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The Volatility of Earnings: Evidence from High-Frequency Firm-Level Data

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Abstract
The first contribution of this paper is to use UK monthly firm-level data to show that there is a large amount of transitory volatility in firm-level average earnings from month to month. We conclude that this cannot all be explained away as the consequence of measurement error, composition effects or variation in remunerated hours i.e. we suggest this volatility is real. The second contribution of the paper is to argue that this volatility cannot be interpreted as high flexibility in the shadow cost of labour to employers because of sizeable frictions in the labour market. Indeed we point out that it is the existence of frictions that allow the volatility to exist. Consequently we argue that this volatility would be expected to have only small allocational consequences and that measures of base wages are more useful in drawing conclusions about wage flexibility.

Key words: Wages, wage flexibility
JEL: E24; J30

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Introduction

The stickiness, real or nominal, of wages has been a central issue in macroeconomics since at least the 1930s. Without some rigidity it seems difficult to explain why monetary policy is often found to have real effects in the short-run and without real wage rigidity it is hard to explain why real wages seem to have rather low cyclicality relative to employment and unemployment. We think it fair to say that there remains, to this day, no widespread consensus on the subject and it remains an active area for research.

In recent years that research has turned its attention to the explosion in the availability of microeconomic data. That is understandable as there is probably a limited amount that can be concluded from an analysis of aggregate wages alone. Examples of such initiatives are the International Wage Flexibility Project run by the Brookings Institution (see Dickens et al, 2006, 2009, for a summary of this) and the Wage Dynamics Network (WDN) run by the European Central Bank (ECB) (see ECB, 2009, for a summary of this).

However the increasing availability of micro data has created as well as solved problems as the complexity of this data has made it unclear how to interpret it for the purposes of understanding wage rigidity. When working with an aggregate wage series one can maintain the assumption that this is the only wage in the economy, the one represented by `w' in the macro-model that is also the shadow cost of labour to employers. But, when confronted with the richness of micro-data, matters become more complicated. If all types of wage data showed similar patterns of rigidity, then one could reasonably assume this to be the rigidity in the shadow cost of labour. But, it is becoming apparent that different types of wage data show different degrees of wage rigidity and the question then arises as to which is the more appropriate measure of the shadow price of labour. There are three broad types of micro-data on wages whose rigidity has been investigated in the literature.

First, there are, studies of wage settlements, either from databases or from surveys of firms (e.g. Blinder and Choi, 1990; Bewley, 2002 or that conducted by the ECB as part of its WDN programme – see ECB, 2009). These indicate that nominal wage cuts are extremely rare - for example, ECB (2009) found that only 2.3% of firms reported ever cutting wages in the 5 years preceding the survey (which was in 2008). However, in the crisis wage cuts in some countries have been more frequent than this. These studies also generally find that wages are adjusted infrequently, most commonly annually in a fixed month (that varies across firms)[1] .

Secondly, there are studies of the base wages received by individuals either from social security data (e.g. Lunnemann and Wintr, 2009, for Luxembourg; Sigurdsson and Sigurdardottir, 2014, for Iceland) or from surveys that are used to construct aggregate wage indices (Le Bihan, Montornes and Heckel, 2012, for France). Like the studies of settlements, these studies tend to find evidence for nominal wage rigidity and occasional rather than continual increases in wages. The studies of settlements and base wages are broadly consistent and suggest that the shadow cost of labour to employers has considerable rigidity.

In contrast, analyses of individual data on actual earnings often find considerable volatility in wages, including a sizeable proportion of wage cuts – see, for example, Card and Hyslop (1996), Altonji and Devereux (2000), Gottschalk (2005), Barratieri et al (2014) for the US or Smith (2000), Nickell and Quintini (2003), Elsby (2009) for the UK, Holden and Wulfsberg (2009) for Europe). These studies often do find some evidence, after discarding 'problematic' observations, for nominal wage rigidity. But it can be that a high fraction of observations are discarded and there is a concern that some meaningful wage flexibility is hidden in the discarded observations.

The difference in conclusions between studies based on individual and settlement/base wage data is most commonly reconciled by assuming that much of the observed individual level wage volatility is measurement error i.e. not real. This line of argument has been pursued most thoroughly by Gottschalk (2005) and Barratieri, Basu and Gottschalk (2014). And because this wage volatility is not real it is easy to then argue that this wage volatility does not affect the shadow price of labour to employers and, consequently, should not have any allocational consequences. Implicitly it is argued that the studies based on settlements and base wages are most informative about rigidity in the shadow cost of labour to employers.

If however, some of the volatility in actual earnings is real and not just measurement error then there is an open question about whether this volatility has allocational consequences. Although most studies of individual wage data use self-reported earnings that are very likely to contain substantial measurement error, the

[1] Olivei and Tenreyro (2010) show how differences across countries in the timing of response to monetary shocks can be linked to different seasonal patterns in wage-setting.

study of Sigurdsson and Sigurdardottir (2014) uses very high-quality social security data and shows that actual wage payments (even after excluding overtime) do show much less rigidity and more volatility than base wages. And, in contrast to base wages, the actual wage measure is the payment from employers to workers so might be expected to influence employment decisions.

The first contribution of this paper is to add to this small literature on the volatility in actual payments from employers to workers. It uses the UK's Monthly Wages and Salaries Survey (MWSS) to investigate the patterns in earnings changes at the firm-level and the Labour Force Survey (LFS) to provide added information about wage volatility at the individual level. We do find considerable volatility in actual wage payments which, as they are real payments from employers to workers, we might expect it to have allocational consequences.

The second contribution of the paper is to provide a theoretical argument for what should be used as the shadow cost of labour to employers. We argue that the volatility in actual wages is largely transitory in nature, and that this can exist because labour market frictions (caused by hiring and, possibly, firing costs) mean there are typically rents in the employment relationship. In the presence of these rents, the true shadow cost of labour will be influenced only to a small degree by the large transitory fluctuations observed in the payments from employers to workers, and, as a consequence the allocational consequence will be small. For deciding on the extent of volatility in the shadow price of labour it is likely that base wages may be better measures of the 'permanent' wage.

This conclusion has certain parallels in the literature on price rigidity. There the early studies simply measured the frequency of price changes (e.g. Bils and Klenow, 2004), with the presumption that price changes, when they occur, must be with the purpose of balancing demand and supply. But it was pointed out that many observed price changes are temporary i.e. like 'sales' that would not seem to be motivated by the balancing of demand and supply (e.g. Nakamura and Steinsson, 2008). Guimaraes and Sheedy (2011) present a model in which there is a reason for sales and show that the counting of price changes is not a realistic guide to the extent to which monetary policy has real effects. Similarly, here, it is argued that earnings data has real volatility that is unrelated to wage flexibility that allocates labour .

The plan of the paper is as follows. The next section describes the UK's Monthly Wages and Salaries Survey (MWSS). The second section then documents the remarkable amount of transitory movements in paybill per head in this data set, the main new empirical stylized fact shown in this paper. The third section then investigates possible reasons for this, discussing measurement error, employment fluctuations, hours variation (using the LFS) and individual wage variation as possible causes. The conclusion is that although hours variation and employment fluctuations can explain some of the observed wage volatility there remains a considerable amount that cannot be explained. The fourth section shows that, in spite of the large observed volatility in wages we do note that one can detect an annual pattern in wage growth, consistent with annual pay settlements and survey evidence. Finally the fifth section offers a simple model to assess the importance of the wage volatility for flexibility in the shadow cost of labour to firms.

Our conclusion is that there is considerable transitory volatility in the payments from employers to workers but that this is likely to have only small effect on the allocation of labour because of frictions in the labour market. Measures of base wages are likely to be more informative about rigidity in the shadow cost of labour to employers.

1. The Monthly Wages and Salaries Survey

The Monthly Wages and Salaries Survey (MWSS) is a survey conducted by the Office for National Statistics (ONS) of approximately 9,000 businesses per month in Great Britain. It started in 1989 but underwent a major re-design in 1999 so we use data for the period January 2000 to May 2010 inclusive, though not all variables are available for this entire period. The MWSS is carried out monthly so its data are much higher frequency than data used in most other papers on the topic of wage flexibility[2]. Given that most UK workers are now paid by the month it is not meaningful to go to a higher frequency.

The sampled businesses are required by law to return the MWSS. The sample is selected from the Inter-Departmental Business Register (IDBR), a comprehensive register of UK businesses used by the government for statistical purposes. Every business with more than 1,000 employees is surveyed every month. Below this

[2] Lunnemann and Wintr, (2009) and Sigurdsson and Sigurdardottir (2014) are the only other papers we have been able to find with monthly data. The matched employer-employee data sets that are increasingly common (e.g. Barth et al, 2011, for the US LEHD and Card, Heining and Kline, 2013, for the German IAB data) have –at best – quarterly information on earnings and often it is aggregated to the annual level.

threshold, sampling is random. However, employers with fewer than 20 employees are not sampled. Once selected into the sample these employers remain in it for 5 years. The unit of response is what is known as a ‘reporting unit’. For single-establishment firms this is both a firm and an establishment (which is known in the jargon as a ‘local unit’). For multi-establishment firms, the reporting unit (typically the head office) is defined as the aggregation of the associated local units. So the unit of observation is the firm rather than an establishment though we can identify which firms have only one establishment.

The data from the MWSS are used to produce the Average Weekly Earnings and the Average Earnings Index, the main macroeconomic series on earnings used in the UK[3]. The MWSS collects total gross pay from individual firms for both weekly-paid and monthly-paid staff, as well as total bonus payments and any pay arrears. In our analysis we use the paybill excluding bonuses and arrears – inclusion of these other payments simply adds to the volatility as one would expect. Information on employment is also collected and we use this to compute average earnings per head for weekly- and monthly-paid staff. We have this information for the period May 2000 to December 2008 inclusive. For a longer sample period – January 2000 to May 2010 - we also have a combined measure of total pay bill and total employment (the monthly-paid wage bill is multiplied by 84/365 to convert to a weekly basis). This means we have up to three measures of weekly earnings – separately for weekly and monthly-paid workers and for the aggregate.

Some descriptive statistics are presented in Table 1. Almost all plants have some monthly-paid staff but less than half have any weekly-paid staff. As one would expect, average weekly earnings are lower for the weekly-paid than for the monthly-paid. For overall average weekly earnings, the monthly-paid staff are much more important being over 75% of total employment on average and 80% of the total wage bill. Figure 1 also shows the mean log wage growth for each month in the sample. The mean is 0.3% per month, corresponding to an annual rate of 3.6%, what we would expect for this sample period. Notice that this is a period in which wage growth was fairly constant pre-crisis but then fell. However, there are marked

[3] The closest equivalent series for the US, the Employment Cost Index, is collected using a very different methodology. See LeBow, Saks and Wilson (2003) for a study of wage flexibility underlying this survey.

seasonal fluctuations. But this aggregate stability hides a lot of variability at the micro level as the next section documents.

2. Wage Volatility in the Monthly Wage and Salary Survey

In this section we present some basic statistics designed to convey some sense of the size of earnings volatility in the data. The main variable used is the month-on-month change in log average pay bill per head – with some abuse of language we call this the percentage increase in earnings. We also consider the change in earnings over a period longer than a month.

Table 2 presents some basic statistics on the distribution of the monthly change in earnings. The first panel shows the results for all workers, the second panel for weekly-paid workers and the third panel for monthly-paid workers. The first column presents the unweighted distribution and the second column an employment-weighted distribution. The employment weights we use are from the IDBR – this is a data source for employment independent of MWSS so will not induce measurement error through division bias (though the IDBR size classification may itself have some measurement errors). The unweighted distribution shows a very high prevalence of earnings cuts (46.8%) while the employment-weighted distribution shows a lower incidence (46.0%) indicating that there is less variation in earnings changes in larger firms, something we will verify and attempt to explain later. This is not surprising given that plant-level average earnings will be affected by changes in hours and employment composition so would be unlikely to show a ‘spike’ at a zero change.

For this reason, we focus on the distribution of earnings changes. It is remarkable that there are some extremely large changes in log average earnings reported. For example, for all workers the 5^{th} percentile is -12.6 log points and the 95^{th} percentile is 13.2 log points. Panel B of Table 2 shows that there is more volatility in average earnings among the weekly-paid but Panel C shows that the overall variation among the monthly-paid is quite similar to that for all workers (as one would expect given that Table 1 showed that monthly-paid workers make up most of employment and the paybill). There is no particular time series pattern to the fraction of wage cuts – the fraction reporting wage cuts bigger than 5% each month is shown in Figure 2.

Table 2 also presents data on wage volatility over longer time horizons - 3, 6 and 12 months. Because earnings are rising on average the incidence of wage cuts falls as one lengthens the time horizon – one can explain this largely by the upward trend in the average level of earnings. But there remains a lot of volatility even over the 12-month horizon.

Table 3 summarizes the distribution of earnings changes by plant size where plant size is defined using the categories in the IDBR i.e. a different data source from the MWSS. As one can see there is less dispersion in earnings changes in large firms for all workers and the monthly-paid though little difference for the weekly-paid. However, earnings volatility is still very marked even in the largest employers. The second and third columns of Table 4 split the sample into public and private sectors – there is more earnings volatility in the private than public sectors but there is still quite a lot in the public sector e.g. the 5^{th} percentile of monthly changes in log average earnings is -0.05 and the 95^{th} percentile 0.059. As we know there are no actual wage cuts in the public sector this should be an indication that further investigation is needed.

One might be interested in whether these cuts in earnings are temporary or permanent. One way to get some idea of this is to look at the autocovariance function and/or correlogram for earnings changes. The autocovariance function for the three measures of log weekly earnings is presented in Figure 3a and the correlogram in Figure 3b where we go up to lags of 30 months i.e. 2.5 years. These are computed using all available observations but the results are very similar if one includes only a balanced panel. There are a number of features of Figure 3a worth noting. First one can see the greater volatility in the earnings of weekly-paid staff but that the volatility in the total is closer to the volatility in the earnings of the monthly-paid staff. But what is also very striking is the negative covariance between wage changes this month and last month. This suggests that a lot of the wage volatility in monthly earnings growth results from very temporary shocks to the level of monthly earnings. This is true for all three measures of earnings and Figure 3b shows that the auto-correlogram is similar for all three earnings measures. It is also noticeable that there is a positive covariance at the yearly frequency indicating the importance of seasonal effects. And that correlations other than the first lag and yearly lags are very close to zero. A simple model that does a good job in explaining earnings is one in which ‘permanent’ earnings follow a random walk with some seasonal component and there are transitory shocks to the level of earnings. If we ignore the seasonal effects this can be written as:

$$\Delta w_{it} = \delta_t + \varepsilon_{it} + \Delta u_{it} \qquad (1)$$

Where δ_t is a time effect, ε_{it} a transitory shock to earnings growth and u_{it} a transitory shock to the level of earnings. This evidence provides clues about the likely explanation of the observed volatility in earnings, namely that it represents very transitory shocks. That should immediately indicate to us that the source is not perhaps wage cuts of the type economists have in mind as being necessary to clear labour markets.

This section has documented a large amount of high-frequency volatility in average earnings per head at firm level[4]. We now turn to consider explanations. Although much of the literature aims to explain wage cuts we focus our attention on measures of volatility like the standard deviation in earnings growth. With the firm-level data at our disposal this seems more appropriate.

3. Explanations for the Observed Wage Volatility

The over-riding impression from the MWSS data is that there is a lot of high-frequency volatility in earnings per head at the plant level. There are a number of possible explanations for this and, in this section, we try to evaluate them. We put them in three categories – measurement error, volatility caused by changes in the composition of employment, and volatility in individual earnings (that might be caused by volatility in hours or in earnings per hour). We consider these in turn.

a. *Measurement Error*

First, there is measurement error – it may simply be that the data is wrong. One might be inclined to this view because of the apparent transitory nature of the shock to earnings indicated by the correlogram of Figure 3a. The measurement error interpretation of observed transitory volatility in earnings has been pursued most actively by Gottschalk (2005) and Battieri, Basu and Gottschalk (2014) and most studies of wage flexibility using individual data take steps to mitigate the effects of measurement error on their findings.

Of course there must be some element of truth in this explanation as all data sets do contain measurement error though the extent of the problem will vary across

[4] This complements studies of the volatility of individual earnings, typically at 1 or 2-year frequencies – see, for example, Gottschalk and Moffitt (2009), Shin and Solow (2011), Ziliak et al (2011) for the US and Dickens (2000), and Cappelari and Jenkins (2013) for the UK.

datasets. But, there are a number of reasons to think that the earnings volatility in the MWSS is not primarily measurement error. First, one might expect that measurement error in this type of data comes from approximation, that firms cannot be bothered to find out exactly their paybill and employment in any month and simply report a rough estimate. If this was the case we might expect to see rounding in responses but we do not. Table 5 shows the proportion of observations in which there is rounding in responses and the bottom line is that there is no evidence for rounding. In fact, it is extraordinary how precise are many of the answers.

This precision derives from the nature of the survey. Large firms who have to respond every month normally automate their submission to make it a dump from the payroll database. This is then submitted to the ONS. On the ONS end they are conscious of the volatility documented here and flag up any outliers and go back to the firms to query it and clarify the reason. There is often a long-term personal relationship between the person in the ONS and the person submitting the information from the firm.

The history of the survey also suggests that measurement error cannot explain everything. While the volatility in earnings might be largely unknown to economists there is indication that those involved with the construction and use of the aggregate earnings indices derived from it are aware of the phenomenon and, while their first inclination was to think it reflected poor data quality (their equivalent of the academics' measurement error) the phenomenon has persisted even after the best attempts to eliminate it. From the perspective of a user of the aggregate earnings series, the problem is that the volatility in the underlying micro data is so large as to have non-trivial implications for the aggregate series in some situations[5]. In the late 1990s institutions like the Bank of England were highly critical of the Average Earnings Index because it felt that it was not fit for their purposes. This led to the Turnbull-King Report to the Government (Sedgwick and Weale, 1999, Chambers, Weale and Youll, 2000) that made a number of suggestions for improving the index. But none of these suggestions have eliminated the volatility and the ONS is still faced with the problem of a lot of volatility that, even after close investigation, seems to be real.

[5] Outliers are actively investigated and sometimes eliminated from the published aggregate series if their influence on the aggregate is judged to be unduly large.

Nonetheless, there is some indication that some of the responses reflect measurement error. Some establishments report extremely large changes in employment and the mean of the absolute value of the monthly turnover rate is 4%, much too large to be compatible with what we know about worker flows and other measures of job reallocation in the UK. But this is caused by a few extremely large outliers – the median absolute turnover rate (a measure of job reallocation) is a much more plausible 1.1% per month. It is also worth noting that these outliers in employment changes also tend to report very large absolute values of changes in log average earnings – as indicated in columns (4) through (6) of Table 6. One possible explanation for these outliers is an instability of the 'reporting unit' – that suddenly the reporting unit changes to encompass a different number of local units. This would tend to produce a large sudden change in employment associated with large reported changes in earnings per head. However, over 90% of reporting units have the same local units over a period of 10 years.

However, it is clear that even if one excludes these 'suspect' observations, there remains a large amount of earnings volatility – the third column of Table 6 shows that the standard deviation in monthly earnings growth is 0.067 for those establishments that report no change in employment so are unlikely to have changes in reporting units. And the last two columns show that the volatility remains substantial for single-plant firms even after excluding those that report very large changes in employment. Hence it seems very likely that much of the observed volatility is real and reflects the actual payments in a given month from an employer to her workers. We now move on to a consideration of the reasons for this.

b. *Changes in the Composition of Employment*

Earnings per head will change when the composition of employment changes in such a way as to alter the average earnings of workers. Let us consider how much volatility we would expect such changes to induce[6]. Suppose there is variation in earnings across workers within a firm and that the variance of earnings within the firm is given by σ_w^2. Suppose there are N workers in the firm and that each of them quits

[6] The best way to estimate the importance of the changing composition of employment would be to use matched employer-employee data that is increasingly available in many countries (see, for example, Barth et al, 2011; Card, Heining and Kline, 2013) though not the UK. But, with few exceptions (e.g. Sigurdsson and Sigurdardottir, 2014) this data is at best available at quarterly and often only annual frequencies limiting the potential use for investigating the issues discussed in this paper.

each month with probability q. Assume any worker who quits is replaced within the month so that the overall employment in the firm remains constant (one could also consider the case where there is no replacement of the worker with a similar conclusion). Assume that quits are randomly drawn from within the workforce and that new recruits get a wage drawn at random from the wage distribution. Assume that once hired at a particular wage W_i^r, this does not change so that the only possible source of change in average earnings per head is from labour turnover. The change in average wages at firm-level, $\Delta\overline{W}$, will be given by:

$$\Delta\overline{W} = \frac{1}{N}\sum_i Q_i\left[W_i^r - W_i\right] \tag{2}$$

Where W_i is the wage received by worker i and Q_i is a binary variable taking the value 1 if worker i quits and zero otherwise. $\Delta\overline{W}$ has mean zero and the variance is given by:

$$Var\left(\Delta\overline{W}\right) = \frac{2q\sigma_w^2}{N} \tag{3}$$

This shows that we would expect the variance in earnings per head to be positively related to within-firm wage inequality and the overall turnover rate. This is because a higher turnover rate means more changes in people with more potential for wage changes and the greater the within-firm wage inequality the larger this effect will be. We also see that volatility should be negatively related to the size of the firm, essentially because of a law of large numbers. A simple way to think about (3) is to put some orders of magnitude on it. Suppose we used a high estimate for labour turnover of 2% per month, i.e. a value for q of 0.02. For a firm with 100 workers we would then expect that $sd\left(\Delta\overline{W}\right) = 0.02\sigma_w$. If we divided by average earnings this would tell us that the standard deviation of earnings growth relative to average earnings should be one-fiftieth of the coefficient of variation of earnings within the firm. To obtain a standard deviation in earnings growth of 0.06 (the smallest estimate in Table 6) requires a coefficient of variation of earnings within the firm of about 3. This is much too big as the variation of earnings in the economy as a whole is no bigger than 1 and within firms it is very likely to be considerably smaller than that.

These calculations have been based on some specific assumptions to keep things simple that might not be realistic. But changing them may actually strengthen the conclusions. For example, workers who leave are probably likely to be replaced with a similar worker paid similar wages. And quits and recruits are concentrated among the lower earners and this would also tend to lead to lower volatility in average earnings per head as they account for a lower share of the total age bill.

It is likely that some of the observed volatility in earnings changes that is observed in the data is the result of changes in the composition of employment and that this is likely to be particularly important in small firms. But it is also clear that this cannot be the explanation for all of the observed volatility.

c. *Volatility in Hours*

Because the earnings measure is a weekly measure this can come from variation in hours or in hourly earnings. This section considers hours variation – variation in the hourly rate is considered later. Because the MWSS has no hours information we turn to another data set to shed light on this.

The best source of information on hours variation at the individual level comes from the Labour Force Survey (LFS), the UK equivalent to the CPS though it has a quarterly rather than monthly frequency. This provides quarterly information on the level of actual hours worked, as well as the split of those hours into basic hours, paid and unpaid overtime. Table 7 presents some basic information on the distribution of the change in log paid weekly hours over the time intervals one can compute from the LFS (quarterly from 3 to 12 months). The sample is restricted to those who are in the same job (those who change jobs report more variability as one would expect) so that we have a sample of workers who remain in the same firm - this is what is closest to what would be reported in the MWSS.

Table 7 shows a considerable amount of variation in weekly paid hours at the individual level. If we restrict attention to the 3-month horizon for which we have data from both the MWSS and the LFS, the standard deviation in the change log weekly hours as reported in the LFS is 0.34 compared to a standard deviation in the change in log paybill per head of 0.083 if we use the 3-month weighted volatility from the fourth column of Table 2. Taken at face value the volatility in hours can more than explain the observed volatility in earnings.

However, there are a number of problems in accepting this conclusion. First, not all variation in hours is associated with variation in earnings. We might expect earnings will be proportional to hours (and more than proportional if there is an overtime premium) for those who are paid by the hour, but many workers are paid on a monthly basis and their earnings will bear little relationship to hours worked. The final column of Table 7 reports the distribution of the change in reported log weekly earnings in the LFS – unfortunately this is only available at a 12-month interval because earnings information is only collected in the first and fifth waves (and only since 1997). The standard deviation of the change in log weekly earnings is remarkably similar to that for the change in log hours (though the percentiles are rather different). But one cannot conclude that all the variation in the change in log weekly earnings is caused by variation in hours.

To investigate this further Table 8 reports results from regressions of the change in log weekly earnings on the change in log weekly hours. A simple regression of the annual difference in log earnings on the difference in log hours for all workers has a coefficient on log hours of 0.26. But if the sample is restricted to workers who have not changed jobs this falls to 0.18 so that only one-fifth of the variation in hours translates into earnings[7]. The third and fourth columns shows that this is the result of the fact that many people are not paid by the hour – the estimated elasticity for those who are not hourly paid (the third column) is 0.086, while that for those who are paid by the hour is 0.239 (still not one). So if, on average, the response of weekly earnings to variation in weekly hours is about 0.25 then a standard deviation of 0.34 in individual hours would be expected to translate into a standard deviation of 0.085 for weekly earnings.

However this assumes that all hours variation is at firm-level when it is not. Some of the individual variation in hours is due to personal factors that will, by the law of large numbers not contribute to firm-level variation in very large firms (though will always contribute something to the firm-level variance divided by (1/N). On the other hand, there are firm-level shocks that will affect large numbers of workers within the firm – Cooper, Haltiwanger and Willis (2004) report, for US manufacturing firms in the 1970s, a quarterly standard deviation in hours growth at plant level of 0.18. Absent panel data on multiple workers within firms we cannot investigate this precisely but we can get some idea by investigating the reasons for the deviation between actual and usual hours when asked in the LFS. The reasons given are tabulated in Table 9 – half the time it is that hours or overtime varies. Unfortunately

[7] There is an issue of how one interprets this coefficient if one has a classical labour supply model in mind. If the driving force for changes in hours is changes in the hourly pay rate (which it probably isn't) then the reported elasticity should be one plus the labour supply elasticity.

it is not clear whether this is because the demand for the firm's output is varying so should be interpreted as a firm-level shock, or because one is being asked to cover for a sick colleague in which case it is not.

From the discussion above it should be apparent that while it is likely that a non-trivial part of the reported variation in gross weekly earnings does come from hours variation, not all of the earnings volatility can be from those sources so is variation in pay per hour.

d. Variation in Individual Earnings

By a process of elimination we have argued that the explanations above cannot explain all of the volatility we observe in average earnings – hence we must look at volatility in earnings received by individuals. In this section we present evidence on the volatility of earnings at the individual level using the LFS. We report information on three measures of earnings. First, gross weekly earnings as this is the earnings measure closest to that used in the MWSS. As pointed out above hours variation is one potential cause of volatility in weekly earnings. Secondly we use a derived hourly pay measure by dividing gross weekly earnings by a measure of paid hours (both basic and overtime). It is widely recognized that this measure does contain sizeable measurement error[8] - and part of this is that the earnings and hours measures cannot be assumed to refer to the same time period. Finally, in 1999, a direct question on the hourly wage rate was introduced for the approximately 50% of workers who report being paid by the hour – obviously this is not a meaningful concept for workers who are not paid by the hour.

The first row of Table 10 presents some measures of the extent of wage volatility in weekly earnings, hourly pay and, for those where it exists, the hourly rate. We restrict attention to those who are working for the same employer at both wage observations. As has been reported in other studies, there are sizeable wage cuts and a lot of volatility for all three measures though largest for gross weekly earnings. In the more detailed analysis that follows we focus attention on gross weekly earnings because that is closest to the individual earnings measure in the MWSS and because we observe this measure for all workers. Our strategy in the rest of this section is to see how far one can go to reducing the volatility in wage growth.

[8] For example, use of this earnings measure probably led the ONS to overstate the impact of the UK's National Minimum Wage in the late 1990s.

Of course, much of the volatility observed in Table 10 could be measurement error and much of the existing literature that uses earnings reported by individuals focuses on this possible explanation. But, the LFS offers some advantages over surveys like the CPS and PSID as it asks about the source of earnings information, recording, for example, whether the pay slip has been seen (it is for about 20% of workers). It also has information on whether the respondent was a proxy (it is for about one-third of workers) and questions about whether earnings were the same as usual (it is for about 80% of workers). Because we have observations on earnings/wages at two points in time we might have the pay slip observed at neither, either or both observations. We construct a variable that measures the number of times the pay slip has been seen and the number of proxy observations. The first panel of Table 11 then tabulates the standard deviation of the change in log weekly earnings by these variables. As one would expect the fewer times the pay slip is seen and if there is a proxy response the greater the variation in reported wage growth. One can also note that if the pay slip is seen twice, it makes less difference whether there is a proxy response. The biggest variation may come if there is one personal and one proxy response as two proxy responses may mean the same mistake is made twice.

The second panel of Table 11 then reports the incidence of cuts in gross weekly earnings. As one might expect given the previous results, the reported incidence of cuts is greater if the pay slip is not seen and there are proxy responses though perhaps the differences are not as large as one would expect. However the final panel of Table 11 makes it clear that large earnings cuts are much more frequently reported when the pay slip is not seen. However the incidence of cuts in gross weekly earnings greater than 5% remains high at 19% of workers even if pay slips are seen both times and there are personal responses.

To further explore this we restrict the sample in what follows to those individuals for whom we observe both pay slips and have zero proxy responses i.e. the group for which we would expect measurement error to be the smallest. The LFS asks a question about whether earnings are the same as usual. The final column of the first panel of Table 12 shows that about two-thirds of workers report that both their earnings were the same as usual. Though that still leaves one-third of workers for whom at least one of two earnings measures are not the same as usual – these will be one source of volatility. As one might expect, Table 12 shows there is less volatility in earnings and fewer observed earnings cuts among those who report earnings are the same as usual. The most common recorded reason for why earnings differ from usual is because of hours variation. This will obviously be more important for hourly paid as compared to salaried workers. So the bottom two panels of Table 12 split the sample into hourly and salaried workers. The final column shows that 40% of hourly-paid workers report unusual pay as compared to 25% of salaried workers – hours variation is the biggest cause of this discrepancy. For both hourly and salaried workers one sees, as one would expect, greater volatility in earnings for those who report unusual earnings and, also, greater volatility in earnings among hourly-paid as opposed to salaried workers. But, even if we restrict attention to those whose pay slips are seen, with no proxy responses, who are in the same job and who report both earnings to be the same as usual we still have 17% of salaried workers reporting year-on-year falls in earnings and 9% falls greater than 5%. So, however hard one looks one still finds a sizeable amount of volatility in earnings though most of this variation is probably the transitory volatility seen in the MWSS data.

Our conclusion is that there does seem a surprising amount of volatility in the actual wage payments from employers to workers and that it would not be correct to think of all of this as simply measurement error. This conclusion that workers seem to experience a lot of volatility in actual wage payments also runs against the 'implicit contract' literature that argued that wages are smoothed because risk-averse workers' demand for insurance can be met by less risk-averse employers. If workers demand a smooth flow of income means then our proposed explanation for the volatility in earnings cannot be correct. However, workers do absorb a lot of volatility in earnings, volatility that is so routine it is not noticed. When workers are paid by the month (or a week), they have to absorb a considerable variation in their income on a daily basis. The transitory shocks we are considering here are smaller than that most workers face on a monthly basis and simply accept as a fact of life. We all manage our finances (some better than others) to reflect the fact that we only get paid once a month.

4. Evidence for Annual Wage Settlements

Given the previous discussion one might wonder whether there is any evidence at all for wage rigidity in the MWSS. One form of wage rigidity is the idea of annual wage settlements where earnings are raised once a year. If one thinks that this is likely to always happen in the same month then one would expect to be able to detect this. We know from other sources that not all firms have a settlement in the same month so that we need a method to detect firm-specific months.

Our procedure is the following. We restrict attention to the 648 firms in a sample for whom we observe for at least 105 months. We then estimate a model for earnings growth with dummy variables for each month, excluding the constant and allowing for an MA(1) error to reflect our earlier findings. If a monthly dummy is significant we then record that. This has similarities to the procedure used by Gottschalk (2005) and Barattieri et al (2014) to identify increases in wages but is based on the assumption that underlying earnings follow a random walk, an assumption that seems better for our data. This methodology has a couple of potential problems. First, there are other reasons apart from annual settlements that would cause a seasonal change in paybill per head e.g. if there was a seasonal component to demand with associated hours and employment changes. But we would expect these to be temporary so to be associated with a negative effect in the following month. In contrast, annual settlements should not be reversed.

The pattern of our results is shown in Table 13. In the first two columns we record all the monthly coefficients that are positive and those that are significantly different from zero. We see a concentration of 'wage settlements' in April. The third and fourth columns in Table 13 do the same exercise but for negative monthly coefficients. There are more negative than positive coefficients but a lower percentage of them are significantly different from zero. Those that are almost certainly reflect seasonal variation in demand – it is in the autumn that they are most common. The final column of Table 13 records the fractions of wage settlements in different months in the IDS/IRS and CBI settlements database[9]. It is clear that we can pick up the concentration of pay settlements in April in our data and the smaller spike in July but the concentration in January is harder to detect.

5. Interpretation and Implications for the Shadow Price of Labour

The previous sections have argued that there is considerable transitory volatility in the actual payments from employers to workers, much more than in settlements or base wages. This raises the question of which type of data is more informative about

[9] We are grateful to Peter Dolton for providing this data (see Dolton, Makepeace and Tremayne, 2012, for more details on this)

rigidity in the shadow price of labour. In this section, we offer a simple theoretical model to explain why large transitory changes in earnings may not be associated with large employment changes and to provide a theoretical argument for why base wages may be a better measure of the shadow price of labour.

In this section we present a simple, very stylized, model to answer these questions. Consider a job in which the output produced each period t is constant and denoted by Y[10]. Assume that the wage each period is given by:

$$W_t = W\left(1+\varepsilon_t\right) \tag{4}$$

where W is the base wage and ε_t is a transitory shock to the wage that is assumed iid with mean zero and density function $f\left(\varepsilon\right)$. We will not ask where these shocks come from – they will be treated as exogenous. The intention is to consider how much transitory wage volatility can be absorbed without having allocational consequences and to decide whether the base wage, W, or the actual current wage W_t, is more important in influencing employment decisions.

At the start of each period the job is either filled or vacant. After ε_t is revealed the employer has to decide whether to fill it this period. If the job is currently vacant but the employer hires a worker then a hiring cost H is incurred. Define $\Pi\left(\varepsilon\right)$ to be the value of a filled job if the current transitory shock is ε. This is defined after the hiring cost has been paid. Also denote by Π_0 the value of an empty job – this will not depend on ε because of the iid assumption. For simplicity we assume there are no firing costs but the existence of such costs would not alter the point we want to make[11]. Firms will fire the worker if ε is higher than some threshold value that we denote by ε_f [12]. With these assumptions we can write the value function for an employed job as:

$$\Pi\left(\varepsilon\right) = \max_{\varepsilon_f}\left[Y - W\left(1+\varepsilon\right)\right] + \delta\int^{\varepsilon_f}\Pi\left(\varepsilon'\right)dF\left(\varepsilon'\right) + \delta\left[1-F\left(\varepsilon_f\right)\right]\Pi_0 \tag{5}$$

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[10] This assumption of constant output but varying wages is different from that made by Macleod and Malcomson (1993) who consider varying surplus but constant wages. The different assumptions are made to emphasize the point each paper wants to make.

[11] Firing costs are excluded both because they seem less fundamental than hiring costs (e.g. they are the product of laws) and are not particularly large in the UK.

[12] For simplicity we only consider a one-sided model in which the worker always wants the job. It would add only complication to model the worker side of the same problem.

where δ is the discount factor. It should be obvious that the optimal value of ε_f satisfies:

$$\Pi\left(\varepsilon_f\right)=\Pi_0 \tag{6}$$

Now consider the value of an empty job. Firms will not hire a worker if ε is higher than some threshold value that we denote by ε_h. With these assumptions we can write the value function for an empty job as:

$$\Pi_0=\max_{\varepsilon_h} \delta\int^{\varepsilon_h}\left[\Pi\left(\varepsilon'\right)-H\right]dF\left(\varepsilon'\right)+\delta\left[1-F\left(\varepsilon_h\right)\right]\Pi_0 \tag{7}$$

It should be obvious that the optimal value of ε_h satisfies:

$$\Pi\left(\varepsilon_h\right)-H=\Pi_0 \tag{8}$$

(6) and (8) imply that the thresholds for hiring and firing will be the same if there are no hiring costs but differ if there are hiring costs. Now, consider the form of the value functions. Because ε only enters (5) linearly this will be of the form $\Pi\left(\varepsilon\right)=\Pi\left(0\right)-W\varepsilon\equiv\Pi^*-W\varepsilon$ which, combined with (6) and (8) implies that:

$$W\varepsilon_f=\Pi^*-\Pi_0=W\varepsilon_h+H \tag{9}$$

Now, from (5), Π^* must satisfy:

$$\Pi^*=\Pi\left(0\right)=\left(Y-W\right)+\delta\left[\Pi_0+F\left(\varepsilon_f\right)\left(\Pi^*-\Pi_0\right)-W\int_{-\infty}^{\varepsilon_f}\varepsilon' dF\left(\varepsilon'\right)\right] \tag{10}$$

Using (9), (10) can be written as:

$$\begin{aligned}\Pi^*&=\left(Y-W\right)+\delta\left[\Pi_0+W\left(F\left(\varepsilon_f\right)\varepsilon_f-\int_{-\infty}^{\varepsilon_f}\varepsilon' dF\left(\varepsilon'\right)\right)\right]\\&=\left(Y-W\right)+\delta\left[\Pi_0+WG\left(\varepsilon_f\right)\right]\end{aligned} \tag{11}$$

Where $G\left(\varepsilon\right)=F\left(\varepsilon\right)\varepsilon-\int_{-\infty}^{\varepsilon}\varepsilon' dF\left(\varepsilon'\right)$. Similarly we can use (9) to write (7) as:

$$\Pi_0=\delta\left[\Pi_0+WG\left(\varepsilon_h\right)\right] \tag{12}$$

Taking the difference of (10) and (12) and using (9) we have that:

$$W\varepsilon_f=\Pi^*-\Pi_0=\left(Y-W\right)+\delta W\left[G\left(\varepsilon_f\right)-G\left(\varepsilon_f-h\right)\right] \tag{13}$$

Where $h=H/W$, the size of hiring costs relative to the base wage. It is readily checked that (13) has a unique solution for ε_f as the right-hand side has a slope less than W as $G'\left(\varepsilon\right)=F\left(\varepsilon\right)$. (13) can be simplified to yield:

$$\varepsilon_f = \frac{(Y-W)}{W} + \delta\left[G\left(\varepsilon_f\right) - G\left(\varepsilon_f - h\right)\right] \tag{14}$$

(14) can be used to address the size of the fluctuation in actual wage payments that could be absorbed without causing the employer to fire the worker. The first term in (14) is the proportional difference between the marginal product of labour and the base wage and is a lower bound for how much can be absorbed. If this is 20% then (14) says that at least a 20% fluctuation will be absorbed without firing. The intuition for this is straightforward – this much of a shock can be absorbed while the firm still makes positive current profits from the worker.

Of more interest is the second term in (14). This will be zero if the discount factor is zero or hiring costs are zero. But, otherwise it will be positive. The intuition is that firing the worker means that hiring costs will have to be incurred in the future so this acts as a barrier to firing even if current profits from the worker are negative. The important point is that this term can be large. If we take a first-order approximation to (14) around ε_f, then we have, using the fact that $G'(\varepsilon) = F(\varepsilon)$:

$$\varepsilon_f \approx \frac{(Y-W)}{W} + \delta F\left(\varepsilon_f\right)h \tag{15}$$

If we consider a monthly frequency, then δ will be close to 1, $F\left(\varepsilon_f\right)$ is the probability of not firing a worker (which is also close to 1 in the data), and h is the ratio of hiring costs to the monthly base wage. Estimates of hiring costs (see, for example, the review in Manning, 2011, Table 2). are often of the order of 50%-150% of monthly earnings so this term will be very large, showing how hiring costs can explain why there can be large transitory shocks in the wage payments to workers without having allocational consequences. This turns on its head a common argument that the existence of rents allows wage rigidity to exist (e.g. Macleod and Malcomson, 1993; Hall, 2005a,b) - in our case it is the existence of rents that allows large transitory volatility in earnings.

We are also interested in the relative importance of the base wage and the actual current wage in influencing hiring decisions i.e. what is the appropriate shadow price of labour. A worker will be hired if:

$$\Pi^* - \Pi_0 - W\varepsilon_t - hW > 0 \tag{16}$$

Using (13) this can be written as:

$$\left(Y - W_t\right) + \delta W\left[G\left(\varepsilon_f\right) - G\left(\varepsilon_f - h\right)\right] - Wh > 0 \tag{17}$$

Notice that this depends on the actual current wage and, if the firm does not care about the future or there are no hiring costs, it is only the current wage that is relevant. But, in general, (17) also depends on the base wage which appears directly in (17) and also influences ε_f. Note that (17) will be homogeneous of degree 1 in (Y,W,W_t). We are interested in the relative importance of the base wage and current wage in influencing hiring decisions. From inspection of (17) one can see that the current wage has a derivative of 1 in this expression and the question we are interested in is how this compares with the derivative with respect to the base wage, W. The derivative of (17) with respect to the base wage is given by:

$$-h+\delta\left[G\left(\varepsilon_f\right)-G\left(\varepsilon_f-h\right)\right]+\delta W\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]\frac{\partial\varepsilon_f}{\partial W} \tag{18}$$

From (14) we have that:

$$W\frac{\partial\varepsilon_f}{\partial W}=-\frac{\left(Y/W\right)}{1-\delta\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]} \tag{19}$$

So that (18) can be written as:

$$\begin{aligned}&-h+\delta\left[G\left(\varepsilon_f\right)-G\left(\varepsilon_f-h\right)\right]-\frac{Y}{W}\frac{\delta\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]}{1-\delta\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]}\\&\approx-h\left[1-\delta F\left(\varepsilon_f\right)\right]-\frac{Y}{W}\frac{\delta\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]}{1-\delta\left[F\left(\varepsilon_f\right)-F\left(\varepsilon_f-h\right)\right]}\end{aligned} \tag{20}$$

The important point is that when employers discount future profits at a reasonable rate and hiring costs are reasonably large so that it is much more difficult to be hired than fired, then this derivative can be much larger in absolute terms than 1, so that the base wage can be thought of as more influential than the actual current wage payment in the hiring decision. One can use this argument to justify focusing on rigidity in wage settlements or base wages as being more informative about the extent of rigidity in the shadow cost of labour to employments than micro data on actual wage payments.

This model has focused only the firm side in the interests of simplicity. But, one can readily introduce the worker side. If the labour market is frictionless workers will quit jobs whenever the current wage is below their outside option – this will act to limit the amount of transitory wage volatility in any given job. But when there are frictions and it takes time and/or money to get another job, workers will be prepared to absorb large transitory fluctuations in earnings without quitting. The value of a job to a worker will be a function of the permanent and transitory component of the wage with a greater weight on the former.

This model has made the point that the existence of rents (caused in the model by hiring costs) means that large transitory fluctuations in the wage can be absorbed without allocational consequences[13]. This also means that base wages rather than actual wages are more likely to be important in influencing employment decisions.

6. Conclusions

The explosion in the availability of micro data on individual earnings has understandably led to researchers using this data to try to answer perennial questions in macroeconomics about the extent and nature of wage rigidity. In this paper we have argued that care needs to be taken in interpreting such data and that one should not lose track of the fact that it is the cyclicality in the shadow price of labour in which we are ultimately interested.

First, using high frequency firm-level data from the UK we have shown that there is a lot of volatility in average earnings per head at firm level. This volatility is transitory but seems to be real. Some of it is caused by variation in the composition of employment and some of it by variation in hours. But, it also appears that a considerable part is real fluctuations in the payments from employers to individual workers that is not associated with variation in labour input. With the only data available to us being at firm-level this conjecture needs to be checked with individual data from firms but it is consistent with the findings in Sigurdsson and Sigurdardottir (2014) on the volatility in the actual payments from employers to individual workers. This volatility contrasts with the rigidity observed in base wages and in settlements data.

The second conclusion of the paper is that this volatility in actual payments can exist because of frictions in the labour market and that these frictions mean that the base wage rather than actual payments are likely to be more important in determining the shadow price of labour that firms use in making decisions to hire or fire workers.

[13] Such fluctuations could not happen on prices charged for goods that are bought in a spot market and in which the equivalent of the hiring cost is low. The large fluctuations in prices that we see (‘sales’) are probably designed to alter allocational decisions.

Table 1
The Monthly Wage and Salary Survey: Descriptive Statistics

	All Workers – Full Sample	All Workers – Restricted Sample	Weekly-Paid Workers	Monthly-Paid Workers
Number of observations	961026	773021	368777	722230
Number of reporting units	31321	27047	13816	24947
Total Weekly Paybill (£000)	596 (2161)	589 (2136)	168 (1975)	547 (1983)
Employment	1589 (6403)	1597 (6398)	674 (4561)	1368 (5668)
Average Weekly Earnings (£)	406 (219)	399 (213)	280 (469)	452 (593)
Average Log Weekly Earnings	5.87 (0.53)	5.86 (0.53)	5.47 (0.594)	6.32 (0.484)
Average Change in Log Weekly Earnings	0.0029 (0.098)	0.0032 (0.099)	0.0028 (0.202)	0.0029 (0.115)
Average Change in Log Employment	-0.0015 (0.109)	-0.0013 (0.108)	-0.0078 (0.241)	0.0002 (0.114)

Notes.

1. Weekly and monthly-paid figures only relate to firms that report non-zero paybill and employment.
2. Full sample is January 2000-May 2010 inclusive. Restricted sample is August 2000 – December 2008 inclusive.
3. Standard deviations reported in parentheses.

Table 2
The Distribution of Wage Changes over Different Time Horizons

	1-month Unweighted	1-month Weighted	3-month Weighted	6-month weighted	12-month Weighted
Panel A. All Workers					
5th Percentile	-0.126	-0.077	-0.089	-0.093	-0.080
10th percentile	-0.075	-0.045	-0.049	-0.051	-0.033
25th percentile	-0.025	-0.015	-0.014	-0.010	0.010
Median	0.0018	0.0019	0.0076	0.018	0.037
75th percentile	0.031	0.021	0.033	0.048	0.066
90th percentile	0.082	0.053	0.071	0.090	0.110
95th percentile	0.132	0.085	0.108	0.132	0.157
% with wage cut	46.8	46.0	40.1	32.9	19.5
Mean	0.0029	0.0029	0.0094	0.019	0.038
Standard deviation	0.098	0.068	0.083	0.093	0.099
Number of observations	885372	885372	817777	735714	600177
Panel B. Weekly-Paid Workers					
5th Percentile	-0.237	-0.233	-0.270	-0.292	-0.257
10th percentile	-0.143	-0.131	-0.151	-0.166	-0.141
25th percentile	-0.049	-0.040	-0.045	-0.045	-0.023
Median	0.0017	0.0028	0.0088	0.019	0.039
75th percentile	0.057	0.047	0.065	0.084	0.105
90th percentile	0.149	0.139	0.175	0.211	0.232
95th percentile	0.241	0.236	0.300	0.351	0.376
% with wage cut	47.0	46.9	44.6	40.7	31.7
Mean	0.0028	0.0035	0.011	0.023	0.047
Standard deviation	0.202	0.200	0.233	0.254	0.266
Number of observations	337468	336274	307386	272935	217718
Panel C. Monthly-Paid Workers					
5th Percentile	-0.114	-0.075	-0.085	-0.096	-0.097
10th percentile	-0.065	-0.042	-0.046	-0.049	-0.038
25th percentile	-0.020	-0.014	-0.013	-0.009	0.009
Median	0.0008	0.0017	0.007	0.018	0.036
75th percentile	0.027	0.020	0.032	0.046	0.065
90th percentile	0.072	0.050	0.068	0.086	0.107
95th percentile	0.121	0.080	0.103	0.127	0.154
% with wage cut	45.3	45.9	40.1	32.6	20.4
Mean	0.003	0.0024	0.0084	0.017	0.033
Standard deviation	0.115	0.082	0.098	0.110	0.125
Number of observations	669324	667084	613624	548049	440737

Notes.

1. Weights come from the IDBR.

Table 3
The Distribution of Wage Changes by Employer Size

	All (unweighted)	20-99 employees	100-499 employees	500-999 employees	1000+ employees
Panel A. All Workers					
5^{th} Percentile	-0.126	-0.157	-0.130	-0.115	-0.088
10^{th} percentile	-0.075	-0.097	-0.078	-0.067	-0.051
25^{th} percentile	-0.025	-0.035	-0.027	-0.022	-0.017
Median	0.0018	0.0011	0.0020	0.0022	0.0021
75^{th} percentile	0.031	0.042	0.033	0.029	0.023
90^{th} percentile	0.082	0.105	0.084	0.074	0.051
95^{th} percentile	0.132	0.162	0.135	0.121	0.096
% with wage cut	46.8	47.2	47.2	46.7	46.1
Mean	0.0029	0.0028	0.0029	0.0029	0.0032
Standard deviation	0.098	0.113	0.102	0.095	0.076
Number of observations	885372	294928	222740	101142	266562
Panel B. Weekly-Paid Workers					
5^{th} Percentile	-0.237	-0.240	-0.235	-0.233	-0.234
10^{th} percentile	-0.143	-0.155	-0.143	-0.132	-0.133
25^{th} percentile	-0.049	-0.059	-0.052	-0.043	-0.042
Median	0.0017	0.000	0.0016	0.0028	0.0028
75^{th} percentile	0.057	0.066	0.058	0.050	0.050
90^{th} percentile	0.149	0.159	0.149	0.136	0.139
95^{th} percentile	0.241	0.243	0.239	0.231	0.237
% with wage cut	47.0	46.9	47.5	46.8	46.9
Mean	0.0028	0.0021	0.0024	0.0017	0.0034
Standard deviation	0.202	0.187	0.196	0.201	0.206
Number of observations	337468	102171	81287	36947	116869
Panel C. Monthly-Paid Workers					
5^{th} Percentile	-0.114	-0.141	-0.118	-0.110	-0.085
10^{th} percentile	-0.065	-0.082	-0.067	-0.062	-0.048
25^{th} percentile	-0.020	-0.026	-0.022	-0.020	-0.016
Median	0.0008	0.000	0.0012	0.0019	0.0019
75^{th} percentile	0.027	0.032	0.028	0.026	0.022
90^{th} percentile	0.072	0.089	0.075	0.069	0.056
95^{th} percentile	0.121	0.145	0.124	0.114	0.093
% with wage cut	45.3	43.7	46.1	46.4	45.9
Mean	0.003	0.0023	0.0027	0.0031	0.0030
Standard deviation	0.115	0.119	0.110	0.109	0.095
Number of observations	669324	202382	170923	80289	213490

Table 4
The Distribution of Wage Changes by Sector

	All (weighted)	Private Sector	Public Sector
Panel A. All Workers			
5th Percentile	-0.077	-0.093	-0.050
10th percentile	-0.045	-0.056	-0.030
25th percentile	-0.015	-0.019	-0.011
Median	0.0019	0.0022	0.0016
75th percentile	0.021	0.025	0.016
90th percentile	0.053	0.062	0.038
95th percentile	0.085	0.101	0.059
% with wage cut	46.0	46.2	45.7
Mean	0.0029	0.0028	0.0030
Standard deviation	0.068	0.078	0.046
Number of observations	885372	746641	138731
Panel B. Weekly-Paid Workers			
5th Percentile	-0.237	-0.228	-0.239
10th percentile	-0.143	-0.130	-0.132
25th percentile	-0.049	-0.040	-0.041
Median	0.0017	0.0030	0.0025
75th percentile	0.057	0.047	0.046
90th percentile	0.149	0.136	0.141
95th percentile	0.241	0.230	0.241
% with wage cut	47.0	46.7	47.2
Mean	0.0028	0.0031	0.0040
Standard deviation	0.202	0.180	0.222
Number of observations	337468	283369	52905
Panel C. Monthly-Paid Workers			
5th Percentile	-0.114	-0.091	-0.048
10th percentile	-0.065	-0.052	-0.029
25th percentile	-0.020	-0.018	-0.010
Median	0.0008	0.0020	0.0012
75th percentile	0.027	0.023	0.015
90th percentile	0.072	0.059	0.038
95th percentile	0.121	0.097	0.057
% with wage cut	45.3	45.8	46.1
Mean	0.003	0.0023	0.0026
Standard deviation	0.115	0.097	0.050
Number of observations	669324	559369	107715

Table 5
Evidence for Rounding in Responses to the MWSS

Percent	All Workers	Weekly-Paid	Monthly-Paid
Paybill			
Ends in `000’	0.07	0.73	0.00
Ends in `00’	0.22	2.25	0.02
Ends in `0’	0.89	11.95	0.07
Integer	6.61	100	0.28
Employment			
Ends in `000’	0.04	0.04	0.04
Ends in `00’	0.80	0.81	0.75
Ends in `0’	10.41	10.45	10.16

Source: Monthly Wage and Salary Survey
Notes.

1. Employment and Weekly Pay Bill are integers but the monthly paybill can include pence.

Table 6
The Distribution by Employment Changes and Single Plant Firms

	All Firms				Single Plant Firms	
	All (weighted)	No change in employment	Absolute %change in employment <10%	Absolute %change in employment >10%	All (weighted)	Absolute %change in employment <10%
Panel A. All Workers						
5th Percentile	-0.077	-0.080	-0.068	-0.259	-0.112	-0.090
10th percentile	-0.045	-0.043	-0.041	-0.174	-0.064	-0.053
25th percentile	-0.015	-0.011	-0.014	-0.082	-0.021	-0.019
Median	0.0019	0.000	0.0019	0.0027	0.002	0.002
75th percentile	0.021	0.019	0.020	0.094	0.028	0.026
90th percentile	0.053	0.050	0.048	0.186	0.070	0.060
95th percentile	0.085	0.084	0.075	0.275	0.117	0.095
% with wage cut	46.0	38.8	45.9	49.2	46.1	45.8
Mean	0.0029	0.0026	0.0028	0.0051	0.003	0.003
Standard deviation	0.068	0.067	0.057	0.191	0.099	0.073
Number of observations	885372	139682	812763	72609	350784	309981
Panel B. Weekly-Paid Workers						
5th Percentile	-0.237	-0.266	-0.159	-0.459	-0.238	-0.213
10th percentile	-0.143	-0.141	-0.094	-0.311	-0.142	-0.131
25th percentile	-0.049	-0.035	-0.031	-0.127	-0.050	-0.047
Median	0.0017	0.000	0.0029	0.0014	0.002	0.002
75th percentile	0.057	0.039	0.038	0.130	0.057	0.053
90th percentile	0.149	0.129	0.102	0.320	0.147	0.136
95th percentile	0.241	0.242	0.168	0.480	0.246	0.224
% with wage cut	47.0	41.7	46.3	49.6	47.3	47.1
Mean	0.0028	-0.006	0.0036	0.0035	0.002	0.003
Standard deviation	0.202	0.262	0.143	0.351	0.201	0.179
Number of observations	337468	59413	268127	68147	136467	115578
Panel C. Monthly-Paid Workers						
5th Percentile	-0.114	-0.076	-0.066	-0.306	-0.101	-0.085
10th percentile	-0.065	-0.042	-0.039	-0.201	-0.056	-0.050
25th percentile	-0.020	-0.010	-0.014	-0.091	-0.018	-0.017
Median	0.0008	0.000	0.0017	-0.003	0.002	0.002
75th percentile	0.027	0.017	0.019	0.091	0.025	0.023
90th percentile	0.072	0.049	0.047	0.189	0.064	0.057
95th percentile	0.121	0.087	0.073	0.284	0.108	0.092
% with wage cut	45.3	38.7	45.7	51.6	45.1	45.0
Mean	0.003	0.0032	0.0028	-0.008	0.003	0.003
Standard	0.115	0.091	0.069	0.259	0.116	0.095

deviation						
Number of observations	669324	559369	107715	155640	256975	229759

Table 7
The Variability in Paid Hours and Weekly Earnings over Different Time Horizons

	3-month Hours	6-month Hours	9-month Hours	12-month Hours	12-month Earnings
5th Percentile	-0.492	-0.528	-0.546	-0.521	-0.368
10th percentile	-0.262	-0.318	-0.336	-0.333	-0.201
25th percentile	-0.049	-0.098	-0.111	-0.118	-0.039
Median	0.000	0.000	0.000	0.000	0.040
75th percentile	0.040	0.090	0.090	0.080	0.138
90th percentile	0.256	0.318	0.318	0.289	0.305
95th percentile	0.485	0.539	0.539	0.511	0.471
Mean	-0.001	-0.002	-0.005	-0.012	0.045
Standard deviation	0.340	0.374	0.377	0.356	0.347
Number of observations	1069158	663900	3777371	163063	119955

Notes.

1. This data is taken from the LFS for the period 2000-2008 inclusive.
2. The statistics reported are for the distribution of the change in log weekly paid hours for those who have not changed jobs. Results are similar if unpaid overtime is included.
3. The sample sizes fall because the number of observations 3-months apart is larger than the number 12-months apart and because the number of the people in the same job falls as the time interval increases. Reporting the distributions on a consistent sample makes little difference.

Table 8
The Relationship Between the Change in Weekly Earnings and the Change in Weekly Hours
Dependent Variable: Change in Log Weekly Earnings

	(1)	(2)	(3)	(4)
Change in Log Weekly Hours	0.263	0.180	0.086	0.239
	(0.003)	(0.003)	(0.005)	(0.004)
Constant	0.061	0.053	0.051	0.054
	(0.001)	(0.001)	(0.002)	(0.001)
Observations	102743	93690	39090	53951
R-squared	0.072	0.036	0.009	0.063
Sample	All Workers	Workers who have not changed jobs	Workers who have not changed jobs who are not paid by the hour	Workers who have not changed jobs who are paid by the hour

Source: Labour Force Survey, 2000-2008

Table 9
The Reasons Why Hours Differ from Usual

Reason why hours differ from usual	Hourly Paid	Not Hourly Paid	All
Hours/overtime varies	55.55	51.2	53.59
bank holiday	8.11	10.81	9.33
maternity, paternity leave	1.04	1.44	1.22
other leave, holiday	21.38	25.04	23.03
sick or injured	8.68	6.76	7.82
training course	0.67	1.03	0.83
started, changed jobs	0.23	0.12	0.18
ended job	0.15	0.11	0.13
bad weather	0.15	0.09	0.13
labour dispute	0.06	0.03	0.05
economic, other causes	0.38	0.2	0.3
personal, family	1.13	0.98	1.07
other reasons	2.43	2.16	2.31
no reason given	0.01	0.01	0.01
Number of observations			955246

Source: Labour Force Survey, , 2000-2008

Table 10: Volatility in Wage Growth at Individual Level

	Gross Weekly Earnings	Gross Hourly Pay	Hourly Rate	Gross Weekly Earnings	Gross Hourly Pay
5th Percentile	-0.369	-0.361	-0.082	-0.442	-0.392
10th percentile	-0.201	-0.213	-0.027	-0.252	-0.238
25th percentile	-0.039	-0.051	0.000	-0.067	-0.065
Median	0.040	0.048	0.038	0.041	0.048
75th percentile	0.138	0.166	0.085	0.174	0.182
90th percentile	0.305	0.336	0.160	0.394	0.364
95th percentile	0.471	0.485	0.223	0.526	0.526
% with wage cut	31.2	35.3	18.7	34.8	36.8
Mean	0.045	0.054	0.052	0.056	0.056
Standard deviation	0.347	0.341	0.178	0.342	0.342
sample	All	All	All	Those with hourly rate	Those with hourly rate
Number of observations	119955	118798	32331	31095	30956

Source: Labour Force Survey, 2000-2008

Table 11: The volatility in gross weekly earnings: evidence of measurement error

Panel A. The Standard Deviation of the Change in Log Weekly Earnings

	0 proxy responses	1 proxy response	2 proxy responses
0 pay slips seen	0.33	0.38	0.41
1 pay slip seen	0.32	0.35	0.37
2 pay slips seen	0.31	0.32	0.30

Note: Sample size is 118944 with overall standard deviation of 0.35

Panel B. The Fraction of Workers with Observed Falls in Weekly Earnings

	0 proxy responses	1 proxy response	2 proxy responses
0 pay slips seen	0.30	0.33	0.33
1 pay slip seen	0.32	0.34	0.34
2 pay slips seen	0.26	0.29	0.30

Note: Sample size is 118944 with overall fraction of earnings cuts of 0.31

Panel C. The Fraction of Workers with Observed Falls in Weekly Earnings greater than 5%

	0 proxy responses	1 proxy response	2 proxy responses
0 pay slips seen	0.22	0.26	0.26
1 pay slip seen	0.23	0.25	0.27
2 pay slips seen	0.19	0.20	0.22

Note: Sample size is 118944 with overall fraction of earnings cuts of 0.23

Source: Labour Force Survey, 2000-2008

Table 12: The Sources of Wage Volatility

Sample	Standard Deviation of Change in Log Weekly Earnings	Fraction with Falls in Log Weekly Earnings	Fraction with Falls in Log Weekly Earnings >0.05	Number of Observations
All				
All	0.30	0.26	0.18	8089
Both earnings 'same as usual'	0.23	0.21	0.13	5390 (67%)
Not Both earnings 'same as usual'	0.40	0.36	0.29	2699 (33%)
Hourly Paid				
All	0.32	0.29	0.21	5055
Both earnings 'same as usual'	0.25	0.24	0.16	3074 (61%)
Not Both earnings 'same as usual'	0.41	0.37	0.30	1981 (39%)
Not Hourly Paid				
All	0.27	0.21	0.13	2997
Both earnings 'same as usual'	0.22	0.17	0.09	2289 (76%)
Not Both earnings 'same as usual'	0.39	0.34	0.09	708 (24%)

Notes

1. Data from Labour Force Survey, 2000-2008. Sample restricted to those with both pay slips seen and no proxy responses.

Table 13: The Seasonal Pattern in Wage Rises and Pay Settlements

	Coefficient > 0		Coefficient < 0		Pay Settlements
	Fraction of observations	Fraction of Significant Observations	Fraction of observations	Fraction of Significant Observations	
January	6.3	6.1	10.3	11.7	23.2
February	7.5	5.4	9.1	6.0	3.6
March	9.6	8.4	7.1	4.8	4.5
April	12.6	22.3	4.3	3.7	27.6
May	11.0	10.3	5.8	6.0	5.6
June	9.9	9.3	6.8	7.1	5.1
July	8.2	10.1	8.5	7.6	11.1
August	7.1	8.8	9.5	9.4	3.4
September	7.2	4.0	9.4	7.8	3.4
October	6.4	4.0	10.2	11.6	6.2
November	6.7	5.0	9.8	12.8	4.1
December	7.4	6.2	9.2	11.5	2.1
Total Number of Observations	3771	871	4005	733	

Notes.

1. Columns (1) to (4) computed from MWSS.
2. Column (5) kindly provided by Peter Dolton from a database on pay settlements – see Dolton, Makepeace and Tremayne (2012) for details.

Figure 1: Monthly Change in Log Average Earnings

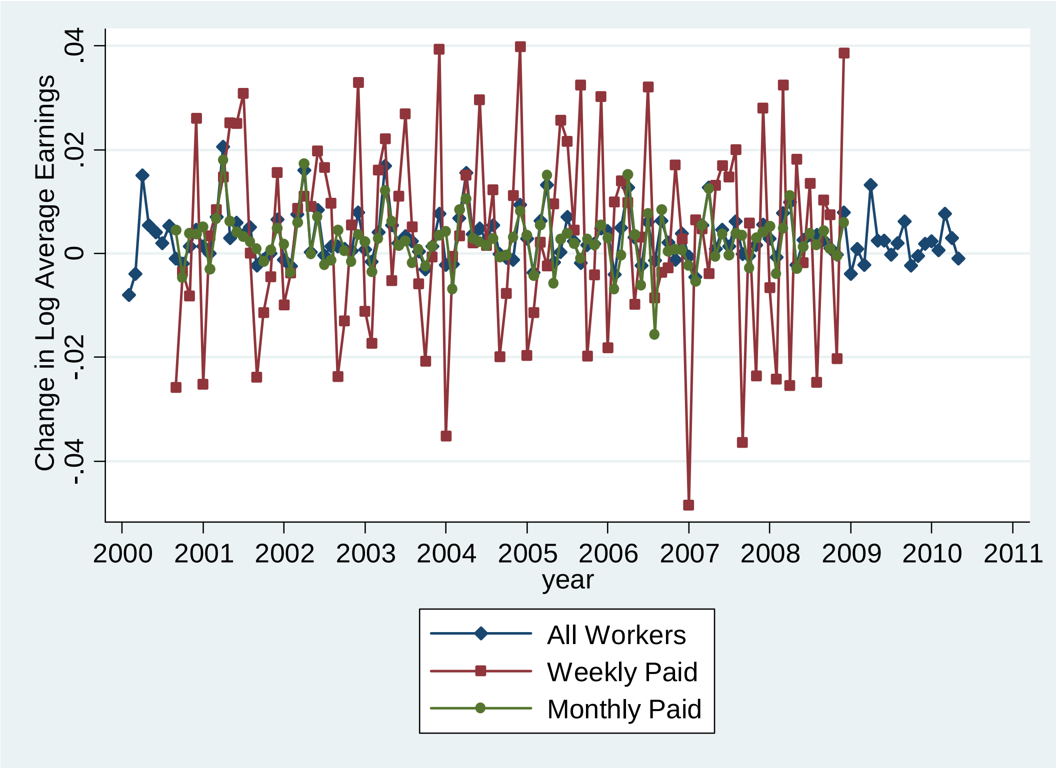


Figure 2: Fraction with Wage Cuts Greater than 5%

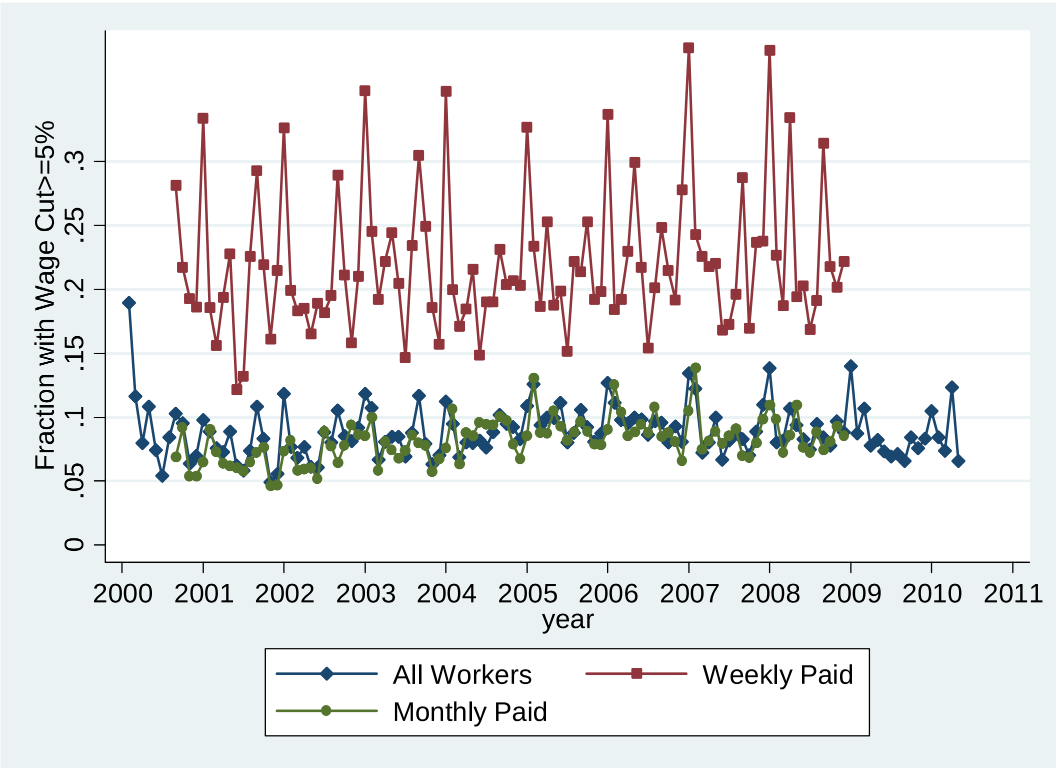


Figure 3a
Covariances Between the Change in Log Average Earnings at Different Lags

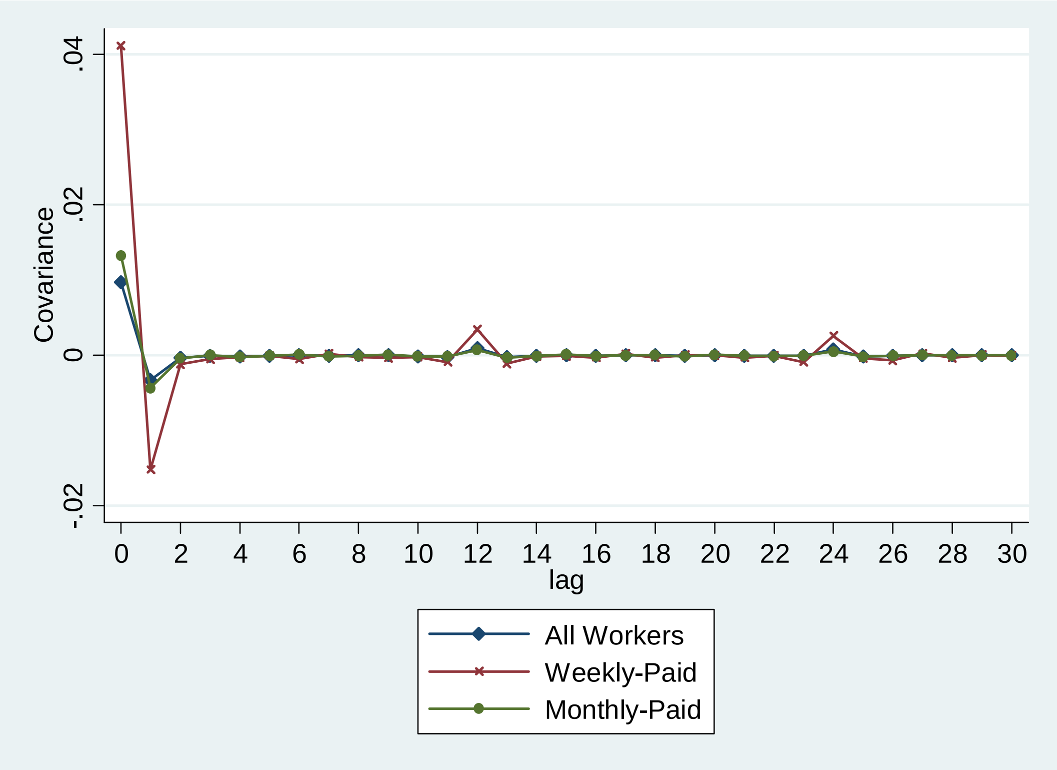
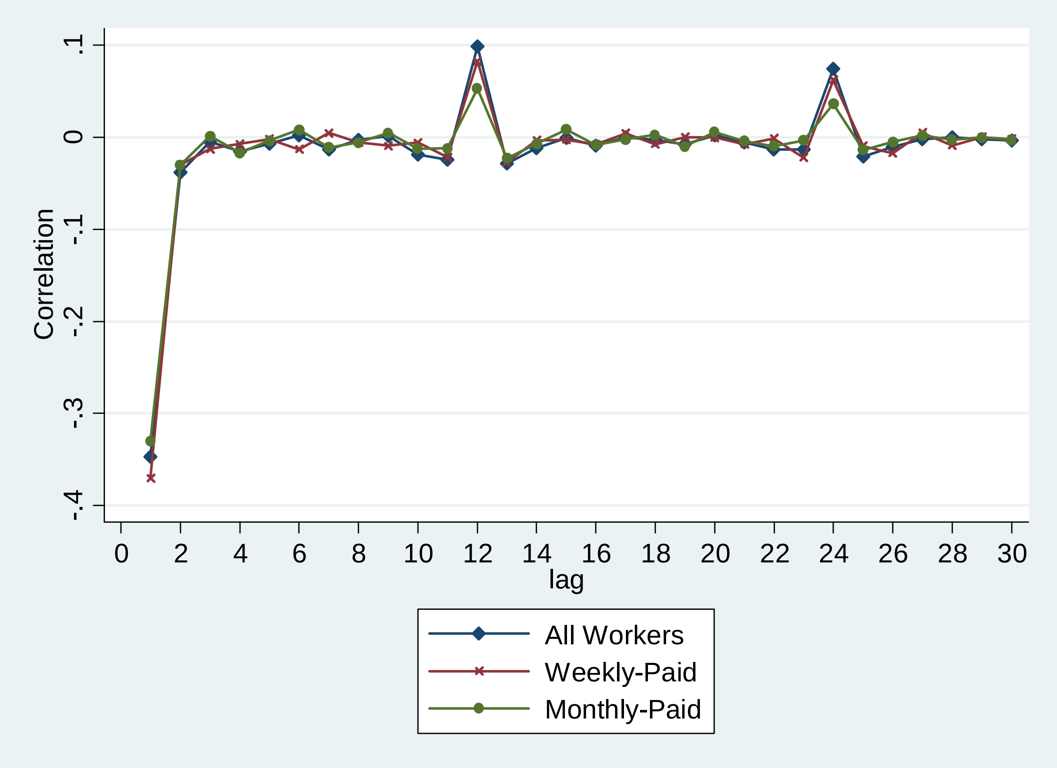


Figure 3b
Correlogram Between the Change in Log Average Earnings at Different Lags



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