ISSN 1936-5330

kcFED Research Working Papers

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November 2012; Updated August 2018
RWP 12-08

Federal Reserve Bank of Kansas City

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Abstract

Evidence from the National Longitudinal Survey of Youth (NLSY) suggests the cyclicality of job duration depends on the worker's prior and future employment status. For example, among matches formed with previously nonemployed workers, those that end with the worker returning to nonemployment have pro-cyclical duration. In contrast, matches that end because the worker switches to another job have counter-cyclical duration. Moreover, differences in starting wages do not account for these observed patterns.

Keywords: Job duration, match quality, business cycles, search and matching, wages.

JEL classification: E24, E32, J21, J22, J62, J63, J64.

*This paper has greatly benefited from the comments of Pok-sang Lam (the Editor) and two anonymous referees. The author also thanks Mark Bils, Yongsung Chang, Mary Daly, Jessica Ford, William Hawkins, Toshihiko Mukoyama, Nick Sly, Willem Van Zandweghe, Benjamín Villena-Roldán, and seminar participants at Rochester and the Kansas City Fed for useful discussions and comments. Excellent research assistance was provided by William Xu and Emily Pollard. The views expressed in this paper are solely those of the author and do not necessarily represent the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System. José Mustre-del-Río is a Senior Economist at the Economic Research Department of the Federal Reserve Bank of Kansas City (E-mail: jose.mustre-del-rio@kc.frb.org).

Knowing how job quality varies over the business cycle is central for many issues in the labor market, yet measuring quality is typically done indirectly since it is unobservable. Indeed, motivated by the seminal work of Bowlus (1995), many subsequent papers have interpreted the observed pro-cyclicality of job duration as evidence of pro-cyclical job quality as lengthy jobs should reflect good matches.[1]

However, the implication that a job's duration reveals its quality (e.g. Jovanovic, 1979) ignores two separate mechanisms that shape the relationship between duration and quality: endogenous job destruction and on-the-job search. First, with endogenous job destruction (e.g. Mortensen and Pissarides, 1994), some low quality matches are created in expansions and destroyed in recessions. All else equal, these low quality matches have pro-cyclical duration. Second, allowing workers to search on-the-job generates matches with counter-cyclical duration that may nonetheless be high quality. Indeed, a high quality match mechanically lasts longer in a recession because employed workers switch jobs less frequently in contractions.[2]

With these two mechanisms in mind, this paper presents new evidence on the cyclicality of job duration, and asks whether duration is a good proxy for match quality. Data from the National Longitudinal Survey of Youth (NLSY) 1979-2010 suggest the cyclicality of job duration varies by the worker's prior and future employment status. For example, matches formed by a previously nonemployed worker who becomes nonemployed once the match ends (*NN matches*) are longer if they start in booms, but are more likely to end as current conditions deteriorate. In contrast, matches formed by a previously nonemployed worker who transitions to another job once the current one ends (*NE matches*) are shorter if they begin in expansions, but are more likely to survive deteriorating current conditions.

Since job duration depends on whether the worker has or will execute a job-to-job transition, the relationship between duration and quality is complex. Returning to the previous examples, the pro-cyclical duration of NN matches is consistent with low match quality: these matches are formed in expansions while quality standards are low, but dissolve in recessions when quality standards rise. Consistently, workers in these matches are the least educated in the analyzed sample. Meanwhile, the duration of NE matches shows how on-the-job search leads to counter-cyclical duration in spite of higher quality. In an expansion, some higher quality NE matches are cut short as workers come into contact with new employers and switch into even better jobs. In a recession, these same matches are longer because the contact rate with prospective employers is lower. Overall, duration alone is not sufficient to characterize quality, but conditioning by prior and future employment status helps disentangle the effects of the previously outlined mechanisms.

Lastly, differences in initial pay do not explain these cyclical differences in duration. This suggests the starting wage may not reflect the true value of these matches and therefore is not the relevant cost used by firms when deciding to form these matches. Rather, work by Kudlyak (2014) argues the correct price is the user cost of labor: the expected difference between the present discounted value of wages paid to a worker hired today versus one hired tomorrow.

The current results suggest the cyclicality of the user cost of labor depends on match heterogeneity, which is proxied by the worker's prior and future employment status. Indeed, the results suggest initial wages understate the true value of NN and NE matches. Firms compensate for the low quality of NN matches by "locking-in" workers at a lower cost in a boom, as wages of prospective hires will be higher tomorrow. Additionally, these lower costs are expected to accrue for a while because of the pro-cyclical duration of these matches. Similarly, firms form NE matches in a boom in spite of their counter-cyclical duration, in part, because of their higher quality, but also because they expect both turnover and wages of future hires to rise as labor market conditions continue to tighten.

This paper is related to several strands of the empirical macro labor literature. The empirical analysis is closely related to the work of Bowlus (1995) who finds that matches starting in recessions are shorter and relates this to match quality being low in recessions and high in booms. This paper complements that work by considering the importance of the worker's pre- and post-employment status for accounting for cyclical variation in match duration and controlling for individual fixed heterogeneity. Distinguishing matches by prior and future employment status of the worker is necessary for finding the pro-cyclical duration of some matches versus the counter-cyclicality of others. This distinction also highlights that the link between duration and quality is obscured by the possibility of on-the-job search.[3] Accounting for individual fixed heterogeneity is critical for the finding that match duration is not solely internalized by initial wages.

Also related is the more recent empirical work of Kahn (2008) and Kahn and McEntarfer (2014). Using firm-level data, Kahn (2008) finds that employment relationships that start in recessions are short-lived. However, once firm heterogeneity is taken into account this effect is reversed, suggesting the importance of firm differences in explaining differences in job duration over the cycle. This paper complements that work by focusing on the worker side. Using U.S. matched employer-employee data, Kahn and McEntarfer (2014) find that downturns hinder the progression of workers toward higher paying firms. This paper is complementary to theirs as it shows how the duration of matches formed by workers who executed a job-to-job transition varies over the cycle and depends on whether the worker becomes nonemployed or switches to another job once the current match ends.

Additionally, Oreopoulos et al. (2012) and Altonji et al. (2016) find large and persistent earnings declines for new graduates entering the labor market during a recession.[4] They find the effect is strongest for the least skilled workers, reminiscent of a cleansing effect. Relative to these papers, the current paper is silent about long-term individual consequences of entering the labor market in a recession versus a boom. However, this paper's finding that NN matches are more likely to end in recessions (i.e. are cleansed) and are formed by less educated workers is consistent with their evidence.

Lastly, this paper is also related to the nascent literature on the user cost of labor. As previously mentioned, Kudlyak (2014) argues the correct labor cost is the user cost of labor and shows that this concept is more pro-cyclical than average wages and wages of new hires. This finding poses issues for a host of search and matching models that typically require wages to be fairly a-cyclical in order to generate empirically plausible vacancy and unemployment dynamics. More recent work by Basu and House (2016) shows that standard DSGE models augmented to replicate the cyclicality of the user cost of labor struggle to match the estimated reactions of key variables to identified monetary shocks. Importantly, the main results of these papers are based on a user cost of labor which assumes a common and a-cyclical separation rate. The results in this paper show separation rate dynamics are far richer, depending on match quality, which can be proxied by the worker's prior and future employment status. Extending the calculation of the user cost of labor along this dimension is an important direction of future research.

The next section discusses the estimation strategy and the data used for the empirical analysis. Section 2 presents the baseline estimation results, while Section 3 shows how many of the main results are not accounted by differences in starting pay. Finally, Section 4 concludes.

1. ESTIMATION AND DATA DESCRIPTION

This section outlines the estimation procedure used to measure the cyclicality of job duration. Then, the relationship between job duration and match quality is discussed, which highlights the importance of accounting for the worker's pre- and post-employment status. Finally, a description of the data is provided.

1.1 Estimation strategy

To assess the cyclicality of job duration, a Cox (1972) proportional hazard model with individual fixed effects is estimated. In the current context, the estimated hazard is interpreted as the instantaneous probability that a match ends today, conditional on surviving (lasting) up until today. This type of model is ideal as it allows for the inclusion of censored observations (i.e. matches that are still active during the sample frame) in the estimation without imposing additional assumptions on the hazard function. With individual fixed-effects this model takes the form:

$$\lambda_i(t|\mathbf{X}(t)) = \lambda_{i,0}(t)\exp(\beta'\mathbf{X}_i(t)) \tag{1}$$

where the subscript indexing the job is omitted for ease of presentation.

$\lambda_{i,0}(t)$ represents the baseline hazard of a job ending at time t. This hazard varies across individuals, but not across jobs for the same individual. This person-specific dependence is novel to the literature and helps alleviates biases arising from unobserved heterogeneity. For example, certain workers may systematically start (or leave) jobs at certain stages of the cycle. Not accounting for these systematic differences across workers will tend to bias inferences of the cyclical properties of job duration.[5]

Next, β is the coefficient vector to be estimated and $\mathbf{X}_i(t)$ is a vector of individual and aggregate controls. Individual characteristics are included in $\mathbf{X}_i(t)$ using indicators for race, educational attainment, and a cubic function in labor market experience. These variables are constant across jobs of the same individual. Aggregate conditions are measured by: the national unemployment rate when the match begins u_0, the current unemployment rate u_t, the square of the current unemployment rate u_t^2, an interaction term between initial and current conditions $u_0 \times u_t$, and year-fixed effects. Naturally, u_0 is constant across a job's entire duration, but potentially differs across jobs that begin in different stages of the cycle. The other aggregate variables vary from one period to the next as the job persists.

Among the aggregate variables, the estimated coefficients of the cyclical variables are central to the analysis. A positive coefficient on u_0 suggests matches starting in expansions are expected to last longer. The current unemployment rate, u_t, captures how current conditions affect hazard rates independent of when the match begins. Like Bowlus (1995) the current unemployment rate is introduced in a nonlinear manner, u_t^2, to help distinguish between the pro-cyclicality of voluntary switches and the counter-cyclicality of involuntary separations or layoffs. The interaction term, $u_0 \times u_t$, captures how initial conditions and current conditions interact. Including this variable is novel and follows the implications of Mortensen and Pissarides (1994), Menzio and Shi (2011), and Lise and Robin (2016): some low quality matches are formed in expansions only to be destroyed as soon as conditions deteriorate.

Year-fixed effects simply capture the unbalanced nature of expansions versus recessions. Expansions are more frequent and longer lasting than recessions, and by construction more matches will be observed in expansions. Not accounting for this unbalanced nature will tend to bias the estimated effects toward what occurs in expansions.

To facilitate the interpretation of the effects of the cyclical variables, the analysis in the next section provides illustrative examples of how their estimates translate into changes in median duration given different sets of aggregate conditions. Specifically, starting in a boom and currently being in a boom reflects a situation where u_0 is one standard deviation below its mean, and u_t is also one standard deviation below its mean. Starting in a boom and currently being in a bust reflects a situation where u_0 is still one standard deviation below its mean, but u_t is one standard deviation above its mean. Recall, the estimation of Equation 1 includes year fixed-effects, which account for the unbalanced duration of expansions versus recessions. Hence in these idealized counterfactuals, the boom-boom example should be thought of as a prolonged expansion, while the boom-bust example is a short expansion. Overall, comparing these cases helps interpret the magnitudes of estimated coefficients of the cyclical variables.

1.2 Match quality and the importance of pre- and post-employment status of the worker

The estimation strategy deliberately focuses on cyclical changes in match duration without making direct reference to match quality.[6] Models like Jovanovic (1979) imply a positive relationship between match quality and duration: when jobs are experienced goods workers remain in jobs that are revealed to be high quality and leave otherwise. However, as mentioned in the introduction, other features of the labor market like endogenous job destruction and on-the-job search may distort this positive relationship.[7]

First, models with endogenous job destruction (e.g. Mortensen and Pissarides, 1994) can generate low quality matches with pro-cyclical duration. In expansions, newly formed matches are of lower quality because high aggregate productivity allows for looser match-specific quality standards. However, once conditions slip these matches are destroyed because they do not meet the stringent quality standards of a recession.

Second, models with on-the-job search (e.g. Nagypál, 2005; Tasci, 2005; Krause and Lubik, 2006) can generate high quality matches with counter-cyclical duration. To illustrate this point, consider a match with high enough quality so that it is not endogenously destroyed in a recession or boom. This match lasts longer if it starts in a recession because the worker is less likely to find a better job through on-the-job search as vacancy creation falls in recessions and rises in booms. Hence, on-the-job search generates counter-cyclical duration.

These examples highlight the potential pitfalls of equating duration with quality, but also suggest what other information is useful in measuring the cyclicality of duration and its relationship with quality. Specifically, in the above examples the pre- and post-match employment outcomes of the worker are key.

For example, low quality matches that are formed in expansions and destroyed in recessions are likely to be formed by previously nonemployed workers who re-enter nonemployment when the match ends (i.e. NN matches). First, nonemployed workers are more likely to have lower reservation wages (compared to currently employed workers), and thus, more likely to accept low quality matches. Second, if some previously nonemployed workers have unobservable characteristics that make them less suitable for higher quality jobs they should also be more likely to re-enter nonemployment once the current match ends.

Separately, matches that end with job-to-job transitions (i.e. NE or EE matches) may be high quality matches regardless of their duration. Identical quality matches last longer if they start in recessions and end sooner if they start in booms, all because of the pro-cyclicality of the job-to-job transition rate.

1.3 Data

The data used in this study come from the National Longitudinal Survey of Youth (NLSY), survey years 1979 through 2010. The NLSY is a nationally representative sample of 12,686 young men and women who were 14-21 years old when first interviewed in 1979. Interviews were conducted annually through 1994 and biennially thereafter.

The NLSY has important advantages over other surveys for studying job duration. Compared to address based surveys, such as the Current Population Survey (CPS), individuals do not drop out of the sample following a change in geographical location, which may be highly correlated with job duration. During each interview participants report information for up to five jobs that can be linked across consecutive interviews. Thus, the NLSY's format allows for more consistent construction of duration variables when compared to surveys such as the Panel Study of Income Dynamics (PSID).[8] Importantly, the NLSY has a much longer panel dimension in comparison to other longitudinal surveys such as the Survey of Income and Program Participation (SIPP), which only follows individuals for a few years.

Following Bowlus (1995), the sample is restricted to males from the main cross-sectional subsamples. The analysis is further restricted to spells that start when the individual is at least 18 years old and not in school. Individuals must work at least 15 hours per week. Spells that end prior to 1979 or lasting less than a month are dropped. Unlike Bowlus (1995), all spells of an individual are considered, rather than restricting the sample to a single random spell per individual. Hence, the sample not only covers more years but also more information per individual. The proposed sampling scheme uses as much data as possible. Alternatively, one could use only the first two observed spells for each individual, as suggested by Chamberlain (1985), or use one randomly chosen spell as suggested by Bowlus (1995). These sampling schemes, in general, will lead to less efficient estimation.[9]

To construct the main sample of jobs and their respective durations, data from the

Employer Roster Survey is used. The sample is restricted to primary jobs; i.e., spells that are contained within the duration of another job are dropped. All jobs satisfying these requirements are used in the estimation. The resulting sample consists of 5,676 spells from 1,905 individuals. Additional details on variable construction appear in A.

The categorization of matches by prior and future employment status of the worker is key for the analysis in the subsequent sections. *E matches* are those formed by workers who performed a job-to-job transition to reach the current job.[10] *N matches* are those formed by workers who were previously nonemployed and were laid off from their last job. With these two definitions in hand, *NN matches* are those where the worker was previously nonemployed and becomes nonemployed once the current match ends. *NE matches* are those where the worker was previously nonemployed and executes a job-to-job transition once the current match ends. Lastly, *EE matches* are those where the worker executed a job-to-job transition to land the current job and executes another one once the current match ends.

Table 1 presents summary statistics for the entire sample and by prior and future employment status of the worker. Note, this sample excludes individuals with only one spell, as fixed-effects cannot be estimated with such individuals. It also excludes spells where the reason the previous (or current) job ended is unknown.[11]

Comparing columns of Table 1 reveals significant heterogeneity and underscores the importance of looking at the worker's employment history. For example, NN and NE matches are shorter, while EN and EE matches are longer. Within N matches, workers in NN matches are older, less educated, and more likely to be a minority. As the results in the next section show, even after controlling for these differences in observables the duration of NN matches has different cyclical properties compared to that of NE matches. Thus, distinguishing between NN and NE matches may proxy for some unobserved heterogeneity driving these results. As mentioned in the previous section, this unobserved heterogeneity may make workers in NN matches less suitable for other jobs and hence why they are not successful in moving up the job ladder compared to workers in NE matches.

Additionally, worth noting are the differences in initial and current conditions each type of match faces. NN and NE matches start when the unemployment rate is higher than average, while EN and EE matches start when the unemployment rate is lower than average. This latter observation is consistent with the fact that these matches start from a job-to-job transition and these transitions are pro-cyclical. Furthermore, matches also face different sequences of current conditions. While NN and EN matches experience on average lower unemployment rates during their existence, NE and EE matches survive higher unemployment rates. As mentioned in Section 1.2, these observations may reflect the higher quality of NE and EE matches compared to NN and EN (the former meet or exceed the higher quality standards of a recession), but also could be a mechanical artifact driven by the pro-cyclicality of the job-to-job transition rate (workers in NE and EE matches are less likely to switch jobs in recessions).

Finally, it is important to highlight that the analysis sample is not representative of the entire U.S. population as it follows men of a particular cohort. In particular, this cohort is young in the late 80s and early 90s, which are relatively tranquil periods, and more established in their career paths in the 2000s, which includes two recessions including the Great Recession. Since job mobility declines with age, results based on this NLSY sample may imply less cyclical variation in job duration compared to a more representative sample of individuals over the same period.

2. EMPIRICAL RESULTS

This section presents the main empirical results of the paper. The first subsection shows that matches starting in expansions are longer compared to matches that start in recessions. Meanwhile, changes in current conditions have offsetting effects on duration leaving it unchanged. The second subsection offers a more nuanced picture of the cyclicality of job duration once separating matches by the worker's pre- and post-employment status. In particular, the duration of NN matches rises if they begin in booms, but falls as current conditions deteriorate. In contrast, the duration of NE matches falls if they begin in booms, and rises as current conditions deteriorate.

2.1 Baseline results

Table 2 presents the results from estimating the hazard in Equation 1 and shows the importance of initial conditions for explaining variation in job duration. The standard errors in parentheses are clustered by time as this is the level of variation of the key explanatory variables (e.g. the initial and current unemployment rates).[12] Column (1) shows the initial national unemployment rate, u_0, has a positive and statistically significant effect on the hazard rate. In other words, matches starting in booms are of longer expected duration. Using a smaller sample and narrower time frame, Bowlus (1995) estimates a coefficient on the initial national unemployment rate of 0.0497, which is very similar to the coefficient presented in Column (1).

Importantly, though, the results in Column (1) do not account for individual unobserved heterogeneity in spite of using multiple spells per individual. Looking at the results in Column (3) shows that accounting for this heterogeneity across individuals increases the size and significance of the coefficient on u_0.

Next, the coefficients involving u_t show the opposing effects that current conditions have on duration. First, the coefficients on u_t and u_t^2 suggest that, holding initial conditions constant, a deterioration in current conditions boosts duration. Second, the negative sign on $u_0 \times u_t$ suggests any benefit from starting a match in a boom is dampened as aggregate conditions deteriorate. Overall, the net effect on duration is a quantitative question that depends on the relative strengths of these two forces.

As an example of the net effect, Table 3 presents how the coefficients in Table 2 translate into changes in median duration. Recall, starting in a boom represents the effect of u_0 being one standard deviation below its mean. Similarly, currently being in a bust represents the effect of u_t being one standard deviation above its mean. The first row of Table 3 presents the estimate of median duration under normal conditions (i.e. both the initial and current unemployment rates at their respective means). The remaining rows show how median duration moves when initial or current conditions change. The numbers in square brackets are 95% confidence intervals for each statistic.[13]

Focusing on Column (1) of Table 3, which is based on the estimates from Column (3) of Table 2, shows that initial conditions have a pro-cyclical relationship with duration. The second row shows median duration rises to 33 months (a 32% increase) if a match begins in a boom. The next row illustrates the importance of current conditions and how they interact with initial conditions. Recall, current conditions have two opposing forces on duration. First, holding initial conditions constant, worsening current conditions boost duration. Second, through their interaction with tight initial conditions, worsening current conditions shorten duration. Comparing the second and third rows of this table shows these two effects cancel out leaving duration unchanged at 33 months.

2.2 Results by previous and future employment status

The previous estimates suggest job duration is pro-cyclical. However, given the mechanisms outlined in Section 1.2, this could be entirely consistent with counter-cyclical match quality. This section explores how conditioning on the previous and future employment status of the worker may further clarify these observations.

For example, the previously measured pro-cyclical relationship between initial conditions and duration may reflect low quality NN matches. These matches are formed by previously nonemployed workers with lower reservation wages, which makes them more willing to enter low quality matches. Additionally, they may have unobservable characteristics that make them less suitable for higher quality jobs, which leads them to re-enter nonemployment when the match ends.

Separately, that a deterioration in current conditions (holding initial conditions fixed) is associated with longer duration may reflect the job-to-job transition rate falling in recessions.

In this case, some higher quality (i.e. good enough to survive the higher quality standards of a recession) NE or EE matches last longer than normal because the worker is unable to find another job quickly.

To address these conjectures, Table 4 presents hazard estimates by the pre- and post-employment status of the worker. Columns (1) and (3) examine NN matches and NE matches, respectively. Columns (5) and (7) consider EN and EE matches, respectively.

The results in Column (1), which are estimated with NN matches, support the first conjecture. The estimated positive coefficient on u_0 suggests these matches are longer if they start in a boom. However, the interaction term $u_0 \times u_t$, which is negative and significant, suggests the duration of these matches falls as current conditions slip, perhaps due to rising quality standards in recessions. Lastly, the coefficients on u_t and u_t^2 suggest that a deterioration in current conditions, holding initial conditions fixed, is also associated with lower duration (except for very small changes in u_t). Thus, deteriorating current conditions unambiguously reduce duration. These findings are consistent with these matches having low quality: they create positive surplus in an expansion when aggregate productivity is high, but not when aggregate productivity declines. Recall, the results in Table 1 show these matches are systematically formed by the least educated workers in the sample.

Meanwhile, the results in Column (3), which are estimated with NE matches, support the second conjecture. First, the estimated negative coefficient on u_0 implies matches that start in booms are shorter. Second, the coefficients on u_t and u_t^2 suggest that a deterioration in current conditions is associated with longer duration. Third, the positive coefficient on the interaction term suggests that slack current conditions also boost duration, provided initial conditions were tight. Overall, deteriorating current conditions unambiguously boost duration. These findings are consistent with the job-to-job transition rate rising in expansions (which reduces duration at the onset of the match) and falling in recessions (which boosts duration as current conditions slip). Importantly, the results from this column help explain the counter-cyclical relationship between current conditions and duration documented in the previous section.

Columns (1) and (3) of Table 5 present the median duration implications of the previous estimates and show the pro-cyclical duration of NN matches and counter-cyclical duration of NE matches. The first row shows that under normal conditions NN matches are roughly as long as NE matches. The second row illustrates the opposite effects that initial conditions have on the two types of matches. While the duration of NN matches rises if they start in booms (from 13 to 113 months), the duration of NE matches falls (from 14 to 9 months). Next, the third row highlights how deteriorating current conditions differentially affect each type of match. For NN matches that start in a boom, a deterioration in current conditions reduces median duration from 113 to 13 months. In contrast, the same experiment on NE matches boosts duration from 9 to 31 months.

Focusing next on matches with previously employed workers, the results in Columns (5) and (7) suggest that conditioning on post-employment status also matters for understanding duration. Indeed, the coefficient estimates in Column (5) are all insignificant, whereas the coefficient on u_0 in Column (7) is positive and statistically significant. That the duration of EE matches tends to rise with tight initial conditions may reflect the fact that in expansions workers who were already in good matches move further up the job quality ladder via job-to-job transitions (which are pro-cyclical) and hence land even better jobs from which they are less likely to be poached. This characterization also explains why NE matches, which also end via a job-to-job transition, are shorter in expansions: NE matches are likely on lower rungs of the job quality ladder and hence workers in these matches are more likely to be poached as new opportunities arise when conditions are initially tight.

To see the pro-cyclical duration of EE matches more directly, Column (7) of Table 5 illustrates the median duration implications of the previous estimates. The second row shows the duration of EE matches rises if they begin in booms, as workers move up the job quality ladder in expansions. The third row shows these matches survive a deterioration in current conditions as their duration continues to increase.

2.3 Summary

The results from the previous section highlight the importance of conditioning on both pre- and post-employment outcomes of the worker for understanding cyclical variation in job duration and how it relates to match quality.

For example, among matches formed by previously nonemployed workers, the cyclical behavior of duration varies by post-employment status. The duration of NN matches rises if they begin in booms and falls as current conditions slip. Meanwhile, the duration of NE matches falls if they begin in booms and rises as current conditions deteriorate. This latter finding is consistent with a pro-cyclical job-to-job transition rate, which makes it more likely for NE matches to end prematurely when conditions are tight, but less likely as labor market conditions slacken and job switching opportunities diminish. The former observation is consistent with NN matches being of low quality. They survive provided times are good and quality standards are low, but end once current conditions deteriorate and quality standards rise.

Among matches with previously employed workers, future employment status also matters. EE matches are longer if they begin in booms and survive deteriorating current conditions. This finding is also due to the pro-cyclicality of the job-to-job transition rate. In expansions, workers who were already in good matches move further up the job quality ladder and land even better jobs from which they are less likely to be poached, at least initially. As current conditions deteriorate these high quality matches survive the higher quality standards of a recession, but are also more likely to last because workers are less likely to switch jobs in recessions. Importantly, this characterization also explains why NE matches, which also end via a job-to-job transition, are shorter if they begin in expansions. NE matches are likely on the lower rungs of the job quality ladder and so workers in these matches are more likely to be poached early on when the market is tight.

3. ARE STARTING WAGES IMPORTANT?

This section extends the results from the previous section and concludes that several of the findings are robust to accounting for cyclical changes in starting pay.[14] In particular, starting wages alone do not fully reflect changes in the duration of NN and NE matches over the cycle.

3.1 Baseline results

To show starting wages do not internalize differences in expected duration over the cycle, Columns (2) and (4) of Table 2 repeat the estimation of Equation 1 but include initial (log) real wages in the regression. Column (2) of this table replicates the Bowlus (1995) finding that initial wages make the estimated coefficient on the initial unemployment rate, u_0, decline in magnitude and become insignificant. However, the Column (4) reveals that once individual fixed-heterogeneity is taken into account initial wages still matter, but so does the initial unemployment rate. Indeed, the estimated coefficient on u_0 is now roughly 0.08, which is not much different from what is reported in Column (3) where starting wages are excluded from the regression. Thus, the results in Column (4) suggest starting wages do not fully adjust to account for changes in duration over the cycle.

To gain insights into whether the results in Column (4) of Table 2 are quantitatively different from those reported in Column (3), the second column in Table 3 presents how median duration varies over the cycle given the current set of estimates. The first row shows that median duration under normal macroeconomic conditions and given an average starting wage is 24 months. The second row shows that median duration rises to 42 months if the match starts in a boom, which is larger than the increase implied by the results that do not control for starting wages. Lastly, the third row shows that a deterioration in current conditions dampens duration. Median duration falls from 42 to 26 months when current conditions turn unfavorable. This contrasts with the results in the previous section that show no change when current conditions deteriorate. This finding is because of the different estimated signs on u_t: the estimate is negative in Column (3), but positive in Column (4). Hence, a deterioration in current conditions by itself dampens duration (except for very large changes in u_t) once starting wages are taken into account.

The last row in Table 3 shows the large quantitative effect that changes in initial wages have on duration. In this scenario a low w_0 represents a 20% decrease in starting wages relative to the cross-sectional mean.[15] The key takeaway from this row is that lower initial wages essentially offset any of the benefits from starting a match in an expansion. For example, if a match starts in a boom, with an average starting wage, and current conditions are tight, then median duration is 42 months. However, all else equal, decreasing the starting wage by 20% reduces median duration to 30 months, or nearly a 30% decrease.

3.2 Results by previous and future employment status

This section mirrors the analysis from Section 2.2 and finds that many of those results are also robust to the inclusion of starting wages in the hazard regression. In particular, even once controlling for starting wages, NN matches are still found to be longer if they begin in expansions and shorter as current conditions slip. Meanwhile, NE matches are shorter if they begin in expansions and longer as current conditions slip. In contrast, the modest pro-cyclical relationship between the duration of EE matches and initial conditions vanishes once accounting for starting wages.

To see these points more clearly, Columns (2), (4), (6), and (8) of Table 4 present estimates by pre- and post-employment status when initial (log) real wages are included in the hazard equation. Columns (2) and (4) examine matches where the worker was previously nonemployed, but distinguish between those where the worker becomes nonemployed (*NN matches*) versus transitions to another job upon dissolution of the current match (*NE matches*). Meanwhile, Columns (6) and (8) present similar estimates, but consider matches where the worker was previously employed (*EN matches* and *EE matches*, respectively).

The estimates in Column (2) reiterate the characterization of NN matches from Section 2.2. The coefficients on the initial unemployment rate (u_0), the square of the current unemployment rate (u_t^2), and the interaction between initial and current conditions ($u_0 \times u_t$), are all statistically significant and of the same sign as in Column (1). Additionally, this column reveals that initial wages are a significant positive predictor of duration.

Turning to Column (4), these estimates reiterate the cyclical differences in the duration of NE versus NN matches. The coefficient on u_0 remains negative and statistically insignificant. Meanwhile, the inclusion of initial wages in the hazard regression increases the size and significance of the quadratic term of the current unemployment rate (u_t^2), and the interaction between initial and current conditions ($u_0 \times u_t$). Lastly, initial wages also have a statistically significant effect on duration.

To gauge the quantitative significance of the previously estimated coefficients, Columns (2) and (4) of Table 5 translate them into changes in median duration over the cycle. The second row of these columns reiterates the differential effects that tighter initial macroeconomic conditions have on NN versus NE matches. While starting in a boom increases the duration of an NN match, the duration of an NE match is unchanged.[16] The third row highlights the importance of current conditions. Worsening current conditions drags down the duration of an NN match, but increases the duration of an NE match. Next, the last row shows that changes in starting wages have significantly larger quantitative effects on the duration of NN matches. For example, low initial wages (i.e. a 20% decline) reduce the median duration of an NN match by 19% (i.e. a decline from 209 to 169 months). Meanwhile, the same experiment on an NE match leaves duration essentially unchanged (i.e. a decline from 15 to 14 months).

Turning next to matches with previously employed workers, Columns (6) and (8) of Table 4 show that initial wages are the only significant predictor of duration. When looking at EE matches, the results in Column (8) suggest that the previously documented pro-cyclical relationship between initial conditions and duration is entirely captured by starting wages.

Columns (6) and (8) of Table 5 present the duration implications of the previous estimates and reiterate the moderate pro-cyclicality of the duration of EE matches. Indeed, the second row of Column (8) reveals that better initial conditions boost the duration of EE matches from 19 to 23 months, which is nearly identical to the results from the previous section. The third row shows that a deterioration in current conditions decreases duration, though the effect is not statistically significant.[17] Lastly, the bottom rows in Columns (7) and (8) show that changes in starting wages have similar influences on the duration of EN and EE matches. For both of these matches, a 20% decrease in starting wages decreases duration by between 17% and 18%.

3.3 Summary

The results from the previous section reveal that differences in initial pay do not fully account for all of the observed differences in job duration documented in Section 2. In particular, even once controlling for initial wages, initial and current macroeconomic conditions still help predict the duration of NN and NE matches.

These results suggest starting wages do not capture the true value or cost of a match. Indeed, work by Kudlyak (2014) suggests that because employment relationships are long lasting and firms are forward-looking the user cost of labor (the expected difference between the present discounted value of wages to a worker hired today versus one hired tomorrow) is the relevant cost when deciding to form a match. Importantly, the current results suggest the user cost of labor not only depends on the cyclical state of the economy, but also on match quality as proxied by the worker's prior and future employment status.

For example, viewed through the lens of the user cost of labor the current results suggest firms "lock-in" workers in NN matches at a lower cost at the onset of a boom. This is because they anticipate wages of prospective hires to rise, consistent with a pro-cyclical new hire wage. Moreover, because of the pro-cyclical duration of NN matches, these lower labor costs are accrued for longer when the match is formed in an expansion. Overall, this helps explain why firms may still want to form (and maintain) low quality NN matches.

Similarly, the current results suggest firms benefit from hiring workers in NE matches during a boom for three reasons. First, wages of prospective hires will be higher tomorrow. Second, future NE matches are expected to be even shorter as the labor market tightens and the job-to-job transition rate rises. Third, these matches are likely of higher quality.

4. CONCLUSION

This paper measures how job duration varies over the business cycle and asks whether duration is a good proxy for match quality. Evidence from the NLSY suggests the cyclicality of job duration depends on the worker's prior and future employment status. The results also suggest match duration may not always be a good signal of match quality. For example, matches formed by previously nonemployed workers who become nonemployed once the match ends (NN matches) are expected to last longer if they start in booms, but are more likely to end as current conditions deteriorate. This pro-cyclical duration is consistent with low match quality: these matches are formed in expansions when quality standards are low, and are dissolved in recessions when standards are high. Consistent with this interpretation, these matches are systematically formed by less educated workers. In contrast, matches formed by previously nonemployed workers who transition to another job when the current match ends (NE matches) are expected to dissolve quickly if they start in booms, but are expected to last longer as current conditions deteriorate. This counter-cyclical duration is consistent with high match quality: these matches hastily end in expansions because the job-to-job transition rate is high, but nevertheless are good enough to survive higher quality standards in recessions, provided the worker is not poached during the prior expansion. Overall, these two observations highlight that quality cannot always be inferred from duration alone, but knowing the worker's employment trajectory helps.

Additionally, this paper finds these patterns are not explained by differences in initial wages. This highlights that the starting wage may not reflect the true value of a match and therefore is not the relevant cost that firms use when deciding to form matches. Because matches are long lasting and firms are forward-looking, the correct price is the user cost of labor as argued by Kudlyak (2014). With this in mind, the current results suggest initial wages understate the true value of an NN match because firms "lock-in" workers at a lower cost in a boom.

Thus, the current findings have potentially important implications for the measurement of the user cost of labor. For example, while Kudlyak (2014)'s calculation of the user cost of labor allows for job duration to depend on the initial and current conditions of the match, it assumes these hazards are independent of the worker's prior and future employment status. Thus, extending her analysis using the current findings is a fruitful direction of research.

Lastly, the firm dimension is an important component missing from the present analysis. The work of Kahn and McEntarfer (2014) highlights the importance of firm heterogeneity for understanding worker flows over the business cycle. Future research could extend the present analysis with matched employer-employee data to provide a richer description of cyclical variation in job duration.

Appendix A: DATA

The data used in the paper comes from the NLSY survey years 1979-2010. The Employer History Roster is used to compile all variables of interest detailed below.

- ***Wages.*** Wages are calculated from the Employer roster variables *EMPLOYERS ALL TIMERATE* , *EMPLOYERS ALL PAYRATE*, and *EMPLOYERS ALL HRLY WAGE.* All wages are deflated by the CPI-U all urban consumers index.

- ***Hours.*** Hours are calculated from the Employer roster variables *EMPLOYERS ALL HOURSWEEK* and *EMPLOYERS ALL HOURSDAY.*

- ***Start and stop dates.*** Dates are calculated from the Employer roster variables *EMPLOYERS ALL STARTDATE ORIGINAL*, *EMPLOYERS ALL STOPDATE*, and

EMPLOYERS ALL STARTWEEK.

- ***Layoffs and quits.*** Layoffs and quits are identified using the variable *EMPLOYERS ALL WHYLEFT.*

Using the variables that contain the start and stop dates for each job report, the start of the match is defined as the week when the job is first recorded. The end of the match is defined as the week when the job is last linked.[18] Gaps within the duration of a match are ignored. This distinguishes this paper's measure of job duration versus tenure on the job.

Appendix B: CALCULATION OF CONFIDENCE INTERVALS OF SURVIVOR FUNCTION

First note that the survivor function $S(t|\mathbf{X}(t))$ is related to the hazard function as:

$$S(t|\mathbf{X}(t)) = S_0(t)^{exp(\beta'\mathbf{X}(t))}$$

where $S_0(t)$ is the baseline survivor function, which is estimated following Breslow (1974), given an estimate of β from the Cox proportional hazard regression in Equation 1.

To construct a confidence interval for the estimated survivor function $\hat{S}(t|\mathbf{X}(t))$, an estimate of its asymptotic variance must be calculated. Following Link (1984) and Tsiastis (1981), the asymptotic variance of $\hat{S}(t|\mathbf{X}(t))$ is approximately:

$$\mathbf{var}\{\hat{S}(t|\mathbf{X}(t))\} \simeq \mathbf{var}\{\hat{S}(t|\mathbf{X}(t))|_{\beta}\} + \partial\hat{S}/\partial\beta'|_{\beta=\hat{\beta}}\mathbf{var}(\hat{\beta})\partial\hat{S}/\partial\beta|_{\beta=\hat{\beta}}.$$

The first term of this equation is the variance of $\hat{S}$ given β, which can be approximated using the formula outlined by Greenwood (1926). The second term of the equation is the variance of $\hat{S}$ associated with the estimation of β by $\hat{\beta}$. This second term is readily calculated given an estimate of $\mathbf{var}(\hat{\beta})$ following in Cox (1972).

Finally, by assuming normality the $100(1-\alpha)\%$ confidence interval of the survivor function is given by the usual expression:

$$\hat{S}(t|\mathbf{X}(t)) \pm z_{\alpha/2}\mathbf{se}\{\hat{S}\}$$

where $z_{\alpha/2}$ is the standard z-score and **se** is the standard error of $\hat{S}$ derived from above. The reported median durations in square brackets in Table 3 and Table 5 are the median durations associated with the upper and lower bounds of this confidence interval.

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Notes

[1] See for example, Barlevy (2002), Moscarini (2003), and Menzio and Shi (2011), among others.

[2]See for example, Nagypál (2005), Tasci (2005), Krause and Lubik (2006), and Mukoyama (2014), among others.

[3]Related to this point is the work of Barlevy (2002).

[4]See also, Kahn (2010) who finds similar results when using the NLSY.

[5]Additionally, each individual's spells are weighted by the inverse of the number of spells observed for them normalized by the number of survey waves to which they respond. Normalizing by the number of

survey waves helps distinguish between individuals who report few long duration jobs lasting over several years versus individuals who report few jobs because of attrition. This allows each individual to contribute equally in the likelihood estimation of Equation 1.

[6]This section is motivated by suggestions from an anonymous referee.

[7]Barlevy (2002) emphasizes that fewer job-to-job transitions in recessions will tend to reduce average match quality (i.e. a sullying effect).

[8]See Brown and Light (1992) for an in depth discussion of the issues when measuring job tenure in the PSID.

[9]Allison (1996) finds that the fixed-effects estimator is nearly always better than the conventional partial likelihood estimator when applied to repeated events (i.e. multiple spells) with unobserved heterogeneity.

[10]A job-to-job transition exists whenever the worker spent at most two weeks not working in between jobs and the previous job ended because of a quit.

[11]The online Appendix shows the main results are robust to relaxing this last restriction.

[12]The online Appendix shows the main results do not change when clustering by job spell, which accounts for correlation across observations of the same spell. Note that allowing for person-level fixed-effects controls for correlation across spells of the same individual.

[13]Details on their construction appear in Appendix B.

[14]See Pissarides (2009) for a summary of the evidence on the cyclicality of wages.

[15]This change is roughly half a cross-sectional standard deviation.

[16]This is similar to the statistically insignificant decline in Column (3), which does not control for starting wages. The difference in point estimates arises from the different size of the coefficient estimates for u_t, which can be seen by comparing Columns (3) and (4) in Table 4. In both cases, though, the coefficients are insignificant.

[17]This finding is different from what is reported in Column (7) where a deterioration in current conditions boosts duration. This comes from the fact that in Column (8) the estimated coefficient on u_t is positive, while in Column (7) the coefficient is negative.

[18]The duration of a job is defined as right-censored whenever the individual is currently working at the job during the time of the interview when the match is last reported.

Table 1. Summary statistics: NLSY sample

	(1)	(2)	(3)	(4)	(5)
	All	NN	NE	EN	EE
Median job duration (in months)	25	16	16	70	22
Avg. age when job starts	29.34	30.01	27.82	30.95	28.42
Avg. unemployment rate when job starts (u_0)	6.51	6.70	6.80	6.26	6.38
Avg. current unemployment rate (u_t)	5.89	5.88	6.26	5.78	6.05
% non-white	20.10%	27.58%	19.88%	17.68%	15.69%
% less than high school	19.24%	25.83%	19.88%	14.15%	17.06%
% high school	48.15%	50.49%	51.18%	49.59%	43.54%
% some college	17.46%	13.82%	18.13%	18.21%	19.62%
% college or more	15.15%	9.86%	10.81%	18.06%	19.78%
# of spells	5,676	1,541	971	1,329	1,835

Table 2. Benchmark hazard estimates

	All		All	
	(1)	(2)	(3)	(4)
u_0	0.05087*	0.04393	0.10256***	0.07545**
	(0.026)	(0.028)	(0.035)	(0.037)
u_t	-0.03955	-0.01510	-0.02589	0.08598
	(0.073)	(0.076)	(0.083)	(0.095)
u_t^2	-0.00633	-0.01054	-0.01314	-0.03430
	(0.016)	(0.018)	(0.021)	(0.023)
$u_0 \times u_t$	0.00923	0.00781	-0.01791	-0.01299
	(0.015)	(0.015)	(0.020)	(0.021)
lnw_0	–	-0.72633***	–	-0.89063***
		(0.051)		(0.076)
Worker fixed-effects?	NO	NO	YES	YES
No. of obs.	199,833	190,817	199,833	190,817

Notes: u_0 denotes the unemployment rate at the time when the match begins. u_t denotes the time-varying current unemployment rate. $u_0 \times u_t$ denotes the interaction between the initial and current unemployment rate. lnw_0 denotes the initial log real wage. Standard errors are clustered by time and appear in parentheses. Regressors not reported: cubic in experience, year fixed-effects, and indicators for race, less than high school education, some college, and college graduate (or more). $+, *, **, ***$ indicate statistical significance at 10%, 5%, 1%, and 0.1% levels.

Table 3. Median duration (in months) over the cycle

	All	
	(1)	(2)
Normal conditions	25	24
	[24,26]	[23,25]
Start boom, current boom	33	42
	[26,43]	[30,57]
Start boom, current bust	33	26
	[28,41]	[21,30]
Low w_0, start boom, current boom	–	30
		[23,40]
Worker fixed-effects?	YES	YES
Control for w_0?	NO	YES

Notes: Median duration is calculated from the survivor function implied by estimating Equation 1. Results for Columns 1 and 2 are based on the estimates from Columns 3 and 4 in Table 2, respectively. Numbers in square brackets represent the median duration implied by the 95% confidence interval of the corresponding survivor function. Details of their construction appear in Appendix B.

Table 4. Hazard estimates by pre- and post-employment status

	NN		NE		EN		EE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
u_0	0.53029***	0.54774***	-0.23980	-0.27729	-0.01570	0.08621	0.14803*	0.10592
	(0.122)	(0.127)	(0.217)	(0.259)	(0.341)	(0.063)	(0.077)	(0.079)
u_t	-0.11605	-0.03769	0.00492	0.30631	0.23553	0.20223	-0.02423	0.07081
	(0.230)	(0.240)	(0.451)	(0.504)	(0.666)	(0.164)	(0.149)	(0.165)
u_t^2	0.15802***	0.16242***	-0.25318*	-0.48500***	0.04883	-0.01895	-0.00509	0.00713
	(0.057)	(0.060)	(0.133)	(0.174)	(0.256)	(0.037)	(0.046)	(0.058)
$u_0 \times u_t$	-0.29763***	-0.31147***	0.24454*	0.45546**	-0.26338	-0.03291	0.00866	0.02776
	(0.059)	(0.061)	(0.126)	(0.177)	(0.231)	(0.032)	(0.047)	(0.053)
lnw_0	–	-0.39574**	–	-0.57845*	–	-0.90436***	–	-0.98787***
		(0.172)		(0.319)		(0.120)		(0.165)
Worker fixed-effects?	YES	YES	YES	YES	YES	YES	YES	YES
No. of obs.	42,861	40,851	24,861	23,813	79,392	76,541	52,719	49,612

Notes: u_0 denotes the unemployment rate at the time when the match begins. u_t denotes the time-varying current unemployment rate. $u_0 \times u_t$ denotes the interaction between the initial and current unemployment rate. lnw_0 denotes the initial log real wage. Standard errors are clustered by time and appear in parentheses. Regressors not reported: cubic in experience, year fixed-effects, and indicators for race, less than high school education, some college, and college graduate (or more). $+, *, **, ***$ indicate statistical significance at 10%, 5%, 1%, and 0.1% levels.

Table 5. Estimated change in median duration (in months) over the cycle by pre- and post-employment status

	NN		NE		EN		EE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Normal conditions	13	15	14	15	17	12	19	19
	[12,14]	[14,17]	[13,15]	[14,16]	[16,19]	[11,13]	[18,21]	[18,20]
Start boom, current boom	113	209	9	15	115	34	24	23
	[34,313]	[66,313]	[4,16]	[6,29]	[14,256]	[8,256]	[18,31]	[17,30]
Start boom, current bust	13	13	31	65	5	3	27	21
	[8,19]	[8,19]	[14,60]	[22,132]	[3,7]	[2,4]	[20,35]	[15,28]
Low w_0, start boom, current boom	–	169	–	14	–	28	–	19
		[51,313]		[6,25]		[7,127]		[13,24]
Worker fixed-effects?	YES	YES	YES	YES	YES	YES	YES	YES
Control for w_0?	NO	YES	NO	YES	NO	YES	NO	YES

Notes: median duration is calculated from the survivor function implied by estimating Equation 1. Results for Columns 1, 3, and 5 are based on the estimates from Columns 1, 3, and 5 in Table 4, respectively. Results for Columns 2, 4, and 6 are based on the estimates from Columns 2, 4, and 6 in Table 4, which control for starting wages lnw_0. Numbers in square brackets represent the median duration implied by the 95% confidence interval of the corresponding survivor function. Details of their construction appear in Appendix B.