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Revisiting the Relationship Between Unemployment and Wages*

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Abstract

We revisit the empirical relationship between wages and labor market conditions. Following work histories in the NLSY79 we document that the relationship between wages and unemployment rate differs across occupations. The results hold after controlling for unobserved match quality. This suggests that evidence about history-dependence of wages obtained from pooled samples conceals significant differences and may provide an imprecise description of earning dynamics. Similar discrepancies emerge when we group workers by education. Sensitivity of wages to unemployment appears related to whether total remuneration entails performance pay components.

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1 Introduction

The sensitivity of wages to aggregate labor market conditions is the subject of a long standing debate. A key question is whether past labor market conditions have any effect on current wages and, if so, why. Most studies on this subject draw inference from samples pooling different types of workers.[1] This paper examines the evolution of wages across broad occupation and education groups and, in particular, their sensitivity to aggregate labor market conditions.

In an influential study Beaudry and DiNardo (1991) show that wages exhibit history-dependence, responding to past labor market conditions. Following Bils (1985) labor market conditions are measured by the aggregate unemployment rate. Beaudry and DiNardo illustrate that the minimum unemployment rate experienced while on-the-job has a significant impact on current wages and crowds out the effect of current unemployment. They interpret the dependence of current wages on past unemployment rates as evidence of implicit contracts between employers and employees. Under this hypothesis it is the contract wage, not the current wage, that adjusts to competitive forces.

The interpretation of these findings has been questioned, and the evidence on wage dynamics has been cast in the alternative context of competitive spot markets in which the accrual of job offers determines match quality and wages. The frequency and quality of job offers are crucial determinants of workers' wage and employment dynamics. This alternative view, suggested by Hagedorn and Manovskii (2013), contends that the correlation between wages and past unemployment is the by-product of selection due to match-specific productivity. Better matches may be selected in periods of low unemployment, which would be reflected in higher wages. After accounting for match quality through cumulative labor market tightness, Hagedorn and Manovskii find that past unemployment no longer matters while current unemployment becomes significant again.

In a related study, Bellou and Kaymak (2016) highlight the importance of focusing on wage growth within a job spell. This restriction eliminates cyclical composition effects in job quality because it only considers the sample of 'job stayers'.[2] Their findings suggest that wage growth does in fact respond to the evolution of the lowest unemployment rate experienced while on the job. This history-dependence is interpreted as evidence of implicit insurance under limited commitment.

Whether or not one subscribes to a particular interpretation of the existing evidence, all of it refers to pooled wage samples. Yet, there is no obvious reason to assume that identical patterns should hold for the wage dynamics of individuals working in different occupations.

[1] One exception is Grant (2003) who analyzes separate cohorts and allows for gender-specific effects.

[2] Match quality proxies based on cumulative labor market tightness drop out upon differentiation.

We begin by replicating baseline results in Beaudry and DiNardo (1991), Hagedorn and Manovskii (2013) and Bellou and Kaymak (2016).[3] Next, we turn to studying the history dependence of wages across broad occupation groups. Our findings lend support to the hypothesis that there are material discrepancies across occupation groups. Differences are substantial: while wages in cognitive jobs are strongly affected by contemporaneous labor market conditions, wages in manual and routine jobs exhibit significant history dependence. We document that similar patterns hold when splitting the sample of workers by education achievement. Wages of college graduates respond only to contemporaneous unemployment. In contrast, wages of high school graduates respond to past unemployment rates, displaying a behavior consistent with that observed for manual and routine jobs.[4]

In the process of reproducing existing results we show that proxies for match quality based on labor market tightness can be de-constructed into two distinct components: individual duration and average tightness. This decomposition does not alter the key conclusion that match quality *always* has a significant effect on wages. The individual duration component is significant throughout our analysis. However average market tightness matters only for some occupations. Following the logic of Hagedorn and Manovskii these patterns indicate that, given some offer arrival rate, the number of offers received increases with employment duration in all occupations; by contrast, average tightness appears to affect the offers' arrival rate in some occupations but not in others.[5]

Overall, our findings indicate that differences exist in the way labor is assessed and remunerated across occupations. In the last part of the paper we propose a possible explanation for these findings, based on imperfect observability of workers' effort. Using information from the NLSY79 about workers' total pay, we show evidence that occupations in which wages are more sensitive to current unemployment also entail a higher occurrence of performance-based earnings. Again, the same pattern is observed when workers are classified by education achievement, pointing to the possibility that occupations involving hard-to-observe productivity may be better suited for performance-based pay schemes and, therefore, exhibit high sensitivity to current conditions.

[3]Like the latter two papers we use data from the National Longitudinal Survey of Youth (NLSY79) between 1979 and 2010.

[4]All results are robust when we estimate specifications for wage differences, which by construction restrict the sample to job stayers.

[5]For a detailed discussion of why average tightness may affect the arrival rate of offers, see recent work by Gottfries and Teulings (2015).

2 Brief Background: Unemployment and Wages

In this section we overview the arguments which shape the empirical analysis linking wage dynamics to aggregate unemployment, and explain how theory guides the organization of longitudinal data and the empirical specifications. In addition, we review the role of match quality proxies based on labor market tightness and show how to express them as the sum of different components.

2.1 Theory and Measurement

To provide context we consider a simple representation of idiosyncratic productivity with unobserved heterogeneity. Let marginal product of worker i in job j at time t be defined as

$$z_{ijt} = \alpha_{ij} S_{ijt} + \beta_i X_{it} + \epsilon_{ijt}, \tag{1}$$

where S_{ijt} is tenure with employer j and X_{it} is years of labor market experience.[6] The unobserved component ϵ_{ijt} consists of aggregate (cyclical) productivity y_t, individual fixed effect a_i, time-invariant match quality m_{ij}, and i.i.d. shock η_{ijt}:

$$\epsilon_{ijt} = y_t + a_i + m_{ij} + \eta_{ijt}. \tag{2}$$

The relationship between wages and cyclical productivity is central to the debate on whether labor market returns are better described as the outcome of implicit contracts or spot markets. Implicit contracts would imply lower sensitivity of wages to contemporaneous aggregate conditions, whereas spot pricing would induce a tighter relationship between the two.[7]

Theory suggests that the optimal contract when only one party is risk-averse is to let the other party carry all risk. If there is full commitment on the side of risk-neutral firms but only limited commitment by risk-averse workers, then workers would always renegotiate their contracts under the most beneficial circumstances experienced while on the job. Therefore the best labor market conditions experienced during a spell with an employer – the minimum unemployment rate since the start of a job – should have an effect on current wages. Beaudry and DiNardo (1991) present a test of this contractual environment. They show that the minimum unemployment rate experienced while on-the-job has a significant impact on current wages and crowds out the effect of current unemployment.

Specifically, they estimate a standard (log) wage equation augmented to include the current

[6] This is similar to the representation in Altonji and Shakotko (1987) and follows Bellou and Kaymak (2016).
[7] For a comprehensive discussion of these issues see Bellou and Kaymak (2016).

unemployment rate and the lowest unemployment rate experienced during a job,

$$w_{i,t+s,t} = \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 u^{min}_{i,t+s,t} + \epsilon_{i,t+s}. \tag{3}$$

In this specification $w_{i,t+s,t}$ is the log wage observed in period $t+s$ for individual i in a job that started in period t, and $X_{i,t+s}$ is a vector of observable characteristics. Current labor market conditions are approximated by U_{t+s}, the unemployment rate in period $t+s$; $u^{min}_{i,t+s,t}$ is the minimum unemployment rate experienced by individual i while on a job that started in period t, and is defined as $u^{min}_{i,t+s,t} = \min\{U_{t+s-k}\}^s_{k=0}$. The error term $\epsilon_{i,t+s}$ includes an individual constant, therefore a fixed-effect specification is estimated.

Beaudry and DiNardo first estimate (3) under the restriction that $\beta_2 = 0$, finding a significant and negative β_1. Their key result is that the inclusion of $u^{min}_{i,t+s,t}$ crowds out the effect of U_{t+s}: the minimum unemployment rate observed on the job has a negative and significant effect on *current* wage and makes β_1 no longer significant.

This finding is revisited by Hagedorn and Manovskii (2013). They argue that the significance of $u^{min}_{i,t+s,t}$, and the crowding out of U_{t+s}, is due to unobserved match quality (m_{ij} in equation 2), and cannot be construed as evidence of implicit contracts. To flesh out this claim they develop a model with on-the-job search, in which wages depend on match quality. Their working hypothesis is that, after controlling for match quality, $u^{min}_{i,t+s,t}$ should no longer matter.

Hagedorn and Manovskii reproduce the original results of Beaudry and DiNardo, then go on to estimate a specification including two proxies for match-specific quality, denoted as q^{eh} and q^{hm}. Their estimating equation is

$$w_{i,t+s,t} = \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 u^{min}_{i,t+s,t} + \gamma_1 \ln q^{eh}_{i,t} + \gamma_2 \ln q^{hm}_{i,t} + \epsilon_{i,t+s}. \tag{4}$$

The match quality proxies turn out to be strongly significant and have the expected positive sign. Moreover, in this specification $u^{min}_{i,t+s,t}$ is no longer significant and U_{t+s} becomes significant again. Hagedorn and Manovskii view these results as evidence that wages are determined in a spot market.

2.2 Measuring Match Quality

The proxies q^{eh} and q^{hm} build on the idea that the number of offers a worker receives is positively correlated with match quality. In Hagedorn and Manovskii's model, if an employed worker receives a job offer and accepts it, then it must be the case that match quality has been weakly improved. Similarly, if a worker receives a job offer and rejects it, then current match quality is preferable to the alternative. Hence a worker who receives many offers has better match quality, whether these offers were accepted or rejected. A key empirical challenge is how to measure the number of offers a worker receives. The reasoning above suggests that labor market tightness, measured before and during a particular job, may convey information about the number of offers. As an example consider a worker i employed in the same job between periods T_{begin} and T_{end}, with $T_{end} > T_{begin}$. If the sum of labor market tightness between T_{begin} and T_{end} is high, and we observe i staying at her job, then i received and rejected relatively many job offers. Therefore i's job must have high match quality. Following this logic, the variable $q_{i,t}^{hm}$ is defined as

$$q^{hm} = \sum_{t=T_{begin}}^{T_{end}} \left(\frac{V_t}{U_t} \right), \tag{5}$$

where V_t is an index of vacancies and U_t is the unemployment rate in period t.

The same line of reasoning implies that match quality in the current job is also sensitive to market tightness in employment periods preceding the current job. In the example above assume that worker i had a different job prior to the current one. Moreover, while working on the previous job the labor market was tight and she received many offers. The fact that she accepted the current job suggests that the quality of the current match is higher. Hence past labor market tightness conveys information about current match quality. The variable $q_{i,t}^{eh}$ is meant to capture past labor market conditions and is defined as,

$$q^{eh} = \sum_{t=T_1}^{T_{begin}} \left(\frac{V_t}{U_t} \right), \tag{6}$$

where $T_1 < T_{begin}$ denotes the first period of the employment cycle, that is, the first period of work after involuntary unemployment.[8]

2.3 Decomposing Match Quality Proxies

Match quality proxies in (5) and (6) are summations of tightness ratios. Their values are constant for a given worker-job pair because summations are taken over completed employment

[8]The interval between T_1 and T_{end} must not be interrupted by involuntary unemployment spells, as this would make it hard to argue for sequential on-the-job renegotiations.

intervals. They can be rewritten as

$$q^{hm} \equiv (T_{end} - T_{begin}) \frac{\sum_{t=T_{begin}}^{T_{end}} \left(\frac{V_t}{U_t}\right)}{T_{end} - T_{begin}} \equiv T_{beg}^{end} \times \bar{q}^{hm}, \tag{7}$$

and

$$q^{eh} \equiv (T_{begin} - T_1) \frac{\sum_{t=T_1}^{T_{begin}} \left(\frac{V_t}{U_t}\right)}{T_{begin} - T_1} \equiv T_1^{beg} \times \bar{q}^{eh}. \tag{8}$$

Equations (7) and (8) illustrate that, if worker i received many job offers while on a job, this could be because she has been employed for a long time (high T_{beg}^{end} and T_1^{beg}) or because average labor market tightness was high ($\bar{q}^{hm}$ and $\bar{q}^{eh}$). We refer to these components as *'duration'* and *'tightness'*. The duration component is a chronological measure of employment and is positively correlated with the number of offers received and rejected.[9] The tightness component is a measure of market quality while employed, and captures the fact that the arrival rate of offers in a given time interval can vary.[10]

We allow these two elements to vary independently in the following specification,

$$\begin{aligned} w_{i,t+s,t} = {} & \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 u_{i,t+s,t}^{min} + \\ & + \gamma_1 \ln \bar{q}_{i,t}^{eh} + \gamma_2 \ln T_{1,(i,t)}^{beg} + \gamma_3 \ln \bar{q}_{i,t}^{hm} + \gamma_4 \ln T_{beg,(i,t)}^{end} + \epsilon_{i,t+s}. \end{aligned} \tag{9}$$

Letting these components free to vary independently has two advantages: (i) it clarifies what drives the remarkable significance of tightness-based proxies; (ii) it highlights key differences in the wage dynamics of different occupation groups, as we show in Section 4.3.

3 Data

The data source for wages and workers' characteristics is the National Longitudinal Survey of Youth (NLSY79). We construct the (weekly) job history for each worker and identify an observation as the wage of a worker at the current job.[11] We construct the minimum and current unemployment rates using the seasonally adjusted unemployment series from the Current Population Survey (CPS). We use the Composite Help Wanted Index constructed by Barnichon (2010) as a measure of vacancies. Details about data are in Appendix A.

[9]The duration component is different from a standard job-tenure effect that is truncated at the observation date. We separately control for standard employer-tenure effects.

[10]The correlation between these components in NLSY data is positive but fairly low, around 10%.

[11]For each week we define the 'main job' as the one with the highest mode of reported hours worked. Past research focuses on male workers. For comparability we follow this convention.

Key to the analysis is the concept of employment cycle. An employment cycle is defined as a continuous spell of employment, possibly entailing a sequence of jobs and employers. The cycle begins in the period when the worker transitions from non-employment to employment, and ends when the worker transitions back to involuntary non-employment.[12]

To measure individual employment cycles, and job spells within each cycle, we follow Wolpin (1992), Barlevy (2008), and Hagedorn and Manovskii (2013). At each interview date the NLSY provides a complete description of jobs held since the last interview, including start and stop dates (week), wage, hours worked, and occupation. In addition one can link employers across interviews and identify a job as a worker's spell with a given employer.

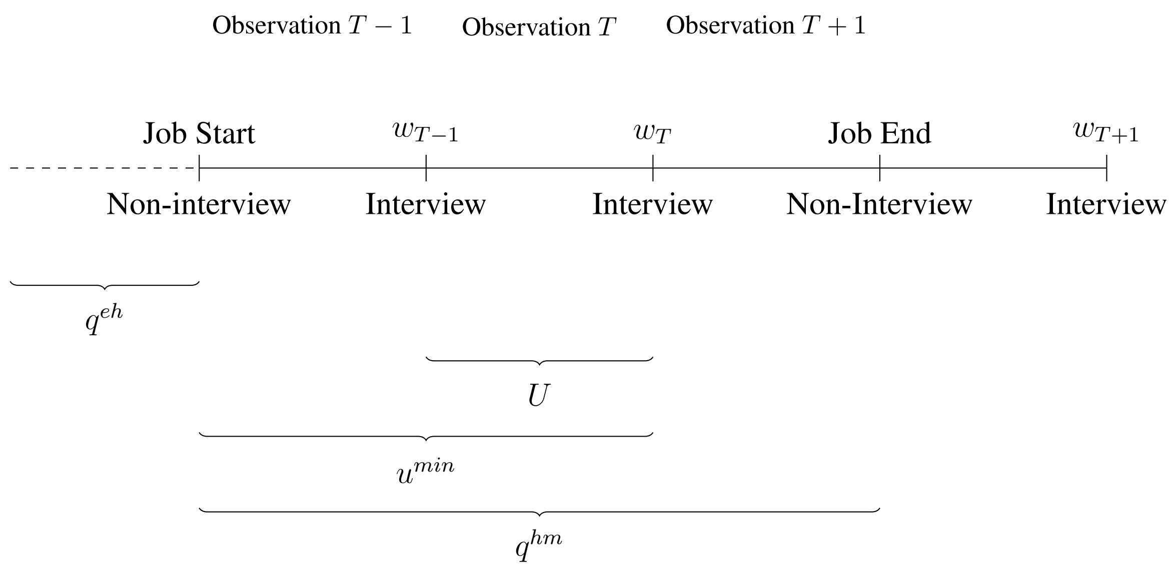
In the NLSY79 the information related to a specific job is only recorded once per interview. Therefore wage changes within a job are recorded only if an individual works at the same job for a period covered by two or more interviews, implying that within-job wage variation is identified using jobs that extend over at least two NLSY interview dates. If a job appeared for the first time in the year T interview, and again in the year $T+1$ interview, then this job counts as two observations within the same employment cycle. Each observation is a wage-job pair. The wage refers to a job that was active at any time between the current and the previous interview date. Thus we view an observation (a wage-job pair) as the wage prevailing over the period between two successive interviews while employed at a particular job, or in any subset of that period during which the job was active.

For illustration consider the example in Figure 1. A worker is interviewed at date $T-2$, begins to work for a specific employer between $T-2$ and $T-1$, is interviewed again at $T-1$, T, and $T+1$, but eventually stops working for this employer at some point between T and $T+1$. Given this sequence of events, we use the wage w_{T-1}, recorded during the first interview, as the wage applying to the period between the start of the job and $T-1$. Similarly, we use the wage w_T for the period between $T-1$ and T, and the wage w_{T+1} for the period between T and the end of the job.

Partitioning the data into employment cycles and job spells allows us to construct the match quality proxies described in Section 2. We use data on aggregate vacancies and unemployment to calculate tightness ratios $\frac{V_t}{U_t}$ and define: (i) q^{eh} as the sum of tightness ratios from the beginning of the employment cycle to the period preceding the start of the current job; (ii) q^{hm} as the sum of market tightness ratios during a job spell. The latter captures past, current and future tightness over the current job spell and reflects the expected match quality of that particular job.

[12] As in Barlevy (2008) and Hagedorn and Manovskii (2013) a separation is considered voluntary if (i) the worker reports a quit, rather than a layoff; and (ii) the interval between the end of the previous job and the beginning of the next is shorter than 8 weeks. Employment cycles may include short periods of non-employment.

Figure 1: Employment Cycles: an Example.



In line with previous research we assign to each observation a *minimum* unemployment rate defined as the lowest unemployment recorded between the start of the job and the date of the current interview (or the job's end date, if it occurs earlier than the interview). The *contemporaneous* unemployment rate is the average unemployment recorded over the period in which a job is active, between consecutive interview dates. Figure 1 illustrates how match quality proxies and unemployment rates are assigned to an observation w_T: q^{eh} is the sum of labor market tightness from the start of the employment cycle until the start of the current job; q^{hm} is the sum of labor market tightness from the start to the end of the current job. Contemporaneous unemployment applies to the interval between $T-1$ and T, and the minimum unemployment refers to the interval between the start of the current job and period T.

To separately examine the wage processes across broad occupation categories we classify occupations as either (i) routine or non-routine; or (ii) cognitive or manual (see Autor and Dorn, 2013). When looking at education groups we separately consider: (i) high school dropouts (less than 12 years of schooling); (ii) high school graduates and those with 'some college' (12 to 15 years of schooling); (iii) college graduates (16 or more years of schooling). More details are in Appendix A.

4 Results

In this section we report estimates for different specifications and samples. First, we use the full data sample and estimate equations (3) and (4), corresponding to the baseline specifications in Beaudry and DiNardo (1991) and Hagedorn and Manovskii (2013). Second, we show how distinguishing between duration and tightness components improves our understanding of the strong effects of match quality proxies. Next, we turn to the analysis of different occupation groups, and complement those results by providing further evidence based on education categories. Finally, we discuss various robustness exercises based on Bellou and Kaymak (2016) and Gottfries and Teulings (2015). As in previous studies we include dummies for age, employer tenure, marital status, industry, union status, SMSA, region, as well as quadratic polynomials for education and year. All specifications control for individual fixed effects.

4.1 Pooled Sample Estimates

Table 1 reports the results. Column (1) illustrates the relationship between contemporaneous unemployment and wages. A significant relationship exists between current unemployment and current wages: a one percentage point increase in contemporaneous unemployment is associated with a 2.26% drop in wages. This result is in line with those of previous studies using similar specifications.

Column (2) reproduces the baseline result of Beaudry and DiNardo. When we include the minimum unemployment experienced during a job the contemporaneous unemployment variable is no longer significant. In contrast, minimum unemployment turns out to be highly significant: a one percentage point increase in minimum unemployment is, on average, associated with a 3.02% decline in current wages.[13]

The third column of Table 1 refers to a specification further extended by adding the log of match quality proxies defined in equations (5) and (6). The q variables are strongly significant, have the expected positive sign and magnitudes comparable to existing estimates. Their inclusion changes the estimated relationship between current wages and different unemployment measures: minimum unemployment is no longer significant and its coefficient is close to zero, while current unemployment becomes significant.[14]

[13]This is in line with results in Beaudry and DiNardo, despite using different data (NLSY79 vs PSID) over a longer sample period. Estimates are also close to those reported by Bellou and Kaymak (2016), who use NLSY data up to 2008 and estimate the coefficient of minimum unemployment at -3.65%. Using NLSY data up to 2004, Hagedorn and Manovskii find that both contemporaneous and minimum unemployment have a significant impact on current wages (respectively, at 5% and 1% significance) but slightly lower magnitudes (respectively, -1.8% and -2.4%, see Table 1 in their paper). Restricting our sample to end in 2004, we also estimate current unemployment to be significant at the 1% level, albeit the magnitude does not materially change.

[14]This result confirms the findings obtained by Hagedorn and Manovskii using a shorter panel. We find the marginal effect of current unemployment to be roughly half their estimate (-0.928 vs. -1.83). This discrepancy becomes smaller when we flexibly control for match quality, as shown below.

Table 1: The relationship between unemployment rate and wages: pooled sample.

	Specification			
Variables	(1)	(2)	(3)	(4)
U	-2.264***	-0.739*	-0.928**	-1.313***
	[0.354]	[0.427]	[0.408]	[0.397]
u^{min}	-	-3.023***	-0.240	-0.898
		[0.590]	[0.567]	[0.682]
$\ln q^{eh}$	-	-	5.20***	-
			[0.551]	-
$\ln q^{hm}$	-	-	6.61***	
			[0.446]	
$\ln \bar{q}^{eh}$	-	-	-	6.11***
				[2.23]
$\ln dur(q^{eh})$	-	-	-	4.22***
				[0.310]
$\ln \bar{q}^{hm}$	-	-	-	-0.236
				[1.84]
$\ln dur(q^{hm})$	-	-	-	6.84***
				[0.479]
Observations	30,585	30,585	29,872	29,872
R-squared	0.587	0.587	0.593	0.596

Note a. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval. Sample sizes vary because the start date of an employment cycle is not always available.

Note b. Estimated coefficients and associated standard errors are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

4.2 Allowing for Distinct Match Quality Components

The inclusion of match quality proxies has a remarkable impact on estimates of the wage-unemployment relationship. The last column of Table 1 shows results for a specification that separately estimates the effects of duration and tightness. This more flexible specification improves precision and makes the effect of contemporaneous unemployment stronger, reinforcing the result in Column (3). Duration of employment, both in current and past jobs, is significant throughout. However, only past labor market tightness $\bar{q}^{eh}$ has a significant (and positive) effect on current wages. Average tightness while on the current job, $\bar{q}^{hm}$, has no detectable effect.

The size and significance of duration effects suggest that the expected number of offers experienced on the job increases with total job duration. Results are more nuanced for labor market tightness. The significance of past tightness confirms that match quality is higher when the current job is accepted after a run of low unemployment and/or high vacancy rates. However, the average tightness prevailing during the current job has no contemporaneous effect on wages. As we show below, this pattern cannot be generalized to all occupation groups.

4.3 Evidence from Occupation Groups

To retain reasonably large, and comparable, sample sizes we focus on broad occupation categories. Table 2 reports results obtained for, respectively, the samples of cognitive (Cog) and manual (Man) occupations. For comparison we reproduce the results from the pooled sample in Column (1). For each group we report results for a specification with aggregate match quality controls (Columns $2a$ and $3a$) as well as a specification that allows for distinct effects of duration and average tightness (Columns $2b$ and $3b$).

Cognitive vs Manual. Separately estimating the effect of match quality components makes a noticeable difference: while neither u^{min} nor U have a significant impact in specifications $2a$ and $3a$, a significant pattern emerges in the more flexible specifications.

Whether or not u^{min} is significant depends on the occupation group, as shown in Columns $2b$ and $3b$. For cognitive jobs the pattern closely resembles the one in pooled data: only current unemployment exhibits a significant coefficient, and match quality hinges on both durations and past tightness, with the effect of the latter even stronger than the one estimated from pooled data.

For manual occupations, however, the results are quite different: the lowest unemployment on the job (u^{min}) has a significant and large effect on wages, while contemporaneous unemployment is no longer significant. This is true after including match quality proxies.[15]

Routine vs Non-Routine. Table 3 focuses on a different classification, as occupations are divided into non-routine (NR) and routine (R). As before, the first column reproduces pooled results with flexible q controls. Columns (2a) and (3a) show group-specific results using aggregate $q's$, while columns (2b) and (3b) do the same for a specification with flexible match quality controls.

[15]For manual occupations average tightness during the current job, $\bar{q}^{hm}$, is negative and significant. This is not consistent with positive selection based on match quality and occurs in no other group or specification.

Table 2: Estimated effects of unemployment on wages, controlling for selection on match quality. cognitive vs manual jobs.

	Aggregate	Cog		Man	
Variables	(1)	(2a)	(2b)	(3a)	(3b)
U	-1.313***	-1.311*	-1.632**	-0.398	-0.933*
	[0.397]	[0.761]	[0.757]	[0.539]	[0.523]
u^{min}	-0.898	0.563	0.690	0.221	-2.110**
	[0.682]	[1.043]	[1.247]	[0.800]	[0.901]
$\ln q^{eh}$		7.03***	-	2.57***	-
		[0.941]		[0.768]	
$\ln q^{hm}$	-	7.10***	-	6.59***	-
		[0.837]		[0.618]	
$\ln \bar{q}^{eh}$	6.11***	-	12.8***	-	-2.57
	[2.23]		[4.30]		[2.90]
$\ln dur(q^{eh})$	4.22***	-	3.18***	-	3.63***
	[0.310]		[0.566]		[0.382]
$\ln \bar{q}^{hm}$	-0.236	-	3.36	-	-5.79**
	[1.84]		[3.19]		[2.60]
$\ln dur(q^{hm})$	6.84***	-	7.20***	-	8.66***
	[0.479]		[0.875]		[0.631]
Observations	29,872	12,254	12,254	12,617	12,617
R-squared	0.596	0.610	0.610	0.601	0.605

Note a. The table shows results for the pooled sample (column 1), and for different occupation groups (cognitive occupations in columns 2a and 2b; manual occupations in columns 3a and 3b).

Note b. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

For non-routine jobs we find little or no evidence of unemployment influencing wages, with only contemporaneous U significant at the 10% level. However, the match quality proxies remain strongly significant, with a pattern similar to the one estimated from pooled data. In fact, $\bar{q}^{eh}$ has an even stronger estimated effect on current wages, suggesting that past labor market tightness does matter for the wage dynamics in non-routine occupations.

Things look very different when we examine results for routine jobs: the impact of both

Table 3: Estimated effects of unemployment on wages, controlling for selection on match quality. non-routine vs routine jobs.

	Aggregate	Non R		R	
Variables	(1)	(2a)	(2b)	(3a)	(3b)
U	-1.313***	-0.963	-1.379*	-0.874	-1.360**
	[0.397]	[0.759]	[0.762]	[0.548]	[0.543]
u^{min}	-0.898	0.226	0.255	-0.00493	-1.908**
	[0.682]	[1.050]	[1.240]	[0.777]	[0.944]
$\ln q^{eh}$	-	5.52***	-	3.57***	-
		[1.02]		[0.760]	
$\ln q^{hm}$	-	7.38***	-	6.53***	-
		[0.873]		[0.650]	
$\ln \bar{q}^{eh}$	6.11***	-	9.61**	-	0.563
	[2.23]		[4.63]		[2.82]
$\ln dur(q^{eh})$	4.22***	-	3.74***	-	3.43***
	[0.310]		[0.619]		[0.393]
$\ln \bar{q}^{hm}$	-0.236	-	2.50	-	-4.33
	[1.84]		[3.57]		[2.64]
$\ln dur(q^{hm})$	6.84***	-	7.88***	-	7.12***
	[0.479]		[0.873]		[0.667]
Observations	29,872	11,494	11,494	13,377	13,377
R-squared	0.596	0.641	0.642	0.619	0.622

Note a. This table shows results for the pooled sample (column 1), and for different occupation groups (non routine occupations in columns 2a and 2b; routine occupations in columns 3a and 3b).

Note b. The notation $\ln \bar{q}^{x}$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^{x})$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

current and lowest unemployment are significant at the 5% level, although the latter effect is estimated to be quite a bit larger (-1.91 *vs* -1.36). As in the case of manual jobs, the only significant match quality controls are the durations $dur(q^{eh})$ and $dur(q^{hm})$. The impact of average tightness is not well identified.

Taking stock of all these results, we conclude that there are large discrepancies in the wage-unemployment relationship across occupation groups. In manual and routine jobs the lowest unemployment experienced on the job is consistently significant and has a sizable effect on current wages. Moreover, in these groups match quality hinges exclusively on employment durations. In fact, average tightness (both past and present) shows little or no impact on wages. This evidence points to different wage determination mechanisms, and suggests that results based on pooled data conceal non-trivial differences, and provide imprecise descriptions of wage dynamics for some occupations.

Interestingly, past labor market tightness matters only when wages are not responsive to u^{min}. This holds for all occupation regressions shown above. We view it as evidence that for some occupations there exists genuine dependence on the best labor market conditions experienced on the job. This dependence is detected even after controlling for match quality. On the other hand, consistent with the intuition of Hagedorn and Manovskii, there are jobs for which the dependence of wages on lowest unemployment is an artifact of higher match quality. For such jobs average tightness is consistently significant.

Table 4: Education proportions (%) in NLSY79 sample, by occupation group

	cognitive	manual	non routine	routine
college graduates	47.10	9.88	46.46	16.25
high school graduates	47.38	66.14	44.37	65.95
high school dropouts	5.52	23.98	9.17	17.80
total	100	100	100	100

Note: Each column shows the share (%) of each education achievement within a given occupation group.

4.4 Evidence from Education Groups

As shown in Table 4 education categories are unevenly represented across occupations. For instance, the cognitive and non-routine groups over-sample workers with more education. We re-estimate our main specifications, equations (4) and (9), for different education groups.[16] Results in Table 5 show that patterns by education mirror those found for occupations. Current unemployment U has a significant effect at the higher-end of the education distribution (college graduates). Column (3b) shows that the coefficient is larger and more precisely estimated when we flexibly control for match quality. The wage-setting mechanism in college jobs allows for responses to current unemployment, as is the case for cognitive jobs. Moreover, just as in the occupation analysis, the non-significance of u^{min} goes hand in hand with the strong significance of $\bar{q}^{eh}$. In contrast, for high school graduates the best labor market

[16]We divide workers into three groups: high school dropouts, high school graduates (including those with some college) and college graduates.

Table 5: Evidence from education groups. Estimated effects of unemployment on wages by education group, controlling for selection on match quality.

	D		H		C	
Variables	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
U	-0.593	-1.276	-0.563	-0.768	-1.682**	-2.253***
	[0.934]	[0.919]	[0.469]	[0.467]	[0.820]	[0.834]
u^{min}	-0.272	-1.548	-0.540	-1.401*	-0.411	-0.484
	[1.232]	[1.340]	[0.667]	[0.816]	[1.252]	[1.448]
$\ln q^{eh}$	6.18***		3.05***		8.11***	
	[1.01]		[0.645]		[1.10]	
$\ln q^{hm}$	4.31***		5.04***		8.36***	
	[0.988]		[0.519]		[0.915]	
$\ln \bar{q}^{eh}$		10.2**		-0.696		17.3***
		[4.29]		[2.22]		[4.79]
$\ln dur(q^{eh})$		3.84***		2.98***		4.25***
		[0.563]		[0.349]		[0.667]
$\ln \bar{q}^{hm}$		-5.80		-0.0359		1.96
		[4.02]		[2.20]		[3.68]
$\ln dur(q^{hm})$		5.15***		5.15***		8.68***
		[1.07]		[0.548]		[0.967]
Observations	5,228	5,228	17,751	17,751	9,009	9,009
R-squared	0.515	0.518	0.549	0.551	0.576	0.577

Note a. This table shows results for three education groups (D= high school dropouts in columns 1a and 2a; H= high school graduates and some college in columns 1b and 2b; C= college graduates in columns 1c and 2c).

Note b. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

conditions (u^{min}) drive the relationship between unemployment and wages, a pattern evident also in routine and manual jobs.

4.5 Robustness

Given the apparent differences across occupation and education groups it is reasonable to ask whether results are sensitive to changes in empirical specification or sampling. Appendix B presents various robustness exercises. In Table B1 we replicate the analysis of pooled data using only observations with non-missing occupation codes. We do this to verify that no systematic error or biases are introduced when occupation is not recorded. We find that the overall patterns are unchanged, both in terms of point estimates and significance.

We also experiment with alternative specifications. First, we follow the approach in Bellou and Kaymak (2016) and difference out all time-invariant characteristics within a given job. By doing so we estimate how wage growth responds to changes in unemployment. First-differencing equation (4) implies that match quality proxies q^{eh} and q^{hm} (invariant within a job) drop out of the specification.[17] By construction the wage growth analysis only uses data for job stayers. Sample sizes are larger in the wage level specifications as they include data for both stayers and switchers. As shown in Table B2, results across occupation and education groups confirm the findings of the analysis based on levels. However, the first-difference specification for the pooled sample implies a significant role for both current and minimum unemployment, with the latter having a larger effect. This implies that wages of stayers are less cyclical than wages of switchers, as originally observed by Bils (1985).[18]

In a second alternative specification we follow the approach of Gottfries and Teulings (2015). They argue, among other things, that the match quality proxies introduced by Hagedorn and Manovskii are poor approximations to the theoretically correct measure of past market tightness. More specifically, they show that one should also include higher order terms of the logged q variables (see Appendix B for a discussion). In Table B3 we report results for wage specifications in levels that include higher order terms for $\ln q^{eh}$ and $\ln q^{hm}$. There appears to be no change from our baseline result.

5 Investigating the Mechanism

The evidence presented so far shows that the evolution of wages over employment cycles varies considerably across occupations. Different sensitivities to current unemployment are consistently detected, and may reflect underlying features of occupations. In this section we

[17]The first-difference is between two consecutive observations for an individual-job pair. Given the data structure, this does not imply a constant time interval.

[18]See also Bellou and Kaymak (2016) and Hagedorn and Manovskii (2013) for NLSY79 data and Haefke, Sonntag, and Van Rens (2013) for CPS data.

present evidence suggesting an explanation based on performance pay.

As documented by Lemieux, Macleod, and Parent (2009, 2012) and Makridis (2014), the incidence of bonus pay varies with features of the job. Performance-pay workers are concentrated in the upper end of the wage distribution, where most jobs entail relatively higher skills. This may be due to productivity being harder, or more expensive, to measure in certain occupations. While for some jobs (e.g. painting a wall) it is fairly easy to assess a worker's impact on output, the same is not easily determined in other occupations (for example, those involving collaborative efforts such as projecting and executing complex structures).

Lemieux, MacLeod, and Parent (2012) use the PSID to estimate the impact of local labor market shocks, measured by the county unemployment rate, for either bonus-pay or fixed-wage jobs. Their work shows that wages in bonus-pay jobs are sensitive to current labor market conditions. In contrast, jobs which entail no performance pay exhibit wage dynamics that are essentially uncorrelated with current unemployment.

These findings point to the possibility that variation in the relative incidence of performance pay jobs (PPJ) may be partly responsible for the differences across occupation and education groups described in Sections 4.3 and 4.4. To explore the relevance of this hypothesis we first confirm that wages in PPJ are very sensitive to labor market conditions, while wages in non-PPJ are not. Then we document that the incidence of PPJ differs across occupation and education groups, and does so in a way consistent with observed wage patterns.

5.1 Wages, Unemployment and Performance Pay

In certain years the NLSY79 questionnaire contains follow-up questions asking whether the worker's remuneration included bonuses or any commissions and piece-rate payments. We use these indicators of performance pay to determine whether a job can be classified as PPJ or not, and to measure the share of PPJ within a group.[19]

Next, we estimate our baseline specification separately for the PPJ and non-PPJ samples. Results are broadly consistent with those obtained from the PSID and county-level unemployment (see Lemieux, MacLeod, and Parent, 2012). Column (1) in Table 6 shows that wages that include some performance-based component are sensitive to both current and minimum unemployment. However, Column (2) indicates no significant effect of unemployment on wages for the non-PPJ sample.

Moreover, the relationship between unemployment and wages in the PPJ sample can be further qualified. Columns (3) and (4) in Table 6 document that sensitivity to different unem-

[19] We also have information about stock options, but do not use it. Including it would make our results even starker, but this information is only available for 2010. Details about measurement are reported in Appendix C.

ployment measures is also associated with union status. Current unemployment affects wages in the subset of non-unionized PPJ, but minimum unemployment co-moves with wages in unionized PPJ.[20]

Table 6: The relationship between unemployment rate and wages: Baseline regressions by PPJ and union status.

Variables	PPJ=1	PPJ=0	PPJ=1 & Union=0	PPJ=1 & Union=1
	(1)	(2)	(3)	(4)
U	-1.591***	-1.181	-1.882**	-0.217
	[0.586]	[0.799]	[0.751]	[1.261]
u^{min}	-3.290**	-0.659	-1.728	-9.372***
	[1.297]	[1.202]	[1.512]	[3.243]
$\ln \bar{q}^{eh}$	27.0***	5.28	32.1***	-2.36
	[5.77]	[3.70]	[6.23]	[26.6]
$\ln dur(q^{eh})$	5.04***	4.08***	3.87***	21.5***
	[0.866]	[0.535]	[0.992]	[4.37]
$\ln \bar{q}^{hm}$	9.33*	2.49	11.1*	13.0
	[5.27]	[4.03]	[5.87]	[26.6]
$\ln dur(q^{hm})$	7.97***	6.05***	8.31***	13.2**
	[1.33]	[0.818]	[1.41]	[5.89]
Observations	7,888	11,568	6,493	1,395
R-squared	0.719	0.619	0.730	0.712

Note a. The notation $\ln \bar{q}^{x}$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note b. Estimated coefficients and associated standard errors are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

How uneven is the incidence of either PPJ or union status across occupation and education groups? Tables 7 and 8 report the relative frequency of PPJ and unionization in our data. Cognitive occupations have a considerably higher occurrence of PPJ and a relatively low occurrence of unionization. This suggests that, in these occupations, compensation arrangements may be key for the sensitivity of wages to current unemployment. The same is observed for

[20]Lack of sensitivity of wages to unemployment in the non-PPJ sample persists when we re-estimate separately by union status. Results are available on request. Details on measurement of union status are in Appendix C.

jobs performed by college graduates.

On the other hand, low incidence of PPJ is associated with weak or no sensitivity to unemployment. For instance consider the sample of non-routine jobs, which consists of non-routine cognitive and non-routine manual occupations. The former group exhibits high PPJ and low unionization, which jointly imply significant sensitivity to current unemployment. In contrast, non-routine manual occupations have low incidence of PPJ, hence no responsiveness to any unemployment measure. These conflicting effects result in responses to unemployment that are almost non detectable for the broad group of non-routine occupations (see Table 3). By the same token, composition effects may also introduce sensitivity to both current and minimum unemployment, as we find for routine jobs. Routine cognitive jobs have the highest share of PPJ and the lowest unionization rate, suggesting sensitivity to current unemployment. In addition, routine manual jobs exhibit the highest share (8%) of jobs that are both PPJ and unionized.[21]

Table 7: Proportion of performance pay jobs (PPJ) and unionized jobs by occupation group.

Fine occupation groups	NRC	NRM	RC	RM
Share PPJ	42%	26%	56%	30%
Share Unionized	24%	19%	12%	29%
Coarse occupation groups	COG	MAN	R	NR
Share PPJ	45%	30%	35%	39%
Share Unionized	21%	28%	26%	23%

Note a. Top Panel: Proportion of jobs with at least one type of performance pay component (Share PPJ) or unionized jobs (Share Unionized) for four fine occupation groups.
Note b. Bottom Panel: Proportion of jobs with at least one type of performance pay component (Share PPJ) or unionized jobs (Share Unionized) for coarse occupation groups (either COG vs MAN or R vs NR).
Note c. Shares based on data for which PPJ and union status are both available. Details in Appendix C.

Similar patterns emerge when looking at education groups. For example, high school graduates display moderate PPJ incidence as well as high unionization, consistent with the observation of no effect from current unemployment and borderline significant sensitivity to minimum unemployment. Unemployment measures have no detectable impact on the wages of high-school dropouts, who exhibit the lowest share of PPJ.

[21]For comparison non-routine manual have only 4% of PPJ unionized jobs, while cognitive occupations are well below 6%.

Table 8: Proportion of performance pay jobs (PPJ) and unionized jobs by education group.

	COL	HSG	HSD
Share PPJ	49%	38%	31%
Share Unionized	20%	29%	18%

Note a. Shares based on data for which PPJ and union status are both available. Details in Appendix C.

6 Conclusions

We document significant differences in the evolution of wages across occupations. Wages in cognitive occupations, and those of workers with college education, respond strongly to current unemployment. The same is not true of wages in manual and routine jobs: in these occupations the wage setting mechanism features a prominent role for the best labor market conditions experienced by workers, as reflected in the minimum unemployment rate recorded while on the job.

These results hold in specifications that allow for match quality controls. We approximate match quality through observed employment durations and through average labor market tightness while employed. While duration-based measures of match quality are consistently significant across occupations, the same is not true for the average tightness proxies.

Consistent differences in wage responses suggest the presence of underlying factors shaping the earning process in different occupations. Using information available in the NLSY79, we show that one such difference is the extent to which compensation is linked to observed performance. The choice of compensation scheme appears to be associated with the sensitivity of wages to current and past unemployment levels.

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A Data

In this section we describe the data sources, as well as how we construct work histories and other relevant variables.

A.1 Data Sources

The main data source is the National Longitudinal Survey of Youth (NLSY79). The NLSY79 is a nationally representative sample of individuals aged 14 to 22 in 1979. The sample period is 1979 to 2010, which makes the maximum age in the sample equal to 53. The NLSY79 consists of three samples: a main representative sample, a military sample, and a supplemental sample designed to over-represent minorities. We only use the main representative sample. Throughout the analysis we focus on males 16 years or older. Observations for which the reported stop date of the job precedes the reported start date, as well as jobs that last less than 4 weeks, are dropped. Following Hagedorn and Manovskii we impose some basic sampling restrictions: (i) all observations for which the reported hours worked are below 15 hours are excluded; (ii) the education variable is forced to be non-decreasing over the life cycle. Wages are deflated using the CPI. Following Barlevy (2008) we only consider observations with reported hourly wages above $\$0.10$ and below $\$1,000$. Only observations for individuals that have completed a long-term transition to full time labor market attachment are used in the analysis. As in Yamaguchi (2010), an individual is considered to have made this transition starting from the first employment cycle that lasts 6 or more quarters. Finally, for each job we assign the mode of hours worked as the relevant value for that job. The reorganized NLSY79 data consists of 34,860 job-wage observations, for a sample of 5,712 individuals. Not all of these observations can be used in the estimation because some control variables may be missing in certain years.

A.2 Jobs and Employment Cycles

We define each job as one subset of an employment cycle during which the employer does not change. Each wage observation in the NLSY79 is linked to a measure of the *current* unemployment rate and to a measure of the *minimum* unemployment rate since the start of the job to which the wage refers. To construct the minimum and current unemployment rates, we use the seasonally adjusted unemployment series from the Current Population Survey (CPS). We use the Composite Help Wanted Index constructed by Barnichon (2010) as a measure of vacancies.[22] We use the crosswalk provided by Autor and Dorn (2013) to link Census occupation codes with Dorn's 'standardized' occupation codes.[23] We classify occupations

[22]https://sites.google.com/site/regisbarnichon/research.

[23]David Dorn's crosswalks are available at http://www.cemfi.es/dorn/data.htm.

into four categories: non-routine cognitive, non-routine manual, routine cognitive, and routine manual.[24] Furthermore, as in Yamaguchi (2012), if a worker reports having the same job between period t and $t+2$, with occupation i in year t, occupation B in year $t+1$, and again occupation i in $t+2$, then we assume that occupation B is misclassified and we correct it to be A. To minimize the effects of other coding errors, we follow Neal (1998) and Pavan (2011) and disregard observations that report a change in occupation within a job (during a spell with the same employer). Industry codes are aggregated up to 15 major categories to make them comparable over time. In order to reduce the effects of industry coding error, and similar to the treatment of occupations, we only consider observations for which there are no industry changes within the job.

B Robustness

This appendix reports details and results for the robustness exercises described in Section 4.5.

B.1 Robustness of Pooled Data Results

Table B1 reports results for pooled data using only observations with non-missing occupation codes. Previous studies of pooled data do not drop these observations. In the pooled data analysis of Section 4.1 we follow this convention. Here we verify how robust those findings are by restricting the sample to the same subset of observations that are used in the occupation-group analysis. The findings are essentially unchanged, both in terms of point estimates and significance.

B.2 Wage Growth Analysis

A key robustness check entails differencing out all characteristics that are invariant within a job. To this purpose we follow Bellou and Kaymak (2016) and estimate a time-differences specification. By first-differencing equation (4) one obtains the following specification,[25]

$$\Delta w_{i,t+s,t} = \tilde{\beta}_0 \Delta X_{i,t+s} + \tilde{\beta}_1 \Delta U_{t+s} + \tilde{\beta}_2 \Delta u^{min}_{i,t+s,t} + \Delta \epsilon_{i,t+s} \qquad \text{(A-1)}$$

The match quality measures q^{eh} and q^{hm} are invariant within a job and are differenced out. The interpretation of coefficients is similar to the previous analysis: if contemporaneous unemployment affects wages, one would expect that changes in current unemployment have a significant effect on wage growth; that is, $\tilde{\beta}_1$ should be negative and significant. If, instead,

[24] This classification replicates the one presented in Cortes and Gallipoli (2014), Table A.1.

[25] A first difference is between two consecutive observations for an individual-job pair. Given data structure, this is not a constant time interval.

Table B1: Aggregate Regressions-Robustness

	Specification				
Variables	(1)	(2)	(3)	(4)	(5)
U	-2.168***	-0.640	-0.881*	-1.344***	
	[0.391]	[0.496]	[0.477]	[0.462]	
u^{min}		-2.880***	0.0980	-0.735	
		[0.651]	[0.626]	[0.752]	
ΔU					-1.587***
					[0.539]
Δu^{min}					-2.766***
					[0.946]
$\ln q^{eh}$			5.46***		
			[0.603]		
$\ln q^{hm}$			6.97***		
			[0.5]		
$\ln \bar{q}_{eh}$				5.57**	
				[2.34]	
$\ln dur(q^{eh})$				4.19***	
				[0.341]	
$\ln \bar{q}_{hm}$				-0.447	
				[1.98]	
$\ln dur(q^{hm})$				7.28***	
				[0.519]	
Observations	25,401	25,401	24,871	24,871	21,953
R-squared	0.589	0.590	0.596	0.599	0.007

Note a. The table shows results for the regression on U on column (1), the Beaudry and DiNardo specification in column (2), the original Hagedorn and Manovskii specification in column (3), the decomposed $q's$ specification at column (4) and the specification of Bellou and Kaymak (2016) in column (5).

Note b. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start date and end date. Significance: *** 1%, ** 5%, * 10%.

Note d. Regression is run only on observations for which occupation codes are non-missing.

the lowest unemployment during a job has a significant effect on wages, changes in the lowest unemployment rate on-the-job should also have an effect on wage growth; that is, $\tilde{\beta}_2$ should be negative and significant. A restriction implicit in the wage growth analysis is that it only uses information about job stayers. Sample sizes are larger in 'wage level' specifications as they include data for both stayers and switchers, exploiting wage variation also from periods in which workers switch jobs.

Table B2: Wage growth and unemployment changes. Specification in first-differences, pooled and by occupation.

	Aggregate	C	M	NR	R
VARIABLES	(1)	(2)	(3)	(4)	(5)
ΔU	-1.215***	-2.453**	-0.796*	-2.912***	-0.535
	[0.428]	[1.057]	[0.466]	[0.970]	[0.462]
Δu^{min}	-2.856***	-0.597	-4.637***	0.219	-5.159***
	[0.837]	[1.566]	[1.092]	[1.641]	[1.079]
Observations	27,741	10,067	11,887	9,567	12,387
R-squared	0.006	0.007	0.008	0.007	0.009

Note: The table reports estimation results obtained from a difference specification of the wage process. Staring from column 1, we report results for the pooled sample, C-cognitive, M-manual, NR-non-routine and R-routine occupation groups. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start date and end date.
Significance: *** 1%, ** 5%, * 10%.

Table B2 reports estimates for the pooled sample, as well as for occupation groups. Results in Columns (2)-(5) are broadly consistent with previous findings. Wage growth in cognitive jobs (Column 2) and non-routine jobs (Column 4) visibly responds to changes in the contemporaneous unemployment. In contrast, wage growth in manual jobs (Column 3) and routine jobs (Column 5) is very sensitive to changes in lowest unemployment on-the-job, and does not respond to changes in contemporaneous conditions. Moreover, the results from the pooled sample (Column 1) indicate a significant role for both current and minimum unemployment, with the latter having a larger effect. This is consistent with the view that wages of stayers are less cyclical than wages of switchers, as discussed by Bils (1985), Bellou and Kaymak (2016), Hagedorn and Manovskii (2013) for NLSY79 data and Haefke, Sonntag, and Van Rens (2013) for CPS data.

B.3 Higher Order Approximations of Labor Market Tightness

In a wide ranging study of the wage setting mechanism Gottfries and Teulings (2015) argue that the match quality proxies introduced by Hagedorn and Manovskii (2013) are poor approximations to theoretically correct measures of labor market tightness. In the context of a wage-posting model Gottfries and Teulings show how current wages depend on labor market

Table B3: Specification with higher order terms. Estimated effect of unemployment on wages, controlling for selection on match quality. (1) Aggregate, (2a) cognitive, (2b) manual, (3a) non routine, (3b) routine

	Aggregate	Cog	Man	Non R	R
Variables	(1)	(2a)	(2b)	(3a)	(3b)
U	-1.277***	-1.586**	-0.845	-1.267*	-1.321**
	[0.396]	[0.749]	[0.523]	[0.765]	[0.541]
u^{min}	-1.078	0.711	-2.803***	-0.291	-2.121**
	[0.678]	[1.256]	[0.908]	[1.266]	[0.960]
$\ln \bar{q}^{eh}$	2.66	3.78	-2.21	3.20	-0.234
	[2.39]	[4.75]	[3.17]	[5.02]	[3.03]
$\ln dur(q^{eh})$	3.48***	2.67***	3.71***	2.78***	3.57***
	[0.476]	[1.01]	[0.631]	[1.04]	[0.613]
$\ln \bar{q}^{hm}$	-2.31	8.21	-17.3***	-4.70	-7.74*
	[3.15]	[6.66]	[4.30]	[6.57]	[4.38]
$\ln dur(q^{hm})$	4.53*	11.7*	-4.08	-0.216	3.61
	[2.74]	[6.17]	[3.50]	[6.02]	[3.53]
$(\ln q^{eh})^2$	0.924**	0.682	0.402	1.32*	0.448
	[0.387]	[0.743]	[0.509]	[0.752]	[0.502]
$(\ln q^{hm})^2$	0.233	-0.453	1.16***	0.767	0.356
	[0.263]	[0.587]	[0.343]	[0.574]	[0.348]
$(\ln q^{hm}) \cdot (\ln q^{eh})$	0.422***	0.896***	-0.0167	0.748***	0.112
	[0.113]	[0.237]	[0.195]	[0.244]	[0.172]
Observations	29,872	12,254	12,617	11,494	13,377
R-squared	0.596	0.610	0.606	0.642	0.622

Note a. This table shows results for the pooled sample (column 1) and for different occupation groups (cognitive, manual, non routine and routine in columns 2a,2b,3a and 3b respectively).

Note b. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

Table B4: Specification with higher order terms. Estimated effect of unemployment on wages, controlling for selection on match quality, by education group (High School Dropouts, High School Grads, College grads)

	D	H	C
Variables	(1)	(2)	(3)
U	-1.262	-0.746	-2.220***
	[0.918]	[0.466]	[0.835]
u^{min}	-1.576	-1.584*	-0.465
	[1.408]	[0.834]	[1.479]
$\ln \bar{q}^{eh}$	6.55	-2.76	7.77
	[4.98]	[2.40]	[5.34]
$\ln dur(q^{eh})$	3.42***	2.36***	4.05***
	[1.17]	[0.550]	[1.09]
$\ln \bar{q}^{hm}$	-3.71	-2.92	6.64
	[7.99]	[3.57]	[7.17]
$\ln dur(q^{hm})$	7.71	2.18	12.5*
	[6.53]	[2.94]	[6.53]
$(\ln q^{eh})^2$	-1.99**	0.588	1.77**
	[0.948]	[0.515]	[0.818]
$(\ln q^{hm})^2$	-0.270	0.304	-0.394
	[0.679]	[0.289]	[0.612]
$(\ln q^{hm}) \cdot (\ln q^{eh})$	0.385	0.306*	1.01***
	[0.287]	[0.157]	[0.275]
Observations	5,228	17,751	9,009
R-squared	0.518	0.551	0.578

Note a. This table shows results for three education groups (D = high school dropouts, in column 1; H = high school graduates and some college, in column 2; C = college graduates, in column 3).

Note b. The notation $\ln \bar{q}^x$, with $x = \{hm, eh\}$, denotes the natural logarithm of the average labor market tightness, and $\ln dur(q^x)$ is the duration of the corresponding employment interval.

Note c. Estimated coefficients (and associated standard errors) are multiplied by 100. All standard errors are clustered by observation start-date and end-date. Results are robust to clustering by individual. Significance: *** 1%, ** 5%, * 10%.

history from the beginning of an employment cycle up to the date in which the current job ends. Letting 'b' denote the end date of the current job, the sum of past labor market tightness over the employment cycle can be written as $\Lambda_b = q_{eh} + q_{hm}$. While it is possible to approximate $\ln \Lambda_b$ using the logs of q_{eh} and q_{hm}, one should also include higher order terms of the logged q variables to account for the fact that $\ln \Lambda_b \neq \ln q_e h + \ln q_h m$. In Table B3 we report results for wage specifications (in levels) that include higher order terms for $\ln q_e h$ and $\ln q_h m$. We find no substantial change relative to our baseline results.

C Performance Pay and Union Status in the NLSY79

The NLSY79 reports partial information about performance pay for the years 1988 to 1990, 1996, 1998 and 2000. For years $1988 - 1990$ individuals were asked whether, in their most current job, earnings were partly based on performance. For years $1996, 1998, 2000$, individuals were asked for each of their jobs if earnings featured any of the following types of compensation: piece rate, commission, bonuses, stock options and/or tips. Therefore in $1996, 1998, 2000$, for each job-individual pair we generate a binary variable indicating if that particular type of compensation was used in determining the pay received for that job. A performance pay observation is then a job-year-individual triplet for which one of following conditions is satisfied:

- The year is $1988, 1999$ or 1990, and the individual reports being paid based on performance;
- The year is $1996, 1998$ or 2000 and the individual reports having earnings based on at least one among tips, commission, bonuses or piece rate.
- It is a job-year-individual triplet pertaining to a job/individual pair that satisfies one of the above two conditions for at least one of the interviews. This imposes the restriction that the performance pay status is constant within a job, adding observations for the years in which the performance pay variables are not available.

In the NLSY79 there are three variables with information on union status. The first (based on the Employer History Roster section of the NLSY questionnaires) states whether an individual is covered by a union or employee contract. It is available for all years. The second variable asks the respondent if he/she is a member of a union or employee association. It is available for year 1979 and from 1986 onwards. The third variable asks the respondent if he/she is covered by a union or employee association. It is available starting in 1994. We assign a union status for an individual whenever at least one of the three variable indicates that a worker is either a member or is covered by a union. Otherwise, we assign a non-union status.