 for panel 1 and 2001 for panel 2) in order to account for attrition and non-response. After the sampling and weighting procedures are applied, panel 1 (panel 2) contains 31,730 (33,739) person-year observations out of an unweighted total of 42,495 (48,190) person-year observations. For the fixed-effect models based on the individual, there are 10,070 and 11,683 groups for panels 1 and 2, respectively. For the fixed-effect models based on the particular person-job, there are 16,115 and 18,950 groups, respectively.

Although the SLID file contains a very broad array of variables that might influence wages, such as visible minority, immigration, and union status, the focus of this study and its antecedents is on those characteristics that are thought to be most directly related to productivity, namely the indicators for human capital.[12] The level of educational attainment is specified by broad educational categories: those with a HS diploma only, those without a HS diploma (which serves as the omitted category), and those with more than a HS diploma. The number of years of FT experience, as well as its square and its cube, are included as continuous regressors. In order to capture non-linear effects among these two underlying control variables, a total of 9 interacted variables are generated and included in the estimating equations.[13]

The sector-year specific effects play an important role in this analysis. The data in the SLID file are categorized according to the North American Industrial Classification System (NAICS, 1997 version) at level 105 and at level 21. In order to obtain wage estimates that are compatible with the employment data drawn from the LFS, we have to use the more aggregated data, but it is likely that using the less aggregated data would have resulted in some very small

[12] Note that any attribute that is time invariant drops out of the estimating equation when the fixed effect estimator is applied.
[13] The three binary variables for the three education groups are each interacted with experience, experience squared, and experience cubed.

cell sizes even if it had been feasible to exploit the detailed level of aggregation. These 21 sectors are listed in Table 2.[14]

Before turning to the key focus of this paper, which is sector-year effects, we examine the purely sectoral effects. These preliminary specifications for the earnings functions contain the control measures for human capital and experience, as well as a binary variable for each of the 21 sectors, with retail trade serving as the omitted category. In all specifications the estimated coefficients for the human capital and experience variables are jointly significant.[15] The results from the two panels, which are not shown, are qualitatively similar. The point estimates for 17 out of 20 industries are significantly different from the estimate for retail trade (the reference category). Average wages are lower than in the retail trade industry only in agriculture and accommodation & food services. Wages tend to be highest in utilities, mining and oil & gas extraction, public administration, and educational services.

Equation (1) is estimated with three different variations. For the first specification, only the observable variables are included, namely all of the experience and educational variables and the sector-year effects. The least squares technique is applied to these linear equations with full weighting and robust estimation based on clustering of the error terms for any individual. For the second specification, the individual fixed effects are included.[16] These fixed effects are replaced in the third specification by individual-job specific effects. The fixed effect equations are estimated from the larger, unweighted sample, as required by the STATA program that was employed for estimation of all of the earnings function specifications based on equation (1).

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[14] PSID-based analysis allows for 26 sectors.

[15] In order to see if our results are consistent with conventional earnings functions, we estimated very parsimonious, linear specifications (including squared terms) of earnings functions without any interaction terms, and the signs of the estimated coefficients of the education and experience variables were as expected.

[16] To give some idea of the sample sizes for the identification of the fixed effect itself, for the male (female) sample of panel 1, there are on average 4.4 (3.9) observations per group for the individual-specific effects. For the male

V. Regression Results

Va) Primary Specifications

A total of 24 versions of the Mincer-style equation (1) were estimated for the first stage of the estimation process. These variations spring from two wage measures (the composite survey wage and the survey wage from the main job), the two genders, the two panels (1993-1998 and 1996-2001), and the three different specifications, namely i) no fixed effects included, ii) fixed effects for individuals, and iii) fixed effects for worker-job matches. Dummy variables are included for each of the sector-year combination allowing for reference categories. The overall explanatory power of these regression models is higher for women than for men, and higher during the earlier period of 1993-1998.[17] In all specifications the estimated coefficients for the education and work experience variables are jointly significant. The explanatory power for the equation with individual fixed effects is much higher (after correcting for the degrees of freedom) than is the case for the equation with the worker-job specific effects. The 'within' effects in the latter case are a bit more important than in the former case, but the 'between' effects are more important for the equations that include the individual-specific fixed effect. Since some individuals hold multiple jobs, the differences between workers are more empirically discernable than the differences between all jobs. Almost all of the estimated parameters for the industry-year effects become insignificant when fixed effects are included for each person-job.

Turning to the stage-two estimates, which comprise the primary regression equations for this paper, the results are organized as follows. Part A consists of the long difference estimates

(female) sample of panel 1, there are on average 2.6 (2.7) observations per group for the individual-job specific effects.

generated from equation (2). These equations have only 21 observations – one for each industry – and the data points reflect first differences in log employment and log wages between the endpoints for each of the two panels. Part B consists of the GLS estimates generated from equation (3). These equations have 126 observations (six years for each industry), and the data points reflect levels of log employment and log wages. Fixed effects are estimated for each sector. Part C resembles Part B, except that the employment variable is smoothed in an effort to account for transitory shocks over the corresponding six-year interval. For each of these three parts, 24 equations are estimated corresponding to the variations (for the earningd equation) described in the paragraph above. In compiling and interpreting the findings, we search for empirical patterns for the estimated coefficient of the employment variable along the lines of the following four dimensions.

- a pattern of point estimates becoming greater in magnitude, and perhaps entering the expected range of 0.1 to 0.3, as one progresses from the specifications of i) no fixed effects included, ii) fixed effects for individuals, and iii) fixed effects for worker-job matches.
- systematic differences between the earlier panel and the later one
- systematic differences between the two different wage measures
- systematic patterns along gender lines

The results for equations (2) and (3) are listed in Table 3 for men and in Table 4 for women. Only the estimated coefficients of the employment variable are listed. While there are many point estimates that are statistically insignificant, there do appear to be some empirical regularities in the findings, and there are some similarities to the results reported in Devereux

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[17] For the equations that do not include the fixed effects, the corrected coefficient of determination is 0.29 for men in panel 1 and 0.24 for panel 2. The corresponding statistics for women are 0.36 for women in panel 1 and 0.31 in

(2005). For instance, most of the point estimates derived from the long-difference estimator are imprecise, although in our case this is less true for the female sample. Most of our point estimates for the fixed effect versions of equation (3) are in the range of 0.1 to 0.3.

First we consider the empirical pattern as starting from the baseline earnings equation (including only the controls for the individual characteristics) and comparing it to the next version of the earnings equation (including fixed effects specific to each individual), and then to the final specification for the earnings equation (including fixed effects specific to each individual-job match). We do uncover an empirical pattern that is consistent with our prior expectation that composition bias is present. This regularity is described as a progression from negative or weak effects to significantly positive effects in the range of 0.1 to 0.3. In the case of women, we discern this pattern in both panels. In the case of men, we do obtain this broad pattern in qualitative terms for panel 1, but for panel 2, we obtain higher point estimates for the specifications that *exclude* the fixed effects.

We turn next to a comparison between the point estimates for individual-specific fixed effects and fixed effects particular to an individual- job match. There does not appear to be much of a discrepancy within the female samples, nor for panel 1 male sample. On the other hand, no evident pattern of any kind was discerned among men in panel 2.[18]

Our estimates reveal some differences between the results drawn from panel 1 (1993-1998) and those drawn from panel 2 (1996-2001). Although they are two totally independent samples, those panels share three years of data, and thus one might expect some degree of

panel 2.

[18] Devereux (2005) reported that among men, the fixed effects specific to the person-industry tended to be slightly lower than the fixed effect specific to the individual in estimated magnitude. In contrast, he found the opposite pattern within his female samples, indicating that the potential for composition bias among women with respect to the individual-industry matches exists, which he conjectures might be associated with industry specific

similarity, particularly in the case of the GLS results. Nevertheless, for both genders, there are some coefficient estimates derived from panel 1 that are significantly different from 0 for which their counterparts from panel 2 tend to be weaker or insignificant. The results are more similar across panels for the specifications including the individual-specific fixed effects.

All of our specifications were estimated for two separate wage measures: the wage of the primary job held during the reference year and the composite wage reported over the reference year. In the case of the female sample, the results tend to be quite robust to this change in the wage measure. In the case of men, however, the findings indicate that the first wage measure is more responsive to employment fluctuations than is the case for the second one for panel 1, while we find the opposite pattern for panel 2.

In regards to the gender-based patterns, the estimates for the female sample tend to be a bit higher than is the case for men, which indicates that average wages earned by women tend to more sensitive to employment fluctuations by industry. In contrast Devereux does not discover major differences across genders in the magnitudes of the estimated coefficients.

In summary of the findings, in three of our four estimating samples, there appears to be evidence of the existence of composition bias stemming from person-specific effects. Most of the heterogeneity appears to stem from individual-specific fixed effects, however, as there is often little difference between the results for the individual-specific fixed effects regressions and the individual-firm fixed effects regressions. We do obtain positive correlations between the evolution of wages and changes in employment levels that are statistically significant in most samples. These findings are somewhat similar to those obtained by Devereux (2005), who found strong evidence of heterogeneity among women compared to men, but our results tend to show

skills. Based on our fixed effects for job-specific (but not industry-specific) matches, we find little evidence of such a pattern.

less of a gender discrepancy.   Even after controlling for worker-job specific effects, wages are responsive to changes in employment.

Vb) Analysis of Simultaneity

In all of the second stage regression analysis, industry employment is used as a proxy for labour demand forces. No account is taken of the fact that the evolution of employment is the product of both supply side and demand side influences. There are two primary sources of supply shocks, namely compositional changes in the labour force along the dimensions of gender and education, and changes in relative wages, that could render the employment variable endogenous. Both Weinberg and Devereux conjecture, however, that demand side shocks should greatly outweigh supply side shocks, and their own empirical results support that assertion.[19] Given the six-year length of our estimating intervals, it seems unlikely that supply-side trends play a major role in determining employment outcomes, but we examine that possibility nonetheless.

We follow the same approach as Weinberg and Devereux, who employ very similar strategies in examining the robustness of their primary empirical results to the presence of supply side shocks. They eschew the approach of instrumental variables in favor of calculating and applying adjustments to the employment variable. The growth in employment that is actually observed for each industry is adjusted by an estimate of the magnitude of that growth quantity which is attributable to supply side influences, which are assumed to be driven by demographic shifts in the labour force. If labour supply was deemed to have expanded (contracted) over the interval, the measure of employment growth included in the equation is lowered (raised) accordingly. The estimates of the labour supply influences occurring over the two estimating intervals are derived from the aggregate changes (summed over all industries) in the employment of the various demographic groups based on an assumption that these evolutions apply more or less evenly to all sectors. The estimated supply shock assigned to each industry is a time-constant share of the aggregate changes in the employment of the various demographic groups that occurred over the time period. The net effect is to reduce (augment) the estimated employment growth for industries that are intensive employers of the groups whose shares of the labour force have risen (fallen).

Specifically, the workforce is divided into six different demographic groups based on gender and educational attainment, which are indexed by g. The first step is to calculate for each sector j within each six-year panel the share of each of the six groups of the total employment of sector j. This share parameter is called theta, is time invariant, and sums to unity across groups within a sector.

$$\theta_{gj} = \sum_{t=1}^{6} E_{gjt} / \sum_{t=1}^{6} E_{jt} \quad \textbf{(4)}$$

The second step is to calculate baseline values for the log employment levels in sector j and the log employment levels of group g in sector j, which are taken as mean values over the two panels (1993-1998 and 1996-2001). The third step is to calculate the differences for each year between the realized values of log employment and the average values taken from the prior step. For demographic groups this variable is dE_g, which appears in the sum of equation (5) below, and for sectors this variable is dE_j. The fourth step is to calculate the adjustment for the supply side shock for each sector for each year, which is the growth rate for log employment in

[19] In the work by Devereux, the adjustment for supply side factors did have a bearing on the results for the period of the 1970s, but little effect on the findings for the 1980s and the 1990s. Weinberg's results were affected little by this adjustment.

each industry based on the assumption that this growth is based shares θ_{gj} of the growth for that demographic group over all industries. This quantity corresponds to the sum that appears in equation (5), which adds across all six groups that are employed in any industry. In the fifth step, the estimate of the change in employment that would have occurred in the absence of supply shocks is obtained by subtracting the quantity from the prior step from the dE_j. Finally, the annual values for the adjusted employment series by sector are calculated by adding the first differences values from the preceding step to the baseline values for log employment.

$$dE_j^* = dE_j - \sum_g \theta_{gj} dE_g \quad \textbf{(5)}$$

The second-stage regression results are extremely robust to this adjustment for supply-side shocks. The point estimates for the parameter measuring the responsiveness between wage changes and employment changes for parts B (the GLS estimates with the unadjusted employment series) and C (the GLS estimates for which the employment data are smoothed by the time trend) are presented in tables 5 (for men) and 6 (for women). There is qualitatively no change, and the estimated magnitudes are quite similar. This finding might be expected given the very high degrees of correlation between the adjusted employment variables and the unadjusted ones, which exceeded 0.99 for most industries for both panel 1 and panel 2, and for both the smoothed employment series and the non-smoothed ones.

VI). Conclusion

The primary topic of this paper is how responsive average wage levels by industry are to low frequency shocks to employment by industry. Abstracting from supply side influences, one expects to observe a positive empirical association across industries between these two variables: demand-side shocks should have direct effects on average wages. We have accounted for changes in the composition of individuals within industries that occur over the estimating interval. The secondary topic of this paper is the difference in wage responsiveness between job stayers and job movers, which we address by examining the degree of wage flexibility within worker-job matches.

Using the longitudinal Canadian data set of the SLID, we estimate earnings equations including fixed effects, retain estimates of sectoral wage effects, and focus on the effects of employment changes. In three of our four estimating samples, there appears to be evidence of the existence of composition bias that would militate toward finding no relationship between changes in average wages by industry and changes in employment. The estimates of that empirical relationship net of fixed effects are within the range reported in the US literature, namely 0.1 to 0.3, which indicates a fairly weak but positive statistical association. Our results tend not to show much of a gender discrepancy.

According to our estimates, there do not appear to be major differences between the point estimates for individual-specific fixed effects and fixed effects particular to an individual- job match. After including the latter in our estimating equations, there is still an explanatory role for the employment changes variable, suggesting that wages do fluctuate to some extent within existing worker-job matches.

Overall the Canadian evidence that we have uncovered appears to be consistent with the evidence drawn from the US literature. Absent any adjustment for composition bias, the empirical correlations across sectors between changes in employment and changes in average wages tend to be weak or even negative, which gives the appearance of wage rigidity in the face of demand shocks. Upon taking account of the evolving composition of labour forces concomitant with low-frequency shocks to labour demand, that correlation becomes small yet positive, indicating that average wages by industry are at least mildly responsive to these shocks. There also is evidence of wage flexibility in the face of employment shocks among job-stayers as well as among job-movers. It appears as though not all adjustment of real wages to employment shocks occurs in the external job market. The empirical findings of the absence of wage rigidity also suggest that regardless of the nature of the heterogeneity among labour forces, the labour supply curves are less than perfectly elastic.

References

Abe, M, Y. Higuchi, P. Kuhn, M. Nakamura, and A. Sweetman (2002) "Worker Displacement in Canada and Japan" in Kuhn, P. editor, *Losing Work, Moving On* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 195-300

Beaudry, P. and D. Green (2005) "Changes in US Wages, 1976-2000: Ongoing Skill Bias or Major Technological Change?" *Journal of Labor Economics* 23, 3, pp. 609-647

Bils, M. (1985) "Real wages Over the Business Cycle: Evidence From Panel Data" *Journal of Political Economy 93, 4*, pp. 666-689

Devereux, P. (2005) "Do Employers Provide Insurance Against Low Frequency Shocks? Industry Employment and Industry wage" *Journal of Labor Economics* 23, 2, pp. 313-340

Devereux, P. (2001) "The Cyclicality of Real Wages Within Employer-Employee Matches" *Industrial and Labor Relations Review* 54, 4, pp. 835-851

Devereux, P. and R. Hart (2005) "Real Wage Cyclicality of Job Stayers, Within-Company Job Movers, and Between-Company Job Movers" Study of Labor (IZA) Discussion Paper No. 1651

Gera, S. and G. Grenier (1994) "Inter-industry wage differentials and efficiency wages: Some Canadian Evidence" *Canadian Journal of Economics* 27,1 pp. 81-100

Geary. P. and J. Kennan (1982) "The Employment-Real Wage Relationship: An International Study" *Journal of Political Economy 90, August*, pp. 854-871

Gray, D. and G. Grenier (1998) "Jobless Durations of Displaced Workers: A Comparison of Canada and the United States", *Canadian Public Policy*, 24, S152-S170.

Gray, D. and G. Grenier (1995) "The Determinants of Jobless Durations of Displaced Workers in Canada", *Applied Economics* 27, 9 (September), pp. 829-839.

Helwege, Jean (1992) "Sectoral Shifts and Inter-Industry Wage Differentials" *Journal of Labor Economics* 10, pp. 55-82

Katz, L. and D. Autor "Changes in the wage structure and earnings inequality" in Ashenfelter, O. and D. Card, editors, *Handbook of Labour Economics*, pp. 1463-1558 New York: Elsevier

McLaughlin, K. and M. Bils (2001) "Interindustry Mobility and the Cyclical Upgrading of Labor" *Journal of Labor Economics* 19, 1, pp. 94-135

Neal, D (1995) "Industry-Specific Human Capital: Evidence from Displaced Workers" *Journal of Labor Economics* 13, pp. 653-677

Parent, D. (2000) "Industry-Specific Human Capital and the wage Profile: Evidence from the NLSY and the PSID" " *Journal of Labor Economics* 18, pp. 306-323

Shin, D. (1994) "Cyclicality of Real Wages Among Young Men" *Economics Letters* 46, pp. 137-141

Solon, G., R. Barsky, and J. Parker (1994) "Measuring the Cyclicality of Real wages: How Important is Composition Bias?" *Quarterly Journal of Economics 109, 1*, pp. 1-26

Weinberg, B. (2001) "Long-term contracts with Industry Specific Human Capital" *Journal of Labor Economics* 19, 1, pp. 231-264

Table 1
Estimates of the Empirical Relationship between changes in employment and changes in average Wages by Industry based on the Survey of Employment, Payroll, and Hours (SEPH), 1991-2000

Average weekly earnings				Average hourly earnings			
Salaried workers				Salaried workers			
Incl. OT	0.125	(0.002)	[.121]	Incl. OT	0.104	(0.008)	[.098]
Excl. OT	0.126	(0.002)	[.124]	NA			
Hourly workers				Hourly workers			
Incl. OT	0.095	(0.004)	[.103]	Incl. OT	-0.006	(0.88)	[-0.01]
Excl. OT	0.092	(0.006)	[.094]	Excl. OT	-0.007	(0.82)	[-0.01]

Notes: The first values reported reflect the estimated coefficient of employment. The value reported in parentheses is the prob. value, and the value in brackets is the corrected coefficient of determination. OT stands for pay for overtime hours. N = 70

Table 2
Description of Industrial Codes
North American Industry Classification System – 1997 scheme (NAICS)

Number	Description
01	Agriculture
02	Forestry and Logging with Support Activities
03	Fishing, Hunting, and Trapping
04	Mining and Oil and Gas Extraction
05	Utilities
06	Construction
07	Durables
08	Non-Durables
09	Wholesale Trade
10	Retail Trade
11	Transportation and Warehousing
12	Finance and Insurance
13	Real Estate and Leasing
14	Professional, Scientific, and Technical Services
15	Management, Administrative, and Other Support
16	Educational Services
17	Health Care and Social Assistance
18	Information, Culture, and Recreation
19	Accommodation and Food Services
20	Other Services
21	Public Administration

Table 3
Effects of Industry Employment Changes on Industry Wages of Men

	Panel 1		Panel 2	
	Current wage	Composite wage	Current wage	Composite wage
Long differences				
Individual characteristics	-0.03 (0.843)	-0.074 (0.651)	0.145 (0.482)	0.253* (0.057)
Fixed-effect individual	0.161 (0.212)	0.092 (0.464)	0.055 (0.762)	0.123 (0.286)
Fixed-effect individual-job	0.097 (0.398)	-0.026 (0.764)	0.109 (0.313)	0.002 (0.985)
GLS – employment data not smoothed				
Individual characteristics	0.049 (0.588)	0.010 (0.912)	0.127 (0.174)	0.184** (0.036)
Fixed-effect individual	0.158** (0.01)	0.120* (0.071)	0.042 (0.551)	0.100* (0.105)
Fixed-effect individual-job	0.150** (0.004)	0.124** (0.034)	0.053 (0.369)	-0.015 (0.801)
GLS – employment data smoothed				
Individual characteristics	0.025 (0.801)	0.010 (0.924)	0.181* (0.093)	0.244** (0.016)
Fixed-effect individual	0.208** (0.003)	0.171** (0.023)	0.118 (0.145)	0.177** (0.011)
Fixed-effect individual-job	0.114* (0.058)	0.070 (0.291)	0.099 (0.144)	0.001 (0.895)

Notes: Prob. values are listed in parentheses. Each value comes from a different regression. Each estimate is a coefficient of log employment on log wages. **significant at 5 % level * significant at 10 % level

Table 4
Effects of Industry Employment Changes on Industry Wages of Women

	Panel 1		Panel 2	
	Current wage	Composite wage	Current wage	Composite wage
Long differences				
Individual characteristics	-0.154 (0.374)	-0.159 (0.371)	-0.146 (0.336)	-0.121* (0.527)
Fixed-effect individual	0.202* (0.075)	0.254* (0.072)	0.166** (0.048)	0.195 (0.069)
Fixed-effect individual-job	0.214 (0.185)	0.254 (0.298)	0.182** (0.013)	0.139 (0.118)
GLS – employment data not smoothed				
Individual characteristics	0.332** (0.034)	0.317** (0.047)	-0.152 (0.120)	-0.092 (0.339)
Fixed-effect individual	0.236** (0.014)	0.267** (0.008)	0.131** (0.008)	0.179** (0.001)
Fixed-effect individual-job	0.296** (0.004)	0.296** (0.004)	0.1488* (0.007)	0.16588 (0.002)
GLS – employment data smoothed				
Individual characteristics	-0.027 (0.879)	-0.029 (0.874)	-0.153 (0.177)	-0.095 (0.392)
Fixed-effect individual	0.271** (0.013)	0.315** (0.006)	0.148** (0.009)	0.185** (0.003)
Fixed-effect individual-job	0.297** (0.011)	0.293** (0.014)	0.198* (0.002)	0.181** (0.003)

Notes: Prob. values are listed in parentheses. Each value comes from a different regression. Each estimate is a coefficient of log employment on log wages. **Denotes significance at the 5 % level, and * denotes significance at the 10 % level

Table 5
Effects of Industry Employment Changes on Average Industry Wages of Men – Adjusted for Supply Side Influences

	Panel 1		Panel 2	
	Current wage	Composite wage	Current wage	Composite wage
GLS estimates – employment data not smoothed				
Individual characteristics	0.046 (0.606)	0.008 (0.921)	0.143 (0.124)	0.198** (0.024)
Fixed-effect individual	0.150** (0.013)	0.113* (0.084)	0.046 (0.518)	0.102* (0.091)
Fixed-effect individual-job	0.144** (0.005)	0.120* (0.037)	0.055 (0.344)	-0.008 (0.892)
GLS estimates – employment data smoothed				
Individual characteristics	0.029 (0.767)	0.017 (0.86)	0.194* (0.073)	0.254** (0.013)
Fixed-effect individual	0.198** (0.003)	0.164** (0.026)	0.123 (0.133)	0.180** (0.01)
Fixed-effect individual-job	0.111* (0.057)	0.067 (0.297)	0.102 (0.133)	0.017 (0.801)

Notes: Prob. values are listed in parentheses. Each value comes from a different regression, and represents the coefficient of log employment on log wages. **Denotes significance at the 5 % level, and * denotes significance at the 10 % level

Table 6
Effects of Industry Employment Changes on Average Industry Wages for Women Adjusted for Supply Side Influences

	Panel 1		Panel 2	
	Current wage	Composite wage	Current wage	Composite wage
GLS estimates – employment data not smoothed				
Individual characteristics	0.320** (0.038)	0.306* (0.052)	-0.137 (0.162)	-0.07 (0.339)
Fixed-effect individual	0.232** (0.015)	0.264** (0.008)	0.131** (0.007)	0.18** (0.001)
Fixed-effect individual-job	0.293** (0.004)	0.291** (0.004)	0.145** (0.008)	0.166** (0.001)
GLS estimates – employment data smoothed				
Individual characteristics	-0.024 (0.891)	-0.027 (0.874)	-0.131 (0.252)	-0.0695 (0.535)
Fixed-effect individual	0.258** (0.016)	0.299** (0.007)	0.150** (0.008)	0.189** (0.003)
Fixed-effect individual-job	0.288** (0.012)	0.283** (0.014)	0.196* (0.002)	0.183** (0.003)

Notes: Prob. values are listed in parentheses. Each value comes from a different regression, and represents the estimated coefficient of log employment on log wages.
**Denotes significance at the 5 % level, and * denotes significance at the 10 % level

Appendix Table
Changes in the log of Average Hourly Wages and employment of salaried employees (SEPH data)

3-digit NAICS	Industry number	Industry Name	Change in hourly real wages			Change in employment		
			1991-1995	1996-2000	1991-2000	1991-1995	1996-2000	1991-2000
113	1	Forestry and logging	0.0138	0.0723	0.0118	-0.1707	-0.2132	-0.3470
211	2	Oil and gas extraction	0.0299	-0.0384	-0.0094	-0.2505	-0.1265	-0.5787
212	3	Mining (except oil and gas)	0.0802	-0.0413	0.0771	-0.1800	0.3147	0.2131
213	4	Support activities for mining and oil and gas extraction	0.1463	-0.1292	0.1767	-0.1506	0.4353	0.4095
236	5	Construction of buildings	0.0304	-0.1035	-0.0789	-0.5451	0.1590	-0.3453
237	6	Heavy and civil engineering construction	0.0745	-0.0051	0.1009	-0.2952	0.0121	-0.2984
238	7	Specialty trade contractors	0.0911	-0.0835	0.0626	-0.4914	-0.2023	-0.4669
311	8	Food manufacturing	0.0755	0.1072	0.1661	-0.0736	-0.0489	-0.0285
312	9	Beverage and tobacco product manufacturing	0.0322	0.1471	0.2247	-0.0918	-0.0179	-0.2160
313	10	Textile mills	0.0928	0.0795	0.1009	0.0073	-0.1076	-0.0603
314	11	Textile product mills	-0.0063	0.0854	0.0441	-0.2619	-0.1407	-0.0484
315	12	Clothing manufacturing	-0.0084	0.0442	-0.0498	-0.1277	-0.1389	0.0139
316	13	Leather and allied product manufacturing	0.0457	0.0931	0.0762	-0.4399	-0.1518	-0.2851
322	14	Paper manufacturing	0.0636	-0.0682	-0.0036	-0.1307	-0.0023	-0.1587
323	15	Printing and related support activities	0.1079	0.0500	0.1658	-0.0153	0.2971	0.2638
324	16	Petroleum and coal products manufacturing	0.0370	0.0265	0.0414	-0.0530	-0.0121	-0.0918
325	17	Chemical manufacturing	0.0991	0.0062	0.1009	-0.1660	0.1834	-0.0648
321	18	Wood product manufacturing	0.0622	-0.0263	0.0610	-0.0041	-0.1839	-0.0289

327	19	Non-metallic mineral product manufacturing	0.0468	-0.0736	-0.0002	0.0362	0.0648	-0.0335
331	20	Primary metal manufacturing	0.0514	0.0373	0.0972	-0.1617	-0.1318	-0.3563
332	21	Fabricated metal product manufacturing	0.0409	0.0425	0.1217	-0.2455	-0.0367	-0.2751
333	22	Machinery manufacturing	0.0874	0.1190	0.2394	-0.0724	0.0524	-0.0983
335	23	Electrical equipment, appliance and component manufacturing	0.0394	0.0234	0.0470	-0.6215	0.5258	-0.1961
336	24	Transportation equipment manufacturing	0.0974	0.0828	0.1816	-0.1042	0.0250	-0.0529
337	25	Furniture and related product manufacturing	0.1097	0.1288	0.2077	-0.2491	0.1535	-0.1211
339	26	Miscellaneous manufacturing	0.1206	0.1425	0.2404	-0.2774	0.2006	-0.1637
411	27	Farm product wholesaler-distributors	0.0814	0.2274	0.2143	-0.3964	0.0319	-0.2870
412	28	Petroleum product wholesaler-distributors	0.1127	0.1644	0.1818	-0.0696	-0.2385	-0.2329
417	29	Machinery, equipment and supplies wholesaler-distributors	0.1048	-0.0097	0.0898	-0.1550	0.1749	-0.0550
418	30	Miscellaneous wholesaler-distributors	0.1380	0.2086	0.2657	0.1749	-0.2553	-0.0301
419	31	Wholesale agents and brokers	0.0620	0.1234	0.1444	-0.0860	-0.0111	-0.0833
441	32	Motor vehicle and parts dealers	0.1320	0.0104	0.1931	-0.2153	0.2078	-0.1734
442	33	Furniture and home furnishings stores	0.0941	-0.0942	0.0127	-0.5897	0.1558	-0.5073
443	34	Electronics and appliance stores	-0.0121	0.0551	-0.0010	-0.2145	0.0875	-0.0915
444	35	Building material and garden equipment and supplies dealers	0.0601	0.0893	0.1307	-0.1538	-0.1193	-0.2182

445	36	Food and beverage stores	0.0812	0.0573	0.0238	-0.2293	-0.4858	-0.4909
447	37	Gasoline stations	-0.1195	0.0239	-0.1462	-0.4057	-1.0277	-1.2963
451	38	Sporting goods, hobby, book and music stores	0.0803	0.0199	0.0795	-0.2537	-0.2722	-0.3973
454	39	Non-store retailers	0.0998	0.0713	0.1111	-0.1701	-0.2726	-0.3285
482	40	Rail transportation	0.0501	0.1196	0.1799	-0.2006	0.0059	-0.2355
483	41	Water transportation	0.0565	0.0589	0.1034	0.1883	-0.0597	0.0041
484	42	Truck transportation	0.0035	-0.1012	-0.0826	-0.0650	-0.3489	-0.2146
485	43	Transit and ground passenger transportation	0.0243	0.1877	0.1026	-0.2056	-0.2642	-0.2754
486	44	Pipeline transportation	0.0805	0.2046	0.3236	0.0135	-0.2519	-0.2804
487	45	Scenic and sightseeing transportation	0.0236	0.0872	0.1067	0.0888	0.0063	0.0670
488	46	Support activities for transportation	0.0723	-0.0353	0.0355	-0.1570	0.1647	-0.0089
491	47	Postal service	0.0638	0.0315	0.0933	-0.1183	-0.0227	-0.1595
493	48	Warehousing and storage	0.0290	-0.0344	0.0303	-0.0155	0.0265	0.0592
515	49	Broadcasting (except Internet)	0.1075	-0.0295	0.0871	-0.0115	-0.5202	-0.5405
517	50	Telecommunications	0.0103	0.0106	0.0179	-0.0130	-0.2912	-0.4267
518	51	Internet service providers, web search portals, and data processing services	0.0638	0.0315	0.0933	-0.1183	-0.0227	-0.1595
522	52	Credit intermediation and related activities	0.0852	-0.0066	0.1062	-0.1465	-0.1036	-0.2936
524	53	Insurance carriers and related activities	0.0883	0.0116	0.1466	-0.1176	0.1244	-0.0220
531	54	Real estate	0.1456	0.0044	0.1956	-0.1643	0.0587	-0.0961
532	55	Rental and leasing services	0.0334	-0.0318	0.0397	-0.1078	-0.1639	-0.4008
541	56	Professional, scientific and technical services	0.0723	-0.0017	0.1132	-0.0081	0.3822	0.3268

561	57	Administrative and support services	0.0392	0.0519	0.0823	0.1638	-0.0257	0.2547
621	58	Ambulatory health care services	0.0878	-0.0941	0.0272	0.0320	-0.0791	-0.2413
622	59	Hospitals	0.0376	-0.0445	-0.0289	-0.2818	-0.6268	-0.7775
623	60	Nursing and residential care facilities	0.0875	-0.0322	0.0637	0.1046	-0.7294	-0.6116
624	61	Social assistance	0.0063	-0.1012	-0.1024	0.1539	-0.0245	-0.0680
712	62	Heritage institutions	0.0955	-0.0046	0.0541	0.1233	0.0423	0.1884
713	63	Amusement, gambling and recreation industries	0.0675	-0.0149	0.0538	-0.0912	0.1529	0.1696
721	64	Accommodation services	0.0459	0.0145	0.0798	-0.2614	0.2183	-0.1609
722	65	Food services and drinking places	0.0217	-0.0137	0.0165	-0.0913	-0.1900	-0.3462
811	66	Repair and maintenance	0.0975	0.0218	0.1009	-0.2174	0.0000	-0.1544
812	67	Personal and laundry services	0.0872	-0.0560	0.0816	-0.1322	-0.3313	-0.4018
911	68	Federal government public administration	0.0149	0.1256	0.1299	-0.0625	-0.0313	-0.1603
912	69	Provincial and territorial public administration	-0.0091	0.0596	0.0457	-0.0981	-0.0418	-0.2069
913	70	Local, municipal and regional public administration	0.1548	-0.0278	0.1575	-0.2557	-0.2046	-0.5788

Figure 1: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1991-2000
(Expressed in terms of differences in the natural logs)

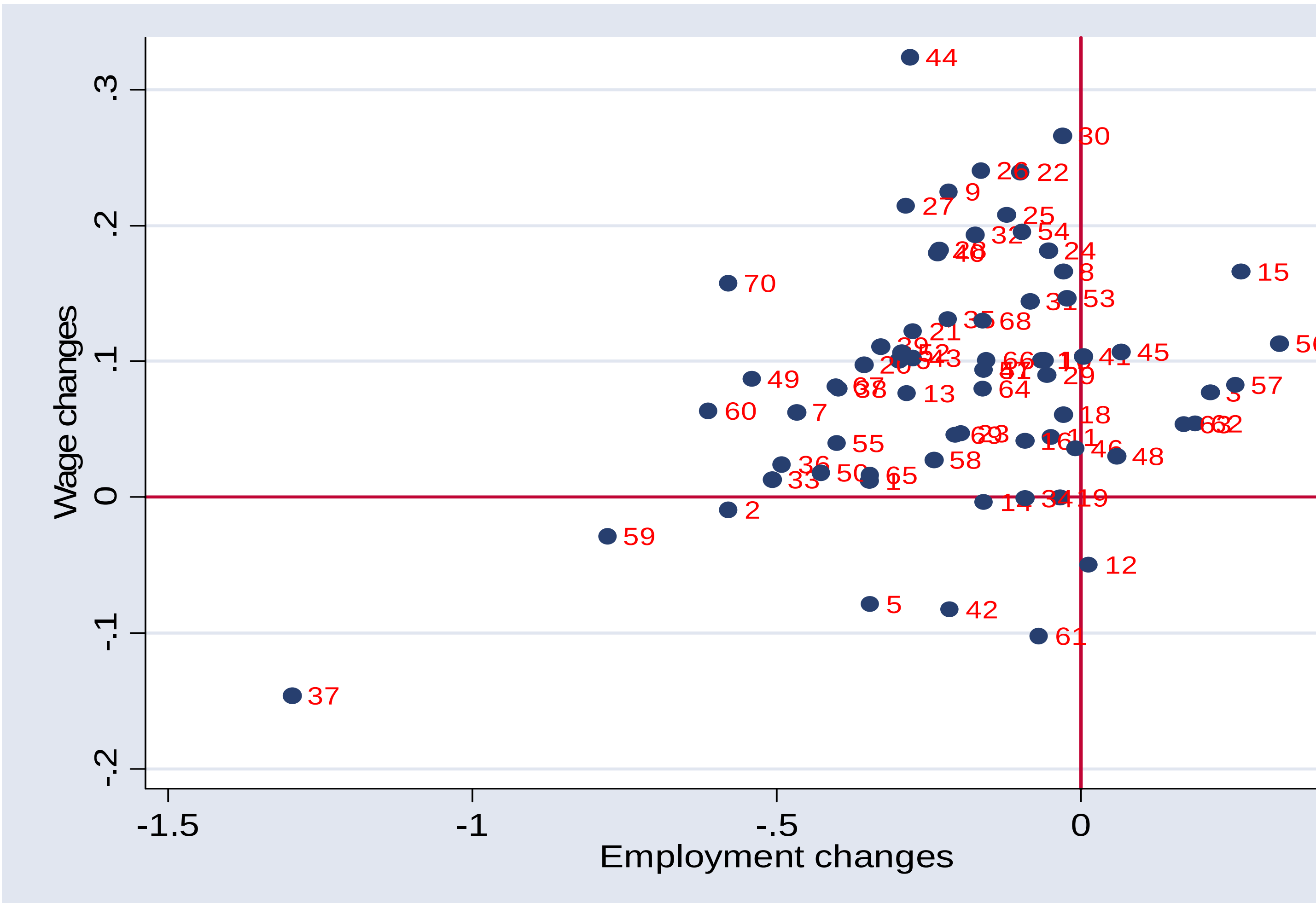

Figure 2: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1991-1995 (expressed in terms of differences in logs)

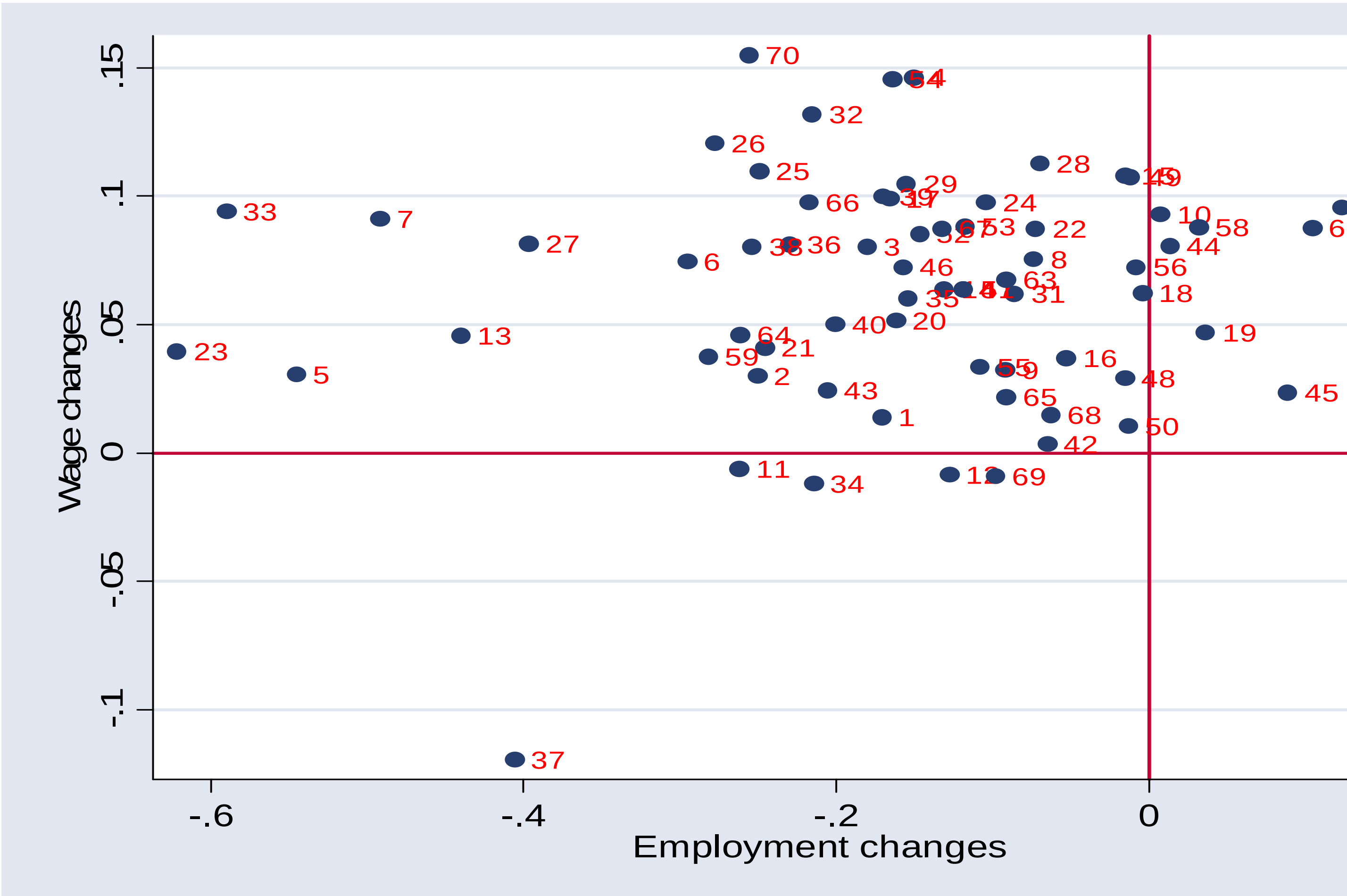

Figure 3: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1996-2000
(Expressed in terms of differences in logs)