

# Revisiting the Relationship Between Unemployment and Wages\*

João Alfredo Galindo da Fonseca<sup>†</sup> Giovanni Gallipoli<sup>‡</sup> and Yaniv Yedid-Levi<sup>§</sup>

July 15, 2016

## Abstract

We investigate 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 provides an imprecise description of earning dynamics. We examine these discrepancies and offer new evidence suggesting that the sensitivity of wages to current unemployment is linked to the prevalence of performance pay.

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\*Financial support from the Social Sciences and Humanities Research Council is gratefully acknowledged. We thank Paul Beaudry and Baris Kaymak for helpful discussions.

<sup>†</sup>UBC, Vancouver School of Economics. E-mail: joaoalfredo.galindodafonseca@alumni.ubc.ca

<sup>‡</sup>UBC, Vancouver School of Economics. E-mail: gallipol@mail.ubc.ca

<sup>§</sup>UBC, Vancouver School of Economics. E-mail: yaniv@mail.ubc.ca

# 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.<sup>1</sup> 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 Bilal (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'.<sup>2</sup> 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.

Existing evidence mostly 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.

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<sup>1</sup>One exception is Grant (2003) who analyzes separate cohorts and allows for gender-specific effects.

<sup>2</sup>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).<sup>3</sup> 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.<sup>4</sup>

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.<sup>5</sup>

Our findings indicate that differences exist in the way labor is assessed and remunerated across occupations. In Section 5 we investigate the mechanism driving these differences and present new evidence highlighting the role played by performance-related pay incentives. Using information from the NLSY79 about workers' total pay, we find that occupations in which wages are more sensitive to current unemployment also exhibit a higher occurrence of performance-based earnings. We also find that jobs in these occupations entail longer durations, and wages that are more responsive to match quality. Oyer (2004) argues that a potential role of performance-related pay is to retain good matches. This new evidence supports the view that firms may be using profit-sharing to retain well-matched workers in particular occupations and this retention motive may help in shaping observed differences in wage dynamics across occupations.

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<sup>3</sup>Like the latter two papers we use data from the National Longitudinal Survey of Youth (NLSY79) between 1979 and 2010.

<sup>4</sup>All results are robust when we estimate specifications for wage differences, which by construction restrict the sample to job stayers.

<sup>5</sup>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

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

where  $S_{ijt}$  is tenure with employer  $j$  and  $X_{it}$  is years of labor market experience.<sup>6</sup> The unobserved component  $\epsilon_{ijt}$  consists of aggregate (cyclical) productivity  $y_t$ , individual fixed effect  $a_i$ , time-invariant match quality  $m_{ij}$ , and i.i.d. shock  $\eta_{ijt}$ :

$$\epsilon_{ijt} = y_t + a_i + m_{ij} + \eta_{ijt}. \quad (2)$$

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.<sup>7</sup>

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

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<sup>6</sup>This is similar to the representation in Altonji and Shakotko (1987) and follows Bellou and Kaymak (2016).

<sup>7</sup>For a comprehensive discussion of these issues see Bellou and Kaymak (2016).

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

$$w_{i,t+s,t} = \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 u_{i,t+s,t}^{min} + \epsilon_{i,t+s}. \quad (3)$$

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  $t+s$ ;  $u_{i,t+s,t}^{min}$  is the minimum unemployment rate experienced by individual  $i$  while on a job that started in period  $t$ , and is defined as  $u_{i,t+s,t}^{min} = \min\{U_{t+s-k}\}_{k=0}^s$ . 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  $\beta_1$ . Their key result is that the inclusion of  $u_{i,t+s,t}^{min}$  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  $\beta_1$  no longer significant.

This finding is revisited by Hagedorn and Manovskii (2013). They argue that the significance of  $u_{i,t+s,t}^{min}$ , 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,  $u_{i,t+s,t}^{min}$  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

$$w_{i,t+s,t} = \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 u_{i,t+s,t}^{min} + \gamma_1 \ln q_{i,t}^{eh} + \gamma_2 \ln q_{i,t}^{hm} + \epsilon_{i,t+s}. \quad (4)$$

The match quality proxies turn out to be strongly significant and have the expected positive sign. Moreover, in this specification  $u_{i,t+s,t}^{min}$  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

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

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,

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

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

### 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

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<sup>8</sup>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

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

and

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

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.<sup>9</sup> 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.<sup>10</sup>

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

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

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.<sup>11</sup> 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.

<sup>9</sup>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.

<sup>10</sup>The correlation between these components in NLSY data is positive but fairly low, around 10%.

<sup>11</sup>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.<sup>12</sup>

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.

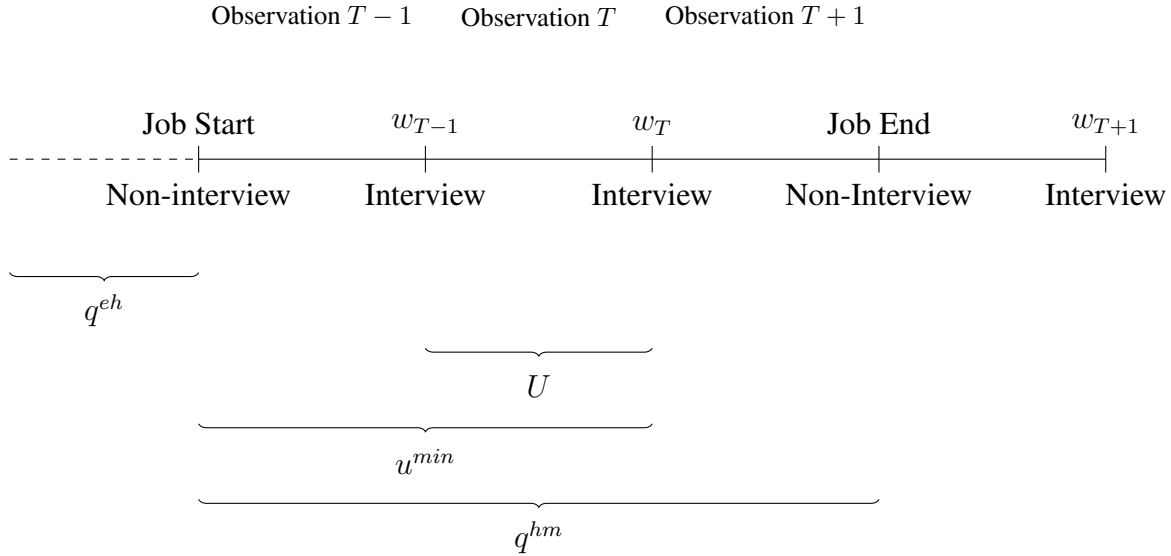
Partitioning the data into employment cycles and job spells allows us to construct the match quality proxies described in Section 2. We use data on aggregate vacancies and unemployment to calculate tightness ratios  $\frac{V_t}{U_t}$  and define: (i)  $q^{eh}$  as the sum of tightness ratios from the 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.

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<sup>12</sup>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 specifica-

tions 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 effect of contemporaneous unemployment drops to one third of that estimated in Column (1) and is only marginally significant at the 10% level. 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.<sup>13</sup>

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.<sup>14</sup>

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<sup>13</sup>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.

<sup>14</sup>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.

Variables	Specification			
	(1)	(2)	(3)	(4)
$U$	-2.264*** [0.354]	-0.739* [0.427]	-0.928** [0.408]	-1.313*** [0.397]
$u^{min}$	-	-3.023*** [0.590]	-0.240 [0.567]	-0.898 [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). In Appendix B we also report results for a specification with no match quality controls: this exercise shows that the original result of Beaudry and DiNardo holds for all occupation groups. This confirms that the inclusion of match quality controls is key to correctly identify the relationship between unemployment and wages.

**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 the effect of contemporaneous unemployment is smaller and only marginally significant at the 10% level. This is true after including match quality proxies.

Interestingly, for manual occupations the average tightness during the current job,  $\bar{q}^{hm}$ , has a negative and significant effect. This contrasts with the non-negative effect estimated for all

other occupation groups and suggests a counter-cyclical composition effect in match quality for manual jobs. Such counter-cyclical composition is consistent with bad matches dissolving at a higher frequency during recessions, as discussed in Bellou and Kaymak (2016) and Bills (1985).

**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.

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 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  $w^{min}$ . 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 2: Estimated effects of unemployment on wages, controlling for selection on match quality. cognitive vs manual jobs.

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

## 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.<sup>15</sup>

<sup>15</sup>We divide workers into three groups: high school dropouts, high school graduates (including those with some college) and college graduates.

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

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

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, in line with the occupation analysis, the non-significance of  $u^{min}$  goes hand in hand with

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.

the strong significance of  $\bar{q}^{eh}$ . In contrast, for high school graduates current unemployment does not exhibit a significant effect while the best labor market conditions ( $u^{min}$ ) appears to be more statistically and economically significant, a pattern reminiscent of our findings for routine and manual jobs.

As we did for occupations, we also replicate the analysis by education group with no match quality controls. The results, reported in Appendix B, indicate a strong and highly significant effect of minimum unemployment in all groups other than high school dropouts. Current unemployment is not significant for all groups. The results for college graduates stand in sharp contrast to the findings obtained using match quality controls.

## 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 C 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.<sup>16</sup> 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

<sup>16</sup>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.



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

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

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).<sup>17</sup>

<sup>17</sup>See also Bellou and Kaymak (2016) and Hagedorn and Manovskii (2013) for NLSY79 data and Haefke, Sonntag, and Van Rens (2013) for CPS data.

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 C 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 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.<sup>18</sup> A complementary explanation is that heterogeneous turnover costs make it more desirable to link pay to the market value of performance, linking wages to firms' outcomes. This argument is spelled out by Oyer (2004) who suggests that workers' retention may be key to understand the prevalence of profit-sharing and performance-related pay components. An implication of this argument is that we should observe a positive association between the prevalence of performance pay and the duration of employment relationships across different occupations.<sup>19</sup>

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. They show that wages in bonus-pay jobs are sensitive to current labor market conditions. By contrast, jobs entailing no performance pay exhibit wage dynamics that are uncorrelated with current unemployment.

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<sup>18</sup>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).

<sup>19</sup>Evidence of such retention motives is presented by Drago and Heywood (1995). They show that profit sharing is more common at firms with highly skilled workers because these workers are expensive to replace. They also find that turnover is negatively associated with profit-sharing.

This evidence points to the possibility that the relative incidence of performance pay jobs (PPJ) is partly responsible for the different wage dynamics observed across occupation groups. To explore this hypothesis we first establish that wages in PPJ are very sensitive to current labor market conditions, while wages in non-PPJ are not. Next, we document that the incidence of PPJ differs across occupation and education groups, and does so in a way consistent with observed wage patterns. Finally, in Section 5.3 we present direct evidence that certain jobs (PPJ, cognitive and non-routine jobs) have significantly higher average durations.

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.<sup>20</sup>

## 5.1 Wages, Unemployment and Performance Pay

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 a 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 unemployment 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.<sup>21</sup>

Oyer (2004) argues that a potential role of performance-related pay is to retain good matches. Our findings on differences in wage dynamics across groups corroborates this insight. As shown in Table 6, both average tightness and job duration play a significant role in wage dynamics for PPJs. This is especially evident when we look at non-union PPJs, for which average tightness measures turn out to be larger and more significant. Non-union jobs are more likely to be jobs in which pay schemes serve the purpose of retaining valuable employees, and our results show that wage dynamics in these jobs exhibit both stronger tightness gradients and

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<sup>20</sup>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 D.

<sup>21</sup>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 D.

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*** [0.586]	-1.181 [0.799]	-1.882** [0.751]	-0.217 [1.261]
$u^{min}$	-3.290** [1.297]	-0.659 [1.202]	-1.728 [1.512]	-9.372*** [3.243]
$\ln \bar{q}^{eh}$	27.0*** [5.77]	5.28 [3.70]	32.1*** [6.23]	-2.36 [26.6]
$\ln dur(q^{eh})$	5.04*** [0.866]	4.08*** [0.535]	3.87*** [0.992]	21.5*** [4.37]
$\ln \bar{q}^{hm}$	9.33* [5.27]	2.49 [4.03]	11.1* [5.87]	13.0 [26.6]
$\ln dur(q^{hm})$	7.97*** [1.33]	6.05*** [0.818]	8.31*** [1.41]	13.2** [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%.

sensitivity to current labor market conditions. These patterns are, to a large extent, apparent also when looking at those skilled occupations where retention through profit-sharing is more common.

## 5.2 Incidence of Performance Pay

Why the prevalence of performance pay differs across jobs is an open question. One hypothesis is that high turnover costs in certain firms induce them to link pay to profits or to measures of ex-post performance. This may be true even if, in the case of large firms, individual performance has only a small influence on firms' profits. The reason for this is that retention considerations (participation constraints) induce firms to use variable compensation as a way

to keep workers when they are most in demand. This line of argument suggests that employee profit-sharing or other forms of performance-related pay should be relatively more attractive in occupations which are in strong demand. This is clearly the case of cognitive and non-routine jobs over the past few decades, as documented for example by Autor and Dorn (2013) and Cortes, Jaimovich, Nekarda, and Siu (2015).

How uneven is the incidence of either PPJ (and 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 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.<sup>22</sup>

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.

### **5.3 Job Duration and Performance Pay**

If turnover and retention motives are in fact leading to performance-related pay schemes, one should also observe longer job durations for PPJs. This in turn would imply that occupations with a high incidence of such pay schemes should have significantly longer job durations. We

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<sup>22</sup>For comparison non-routine manual have only 4% of PPJ unionized jobs, while cognitive occupations are well below 6%.

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

<i>Fine occupation groups</i>				
	NRC	NRM	RC	RM
Share PPJ	42%	26%	56%	30%
Share Unionized	24%	19%	12%	29%
<i>Coarse occupation groups</i>				
	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 D.

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%

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

Table 9: Summary statistics of job durations in different job groups.

	Mean	S.D.	Observations
PPJ=1	49.9	34.0	7,888
PPJ=0	38.6	31.3	11,568
C	40.9	31.0	8,329
M	32.4	29.2	6,988
NR	41.0	31.0	7,709
R	32.8	29.4	7,518

Duration measured in quarters. Figures based on data for which PPJ is available. Details in Appendix D.

report evidence supporting this conjecture in Table 9 where we show the mean and standard deviation of job durations for different groups in our NLSY79 sample. All differences (PPJ vs. non PPJ, cognitive vs. manual, routine vs. non-routine) are extremely significant, at levels well below 1%, and confirm that PPJ jobs, or occupations in which PPJs are more prevalent,

have much higher durations, with all differences being about 8 quarters or more.<sup>23</sup>

## 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 workers' performance and firms' outcomes. The prevalence of performance-related compensation schemes varies across occupations, and is associated with the sensitivity of wages to current and past unemployment levels.

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<sup>23</sup>Durations in Table 9 refer to a sample of workers with relatively strong labor market attachment and are higher than durations for the overall population. We use the same sample as in the main analysis, described in Appendix A. Results, available upon request, are similar when we break down workers by education or when we condition on PPJ status within each occupation group.

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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.<sup>24</sup> We use the crosswalk provided by Autor and Dorn (2013) to link Census occupation codes with Dorn's 'standardized' occupation codes.<sup>25</sup> We classify occupations

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<sup>24</sup><https://sites.google.com/site/registbarnichon/research>.

<sup>25</sup>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.<sup>26</sup> 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 Analysis without Match Quality Controls**

In what follows we report results obtained from a specification with no match quality controls, as the one in Beaudry and DiNardo (1991), for different occupation groups. Minimum unemployment Table B1 shows that only minimum unemployment is significant, in all occupation groups. Its effect is remarkably similar across occupations and precisely estimated around  $-2.5$ . This is in stark contrast to the results obtained in Section 4.3, where we show material differences in the sensitivity to different unemployment measures (current vs minimum) across occupations. This discrepancy confirms that controlling for match quality is of critical importance for the identification of the effects of unemployment on wages.

Similar findings are obtained when grouping workers according to their education. Table B2 shows that current unemployment is never significant, while minimum unemployment on the job has a sizable and significant effect for both high school and college graduates.

## **C Robustness**

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

### **C.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.

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<sup>26</sup>This classification replicates the one presented in Cortes and Gallipoli (2014), Table A.1.

Table B1: Estimated effects of unemployment on wages, by occupation group. No controls for match quality.

	C	M	NR	R
Variables	(1)	(2)	(3)	(4)
$U$	-0.986 [0.745]	-0.272 [0.566]	-0.631 [0.75]	-0.879 [0.579]
$u^{min}$	-2.632** [1.036]	-2.368*** [0.774]	-2.799** [1.088]	-2.576*** [0.755]
Observations	12,513	12,888	11,724	13,677
R-squared	0.606	0.595	0.638	0.613

Note a. Sample sizes vary because the start date of an employment cycle is not always available.

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

Table B2: Estimated effects of unemployment on wages, by education group. No controls for match quality.

	D	H	C
Variables	(1)	(2)	(3)
$U$	-0.571 [0.940]	-0.386 [0.471]	-1.295 [0.813]
$u^{min}$	-1.792 [1.198]	-2.727*** [0.647]	-3.615*** [1.259]
Observations	5,444	18,555	9,170
R-squared	0.51	0.546	0.57

Note a. Sample sizes vary because the start date of an employment cycle is not always available.

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

## C.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

Table B1: Aggregate Regressions-Robustness

Variables	Specification				
	(1)	(2)	(3)	(4)	(5)
$U$	-2.168*** [0.391]	-0.640 [0.496]	-0.881* [0.477]	-1.344*** [0.462]	
$u^{min}$		-2.880*** [0.651]	0.0980 [0.626]	-0.735 [0.752]	
$\Delta U$					-1.587*** [0.539]
$\Delta u^{min}$					-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.

specification. By first-differencing equation (4) one obtains the following specification,<sup>27</sup>

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

<sup>27</sup>A first difference is between two consecutive observations for an individual-job pair. Given data structure, this is not a constant time interval.

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, 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)
$\Delta U$	-1.215*** [0.428]	-2.453** [1.057]	-0.796* [0.466]	-2.912*** [0.970]	-0.535 [0.462]
$\Delta u^{min}$	-2.856*** [0.837]	-0.597 [1.566]	-4.637*** [1.092]	0.219 [1.641]	-5.159*** [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. Starting 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.

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

Variables	Aggregate (1)	Cog (2a)	Man (2b)	Non R (3a)	R (3b)
$U$	-1.277*** [0.396]	-1.586** [0.749]	-0.845 [0.523]	-1.267* [0.765]	-1.321** [0.541]
$u^{min}$	-1.078 [0.678]	0.711 [1.256]	-2.803*** [0.908]	-0.291 [1.266]	-2.121** [0.960]
$\ln \bar{q}^{eh}$	2.66 [2.39]	3.78 [4.75]	-2.21 [3.17]	3.20 [5.02]	-0.234 [3.03]
$\ln dur(q^{eh})$	3.48*** [0.476]	2.67*** [1.01]	3.71*** [0.631]	2.78*** [1.04]	3.57*** [0.613]
$\ln \bar{q}^{hm}$	-2.31 [3.15]	8.21 [6.66]	-17.3*** [4.30]	-4.70 [6.57]	-7.74* [4.38]
$\ln dur(q^{hm})$	4.53* [2.74]	11.7* [6.17]	-4.08 [3.50]	-0.216 [6.02]	3.61 [3.53]
$(\ln q^{eh})^2$	0.924** [0.387]	0.682 [0.743]	0.402 [0.509]	1.32* [0.752]	0.448 [0.502]
$(\ln q^{hm})^2$	0.233 [0.263]	-0.453 [0.587]	1.16*** [0.343]	0.767 [0.574]	0.356 [0.348]
$(\ln q^{hm}) \cdot (\ln q^{eh})$	0.422*** [0.113]	0.896*** [0.237]	-0.0167 [0.195]	0.748*** [0.244]	0.112 [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 [0.918]	-0.746 [0.466]	-2.220*** [0.835]
$u^{min}$	-1.576 [1.408]	-1.584* [0.834]	-0.465 [1.479]
$\ln \bar{q}^{eh}$	6.55 [4.98]	-2.76 [2.40]	7.77 [5.34]
$\ln dur(q^{eh})$	3.42*** [1.17]	2.36*** [0.550]	4.05*** [1.09]
$\ln \bar{q}^{hm}$	-3.71 [7.99]	-2.92 [3.57]	6.64 [7.17]
$\ln dur(q^{hm})$	7.71 [6.53]	2.18 [2.94]	12.5* [6.53]
$(\ln q^{eh})^2$	-1.99** [0.948]	0.588 [0.515]	1.77** [0.818]
$(\ln q^{hm})^2$	-0.270 [0.679]	0.304 [0.289]	-0.394 [0.612]
$(\ln q^{hm}) \cdot (\ln q^{eh})$	0.385 [0.287]	0.306* [0.157]	1.01*** [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%.



### C.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 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  $\ln \Lambda_b \neq \ln q_{eh} + \ln q_{hm}$ . In Table B3 we report results for wage specifications (in levels) that include higher order terms for  $\ln q_{eh}$  and  $\ln q_{hm}$ . We find no substantial change relative to our baseline results.

## D 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.