# The Response of Real Wages to Demand Shocks


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**Abstract**

The paper investigates whether real wages respond positively to demand shocks or not. Using Canadian industry-level aggregate data, I find that real wages of salaried employees respond positively to low-frequency demand shocks from 1991 to 2000, and real wages of employees paid by the hour respond positively to low-frequency demand shocks from 1996 to 2000. Although I cannot adequately control for effects of composition bias and simultaneity bias using currently available data, my results are still reliable.

## I. Introduction

The objective of this paper is to investigate the response of real wages to demand shocks in Canada. These demand shocks include high-frequency demand shocks and low-frequency demand shocks. Most earlier studies of wage behaviour focused on the effects of high-frequency demand shocks on real wages; i.e., the behaviour of real wages over the business cycle. The response of real wages to low-frequency, persistent demand shocks has attracted attention in the U.S. only recently (Weinberg 2001; Devereux 2005), but nothing is known in Canada, even though the longitudinal data needed to answer this question have recently become available (Kuhn 2003).[1]

My interest is sparked by the fact that there is little evidence regarding real wage behaviour in response to long-run demand shocks, and thus there is plenty of room for further undertakings using available Canadian data. In this paper, I use Canada's industry-level annual data to investigate real wage behaviour in the face of low-frequency demand shocks. I find a positive correlation between long-term changes in industry employment and long-term changes in real wages for salaried employees from 1991 to 2000, and for hourly-paid employees from 1996 to 2000. If changes in industry employment are a good proxy for low-frequency demand shocks, my results demonstrate that industry-level real wages respond positively to low-frequency demand shocks in the long-run.

[1] The term "low-frequency demand shocks" refers to shocks that persist over five- or ten-year periods and that don't occur very often. Examples include demand shocks that have led to structural declines in many manufacturing industries over the last few decades.

The structure of this paper is as follows: the next section reviews the theoretical and empirical framework in the literature on real wage behaviour in the face of demand shocks. The following section presents my empirical work, which focuses on real wage behaviour due to low-frequency demand shocks, including descriptions of the data, the regression equations, and the results. Finally, the last section summarizes the results and concludes the paper.

## II. Theoretical and empirical frameworks in the literature

### 1. The response of real wages to high-frequency demand shocks

I first survey the literature on real wage rate behaviour over the business cycle, which is a topic that has been debated by economists for decades. Early theories predict the countercyclical behaviour of real wages over the business cycle.[2] They attribute cyclical labour market fluctuations to shifts of the labour supply curve along the fixed labour demand curve in the short-run. The most well-known example is the model of nominal wage rigidity, which was proposed by Keynes (1936) in his famous publication the *General Theory* (p.17): "In general an increase in employment can only occur through the accompaniment of a decline in real wages. Thus, I am not disputing this vital fact which the classical economists have (rightly) asserted as indefeasible." He argued that this could occur only in the case of rigid nominal wages accompanied by price inflation, which will erode real wages. During

[2] The term "countercyclical" implies a negative relationship between wages and the business cycle. On the other hand, the term "procyclical" implies a positive relationship.

depressions and recessions, the decrease in output price coupled with rigid nominal wages leads to an increase in real wages. Therefore, during the down phases of the business cycle, falling employment is associated with rising real wages. During recoveries and booms, the increase in output price coupled with rigid nominal wages leads to a decrease in real wages; thus during the up phases of the business cycle, rising employment is associated with falling real wages.

These theories, however, were not supported by the early empirical results (Dunlop 1938; Tarshis 1939). Later, Neftci (1978) found evidence in favour of the countercyclical behaviour of real wages over the business cycle using dynamic estimation models. However, Geary and Kennan (1982) showed that Neftci's results do not survive after expanding the sample period. Furthermore, later economists using longitudinal data found strong procyclial behaviour of real wages over the business cycle and argued that the true procyclicality of real wages is obscured in aggregate time series because of a composition bias arising from individual differences (Bils 1985; Solon, Barsky, and Parker 1994; Liu 2003). Therefore, theories that attribute real wage movements to shifts in the labour supply curve were dismissed by the absence of evidence of countercyclical wage behaviour.

Since 1980, theories that attribute cyclical labour market fluctuations to shifts in labour demand curves have become predominant in the literature (Lucas and Rapping 1969). These theories assume that the labour supply curve is fixed in the short-run, but they differ in whether the labour supply curve is positively sloped. Theories that support the procyclical behaviour of the real wage assume that the labour supply curve is positively sloped in the short-run and that real wage movements are caused by shifts in the labour demand curve. When the labour market is robust, one generally expects upward pressure on real wages as labour becomes scarcer. Employers compete for workers and bid up real wages. When the labour market is weak, one generally expects downward pressure on real wages as labour becomes more plentiful. Workers compete for jobs and bid down real wages. Lucas and Rapping's (1969) model of intertemporal substitution in labour supply provides a theoretical basis for the positively sloped labour supply curve in the short-run.

However, most empirical evidence shows that aggregate time-series data on the real wage display little or no cyclicality (neither procyclical nor countercyclical). Lucas (1977) noted that "observed real wages are not constant over the cycle, but neither do they exhibit constant pro- nor countercyclical tendencies" (p.17). The lack of cyclicality of the real wage was explained by the high elasticity of the labour supply curve. Therefore, shifts of the demand curve along a flat supply curve lead to significant output and employment fluctuations and small real wage fluctuations. The highly elastic supply curve was supported by implicit contract theories in which employers provide insurance to employees to against high-frequency demand shocks.

During the past 70 years, dozens of empirical studies have provided evidence on real wage behaviour in order to test alternative theories. There are no unifying results in the empirical literature. Many studies of aggregate time-series data have concluded that real wages are noncyclical (Bodkin 1969; Kennan and Geary 1982), but a few time-series studies have shown countercyclicality (Neftci 1978; Otani 1978; Canzoneri 1978; Chirinko 1980) or procyclicality (Dunlop 1938; Tarshis 1939; Kilduff 1989). Later studies of longitudinal data have provided evidence of strong procyclicality (Bils 1985; Solon, Barsky, and Parker 1994; Liu 2003) and argued that the lack of cyclical behaviour of real wages in time series data is because of a countercyclical composition bias arising from individuals' heterogeneity.

Early studies in the empirical literature usually used aggregate time-series data. Dunlop (1938) observed that real wages and employment are positively related in British data, while Tarshis (1939) observed the same phenomenon in U.S. data. This intuitive finding was regarded as paradoxical during that period. Later, Bodkin (1969) attempted to study real wage behaviour over the business cycle in the U.S. and Canada. He used a regression approach and a frequency table approach with annual time-series data for Canada from 1921 to 1965 and for the U.S. from 1900 to 1965, and quarterly time series data for both countries from 1949 to 1965. Using unemployment rates as the basic cyclical variable, he finds that real wages and unemployment rates are positively related but statistically independent for both countries.

At the end of the 1970s, some economists presented evidence of countercyclical behaviour of real wages using aggregate time series data. They attributed the discrepancy between their findings and previous findings to the level of data aggregation, dynamic specifications and the treatment of overtime pay. Neftci (1978) utilized monthly time-series data for the U.S. manufacturing sector from 1948 to 1971 and found a significantly negative relationship between real wages and employment. He thought that previous studies found positive or insignificant relationships between real wages and employment because they had ignored the problem of dynamics. If employment adjustment is costly, the relationship between real wage fluctuations and movements in employment is not contemporaneous. When he added appropriate distributed lags (k=6,12,18, or 24) into his estimating equation, he found a significantly negative relationship between real wages and employment.[3]

Otani (1978) provided some international comparisons by examining post-war data for fourteen industrial countries. Using annual percentage changes in real wages and industrial output in the manufacturing sector of fourteen industrial countries, he found a significantly negative relationship between real wages and employment in six (Australia, Belgium, France, Japan, Norway, and the U.K.) of the fourteen countries.[4] The Canadian results showed a negative, but insignificant, correlation from 1952 to 1974, while the U.S. results showed a positive, but insignificant correlation from 1952 to 1974. In the same year, Canzonei (1978) estimated a Cobb-Douglas production function using quarterly Canadian data from 1954 to 1970. He found evidence of a negative relationship between real wages and employment within the context of the Canadian economy.

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[3] Bils (1985) has argued that noncontemporaneous wage-employment relationships should be less of an issue with annual data than with the monthly data used by Neftci.

[4] The countries are Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, Switzerland, United States, and United Kingdom.

Chirinko (1980) argued that Otani's empirical work contains two distorting factors. First, real wages for the whole manufacturing sector are influenced by a procyclical composition bias which arises from the aggregation process. Employment in certain high-wage subsectors, such as durable goods manufacturing, is especially sensitive to the business cycle. During a recession, the reduced employment shares of these subsectors produce a downward tendency in the whole-manufacturing average wage. Thus, even if real wages are countercyclical in each subsector, the aggregate manufacturing real wage rates might obscure that countercyclicality and might even appear procyclical. Second, there is a structural break during Otani's sample period. The year 1974 suffered supply shocks caused by OPEC's actions. After eliminating these two distorting factors, Chirinko found a significantly negative relationship in the U.S. from 1955 to 1975 using aggregate time series data.

However, this empirical evidence of a significantly negative relationship was broadly criticized during the 1980s. Geary and Kennan (1982) argued that the negative relationship between real wages and employment found by Neftci (1978) is not one of those "regularities common to all decentralized market economies." They use Haugh's S-test and an F-test in a dynamic regression. Using quarterly time series data for the manufacturing sectors of twelve OECD countries, they found that real wages and employment are statistically independent over the business cycle for most of these twelve OECD countries (it is hard to reject the hypothes of independence for Canada).[5] In particular, they found that independence is not rejected for the U.S., which conflicts with the results of Neftci. They explained the discrepancy by different price deflators and different sample periods. Neftci used the consumption price index as a price deflator, while Geary and Kennan use the wholesale price index. Furthermore, they found that Neftci's results cannot survive the extension of the sample period to 1977.

Later, Kilduff (1989) used an independence test to examine the relationship between real wages and employment. In this independence test, the overall relationship between real wages and employment is decomposed into three parts, which are the feedback from real wages to employment, the feedback from employment to real wages, and the contemporaneous relationship between real wages and employment. Using both aggregate and industry-level monthly data for Canada from January 1961 to November 1982, Kilduff found empirical evidence that contradicted Geary and Kennan's finding for Canada. Kilduff's results show a contemporaneous positive correlation between wages and employment.

Later researchers argued that the absence of the procyclical real wage behaviour in aggregate data is a statistical illusion (Stockman 1983; Solon, Barsky, and Parker 1994; Liu, 2003). Evidence from the U.S. Panel Study of Income Dynamics (PSID) shows that real wages have been procyclical since the 1960s. The discrepancy between results from longitudinal data and aggregate time series data is due to the

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[5] The countries are Australia, Belgium, Canada, Denmark, Germany, Holland, Ireland, Italy, New Zealand, Switzerland, United States, and United Kingdom.

fact that aggregate average statistics are constructed in a way which gives more weight to low-skilled workers during expansions than during recessions.

Stockman (1983) was the first to suggest the possibility of composition bias in published aggregate data. The published aggregate data on average hourly earnings are constructed by dividing total payrolls $B_t$ by total work hours of work $H_t$. Now suppose that the relevant worker population is divided into groups $j=1,2,\ldots J$, with $B_{jt}$ denoting the $j$th group's wage bill, $H_{jt}$ denoting its total hours of work, $S_{it}= H_{jt}/H_t$ denoting its share of the population's hours of work, and $W_{jt}=B_{jt}/H_{jt}$ denoting its average hourly earnings. Then the overall average wage $W_t$ can be expressed as:

$$W_t = \frac{B_t}{H_t} = \sum_{j=1}^{J} \frac{B_{jt}}{H_t} = \sum_{j=1}^{J} \frac{H_{jt} W_{jt}}{H_t} = \sum_{j=1}^{J} S_{jt} W_{jt}. \qquad (1)$$

The aggregate average wage is thus a weighted average of the group-specific average wages, with the groups weighted by their shares of hours of work. The problem is that the shares vary over the business cycle. The hours of work of low-wage groups (young employees or less educated employees) tend to be more cyclically variable than those of high-wage groups. Therefore, the aggregate average wage gives a greater weight to low-wage groups during expansions than during recessions, which leads to a countercyclical composition bias. This composition bias could obscure the true procyclicality of real wages that the typical worker in any group real faces.

To clarify this point, I differentiate the aggregate average wage $W_t$ with respect to a cycle indicator $U_t$. To simplify the problem, suppose there are only two groups, thus $J$=2 with $W_{1t}$>$W_{2t}$ (i.e., group 2 is the low-wage group). Then:

$$\frac{d\ln W_t}{dU_t}=\frac{1}{W_t}\frac{dW_t}{dU_t}=\frac{1}{W_t}\frac{d(S_{1t}W_{1t}+S_{2t}W_{2t})}{dU_t}$$

$$=\frac{1}{W_t}\left[\frac{dS_{1t}W_{1t}}{dU_t}+\frac{dS_{2t}W_{2t}}{dU_t}\right]$$

$$=\frac{1}{W_t}\left[S_{1t}\frac{dW_{1t}}{dU_t}+S_{2t}\frac{dW_{2t}}{dU_t}+W_{1t}\frac{dS_{1t}}{dU_t}+W_{2t}\frac{dS_{2t}}{dU_t}\right]$$

$$=\frac{W_{1t}}{W_t}S_{1t}\frac{d\ln W_{1t}}{dU_t}+\frac{W_{2t}}{W_t}S_{2t}\frac{d\ln W_{2t}}{dU_t}+\frac{W_{1t}}{W_t}\frac{dS_{1t}}{dU_t}+\frac{W_{2t}}{W_t}\frac{dS_{2t}}{dU_t}.$$

Suppose that both groups experience the same real wage cyclicality: $\beta_3 = d\ln W_{1t}/dU_t = d\ln W_{2t}/dU_t$. Then

$$\frac{dW_t}{dU_t}=\beta_3\left(\frac{W_{1t}S_{1t}+W_{2t}S_{2t}}{W_t}\right)+\frac{W_{1t}}{W_t}\frac{d(1-S_{2t})}{dU_t}+\frac{W_{2t}}{W_t}\frac{dS_{2t}}{dU_t}$$

$$=\beta_3+\left(\frac{W_{2t}-W_{1t}}{W_t}\right)\frac{dS_{2t}}{dU_t}\quad (W_t=S_{1t}W_{1t}+S_{2t}W_{2t}).$$

If $dS_{2t}/dU_t$>0, then $d\ln W_t/dU_t <\ \beta_3$. In other words, if $dS_{2t}/dU_t$ is more procyclical ($dS_{2t}/dU_t$>0), the measured aggregate wage cyclicality $d\ln W_t/dU_t$ is less procyclical than the true wage cyclicality $\beta_3$ faced by each group of workers.

In order to control for this composition bias, the most straightforward method is to construct a wage measure without cyclically shifting weights. If one has access to longitudinal data, one could hold composition constant by following exactly the same workers over time with fixed weights. Therefore, later researchers usually used longitudinal data to investigate real wage behaviour over the business cycle. (Bils 1985; Solon, Barsky, and Parker 1994). Early studies using published aggregate data only do regressions of the average wage rate on employment or the unemployment rate, based on following equation in first-differences:

$$\Delta \ln W_t = \alpha_0 + \alpha_1 \Delta E_t + \varepsilon_t, \quad (2)$$

Where $\Delta$ denotes the first difference of a variable.

Later studies using longitudinal data could include employees' time-variant characteristics and employees' time-invariant characteristics the regression, leading to the following modification of equation (2):

$$\Delta \ln W_{i,t} = \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta X_{i,t} + \upsilon_t . \quad (3)$$

Equation (3) not only accounts for the effects of time-variant characteristics $\Delta X_{i,t}$ (such as work experience), but also controls for the effects of observed time-invariant characteristics (such as race and educational level), and unobserved time-invariant characteristics (such as motivation and ability) by differencing out their effects.

Using longitudinal data from the National Longitudinal Survey (NLS) and an equation similar to equation (3), Bils (1985) found that real wages move strongly procyclically with employment. He also found that the aggregate average wage is countercyclically biased by young workers who enter the work force in high employment periods having 19 percent lower wages than young workers (same age and same work experience) who have already been in work force. However, he thought "This bias is unimportant relative to the very procyclical wage behaviour found here." (p.684) He attributed the discrepancy between his results and previous results to the treatment of overtime and different sample periods. He thought previous studies did not include overtime earnings in their wage measures. Since overtime hours exhibit procyclical behaviour, this gives previous estimates a countercyclical bias.

Solon, Barsky, and Parker (1994) thought Bils overlooked the impacts of composition bias because he only consider the composition bias arising from the tendency for young workers who enter the work force in high employment periods to have lower wages than young workers (same age and same work experience) who have already been in the work force, but he ignored the tendency for young workers to be paid less and have much more cyclically variable hours of work than experienced workers. In order to demonstrate the importance of the effects of composition bias, they first used longitudinal data from the PSID and found strongly procyclical real wage behaviour. Then they aggregated the PSID data and purposely distorted the aggregation process by imposing the same sort of weighting used in the published aggregate data. The results from these distorted PSID data displayed an insignificant correlation between real wages and employment, similar to the results from published aggregate data. This implies that composition bias is quantitatively important.

A recent paper by Liu (2003) also indicated the importance of controlling for composition bias arising from variation in labour quality in the business cycle. He presented an international comparison by examining cross-sectional data in Canada, the U.S., and U.K. He found that real wages are strongly procyclical in Canada, the

U.K. and the U.S.[6] However, when he used government-published real aggregate hourly wages, the estimated correlation between the hourly wage and hours worked varies from –0.58 in Canada to 0.57 in the U.K. Therefore, he concluded that controlling for composition bias arising from employees' quality is essential for the empirical work.

In summary, cyclical labour market fluctuations in the short-run are caused by demand shifts. However, whether the real wage is procyclical or not depends on the slope of the labour supply curve. If the labour supply curve is positively sloped, real wages exhibit procyclical behaviour over the business cycle. If the labour supply curve is flat, real wages are rigid over the business cycle. Recent researchers argue that the absence of procyclicality of real wages in published aggregate time-series data is due to composition bias arising from changes in labour quality over the business cycle. Using longitudinal data with fixed weights, they find strongly procyclical behaviour of real wages over the business cycle. The issue of composition bias is also important to the studies of the response of the real wage rate to low-frequency, persistent demand shocks, as the next subsection will show.

## 2. The response of real wages to low-frequency demand shocks

I now turn to the literature on real wage behaviour in the face of long-run demand shocks. This subject has attracted attention only recently. In the United

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[6] Haoming Liu used annual data for Canada from 1981 to 1994, for the U.K. from 1973 to 1993, and for the U.S. from 1975 to 1994. He also used quarterly data for Canada from 1981:1 to 1994:4, for the U.K. from 1979:1 to 1993:4, and for the U.S. from 1979:1 to 1993:4.

States, Weinberg (2001) and Devereux (2005) have investigated the response of real wages to low-frequency, persistent demand shocks. Using industry employment growth rates and unemployment rates as measures of these low-frequency demand shocks, they examine the relationship between changes in real wages and low-frequency demand shocks. Weinberg found that real wages do not respond to low-frequency demand shocks, while Devereux found that real wages respond positively to low-frequency demand shocks.

Using the annual CPS data from 1971 to 1991, Weinberg (2001) found that industry real wages do not respond to low-frequency demand shocks. He used the change in the log of hours worked and the change in the log of industry unemployment rates to measure industry demand shifts.[7] His regression model is

$$\Delta w_{t_i - t_0, i, g} = \beta_{0,g} + \beta_{1,g} \Delta H_{t_1 - t_0, i, g} + \beta_{2,g} \Delta U_{t_1 - t_0, i, g} + \varepsilon_{i,g}, \qquad (4)$$

where $\Delta w_{t_i - t_0, i, g}$ denotes the change in the log of the wage from $t_0$ to $t_1$ for workers in industry $i$ of gender $g$; $\Delta H_{t_1 - t_0, i, g}$ denotes the change in the log of total hours worked; and $\Delta U_{t_1 - t_0, i, g}$ denotes the change in the log of industry-level unemployment. If long run demand shocks have effects on industry real wage movements, $\hat{\beta}_1$ should be positive and $\hat{\beta}_2$ should be negative.

Weinberg divided his sample into two 10-year intervals (1971-1981 and 1981-1991) and four 5-year intervals (1971-1976, 1976-1981, 1981-1986 and

[7] A persistent increase in the demand for labour in an industry will lead to a persistent increase in hours worked and a decline in unemployment. Annual hours worked were computed as the product of the number of weeks worked and usual weekly hours for individuals who are reported to work in that industry. The unemployment rate was calculated as the difference between the number of weeks in the labour force and the number of weeks worked divided by the number of weeks in the labour force.

1986-1991) and estimated equations for men and women respectively. There are in total twelve sets of results, most of which indicated no relationship between industry real wages and low-frequency demand shocks. Weinberg considered the effect of the baby boom cohort and the increase in labour force participation among women during the 1970s as additional independent variables. However, the results do not change after he included these demographic shift effects into his regression model.

To explain his results, Weinberg proposed two models which predict no relationship between real wages and low-frequency demand shocks. In the first model, industry-specific human capital is not important, and thus there are no barriers to interindustry mobility. After negative demand shocks, workers can find new jobs in other industries without suffering a decrease in real wages. In the second model, industry-specific human capital is important and creates barriers to interindustry mobility. However, workers' real wages are rigid because employers insure their real wages against low-frequency demand shocks. In summary, whether industry-specific human capital is important or not determines which model is applicable.

In order to demonstrate the importance of industry-specific human capital, Weinberg compared the employment responses of young workers to those of experienced workers. The hypothesis is that if industry-specific human capital is important and creates barriers to interindustry mobility, the changes in employment of experienced workers will be less sensitive than those of young workers to the occurrence of a demand shock. To find empirical evidence, he used repeated cross-sectional data from the March Current Population Survey (CPS) annual demographic file. He divided his sample into two subsets: young workers with 0-9 years of working experience, and experienced workers with 10-39 years of working experience. The regression model for this part of his study is

$$\ln\left(\frac{e_{igct}}{e_{igct-1}}\right) = \beta_{0,gc} + \beta_{1,gc} * \ln\left(\frac{h_{it}}{h_{it-1}}\right) + \varepsilon_{igct,t-1}, \qquad (5)$$

where $\ln\left(\frac{e_{igct}}{e_{igct-1}}\right)$ denotes the change in the log of employment of workers of gender $g$ in age group $c$ in industry $i$ from $t$ to $t-1$. It measures the employment responses of different types of workers. $\ln\left(\frac{h_{it}}{h_{it-1}}\right)$ denotes the change in the log of hours worked in industry $i$ at time t for all workers, which measures changes in demand conditions.[8]

The results show that the estimated coefficients $\hat{\beta}_1$ for the young worker group are greater in magnitude than those for experienced workers. In other words, demand shocks have greater effects on the employment response of young workers than on that of experienced workers, which suggests the importance of industry-specific skills. Therefore, Weinberg accepted the second model in which workers' real wages are rigid in response to low-frequency demand shocks.

In contrast to Weinberg, Devereux (2005) found that industry real wages do respond to low frequency, persistent demand shocks. He based his empirical analysis on longitudinal data from the U.S. Panel Study of Income Dynamics (PSID) from

[8] Weinberg did not include the rate of unemployment in equation (4) because it is related to employment rates.

1971 to 1991. He uses industry employment figures as measures of industry demand shocks and finds a robust positive relationship between industry real wages and industry employment. He carried out his empirical analysis in two steps. In the first step, he used micro data to construct a composition-constant value of industry wages, which is the estimated value of the average wage rate in an industry after controlling for individuals' observed and unobserved characteristics. The regression equation is:

$$\ln w_{ijt} = \beta_1 + \beta_2 x_{it} + \sum_{j=1}^{J} \sum_{t=1}^{T} \phi_{jt} D_{jt} + f_i + \varepsilon_{ijt} . \qquad (6)$$

This approach is designed to account for the fact that the productive attributes of workers, which are so important in determining their wages, evolve over time. The dependent variable is $lnw_{ijt}$, which is the log wage of individual $i$ in industry $j$ at time $t$. The vector $x_{it}$ represents observed individual characteristics. $D_{jt}$ reflects the interactions of industry dummy variables and year dummy variables with each other, and is equal to 1 if the observation is from industry $j$ in year $t$ and 0 otherwise. The error terms have a permanent individual-specific component ($f_i$) and a random component ($\varepsilon_{ijt}$). The permanent individual-specific component ($f_i$), which controls for permanent unobserved individual attributes (e.g., ability and motivation), can be included in equation (6) by using longitudinal data and applying the fixed effects estimator. The estimated coefficient $\phi_{it}$ reflects the composition-constant industry wage rate, which is the estimated value of the average industry wage rate after controlling for individuals' observed and time invariant unobserved characteristics.

In the second step of his estimation procedure, the change in composition-constant industry wage rates is regressed on the change in industry employment. The estimating equation is

$$\Delta\hat{\phi}_{jt} = \delta_1 + \delta_2 \Delta \ln E_{jt} + u_{jt}. \qquad (7)$$

In this step, the unit of observation is the industry. The crucial estimated coefficient is $\hat{\delta}_2$, which indicates the relationship between industry real wages and industry employment. Devereux used a longer sample period than Weinberg (1971-2001), and he divided his sample into three 10-year intervals and estimated the effects for men and women separately. The results consist of a strong positive correlation between industry real wages and industry employment, which indicates that real wages respond positively to low-frequency demand shocks.

The discrepancy between the empirical results of Weinberg and Devereux could arise from two issues, namely composition bias and simultaneity bias. Simultaneity bias, in general, is caused by the possibility that the measures of demand conditions (hours worked, unemployment rate, and employment rate) are affected by supply shocks as well as exogenous demand shocks. For example, if there is some demographic change in labour supply (such as an increase in the propotion of highly-educated workers), industry employment will change even without demand shocks. This makes identification of demand shocks problematic. However, simultaneity is not likely to be a problem here because neither Weinberg nor Devereux ignores this problem. They both purge supply shocks from their measures of demand conditions.

The methods Devereux and Weinberg used to deal with this problem are similar.

They divided workers into several demographic groups by race, gender, and education level. They chose a base time period (such as 1971-75) and calculated the proportion of each demographic group in each industry over the base time period. Then they calculate the employment change in each industry that resulted purely from the change in the proportion of demographic groups, and subtract this term from the log of industry employment to exclude the effects of supply shocks.

Composition bias probably is the key source of the discrepancies between the empirical relationships between real wage changes and employment changes estimated by the two papers. As I mentioned in the first subsection, research on the cyclical behaviour of wages shows that the true inherent pro-cyclicality of real wages is obscured because of composition bias (Solon, Barsky, and Parker 1994; Liu 2003). Devereux in particular thought that the composition bias arising from unobserved individual heterogeneity as well as observed heterogeneity is the reason why Weinberg did not find the positive relationship between industry real wages and employment.

Actually, Weinberg did not ignore the problem of composition bias. He thought that in the face of long-run demand shocks, the workers' movements are mainly between industries, not between employment and unemployment, so the potential bias is not as serious as that in previous research on real wage behaviour during the business cycle. In order to address this problem, he added tenure and experience in the workers' current job as independent variables to regression model (4). His empirical results show that the effect of composition bias does exist but is quite small. Therefore, Weinberg concluded that the lack of the positive relationship in his empirical results is not due to composition bias.

On the other hand, Devereux argued that Weinberg did not control for composition bias at all because he only used repeated cross-section data. Devereux thought that it is necessary to use longitudinal data and a fixed effects estimator so that both observed and unobserved individual characteristics can be captured in the estimation process. Using cross-sectional data, only observed characteristics such as education and work experience can be captured, but unobserved characteristics such as ability and motivation cannot be excluded from the regression equation.[9] Cross-sectional data are collected from surveys in which different individuals are interviewed over time, while longitudinal data are collected from the surveys which track the same individuals over time. Therefore, using longitudinal data, one could further control for these unobserved characteristics, which are usually unchanged over time for individuals.

In order to demonstrate his point, Devereux compared regression results from three different regression models. The first one is

$$\ln w_{ijt} = \beta_1 + \sum_{j=1}^{J}\sum_{i=1}^{T}\phi_{jt}D_{jt} + \varepsilon_{ijt}. \tag{8}$$

This is a variation on equation (6). The vector $x_{it}$ in equation (6), which is used to control for observed individual heterogeneity, is excluded. In the second equation, he

[9] Haoming Liu (2003) also said that the most obvious disadvantage of using cross-sectional data over panel data is that it is much more difficult to control for variations in unobserved labour quality. Therefore, the quality-adjusted wages constructed from cross-sectional data might still be subject to composition bias caused by variations in unobserved labour quality. If unobserved and observed labour quality move in the same direction, the procyclicality of the wage series adjusted only for observed quality would be weaker than its true value.

included $x_{it}$, but used the ordinary least squares estimator (OLS) instead of the fixed effects estimator. This implies that he only controlled for observed characteristics but did not control for unobserved characteristics. The third specification is his original model. He compared regression results from these three regression models and found that a positive relationship between industry real wages and industry employment for women and men during the 1970s only appears in the third specification. Thus he concluded that controlling for composition bias due to individuals' unobserved characteristics is essential to generate the positive relationship.

### 3. Summary

The literatures on real wage behaviour in response to high-frequency and low-frequency demand shocks are related but not identical. First, studies of the effect of high-frequency demand shocks on real wages viewed the labour supply curve as fixed in the short-run. Therefore, simultaneity is not considered a problem in studies of the effects of high-frequency demand shocks. In contrast, simultaneity cannot be avoided in the study of low-frequency demand shocks because the labour supply curve is not fixed in the long-run. Second, the implicit contract model is a good explanation for short-run wage rigidity, but cannot explain long-run wage rigidity, which is support by the morale model, because the morale model could be self-enforcing in the long-run. Third, the long-difference approach is used in empirical work on the behaviour of real wages in the face of low-frequency shocks in order to distinguish low-frequency shocks from high-frequency shocks. Finally, studies on real wage behaviour over the business cycle usually use economy-wide data, while studies that focus on low-frequency shocks use industry-level data.

In summary, the crucial issue in studies of real wage behaviour in response to demand shocks is whether the real wage is rigid or not. Recent economists argue that after controlling for composition bias by using longitudinal data, they find significantly positive effects of demand shocks on real wages. However, further studies are needed. Using longitudinal data usually results in a smaller sample size and a shorter sample period than using aggregate data. Besides, admitting the superiority of longitudinal data does not provide any explanation for the conflicting findings of half a century worth of research that employed aggregate data. Therefore, the best empirical strategy is to use both aggregate data and longitudinal data, and then compare and analyze the results.

## III. Empirical work

While in the last section I reviewed the literature on real wage behaviour in the face of both high-frequency demand shocks and low-frequency demand shocks, in this section I only focus on investigating real wage behaviour in response to low-frequency demand shocks in Canada. I start with estimating the effects of low-frequency demand shocks on real wages for all employees in an industry. Then I look at whether the potential problems of simultaneity and composition bias affect the results. For the former, I use an instrumental variable approach. For the latter, I estimate the effects of low-frequency demand shocks using data disaggregated by gender and age.

### 1. Data

In order to investigate the behaviour of real wages across industries in response to low-frequency demand shocks in Canada, the best empirical strategy would be to carry out regression analysis using aggregate data, repeated cross-sectional data and longitudinal data (all have been used in previous studies), and compare the results. Weinberg (2001) used repeated cross-sectional data and found that wages are rigid in response to low-frequency demand shocks. Later Devereux (2005) used longitudinal data and found a positive relationship between industry real wages and industry employment. According to Devereux, the advantage of longitudinal data is that it enables researchers to control for composition bias arising from both observed and unobserved characteristics of workers.

While aggregate and cross-sectional data are readily available for Canada, the only longitudinal data set that covers a sufficiently long period to examine the effects of low-frequency demand shocks is the Survey of Labour Income Dynamics (SLID). However, the subset of the SLID that is available to public users is only two years (1993-1994) long and only provides information on broad industry categories. Because of these constraints imposed by the availability of longitudinal data from SLID, the empirical work in this paper is based on aggregate annual data. I choose industry-level data in my empirical work. Industry-level data was chosen by both Weinberg and Devereux in order to increase the degrees of freedom in their long-difference approach. The time span of existing data sources may include no more than two or three ten-year intervals, thus disaggregating data only by time cannot lead to sufficient observations to make the estimation feasible. The solution is to disaggregate data by industry as well as time. This method is based on the assumption that the wage adjustment process is the same in all industries, which may not be true in the real world.

In my empirical work I use data from three different sources: the Survey of Employment, Payroll and Hours (SEPH); Productivity Measures, Inputs and Outputs by Industry in current and constant dollars (PM); and the Labour Force Survey (LFS). The SEPH data are used to estimate the effects of low-frequency shocks on real wages for all employees in an industry. The SEPH data are based on detailed industry classification, resulting in a relatively large number of observations for the estimation. Moreover, the SEPH data are available from 1991 to 2000, which is long enough to examine five- and ten-year intervals.

The disadvantage of the SEPH data are that they are not disaggregated by gender and age, which makes it difficult for me to analyze the effects of composition bias arising from the employees' gender and age. Therefore, I do complementary estimation using data from the LFS which are disaggregated by gender and age. The disadvantage of the LFS data is that they are based on a highly aggregated industry classification, which results in only 16 observations for the estimation. Another complementary estimation using the PM data is used to analyze the effects of the simultaneity problem. The PM data are based on the same industry classification as that of the national accounts, which enables me to use industry-level real GDP as an instrumental variable.

Data from the SEPH are used to estimate the effects of low-frequency shocks on real wages for all employees in an industry without controlling for composition bias or simultaneity. The SEPH is Canada's only source of detailed information on the number of paid employees, payrolls, and hours at disaggregated industry, provincial and territorial levels. The SEPH defines an "employee" as "any person drawing pay for services rendered or for paid absences and for whom the employer must complete a Canada Customs and Revenue Agency T-4 supplementary form."[10] It classifies employees into three categories: "salaried employee(s)," whose basic remuneration is in the form of a fixed amount for at least one week; "employee(s) paid by the hour," whose basic wage is expressed as an hourly rate; "other employee(s)," whose basic remuneration is in the form of commissions, piece rates, milage allowances, etc. Data are available for salaried employees and employees paid by the hour. I examine the real wage behaviour of salaried employees and employees paid by the hour separately because they operate in different labour markets.

Weinberg (2001) used annual hours worked and unemployment to measure labour input, while Devereux (2005) used only industry-level employment to measure labour input. Employment is a popular measure of labour input in the literature (Neftci 1978; Geary and Kenna 1982; Kilduff 1989; Haoming Liu; 2003;

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[10] The definition is provided by Statistics Canada.

Devereux 2005). If hours or weeks of work were fixed, this would probably be an ideal measure of labour input, but hours or weeks of work are not necessarily fixed in the real world. I think this is why Weinberg also uses annual hours worked to measure labour input. The SEPH does not provide data on annual hours worked, and thus I only use employment to measure labour input in my empirical work.

Weinberg used average weekly wages to measure the price per unit of labour input, while Devereux used average hourly wages to measure the price per unit of labour input. In the SEPH, "average weekly earnings" (AWE) are obtained from the questionnaires.[11] "Average hourly earnings" (AHE) is calculated by Statistics Canada by dividing AWE by the average number of working hours in a week. Therefore, AWE do not suffer bias arising from measurement errors in working hours, but it is difficult to identify whether changes in AWE are the results of variations in weekly working hours or in hourly wages. I am going to use both AWE and AHE to measure the price per unit of labour input and then compare the results.

Data on industry-level employment are retrieved from CANSIM Table 281-0024 that is based on the 2002 North American Industry Classification System (NAICS). Data on the AWE of salaried employees and employees paid by the hour are retrieved from CANSIM Table 281-0027. Data on the AHE of salaried employees is retrieved from CANSIM Table 281-0036, and of employees paid by the hour are

[11] "AWE represents the gross dollar value before deductions for income taxes, employment insurance contributions etc…, including regular pay, overtime and portion of bonuses, commissions and other type of special payments. The payroll concept excludes dollar amounts that are taxable allowances and benefits, certain types of non-wage compensation as well as employer contributions to employment insurance, Canada/Quebec pension plans, provincial medical plans, workers compensation and other welfare plans. Some annual special payments are excluded while other lump sum special payments are adjusted to coincide with the reference week period." (Statistics Canada internal document)

retrieved from CANSIM Table 281-0030. For each of these two wage measures, I consider two cases: including overtime and excluding overtime. In summary, there are seven different wage measures in total: AWE of salaried employees including overtime, AWE of salaried employees excluding overtime, AWE of employees paid by the hour including overtime, AWE of employees paid by the hour excluding overtime, AHE of salaried employees including overtime, AHE of employees paid by the hour including overtime, AHE of employees paid by the hour excluding overtime.[12] For the employment and wage data, I chose industries based on the 3-digit NASIC code, resulting in 70 industry groups for the analysis.

Data from the LFS are used to analyze the effects of composition bias. Employment data are retrieved from CANSIM Table 282-0008. "Average hourly earnings" (AHE) data are retrieved from CANSIM Table 282-0072. In the LFS, "earnings" refers to "the reporting of earnings before taxes and other deductions, and includes tips, commissions and bounces." AHE is calculated by Statistics Canada in conjunction with "usual paid work hours per week." These employment and wage data are disaggregated by gender and age as well as by industry. The age groups in the LFS include three categories: 15-24 years old, 25-54 years old, and 55 years old and over. Unfortunately, the LFS data are based on a highly aggregated industry classification (the 2-digit 2002 NAICS), which results in only 16 observations.

Data from the PM are used to analyze the effects of simultaneity bias. I use "employment" to measure labour input. Since data on "annual hours worked" are

[12] Data on AHE of salaried employees are not available for the excluding overtime case

available in the PM, I also use "annual hours worked" to measure labour input. I construct a wage measure named "average hourly labour income" (AHLI) by dividing "labour income" by "annual hours worked".[13] This wage measure is more comparable with the data from the SEPH and the LFS. Data on all these are variables are retrieved from CANSIM Table 383-0009. I exclude self-employed employees because the focus here is on the decisions being made by employers. Finally, I use industry-level Gross Domestic Product (GDP) at basic prices (1992 constant dollars) as an instrumental variable for the potential endogenous variable in my estimating equation. Data on GDP are retrieved from CANSIM Table 379-0017. Data on employment, AHLI and real GDP are based on the 3-digit 1997 NAICS, which results in 51 observations.

Prior to estimation, all variables are converted to natural logs. Table 1 summarizes the means and the standard deviations of changes in the log of all the variables. In the SEPH data, for salaried employees, the mean changes in the three wage measures are similar.[14] For employees paid by the hour, from 1991 to 1995 the mean changes in the four wage measures are quite similar.[15] However, during the periods 1996-2000 and 1991-2000, the mean changes in AWE are absolutely bigger than those in AHE. A comparison of the standard deviations of real wages and employment further indicate that changes in real wages are less variable than those

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[13] Labour income consists of the wages, salaries and supplementary labour income earned for employee jobs.

[14] For salaried employees, there are three wage measures: AWE including overtime, AWE excluding overtime, AHE including overtime.

[15] For employees paid by the hour, there are four wage measures: AWE including overtime, AWE excluding overtime, AHE including overtime, and AHE excluding overtime.

in employment for both types of employees.

For the PM data, from 1997 to 2001, on average, AHLI, annual hours worked and employment all increase. In addition, a comparison of the standard deviations of these three variables shows that changes in AHLI are less variable than changes in annual hours worked and employment. For the LFS data, from 1997 to 2001, on average both AHE and employment increase, but mean increases in employment are more variable across industries than those in wages.

It is hard to compare the PM data, the LFS data and the SEPH data since the PM data are based on the 3-digit 1997 NAICS, the LFS data are based on the 2-digit 2002 NAICS, and the SEPH data are based on the 3-digit 2002 NAICS. Furthermore, the LFS and PM data cover all employees, while the SEPH data are only available for salaried employees and employees paid by the hour separately. However, I can observe that the mean changes in the LFS measure of AHE for all employees seems to be almost identical to the mean change in AHE including overtime for salaried employees from the SEPH, and larger in absolute value than the mean change in other AHE measures from the SEPH.

Figures 1-3 are based on Table 2, which includes changes in the log of AHE and employment of salaried employees from the SEPH. They show a simple graphical illustration of the statistical relationship between changes in industry employment and industry hourly wages for salaried employees. In these figures, industries are labelled by the numbers assigned to each industry in Table 2. I add both a horizontal and a vertical zero-line that divides the figures into four zones. In Zone 1, positive wage changes are accompanied by positive employment changes. In Zone 2, positive wage changes are accompanied by negative employment changes. In Zone 3, negative wage changes are accompanied by positive employment changes. Finally, in Zone 4, negative wage changes are accompanied by negative employment changes. Figure 1 suggests a positive relationship between changes in industry-level employment and real wages during the 1990s. Most industries' employment changes and wage changes are strongly positively correlated. In some industries, such as hospitals (industry 59), gasoline stations (industry 37), oil and gas extraction (industry 2), construction of buildings (industry 5), trunk transportation (industry 42), and social assistance (industry 61), employment was shrinking during the last decade. Oil and gas extraction experienced a large decrease in employment (-43.94%), but its real wage level is almost unaffected (-0.93%). The industry that is the most depressed is retail gasoline, whose wage level and employment level were falling during the 1990s (hourly wages decrease by 13.6%, and employment decreases by 72.65%). Throughout the 1990s the number of gasoline stations fell dramatically because the oil companies integrated their retail operations and closed down thousands of gasoline stations. This is probably the reason for the decreases in both employment and wage rates in the "retail gasoline" sector during the 1990s in Canada.

In other industries, such as support activities for mining and oil and gas extraction (industry 4), printing and related support activities (industry 15), professional, scientific and technical services (industry 56), and administrative and support services (industry 57), employment expanded during the 1990s. The service sectors experienced a greater increase in employment than the goods sectors, especially in the administrative, professional, scientific, and technical services sector, due to the development of new technology. Other industries are characterized by an increase in real hourly wages but a decrease in employment; for example, pipeline transportation (industry 44). The number of people employed by the pipeline transportation sector has slowly decreased since 1990, but employees in the pipeline transportation sector enjoyed an increase in average hourly wages (38%).

The positive relationship observed in Figure 1 is less obvious during the sub-periods 1991-1995 and 1996-2000. Figure 2 shows that during the period 1991-1995, most industries are characterized by an increase in real wages and a decrease in employment. In Figure 3, for the period 1996-2000, the positive relationship cannot be observed either. These two figures show that Gasoline stations (industry 37) suffer decreases in both real wages and employment from 1991 to 1995, while their employment recovers a little bit from 1996 to 2000 with a further decrease in real wags. Administrative and support services (industry 57) experience both an increase in real wages and an expansion in employment from 1991 to 1995, with a further increase in real wages and unchanged employment from 1996 to 2000.

## 2. Estimating equations and Results

Both Weinberg (2001) and Devereux (2005) used long differences over five- and ten-year intervals in their studies of real wage behaviour in the face of low-frequency demand shocks, in order to distinguish low-frequency demand shocks from high-frequency demand shocks. However, the estimating equations they used are different. Weinberg used growth in annual hours worked and changes in industry-level unemployment to measure labour input, while Devereux only used changes in industry-level employment to measure labour input. The reason why they used different specifications was discussed in the previous subsection. In my empirical work, I use changes in the log of employment to measure labour input. The estimating equation is:

$$\Delta w_{i,t_1-t_0} = \beta_0 + \beta_1 \Delta E_{i,t_1-t_0} + \varepsilon_{it} . \qquad (9)$$

The dependent variable is $\Delta w_{i,t_1-t_0}$, which represents the change in the log of AHE or AWE in industry $i$ between $t_1$ and $t_0$. The independent variable is $\Delta E_{i,t_1-t_0}$, which denotes the changes in the log of employment in industry $i$ between $t_1$ and $t_0$.

Table 3 reports the results using the SEPH data for both salaried employees and employees paid by the hour. Table 3 includes four sub-tables. Table 3.1 reports the results for AWE of salaried employees; table 3.2 reports the results for AWE of employees paid by the hour; table 3.3 reports the results for AHE of salaried employees; and table 3.4 reports the results for AHE of employees paid by the hour. I consider the results for salaried employees and employees paid by the hour separately since they operate in different labour markets

For salaried employees, the results appear in table 3.1 and table 3.3. I first consider the case including overtime and start with the results for diagnostic tests. The Jarque-Bera test and Goodness of Fit test are tests for normality. The results show that the equations using both AWE and AHE over five-year intervals (1991-1995 and 1996-2000) suffer the problem that error terms may not be normally distributed. The only exception is the equation using AHE from 1996 to 2000. Since the sample size is small (70 observations), I still choose to trust the t-statistics. The Koenker test and the BPG test are tests for heteroskedasticity. The only evidence of heteroskedasticity is in the equation using AWE from 1991 to 1995. Table 3.1 reports robust standard errors for this period.

The results for the RESET, FRESETL, and FRESETS tests for specification error show evidence of specification errors in the equation using AWE from 1991 to 2000. There may also be specification error in the equation using AWE from 1991 to 1995, where the RESET and FRESETL tests lead to opposite conclusions. In contrast, equations using AHE pass almost all diagnostic tests. Furthermore, $R^2$ and adjusted $R^2$ are low for all equations, implying that the explanatory power of the model is poor. This is not surprising since I include only one independent variable.

After reviewing the results of diagnostic tests, I turn to the signs and significance of the slope coefficients. The estimated coefficients $\hat{\beta}_1$ of equations using AWE and AHE over five- and ten-year intervals are similar. From 1991 to 1995, the estimated coefficients $\hat{\beta}_1$ are positive in sign, small in magnitude, and statistically insignificant, while from 1996 to 2000, they are negative in sign, small in magnitude and insignificant. From 1991 to 2000, the estimated coefficients $\hat{\beta}_1$ are positive and significant at the 1% level of significance (0.125 for AWE and 0.104

for AHE), which is close to Devereux's results for U.S. data.[16] Devereux's ten-year results (from 1991-2001) for both men and women are significantly positive and range in magnitude from 0.1 to 0.3. The case where overtime is excluded similar to the case where overtime is included. In summary, for salaried employees, real wages respond positively in the face of low-frequency demand shocks from 1991 to 2000. However, this positive response cannot be found in five-year intervals.

For employees paid by the hour, results are found in table 3.2 and table 3.4. I first consider the case including overtime. The results of diagnostic tests are not good for all equations except that for the period 1996-2000. The tests show evidence of a normality problem for equations using AHW in five-year intervals. According to the tables, equations for the period 1996-2000 pass the tests for heteroskedasticity. Equations for the other two periods all suffer from heteroskedasticity, except for the equation using AWE from 1991 to 2000, so tables 3.2 and 3.4 report robust standard errors. The tests for specification error present similar results. Only the equations for the period 1996-2000 pass the tests for specification error.

It is interesting to note that the period 1996-2000 is not only the period which passes the tests for heteroskedasticity and specification error, but also the period in which the estimated coefficients $\hat{\beta}_1$ are positive and significant at the 1% level of significance for both wage measures (0.106 for AWE and 0.154 for AHE). From 1991 to 1995, the estimated coefficients $\hat{\beta}_1$ are positive in sign, small in magnitude, and statistically insignificant. From 1991 to 2000, the results show opposite results

[16] The results are the same whether overtime is included or excluded.

for the two wage measures. The estimated coefficient $\hat{\beta}_1$ is insignificantly negative for the equation using AHE, but is positive and significant at the 1% level of significance for the equation using AWE. Since AHE is calculated by dividing AWE by average weekly hours, it may suffer from measurement errors. In addition, the result of estimation using AWE is more reliable since this estimation passes all diagnostic tests, while estimation using AHE suffers from heteroskedasticity and specification error problems. In summary, for employees paid by the hour, evidence from using AWE and AHE shows that real wages respond positively in the face of low-frequency demand shocks from 1996 to 2000.

Thus before further investigation of the effects of simultaneity and composition bias, the SEPH data show some evidence on a positive response of real wages in the face of low-frequency demand shocks. The positive response is found for salaried employees from 1991 to 2000 and for employees paid by the hour from 1996 to 2000. It is therefore interesting to take a close look at the behaviour of the real wages of these two types of employees from 1996 to 2000. For salaried employees, the results are insignificantly negative, while for employees paid by the hour, the results are significantly positive, which implies that from 1996 to 2000, the real wages of employees paid by the hour are flexible and respond positively to low-frequency demand shocks, while the real wages of salaried employees are rigid. The different results for these two types of employees are possible since they operate in different labour markets.

Before I draw any conclusions, two issues that affect the validity of the results should be addressed. One is composition bias and the other is simultaneity bias. Composition bias could arise from workers' observed and unobserved characteristics, such as age, gender, work experience, etc. If wages depend on age, sex, and other worker characteristics, then changes in the composition of the labour force will change average wages even if there are no demand shocks. Does composition bias affect my empirical results? In order to answer this question, I use the LFS data to estimate equation (9), first for all employees and then further disaggregated by age and gender. My strategy is to compare the results for all these estimations and to see whether the results change after I control for employees' age and gender.[17] The results are summarized in Table 4. Table 4 includes two sub-tables. Table 4.1 summarizes the results for equations using data disaggregated by gender and age, while table 4.2 reports the comparison between the SEPH data for salaried employees and employees paid by the hour and the LES data for all employees.

Once again I start with the results of diagnostic tests. The tests for normality show good results for all equations. The only clear evidence of heteroskedasticity is found for females aged 55 years or over. There may also be heteroskedasticity for females from 15 to 24 years old, where the Koenker test and the BPG test show opposite results. Table 4.1 reports robust standard errors. Evidence of specification error can be found in the equations for all employees. This evidence disappears after I disaggregate the data by age and gender.

Unfortunately, the estimated coefficients $\hat{\beta}_1$ for all employees and

[17] There are some aspects of labour force composition that I could not control for.

subgroups of employees are statistically insignificant, which does not provide any information about the importance of composition bias. Fortunately, Devereux found that controlling for composition bias enhances the positive relationship between industry real wages and industry employment. Therefore, the significantly positive relationship obtained using the SEPH data is still reliable because controlling for composition bias is unlikely to weaken it.

The different results from using the LFS and the SEPH data are probably due to the fact that the LFS data are based on a more highly aggregated industry classification (the LFS data are based on the 2-digit NAICS, while the SEPH data are based on the 3-digit NAICS). For example, the changes in real wages are not homogeneous for all manufactoring industries. In other words, the highly aggregated industry classification cannot capture the real wage changes in every manufactory industries. Another possibility is that the different results from using the LFS and the SPEH data are due to differences between the SEPH and the LFS other than in the level of aggregation of the data. In order to address this possibility, I aggregate the SEPH data and see if the parameter estimates become insignificant. The estimation results using aggregate AHE (based on the 2-digit NAICS) for salaried employees and employees paid by the hour are summarized in table 4.2, where they are compared with the results from the LFS data for all employees.[18]

Recall that the result of estimation using AHE based on the 3-digit NAICS of salaried employees from 1996 to 2000 is insignificantly negative (Table 3.3), and of

[18] The data on AHE are not available for all employees in the SEPH.

employees paid by the hour significantly positive (Table 3.4). In table 4.2, using AHE based on the 2-digit NAICS from the SEPH, the signs of estimated coefficients $\hat{\beta}_1$ do not change, but they become insignificant. Furthermore, the value of the estimated coefficients $\hat{\beta}_1$ using the 2-digit NAICS AHE become smaller than those using 3-digit NAICS and AHE form the SEPH. Therefore, the different results of using the SEPH and the LFS data are probably due to high-level industry classifications.

The problem of simultaneity results from the possibility that the fluctuations in industry employment are generated by supply shocks as well as demand shocks. I use an instrumental variables approach to analyze this problem. Possible candidates for instrumental variables for the change in employment are shipments or indicators of production based on the same industrial classification. These are fairly good indicators of demand shocks. They would be correlated with employment changes and perhaps uncorrelated with the disturbance term in my regression, as they would be independent of any labour supply shocks. Real GDP based on the 1997 NAICS is the only available source for the instrumental variable. Because the SEPH data are based on the 2002 NAICS, which is not consistent with the real GDP data, I use the PM data, which is also based on the 1997 NAICS. In the PM data, I use annual hours worked and employment as measure of labour input and I use AHLI as a measure of the price of labour input. The estimation equation is

$$\Delta w_{i,t_1-t_0} = \beta_0 + \beta_1 * \Delta E_{i,t_1-t_0} + \beta_2 * \Delta h_{it_1-t_0} + \varepsilon_{it}, \qquad (10)$$

where $\Delta w_{i,t_1-t_0}$ denotes the change in the log of AHLI in industry $i$ between $t_1$ and $t_0$.

$\Delta E_{i,t_1-t_0}$ denotes the change in the log of employment in industry $i$ between $t_1$ and $t_0$, and $\Delta h_{it_1-t_0}$ denotes the change in the log of annual hours worked in industry $i$ between $t_1$ and $t_0$.

Table 5 reports the results of OLS estimation using this equation. Evidence of normality is found in this equation. Again, since it is a small sample (only 51 observations), I choose to trust the t-statistics. The results of other diagnostic tests show that the equation does not suffer the problems of heteroskedasticity and specification errors. However, the estimated results are paradoxical. The estimated coefficient $\hat{\beta}_1$ is positive and significant at the 1% level of significance, but the estimated coefficient $\hat{\beta}_2$ is negative and significant at the 1% level of significance. This result may due to the problem of multicollinearity.[19] When I use real GDP as the instrumental variable for changes in the log of employment and changes in the log of hours worked, the Hausman tests show that neither employment not hours worked is endogenous. However, this result may not be reliable because probably I do not have enough instruments or real GDP is not a good instrumental variable. In this case, the 2SLS estimates are not reliable either.

Devereux thought that supply shocks are probably an unimportant source of industry employment change. He also provides empirical evidence that the positive relationship between industry employment and industry wages does not change after

[19] The coefficient of correlation between hours worked and employment is 0.979, which is indicative of a high correlation. When I drop hours worked from the regression equation, the estimated coefficient of employment is insignificantly negative. When I drop employment from the regression equation, the estimated coefficient of hours worked is negative and significant at the 1% level of significance. These results may due to the possibility that aggregate real wages suffer composition bias.

he excludes the effects of supply shocks. Therefore, I can expect that the problem of simultaneity will not affect, or at least will not weaken the positive relationship I obtained.

In summary, using the SEPH data I find that low-frequency demand shocks do affect real wages for salaried employees from 1991 to 2000, and for hourly-paid employees from 1996 to 2000. Although the currently available data does not allow me to control adequately for the effects of composition bias and simultaneity bias, these positive relationships are still reliable, because in the literature, neither controlling for the composition bias nor controlling adequately for simultaneity bias has weakened the positive relationship.

## IV. Conclusion

In this paper I investigate the behaviour of real wages in response to demand shocks. I review the literature on real wage behaviour in the face of both high-frequency and low-frequency demand shocks. My empirical work focuses on the response of real wages to low-frequency demand shocks. Using industry-level data, I find that real wages of salaried employees respond positively to low-frequency demand shocks from 1991 to 2000, while real wages of employees paid by the hour respond positively to low-frequency demand shocks from 1996 to 2000. Although the currently available data do not enable me to control for composition bias and simultaneity bias, my results are still reliable.

Two issues are left to further research. First, future researchers who are interested in this topic should use both longitudinal data and aggregate data and compare the results. Neither aggregate data nor longitudinal data are ideal. Longitudinal data enable one to control for composition bias arising from different workers' characteristics, but they are usually not long enough for studies of real wage behaviour in the face of low-frequency demand shocks. Besides, using both kinds of data, one could quantify the effects of composition bias. The importance of composition bias has been quantified in the literature on real wage behaviour in response to high-frequency shocks (Solon, Barsky, and Parker 1994), but nothing is known with respect to low-frequency demand shocks. Furthermore, controlling for composition bias would probably unearth a positive response of real wages to low-frequency demand shocks in other periods. Therefore, the best strategy is to use both aggregate data and longitudinal data and compare the results.

Second, it is important to identify ideal measures of labour input. Using employment as a measure of labour input is reliable when hours or weeks of work do not change during the sample period. However, both change in the real world. Therefore, one should consider using an additional measure of labour input (such as annual hours worked) to take into account the changes in hours and weeks of work. In this case one should be careful because including annual hours worked may cause a multicollinearity problem. In summary, it would be interesting and useful to provide further information on real wage behaviour in response to low-frequency demand shocks in Canada when a viable data set becomes available.

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## Table 1. Means and Standard Deviations of Variables

### Data from the Survey of Employment, Payroll and Hours (SEPH) 1991-2000

**Change in the log of real Average weekly earnings (including overtime)**

| | 1991-1995 | | 1996-2000 | | 1991-2000 | |
|---|---|---|---|---|---|---|
| | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour |
| Mean | 0.059 | 0.038 | 0.042 | 0.020 | 0.103 | 0.072 |
| Std. Dev. | 0.053 | 0.066 | 0.079 | 0.091 | 0.090 | 0.105 |

**Change in the log of real Average weekly earnings (excluding overtime)**

| | 1991-1995 | | 1996-2000 | | 1991-2000 | |
|---|---|---|---|---|---|---|
| | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour |
| Mean | 0.056 | 0.041 | 0.042 | 0.019 | 0.102 | 0.068 |
| Std. Dev. | 0.052 | 0.067 | 0.080 | 0.090 | 0.090 | 0.106 |

**Change in log of real Average hourly earnings (including overtime)**

| | 1991-1995 | | 1996-2000 | | 1991-2000 | |
|---|---|---|---|---|---|---|
| | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour |
| Mean | 0.063 | 0.029 | 0.029 | -0.003 | 0.088 | 0.039 |
| Std. Dev. | 0.046 | 0.060 | 0.080 | 0.080 | 0.088 | 0.091 |

**Change in log of real Average hourly earnings (excluding overtime)**

| | 1991-1995 | | 1996-2000 | | 1991-2000 | |
|---|---|---|---|---|---|---|
| | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour |
| Mean | N.A. | 0.033 | N.A. | -0.004 | N.A. | 0.038 |
| Std. Dev. | N.A. | 0.059 | N.A. | 0.083 | N.A. | 0.093 |

**Change in log of Employment**

| | 1991-1995 | | 1996-2000 | | 1991-2000 | |
|---|---|---|---|---|---|---|
| | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour | Salaried employees | Employees paid by hour |
| Mean | 0.0483 | -0.142 | -0.061 | 0.180 | -0.191 | 0.248 |
| Std. Dev. | 0.335 | 0.169 | 0.255 | 0.266 | 0.264 | 0.374 |

## Data from the survey of Productivity Measures, Inputs and Outputs by Industry in Current and Constant Prices (PM) 1997-2001

| | Change in log of real Labour income per hour worked | Change in log of Hours worked | Change in log of Number of employees | Change in log of real GDP |
|---|---|---|---|---|
| Mean | 0.069 | 0.065 | 0.070 | 0.173 |
| Std. Dev. | 0.056 | 0.134 | 0.125 | 0.107 |

## Data from the Labour Force Survey (LFS) 1997-2001

**Log Change in Employment Rate**

| | All employees | Female 15-24 years old | Female 25-54 years old | Female 55 years old and over | Male 15-24 years old | Male 25-54 years old | Male 55 years old and over |
|---|---|---|---|---|---|---|---|
| Mean | 0.067 | 0.147 | 0.049 | 0.248 | 0.115 | 0.032 | 0.151 |
| Std.Dev. | 0.116 | 0.173 | 0.134 | 0.223 | 0.247 | 0.100 | 0.171 |

**Log Change in Hourly wages**

| | All employees | Female 15-24 years old | Female 25-54 years old | Female 55 years old and over | Male 15-24 years old | Male 25-54 years old | Male 55 years old and over |
|---|---|---|---|---|---|---|---|
| Mean | 0.028 | 0.031 | 0.038 | 0.000 | 0.043 | 0.030 | 0.045 |
| Std.Dev. | 0.025 | 0.048 | 0.029 | 0.059 | 0.054 | 0.028 | 0.058 |

**Table 2. Changes in the log of AHW 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 |

**Table 3. Results for data from the SEPH**

**Table 3.1 Changes in the log of AWE for Salaried Employees**

| **Including overtime** | | | | |
|---|---|---|---|---|
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.065 | 0.039 | 0.127 |
| | | (9.242) | (4.014) | (10.15) |
| | | (0.000) | (0.000) | (0.000) |
| $\beta_1$ | | 0.040 | -0.046 | 0.125 |
| | | (0.900) | (-1.248) | (3.242) |
| | | (0.371) | (0.216) | (0.002) |
| $R^2$ | | 0.0165 | 0.0224 | 0.134 |
| Adjusted $R^2$ | | 0.002 | 0.008 | 0.121 |
| Number of observations | | 70 | 70 | 70 |
| Test for normality: | Jarque-Bera test: | 190.494 (0.000) | 7.8735 (0.020) | 0.105 (0.949) |
| | Goodness of Fit test: | 3.7315 (0.155) | 13.791 (0.001) | 3.280 (0.194) |
| Test for Heteroskedaticity: | KOENKER test: | 1.677 (0.432) | 1.153 (0.562) | 1.931 (0.381) |
| | BPG test: | 7.772 (0.021) | 1.322 (0.516) | 2.007 (0.367) |
| Test for Specification errors: | RESET test: | 1.180 (0.324) | 2.047 (0.116) | 2.696 (0.053) |
| | FRESETL test: | 2.325 (0.043) | 1.717 (0.333) | 2.394 (0.038) |
| | FRESETS test: | N.A. | N.A. | N.A. |
| **Excluding overtime** | | | | |
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.062 | 0.039 | 0.126 |
| | | (7.575) | (4.014) | (10.11) |
| | | (0.000) | (0.000) | (0.000) |
| $\beta_1$ | | 0.038 | -0.044 | 0.126 |
| | | (1.028) | (-1.180) | (3.279) |
| | | (0.308) | (0.242) | (0.002) |
| $R^2$ | | 0.0153 | 0.0201 | 0.1365 |
| Adjusted $R^2$ | | 0.0008 | 0.0056 | 0.1238 |
| Number of observations | | 70 | 70 | 70 |
| Test for normality: | Jarque-Bera test: | 157.33 (0.000) | 6.648 (0.036) | 0.264 (0.876) |
| | Goodness of Fit test: | 4.877 (0.087) | 12.464(0.002) | 4.752 (0.093) |
| Test for Heteroskedaticity: | KOENKER test: | 1.689 (0.430) | 1.601 (0.449) | 1.042 (0.594) |
| | BPG test: | 7.263 (0.026) | 1.706 (0.426) | 1.170 (0.557) |
| Test for Specification errors: | RESET test: | 0.944 (0.425) | 2.123 (0.106) | 2.603 (0.059) |
| | FRESETL test: | 2.072 (0.069) | 1.243 (0.297) | 2.207 (0.054) |
| | FRESETS test: | N.A. | N.A. | 2.020 (0.076) |

Notes:

1. The term AWE refers to "Average weekly earnings".
2. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
3. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 3.2 Changes in the log of AWE for Employees paid by the hour**

| **Including overtime** | | | | |
|---|---|---|---|---|
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.037 | 0.001 | 0.048 |
| | | (4.896) | (0.083) | (3.392) |
| | | (0.000) | (0.934) | (0.001) |
| $\beta_1$ | | 0.019 | 0.106 | 0.095 |
| | | (0.437) | (2.712) | (2.987) |
| | | (0.664) | (0.008) | (0.004) |
| $R^2$ | | 0.0098 | 0.0976 | 0.116 |
| Adjusted $R^2$ | | -0.0048 | 0.0843 | 0.103 |
| Number of Observations | | 70 | 70 | 70 |
| Test for normality: | Jarque-Bera test: | 4.614 (0.100) | 2.912 (0.233) | 2.887 (0.236) |
| | Goodness of Fit test: | 3.344 (0.188) | 4.430 (0.109) | 9.181 (0.010) |
| Test for Heteroskedaticity: | KOENKER test: | 18.639 (0.000) | 0.388 (0.824) | 0.848 (0.654) |
| | BPG test: | 27.098 (0.000) | 0.560 (0.756) | 1.207 (0.547) |
| Test for Specification errors: | RESET test: | 4.130 (0.010) | 0.676 (0.570) | 3.013 (0.036) |
| | FRESETL test: | 4.575 (0.001) | 0.812 (0.564) | 1.477 (0.201) |
| | FRESETS test: | N.A. | N.A. | 1.462 (0.206) |
| **Excluding overtime** | | | | |
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.042 | -0.002 | 0.045 |
| | | (5.094) | (-0.170) | (3.098) |
| | | (0.000) | (0.866) | (0.003) |
| $\beta_1$ | | -0.006 | 0.117 | 0.092 |
| | | (-0.245) | (3.047) | (2.850) |
| | | (0.807) | (0.003) | (0.006) |
| $R^2$ | | 0.0009 | 0.1202 | 0.1067 |
| Adjusted $R^2$ | | -0.0138 | 0.1072 | 0.0935 |
| Number of Observations | | 70 | | |
| Test for normality: | Jarque-Bera test: | 31.981 (0.000) | 2.743 (0.254) | 4.559 (0.102) |
| | Goodness of Fit test: | 3.832 (0.147) | 5.669 (0.059) | 12.773 (0.002) |
| Test for Heteroskedaticity: | KOENKER test: | 21.391 (0.000) | 0.362 (0.835) | 1.446 (0.485) |
| | BPG test: | 48.606 (0.000) | 0.513 (0.774) | 1.884 (0.390) |
| Test for Specification errors: | RESET test: | 6.473 (0.001) | 0.716 (0.546) | 1.912 (0.136) |
| | FRESETL test: | 6.248 (0.000) | 1.052 (0.401) | 1.079 (0.385) |
| | FRESETS test: | N.A. | N.A. | 1.084 (0.352) |

Notes:

1. The term AWE refers to "Average weekly earnings".
2. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
3. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 3.3 Changes in the log of AHE for Salaried Employees**

| **Including overtime** | | | | |
|---|---|---|---|---|
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.066 | 0.028 | 0.108 |
| | | (9.201) | (2.827) | (8.673) |
| | | (0.000) | (0.000) | (0.000) |
| $\beta_1$ | | 0.020 | -0.019 | 0.104 |
| | | (0.618) | (-0.489) | (2.725) |
| | | (0.539) | (0.626) | (0.008) |
| $R^2$ | | 0.0056 | 0.0035 | 0.0984 |
| Adjusted $R^2$ | | -0.0090 | -0.0111 | 0.0852 |
| Number of Observations | | 70 | 70 | 70 |
| Test for normality: | Jarque-Bera test: | 17.194 (0.000) | 1.734 (0.420) | 0.961 (0.619) |
| | Goodness of Fit test: | 2.8484 (0.241) | 3.627 (0.163) | 2.198 (0.333) |
| Test for Heteroskedaticity: | KOENKER test: | 1.775(0.412) | 0.717(0.699) | 0.158 (0.924) |
| | BPG test: | 3.503(0.174) | 0.599(0.741) | 0.184 (0.912) |
| Test for Specification errors: | RESET test: | 0.540(0.656) | 1.916(0.136) | 2.118 (0.108) |
| | FRESETL test: | 1.012(0.426) | 0.938(0.474) | 1.712 (0.133) |
| | FRESETS test: | N.A. | N.A. | 1.341 (0.253) |

Notes:

1. The term AHE refers to "Average hourly earnings".
2. Data on average hourly earnings for salaried employees are not available for the case of excluding overtime.
3. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
4. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 3.4 Changes in the log of AHE for Employees paid by the hour**

| **Including overtime** | | | | |
|---|---|---|---|---|
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.028 | -0.030 | 0.040 |
| | | (3.716) | (-3.060) | (3.467) |
| | | (0.000) | (0.003) | (0.001) |
| $\beta_1$ | | 0.021 | 0.154 | -0.006 |
| | | (0.530) | (4.943) | (-0.145) |
| | | (0.598) | (0.000) | (0.885) |
| $R^2$ | | 0.0138 | 0.2644 | 0.0006 |
| Adjusted $R^2$ | | -0.0007 | 0.2535 | -0.0141 |
| Number of Observations | | 70 | 70 | 70 |
| Test for normality: | Jarque-Bera test: | 61.510 (0.000) | 19.416 (0.000) | 0.052 (0.974) |
| | Goodness of Fit test: | 4.922 (0.085) | 1.453 (0.484) | 1.678 (0.432) |
| Test for Heteroskedaticity: | KOENKER test: | (15.030) (0.000) | 0.100 (0.951) | 10.184 (0.006) |
| | BPG test: | 47.981 (0.000) | 0.211 (0.895) | 10.838 (0.004) |
| Test for Specification errors: | RESET test: | 1.516 (0.219) | 1.413 (0.247) | 9.294 (0.000) |
| | FRESETL test: | 2.933 (0.014) | 1.037 (0.410) | 5.666 (0.000) |
| | FRESETS test: | N.A. | N.A. | N.A. |
| **Excluding overtime** | | | | |
| Coefficient | | 1991-1995 | 1996-2000 | 1991-2000 |
| $\beta_0$ | | 0.032 | -0.034 | 0.040 |
| | | (4.529) | (-3.378) | (2.984) (3.454) |
| | | (0.000) | (0.001) | (0.004) (0.001) |
| $\beta_1$ | | 0.010 | 0.166 | -0.007 |
| | | (0.481) | (5.226) | (-0.2266) (-0.162) |
| | | (0.632) | (0.000) | (0.821) (0.872) |
| $R^2$ | | 0.0034 | 0.2866 | 0.0008 |
| Adjusted $R^2$ | | -0.0113 | 0.2761 | -0.0139 |
| Number of Observations | | 70 | | |
| Test for normality: | Jarque-Bera test: | 46.928 (0.000) | 16.2135 (0.000) | 1.519 (0.468) |
| | Goodness of Fit test: | 4.198 (0.123) | 2.625 (0.269) | 1.475 (0.478) |
| Test for Heteroskedaticity: | KOENKER test: | 17.699 (0.000) | 0.080 (0.961) | 9.179 (0.010) |
| | BPG test: | 52.470 (0.000) | 0.168 (0.920) | 12.098 (0.002) |
| Test for Specification errors: | RESET test: | 1.183 (0.323) | 1.836 (0.149) | 8.670 (0.000) |
| | FRESETL test: | 2.895 (0.015) | 1.328 (0.258) | 5.445 (0.000) |
| | FRESETS test: | N.A. | N.A. | N.A. |

Notes:

1. The term AHE refers to "Average hourly earnings".
2. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
3. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 4. Results for data from the LFS**

**Table 4.1 Changes in the log of AHE of Female and Male by different age groups**

| **Female** | | | | |
|---|---|---|---|---|
| Coefficient | | 15-24 years old | 25-54 years old | 55 years old and over |
| $\beta_0$ | | 0.037 | 0.037 | -0.005 |
| | | (3.092) | (4.555) | (-0.460) |
| | | (0.008) | (0.000) | (0.652) |
| $\beta_1$ | | -0.040 | 0.023 | 0.022 |
| | | (-0.476) | (0.396) | (0.364) |
| | | (0.641) | (0.698) | (0.721) |
| $R^2$ | | 0.0213 | 0.011 | 0.0068 |
| Adjusted $R^2$ | | -0.0486 | -0.060 | -0.0641 |
| Number of Observations | | 16 | 16 | 16 |
| Test for normality: | Jarque-Bera test: | 0.699 (0.705) | 0.249 (0.883) | 0.0718 (0.965) |
| | Goodness of Fit test: | 2.720 (0.257) | 1.149 (0.563) | 7.012 (0.030) |
| Test for Heteroskedaticity: | KOENKER test: | 8.092 (0.017) | 2.797 (0.247) | 6.324 (0.042) |
| | BPG test: | 4.282 (0.118) | 1.944 (0.378) | 5.354 (0.069) |
| Test for Specification errors: | RESET test: | 1.731 (0.218) | 1.854 (0.196) | 0.451 (0.721) |
| | FRESETL test: | 1.201 (0.394) | 0.669 (0.679) | 1.766 (0.233) |
| | FRESETS test: | N.A. | N.A. | N.A. |

| **Male** | | | | |
|---|---|---|---|---|
| Coefficient | | 15-24 years old | 25-54 years old | 55 years old and over |
| $\beta_0$ | | 0.050 | 0.026 | 0.478 |
| | | (3.430) | (3.804) | (2.359) |
| | | (0.004) | (0.002) | (0.033) |
| $\beta_1$ | | -0.067 | 0.113 | -0.018 |
| | | (-1.216) | (1.688) | (-0.197) |
| | | (0.244) | (0.114) | 0.847 |
| $R^2$ | | 0.095 | 0.169 | 0.0028 |
| Adjusted $R^2$ | | 0.0309 | 1.1098 | -0.0685 |
| Number of Observations | | 16 | 16 | 16 |
| Test for normality: | Jarque-Bera test: | 0.560 (0.756) | 0.334 (0.846) | 0.558 (0.756) |
| | Goodness of Fit test: | 1.230 (0.541) | 1.149 (0.563) | 2.720 (0.257) |
| Test for Heteroskedaticity: | KOENKER test: | 4.400 (0.111) | 0.704 (0.703) | 1.228 (0.541) |
| | BPG test: | 3.499 (0.174) | 0.509 (0.775) | 0.715 (0.699) |
| Test for Specification errors: | RESET test: | 4.535 (0.027) | 0.822 (0.508) | 0.377 (0.771) |
| | FRESETL test: | 2.673 (0.100) | 5.254 (0.018) | 0.761 (0.620) |
| | FRESETS test: | N.A. | N.A. | N.A. |

Notes:

1. The term AHE refers to "Average hourly earnings".
2. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
3. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 4.2 Comparison between the SEPH data and the LFS data of all employees**

| Coefficient | | The LFS data | The SEPH data Salaried employees | The SEPH data Employees paid by the hour |
|---|---|---|---|---|
| $\beta_0$ | | 0.027 | 0.008 | -0.005 |
| | | (3.610) | (0.557) | (-0.251) |
| | | (0.003) | (0.586) | (0.806) |
| $\beta_1$ | | 0.024 | -0.008 | 0.060 |
| | | (0.434) | (-0.860) | (0.478) |
| | | (0.671) | (0.933) | (0.640) |
| $R^2$ | | 0.0133 | 0.0005 | 0.0160 |
| Adjusted $R^2$ | | -0.0572 | -0.0709 | -0.0542 |
| Number of Observations | | 16 | 16 | 16 |
| Test for normality: | Jarque-Bera test: | 0.655 (0.721) | 0.665 (0.717) | 2.961 (0.228) |
| | Goodness of Fit test: | 6.240 (0.044) | 1.800 (0.406) | 2.592 (0.274) |
| Test for Heteroskedaticity: | KOENKER test: | 2.249 (0.325) | 4.623 (0.100) | 2.141 (0.343) |
| | BPG test: | 3.190 (0.203) | 2.833 (0.243) | 3.028 (0.2200 |
| Test for Specification errors: | RESET test: | 4.553 (0.026) | 3.595 (0.050) | 0.209 (0.888) |
| | FRESETL test: | 5.150 (0.019) | 1.718 (0.234) | 0.983 (0.494) |
| | FRESETS test: | N.A. | N.A. | N.A. |

Notes:

1. For mated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
2. For the statistics of diagnostic test, the p-values are in parentheses.

**Table 5. Results for data from the PM**

| Coefficient | | Including HW and EM |
|---|---|---|
| $\beta_0$ | | 0.065 |
| | | (8.630) |
| | | (0.000) |
| $\beta_{1\,(em)}$ | | 1.172 |
| | | (4.637) |
| | | (0.000) |
| $\beta_{2\,(h)}$ | | -1.199 |
| | | (-5.082) |
| | | (0.000) |
| $R^2$ | | 0.3740 |
| Adjusted $R^2$ | | 0.3479 |
| Number of Observations | | 51 |
| Test for normality: | Jarque-Bera test: | 1.339 (0.512) |
| | Goodness of Fit test: | 10.926 (0.001) |
| Test for Heteroskedaticity: | KOENKER test: | 1.095 (0.955) |
| | BPG test: | 1.478 (0.916) |
| Test for Specification errors: | RESET test: | 2.274 (0.093) |
| | FRESETL test: | 1.461 (0.215) |
| | FRESETS test: | 1.558 (0.184) |

Notes:

1. The term HW refers to "annual hours worked", and the term EM refers to "number of employees".
2. For estimated coefficients, the t-statistics are in the first parentheses and the p-values are in the second parentheses. These t-statistics and p-values are robust after adjustment for heteroskedasticity.
3. For the statistics of diagnostic test, the p-values are in parentheses.

**Figure 1: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1991-2000**

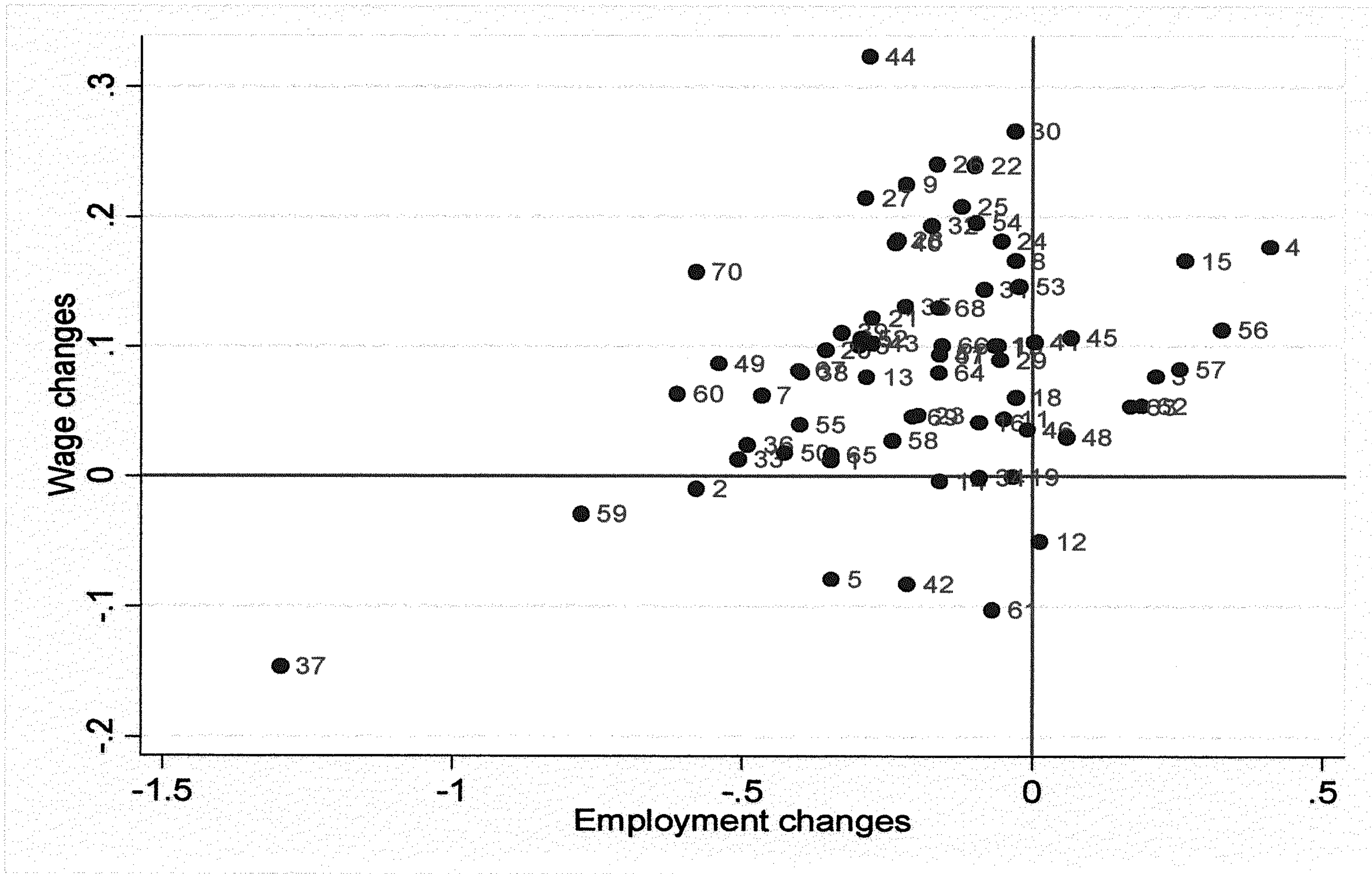

**Figure 2: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1991-1995**

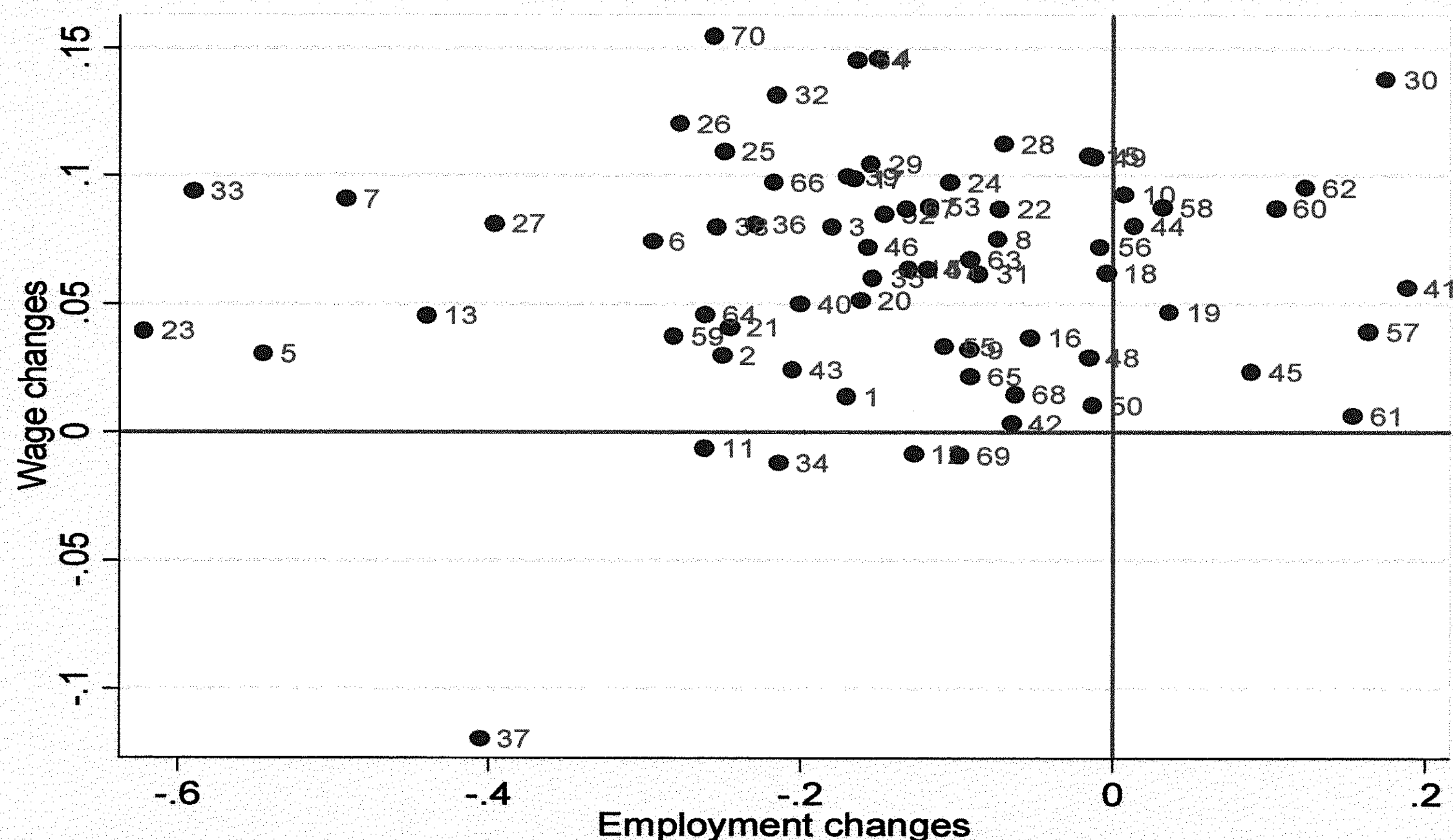

**Figure 3: Plots of Industry Employment Changes (x-axis) against Industry Wage Changes (y-axis) for years 1996-2000**