Job Ladders and Growth in Earnings, Hours, and Wages

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Abstract

We consider the impact of the recent slowdown in the job ladder on wage and earnings growth in the U.S. from 1996 to 2015. At the micro level, we confirm new hire wages exhibit more cyclicity than those of incumbent workers and attribute this to a permanent component of wages that persists through a match quality effect. We then develop an accounting method that aggregates individual wage changes to analyze how worker transitions across and within employers impact growth in the national average. New hire earnings growth is part of a dynamic process that mostly cancels itself out in the aggregate, such that observed growth in this period can be attributed to changes in compensation among incumbent workers. We find hours growth along the job ladder has a substantial impact on the patterns of earnings growth.

JEL codes: J63, E24, J31, E32
Keywords: job ladder, business cycles, real wage stagnation

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1 Introduction

Wage growth in the U.S. has been sluggish since the late 1990s, only showing signs of a recovery in 2015. A number of papers argue this stagnation is due to historic lows in the rate at which workers change employers, which may have inhibited movement to higher paying jobs. While a slowdown of workers moving along this job ladder may have impacted earnings through a variety of mechanisms, the main evidence provided in support of these arguments has been a high degree of correlation between wage growth and the frequency of employment transitions.\(^1\)

In this paper, we aim to determine the extent to which the recent slowdown in the job ladder explains the lack of earnings and wage growth observed in the U.S. between 2000 and 2014. We first investigate the increases in earnings, hours, and wages of individual workers moving onto and up the job ladder. Specifically, we follow Bils (1985) and use a reduced-form model to estimate earnings and wage sensitivity to the unemployment rate. Like Gertler and Trigari (2009), we take match quality into account. We then use an accounting framework that builds on Daly and Hobijn (2016) to distinguish between new hires from nonemployment and those from another employer. This method allows us to detail how these worker transitions influence the evolution of aggregate earnings, hours, and wages in the U.S. over the business cycle. Lastly, we compare the cyclical properties of transitory and persistent drivers of growth on aggregate earnings and wage growth among new hires separate from incumbent workers. Our analysis uses the universe-level matched employer-employee data that distinguish earnings from wages through administrative records on individual hours paid by employers.

Our empirical analysis reveals several striking findings. We obtain decisively mixed evidence of excess earnings and wage cyclicality among new hires compared to incumbent workers once we control for time-invariant match quality effects. Moreover, we find the excess cyclicality of new hire wages observed in the literature is predominantly accounted for by the response of the permanent component of wages that persists throughout an employer-employee match, not the transitory effect of new hires that disappears after one quarter. We interpret this as limited evidence of sticky wage

\(^1\)See Moscarini and Postel-Vinay (2017a) for a survey of theory and empirical evidence on the job ladder. For evidence on the correlation between wage growth and employment transitions, see Faberman and Justiniano (2015), Hyatt and McElroy (2017), Karahan et al. (2017), and Moscarini and Postel-Vinay (2017b). While these papers suggest employment transition rates drive wage growth, both series are procyclical and may be driven by labor market or other economic conditions. Moreover, there is a possibility that changes in earnings or wages drive workers to change employers, which has been explored in papers including Molloy, Smith, and Wozinak (2014), Hyatt and Spletzer (2016), and Hyatt et al. (2018).
contracts that are staggered across time and updated at the start of an employment spell. In the aggregate, we find that direct gains from movements onto and up the job ladder have a limited ability to explain sluggish earnings growth between 2000 and 2014. While workers experience substantial gains after changing employers, new hires from nonemployment tend to receive lower earnings and create a drag on aggregate growth. Average earnings growth for all new hires weighted by their employment share—which we define to be their contribution to aggregate growth—is always negative, even during times in the business cycle when the job ladder is particularly active. Moreover, we find that, while much of the literature has focused on the adjustment of wages across the business cycle, changes in hours also play a role in explaining the evolution of earnings. Our conclusion is that earnings and wage growth of job stayers is the key driver of the aggregate growth patterns we observe over this period.

We begin our paper at the micro-level by examining earnings growth associated with individual workers moving onto and up the job ladder. To do this, we model earnings as a function of individual observables and aggregate labor market conditions and use a linear regression specification following Bils (1985) who emphasized that the wages of new hires adjust to changes in unemployment differently from those of job stayers. More recently, Gertler and Trigari (2009) used survey data to measure this excess responsiveness of new hire wages and found suggestive evidence that it is driven by persistent employer-employee match effects. Using our linked employer-employee dataset, we confirm their finding for new hire earnings and wages and also show that match effects account for most of the excess cyclicalality exhibited by new hires.

While we examine cyclicalality of individual worker earnings and wages, we are ultimately interested in how it translates to the cyclical properties of aggregate earnings and wage growth over the past twenty years. Many studies have found only weak empirical evidence of procyclicality in aggregate wage growth while theoretical models yield mixed predictions of cyclicality; see Daly and Hobijn (2016). We introduce an accounting framework that aggregates the microdata used in our regression analysis to create a time series of average earnings and wage growth that can be decomposed

\[ \text{\textsuperscript{2}} \text{A couple of recent contributions also suggest a strong role for match effects. Hagedorn and Manovskii (2013) document an empirical relationship between wages and cumulative labor market tightness over the life of a particular employer-employee match. They conclude that since workers move more quickly from worse to better matches in better labor markets, much of the measured cyclical relationship between unemployment and wages is driven by match quality. A similar argument is made by Gertler, Huckfeldt, and Trigari (2018), who find employer-to-employer transitions, rather than hires from nonemployment, account for the excess cyclicalality in new hire wages. While we find different results regarding the role of new hires from nonemployment in wage cyclicality, their broader argument that cyclical match effects lead to much of the apparent excess cyclicalality of new hire wages is certainly confirmed here.} \]
into contributions by incumbent workers and new hires. Following Topel and Ward (1992), we compare outcomes before and after employment transitions to measure increases associated with workers changing employers and distinguish these gains from those of employees who work for the same employer. While Topel and Ward (1992) only applied their accounting method to a set of continuously employed workers, we propose an extension of their method that follows Daly and Hobijn (2016) and account for new hires from nonemployment as well as incumbent workers exiting employment.

Breaking down aggregates in this way reveals that gains from movements along the job ladder have only a limited role in explaining the evolution of average earnings. While workers changing employers add about 0.4 percent during times of economic expansions and recessions and workers exiting employment add approximately 3.0 percent over the same time period, both contributions are wholly offset by new hires from nonemployment which subtract roughly 3.5 percent on net in the average quarter. By contrast, job stayers contribute, on average, just over 0.3 percent but their earnings increases largely account for cyclical changes and the especially strong gains in the late 1990s and 2015. These findings suggest that appealing to Topel and Ward (1992) and their argument regarding the importance of employment transitions for individual earnings gains should be done with caution when attempting to understand changes in the aggregate.3 If the pace of the job ladder is the reason for sluggish earnings growth between 2000 and 2014, it is due to indirect mechanisms rather than the direct returns to changing employers.

Our accounting method also shows that the cyclical job ladder moves workers from jobs that offer low hours to those that provide more hours. Half of the earnings gains associated with new hires from another employer are due to changes in hours while the rest are the result of changes in wages. This evidence supports the existence of a cyclical hours job ladder where workers leave low-hours jobs for ones that offer greater hours much more frequently than the reverse. Our findings echo Altonji and Paxson (1986) and Chetty et al. (2011), who highlighted how frictions within job matches restrict the feasible choice of hours. Given that hours and wages are components of earnings, the existence of an active hours ladder implies that earnings growth, but not necessarily wage growth, follows the contribution of job stayers. In fact, we find hours growth among new hires results in their earnings growth.

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3Researchers including Davis and Haltiwanger (2014), Molloy, Smith, and Wozniak (2014), and Hyatt and Spletzer (2016) cite the empirical findings of Topel and Ward (1992) when considering the consequences of declining employment transition rates after 2000, as have policymakers as seen in the Economic Report of the President (2015). More generally, it is quite common to cite the empirical findings of Topel and Ward (1992) to link employer-to-employer transitions to cyclical wage growth. Recent examples of this include, among many others, Mukoyama (2014), Gertler, Huckfeldt, and Trigari (2018), and Haltiwanger et al. (2018).
contribution being largely canceled out—an effect that is not present when examining wages alone.

Lastly, we integrate our regression estimates into our decomposition to distinguish between transitory and persistent factors affecting aggregate earnings growth. We find match effects account for nearly all of the negative effect of new hires from nonemployment as well as nearly all of the positive effect of new hires from another employer and incumbent workers exiting employment. These findings highlight the role of the job ladder in the evolution of these match effects and consequently explains how new hire earnings growth is part of a dynamic process that cancels itself out. While our analysis rules out transitory cyclical factors as the dominant source of earnings growth, it provides rich motivation for future quantitative work to explain the mechanisms that underlie observed earnings changes.

The remainder of the paper proceeds as follows. In Section 2, we describe the data used for our analysis. In Section 3, we present evidence from a regression framework as well as an aggregation method that explores the cyclicality of earnings and wages for job stayers and new hires. In Section 4, we incorporate the fitted values from our regression estimates into a growth decomposition by worker type and explore the role of permanent and transitory in accounting for growth in earnings and wages. A brief conclusion follows in Section 5.

2 Data

We use matched employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau; see Abowd et al. (2009). These data consist of total quarterly earnings reported by employers for the administration of state unemployment insurance (UI) programs and are provided by states to the Census Bureau as part of the Local Employment Dynamics federal-state partnership. Earnings include compensation such as wages and salaries, tips, and bonuses and are reported for the vast majority of private sector employment.\footnote{For details on our earnings concept, see Appendix A}

Since data availability varies by state, we use two datasets for our analysis. The first uses a one percent sample of a set of eleven states that consistently have earnings data available from 1996 to 2016.\footnote{These states are California, Colorado, Idaho, Illinois, Kansas, Maryland, Montana, North Carolina, Oregon, Washington, and Wisconsin.} Since most of these states do not collect hours data, we impute hours values using models estimated on a second dataset composed of a one percent sample of a set of four states that has hours
data available between 1994 and 2016.\textsuperscript{6} \textsuperscript{7} Note that employers report hours paid rather than hours worked, so the cyclicality of hours may not line up exactly with measures from household surveys, such as the Current Population Survey (CPS).\textsuperscript{8} Not all states in our four state dataset have hours data available in the early years of our time series, making that dataset an unbalanced panel of states that over-represents more recent years. Moreover, labor force composition effects may bias these results relative to the country as a whole or the business cycle. This issue is largely solved for our eleven state dataset as our imputation method assigns hours to workers with similar observable characteristics (Rubin, 1987).

The data use agreement under which this research was conducted places restrictions on the release of state-specific findings. Results are therefore pooled and all figures in the main text of this paper use the eleven state dataset since hours observations in that dataset are mostly imputed and consequently are not restricted by data use agreements. Moreover, any time series results for the four state dataset are only shown when all four states are available.

3 Cyclicality of Aggregate Earnings and Wages

To better capture how earnings and wage growth relates to movements onto and up the job ladder in varying labor market conditions, we follow Bils (1985), Haefke, Sonntag, and van Rens (2013), and Gertler and Trigari (2009) and use a reduced-form model to estimate earnings and wage sensitivity and wages of individual workers to the unemployment rate. This method allows us to measure earnings and wage cyclicality – or wage stickiness – at a disaggregated level where we can control for labor market composition. Pissarides (2009) argues it is critical to separate wages of newly hired workers from aggregate measures of wage changes to properly capture wage cyclicality. Gertler, Huckfeldt, and Trigari (2018) also find that any differences in wage cyclicality specific to new hires are an artifact of changes in the composition of the labor force which varies over time. To understand the extent to which measures of cyclicality differ when aggregate data is used instead of microdata, we introduce an accounting framework. This framework creates a time series of average earnings and wages growth by aggregating the microdata used in our regression analysis and separates it into contributions by

\textsuperscript{6}These states are Minnesota, Oregon, Rhode Island, and Washington. See also Kurmann, McEntarfer, and Spletzer (2016).
\textsuperscript{7}For details on our hours imputation, see Appendix B.
\textsuperscript{8}For a comparison of our series with other available data on earnings, hours, and wages, see Appendix C.
incumbent workers and new hires. We then compare our regression results with the correlations between these components and the change in the unemployment rate.

3.1 Regression with Employer-Employee Match Effects

Our empirical specification for our reduced-form model is as follows:

\[ y_{it} = u_t (\gamma_1 + q_{it} \gamma_2 + n_{it} \gamma_3) + x_{it} \beta + \nu_{it}. \]  

(1)

where \( y_{it} \) denotes earnings or wages for worker \( i \) at time \( t \), \( u_t \) is the unemployment rate, \( x_{it} \) is a row vector of time-varying observable characteristics, and \( \nu_{it} \) is the residual.

Since most studies have found that the wages of newly hired workers respond to the unemployment rate more than those of incumbent workers, we have more than one parameter for the unemployment rate. \( \gamma_1 \) captures changes associated with the unemployment rate for all workers with earnings at time \( t \), namely job stayers and new hires. We also include parameters \( \gamma_2 \) and \( \gamma_3 \), which capture how new hires from another employer \( q_{it} \) and those from nonemployment \( n_{it} \), respectively, in time \( t \) may experience differential changes with the unemployment rate. Note these interaction terms mean \( \gamma_1 \) can be interpreted as the change specific to job stayers while \( \gamma_2 \) and \( \gamma_3 \) are measures of excess cyclicality for new hires relative to job stayers.

Marginal effects for our row vector of time-varying observable characteristics is given by vector \( \beta \) and includes age, job tenure, dummy variables indicating whether a worker is newly hired from another employer or nonemployment, dummy variables indicating whether it is the last quarter of a specific employer-employee match (with separate dummy variables and parameters for whether job spells are followed by employment or nonemployment), as well as time trends and seasonal effects that are specific to each worker type (i.e. stayers, new hires from another employer, and new hires from nonemployment). Time invariant worker characteristics such as sex, race, ethnicity, and level of education completion are not included as they are collinear with our fixed effects.

We assume the residual is additively separable into two components:

\[ \nu_{it} = \alpha_{it} + \epsilon_{it}, \]  

(2)

where \( \epsilon_{it} \) is the i.i.d. error term and \( \alpha_{it} \) is an effect that persists over time. We allow \( \alpha_{it} \) to take one of two forms. First, for comparison to most of the literature, we follow Bils (1985) and assume
α_{it} = \alpha_i$, that is, each person has a time invariant effect.\(^9\) Second, we follow a specification explored by Gertler and Trigari (2009), which allows $\alpha_{it} = \alpha_{ij}$ for any match between person $i$ and employer $j$ that exists at time $t$. This empirical strategy avoids biased results if the estimated person effect differs from the true match effect $\alpha_i - \alpha_{it}$ and this deviation is related to the dependent variable of interest $y_{it}$ and the unemployment rate. There is ample recent evidence to suggest that using person effects alone result in biased estimates of cyclicalility since the distribution of matches changes over the business cycle. Haltiwanger et al. (2018) and related studies find movement from worse to better job matches is procyclical, suggesting average match effects may be higher when the unemployment rate is lower. Moreover, we assume match effects are related to the dependent variables of our regressions. This extension captures both persistent and transitory components of cyclicalility: the match effect $\alpha_{ij}$ is the permanent component that lasts throughout a job spell and $\gamma_2$ and $\gamma_3$ are transitory excess cyclicalities that disappear after one quarter.\(^{10}\)

Tables 1 and 2 present our regression results for earnings and wages, respectively, of all workers employed in time $t$.\(^{11}\) Each table provides regression estimates from our four state and eleven state datasets. Note that both datasets do not include imputed earnings observations and that our four state dataset contains no imputed hours observations while our eleven state dataset contains partially imputed hours data.

Consistent with previous findings in Bils (1985) and the related literature, we find job stayer earnings and wages are procyclical. In response to a one percent increase in the unemployment rate, job stayer earnings in our four state dataset decrease by 1.7 percent with person-specific fixed effects and 0.9 percent with match-specific fixed effects. When considering the larger eleven state dataset, the response of job stayers is slightly smaller in the person-specific regression but consistent with the four state results when considering match quality. Differences in the cyclicalility of earnings among job stayers are therefore relatively small between our datasets, both of which do not include imputed earnings observations. For wages, we find similar magnitudes of cyclicalility among job stayers. Wages in the four state dataset decline by 1.0 percent and 0.5 percent with person- and match-specific fixed effects, respectively. Regressions run with our eleven state dataset lead to estimates that are the same

\(^9\)We use person-specific fixed effects here. For the results of an empirical strategy that estimates the first difference of equation (1), see Appendix Table E1.

\(^{10}\)Match effects will pick up a variety of effects, including match quality and any persistent effects of labor costs, as in Kudlyak (2014), among others.

\(^{11}\)Results are similar when we exclude workers who were recalled to previous jobs and new hires from nonemployment who were nonemployed for long durations (i.e. eight or more quarters). Results are available upon request.
Table 1: Earnings Regressed on the Unemployment Rate

<table>
<thead>
<tr>
<th></th>
<th>Person</th>
<th>Match</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Four States</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job Stayers ($\gamma_1$)</td>
<td>-0.017***</td>
<td>-0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Another Employer ($\gamma_2$)</td>
<td>-0.016***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>New Hires from Nonemployment ($\gamma_3$)</td>
<td>-0.010***</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations (Millions)</td>
<td>2.8</td>
<td>2.8</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.836</td>
<td>0.940</td>
</tr>
<tr>
<td><strong>Eleven States</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job Stayers ($\gamma_1$)</td>
<td>-0.014***</td>
<td>-0.009***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Another Employer ($\gamma_2$)</td>
<td>-0.015***</td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Nonemployment ($\gamma_3$)</td>
<td>-0.010***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations (Millions)</td>
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<td>29.9</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.779</td>
<td>0.920</td>
</tr>
</tbody>
</table>

Notes: Regressions were run using disaggregated data from our four state (top set of results) and our eleven state (bottom set of results) datasets. Both datasets have non-imputed earnings data. Earnings series are presented in 2014 constant dollars. See text for specification details.

in sign and close in magnitude, despite relying on imputed hours data to construct the wage variable.

We also find that earnings and wages for new hires are procyclical. In the four state dataset, earnings for workers changing employers decrease by 3.3 percent with person-specific fixed effects and 1.0 percent with match-specific fixed effects in response to a one percent increase in the unemployment rate. Meanwhile, earnings for new hires from nonemployment decrease by 1.0 percent and 0.8 percent in the person- and match-specific regressions, respectively. Results for the eleven state dataset are essentially the same and wages in both datasets tell a similar story although the magnitudes of the estimates are smaller than those of earnings.

We compare the degree of cyclicality of earnings and wage among new hires with that of incumbent workers. This comparison is important because any significant differences in cyclicality between these groups can be interpreted as evidence of sticky wage contracts that can be adjusted at a higher
Table 2: Wages Regressed on the Unemployment Rate

<table>
<thead>
<tr>
<th>Fixed Effects:</th>
<th>Person Match</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Four States</strong></td>
<td></td>
</tr>
<tr>
<td>Job Stayers ($\gamma_1$)</td>
<td>$-0.010^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Another Employer ($\gamma_2$)</td>
<td>$-0.009^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>New Hires from Nonemployment ($\gamma_3$)</td>
<td>$-0.004^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations (Millions)</td>
<td>2.8</td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.861</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Eleven States</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Stayers ($\gamma_1$)</td>
<td>$-0.009^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Another Employer ($\gamma_2$)</td>
<td>$-0.011^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Nonemployment ($\gamma_3$)</td>
<td>$-0.007^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations (Millions)</td>
<td>29.9</td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.646</td>
</tr>
</tbody>
</table>

Notes: Regressions were run using disaggregated data from our four state (top set of results) and our eleven state (bottom set of results) datasets. Our four state dataset has non-imputed wages data while our eleven state dataset has mostly imputed wages data. Wages series are presented in 2014 constant dollars. See text for specification details.

frequency for new hires than job stayers as aggregate conditions change. Like Gertler, Huckfeldt, and Trigari (2018), our results show that whether new hires exhibit excess cyclicity relative to job stayers depends on the model specification. New hire earnings and wages are more cyclical than job stayers when person-specific fixed effects are used but show substantially less cyclicity when controlling for match quality. Interestingly, whether our findings indicate new hires are more or less cyclical than job stayers in the match-specific regressions varies by which dataset we use. Our four state dataset results suggest that earnings for new hires from another employer are no more cyclical than those of job stayers while earnings for new hires from nonemployment are less cyclical than those of job stayers.\textsuperscript{12} However, results for our eleven state dataset show the opposite. Earnings for new hires

\textsuperscript{12}The offsetting transitory effect of the unemployment rate seen in our four state dataset results is somewhat surprising. One potential explanation could be that the frequency and magnitude of hiring bonuses are not as tied to economic conditions as salaries or wages, which might make new hires somewhat less cyclical than job stayers. Given data limitations,
from another employer are more cyclical than those of job stayers while new hires from nonemployment do not exhibit any additional cyclicity. We also find statistically significant decreases in wage cyclicity among all new hires compared to job stayers in the four state dataset but observe increases in the eleven state dataset. Regardless, differences with job stayers are no greater than 0.2 percent in magnitude when match-specific fixed effects are included, compared to 1.6 percent when person-specific fixed effects are used. Match quality therefore accounts for most of the excess cyclicity of new hire wages in the empirical work that follows Bils (1985). In other words, it is the response of the permanent component of wages that persists throughout an employer-employee match, and not the transitory effect of new hires that disappears after one quarter, that predominantly accounts for the excess cyclicity of new hire wages observed in the literature. We return to and expand upon this point in the next section.

Employer-employee match effects may be driven by two distinct mechanisms. One mechanism is the fundamental quality (or productivity) of particular employer-employee matches, which is emphasized in the recent work of Hagedorn and Manovskii (2013) and Gertler, Huckfeldt, and Trigari (2018). It may be that workers are less likely to move into matches that are a better fit for them during recessions. Alternatively, it may be that labor is simply less costly during recessions due to labor market slack and diminished worker bargaining power. As a result, the quality (or productivity) of the match does not necessarily have an explanatory effect if there is a long-term contract for compensation at the start of a job. This mechanism, captured by the presence of sticky wages, has recently been explored by Shimer (2005) and Pissarides (2009) as a way to resolve the employment-volatility puzzle and highlights how labor market search models struggle to have employment rather than wages respond to changes in economic conditions. On their own, our results do not allow us to distinguish between the two.13

we are unable to test that mechanism here.

13Martins, Solon, and Thomas (2012) demonstrate that the wages of entry-level jobs respond to labor market conditions, which suggests these responses reflect compensation changes not purely driven by job quality. More recently, Gertler, Huckfeldt, and Trigari (2018) measure whether new hire wages of workers in employer-to-employer transitions are more responsive to the unemployment rate than those of workers hired from nonemployment. They argue that, if wage cyclicity is driven by employer-to-employer transitions, then this indicates the cyclical job ladder, which is generally understood to move workers from less productive to more productive matches, explains measured wage cyclicity. They implement this test using data from the Survey of Income and Program Participation and find the excess wage cyclicity of new hires is driven by employer-to-employer transitions rather than hires from nonemployment. Our matched employer-employee data does not confirm their results and we find instead that the wage response of new hires from nonemployment is similar to that of workers undergoing an employer-to-employer transition.
3.2 Comparing Disaggregated and Aggregated Correlations

Now that we have substantial evidence of procyclical earnings and wages at the individual worker level, we turn to the cyclicality of overall earnings and wages. We introduce an accounting framework that aggregates the microdata used in our regression analysis to create a time series of average earnings and wage growth that can be decomposed into contributions by incumbent workers and new hires. Each of these components can be further separated into average growth and employment shares for each worker type. We then calculate correlations between these factors and the change in the unemployment rate and compare them with our regression results to better understand how measures of cyclicality differ when microdata and aggregate data are used.

Let earnings, hours, and wages for worker $i$ in time $t$ be generically expressed as $y_{it}$. We denote the average for all workers at time $t$ as $\bar{y}_t$ and growth in this aggregate from time $t - 1$ to time $t$ as $\Delta \bar{y}_t$. We use worker types defined in Hyatt et al. (2017) and assign indicator variables for job stayers, new hires from another employer, new hires from nonemployment, and incumbent workers exiting employment to be $s_{it}$, $q_{it}$, $n_{it}$, and $r_{it}$, respectively. We moreover denote the total number of each worker type as $S_t$, $Q_t$, $N_t$, and $R_t$, respectively. The number of workers employed is then $D_{t-1} = S_t + Q_t + R_t$ at time $t - 1$ and $D_t = S_t + Q_t + N_t$ at time $t$. Given this notation, we can express the change in the average from time $t - 1$ to time $t$ as:

$$\Delta \bar{y}_t = \frac{\sum_i s_{it}y_{it}}{D_t} + \frac{\sum_i q_{it}y_{it}}{D_t} + \frac{\sum_i n_{it}y_{it}}{D_t} - \frac{\sum_i s_{it}y_{it-1}}{D_{t-1}} - \frac{\sum_i q_{it}y_{it-1}}{D_{t-1}} - \frac{\sum_i r_{it}y_{it-1}}{D_{t-1}}. \quad (3)$$

Since an average equals the weighted sum of the averages of its components, we can think of aggregate growth in terms of employment shares and average earnings for all worker types in times $t - 1$ and $t$. This gives us:

$$\Delta \bar{y}_t = \left( \frac{S_t}{D_t} \frac{\sum_i s_{it}y_{it}}{S_t} + \frac{Q_t}{D_t} \frac{\sum_i q_{it}y_{it}}{Q_t} + \frac{N_t}{D_t} \frac{\sum_i n_{it}y_{it}}{N_t} \right) - \left( \frac{S_t}{D_{t-1}} \frac{\sum_i s_{it}y_{it-1}}{S_t} + \frac{Q_t}{D_{t-1}} \frac{\sum_i q_{it}y_{it-1}}{Q_t} + \frac{R_t}{D_{t-1}} \frac{\sum_i r_{it}y_{it-1}}{R_t} \right).$$

Because job stayers and new hires from another employer are employed in times $t - 1$ and $t$, we can separate the change in their averages from the change in their shares. Regrouping terms in this way
allows us to consider aggregate growth due to factors other than changes in labor market composition. We can now express the change in the overall average as:

\[ \Delta \bar{y}_t = S_t \frac{D_t \sum_i s_{it} \Delta y_{it}}{S_t} + \frac{Q_t}{2} \frac{Q_t \sum_i q_{it} \Delta y_{it}}{Q_t} + \]

\[ N_t \left( \frac{\sum_i n_{it} y_{it-1}}{N_t} - \bar{y}_t \right) \]

\[ \frac{2}{2} \frac{\sum_i s_{it} \Delta y_{it}}{S_t} \]

\[ Q_t \left( \frac{\sum_i q_{it} y_{it-1}}{Q_t} - \bar{y}_t \right) \]

where \( \bar{y}_t \) is the weighted average for job stayers and new hires from another employer, i.e.

\[ \bar{y}_t = S_t \frac{2}{S_t + Q_t} \left( \frac{\sum_i s_{it} (y_{it} + y_{it-1})}{2S_t} \right) + \]

\[ \frac{Q_t}{2} \frac{Q_t \sum_i q_{it} (y_{it} + y_{it-1})}{2Q_t} \].

The formulation for \( \Delta \bar{y}_t \) in equation (4) makes an intuitive distinction between its terms, which we refer to as the respective contributions of job stayers, new hires from another employer, new hires from nonemployment, and incumbent workers exiting employment. Each contribution is basically a weighted average. For job stayers and new hires from another employer, their average growth is multiplied by their average share. Since new hires from nonemployment and incumbent workers exiting employment move from having no earnings and not contributing to the average to having earnings and contributing to the average or vice versa, their contribution is a function of how different they are from the continuously employed in times \( t - 1 \) and \( t \) (i.e. \( \bar{y}_t \)) and their share. Note the more their average differs from \( \bar{y}_t \), the more their dynamics affect the overall average.

Table 3 presents correlations obtained from a regression of the terms in equation (4) and their subcomponents on the change in the unemployment rate. Note again that we refer to each term as a contribution for a given worker type and this contribution is essentially their average growth in earnings and wages weighted by their respective employment share. We also calculate the correlations of their average growth in earnings and wages alone (i.e. without their respective employment share), as these measures are the most comparable to our regression results.

Looking at the first and third columns, we confirm the findings of our regression analysis and see average growth in earnings and wages is procyclical for job stayers \((\frac{\sum_i s_{it} \Delta y_{it}}{S_t})\) and new hires \((\frac{\sum_i q_{it} \Delta y_{it}}{Q_t})\) and \(\frac{\sum_i n_{it} y_{it-1}}{N_t} - \bar{y}_t\). However, this is not the case when we look at the contributions of each worker type. While the contributions of stayers \((\frac{S_t}{2} \frac{2}{2} \frac{\sum_i s_{it} \Delta y_{it}}{S_t})\) and new hires from an-
Table 3: Regression of Components with Changes in the Unemployment Rate

<table>
<thead>
<tr>
<th>Component</th>
<th>Formula</th>
<th>Earnings</th>
<th>Hours</th>
<th>Wages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>$\Delta \tilde{y}_t$</td>
<td>-0.546</td>
<td>-0.235</td>
<td>-0.311</td>
</tr>
<tr>
<td>Stayers Contribution</td>
<td>$\frac{S_t}{D_t} + \frac{S_{t-1}}{D_{t-1}} \Sigma q_{it} \Delta y_{it} \frac{S_t}{S_{t-1}}$</td>
<td>-0.531</td>
<td>-0.171</td>
<td>-0.359</td>
</tr>
<tr>
<td>Avg. Growth</td>
<td>$\Sigma q_{it} \Delta y_{it}$</td>
<td>-0.580</td>
<td>-0.187</td>
<td>-0.393</td>
</tr>
<tr>
<td>Emp-to-Emp. Contribution</td>
<td>$\frac{Q_t}{D_t} + \frac{Q_{t-1}}{D_{t-1}} \Sigma r_{it} \Delta y_{it} \frac{Q_t}{Q_{t-1}}$</td>
<td>-0.202</td>
<td>-0.101</td>
<td>-0.101</td>
</tr>
<tr>
<td>Avg. Growth</td>
<td>$\Sigma r_{it} \Delta y_{it}$</td>
<td>-6.263</td>
<td>-2.838</td>
<td>-3.426</td>
</tr>
<tr>
<td>New Hires from Nonemp. Contribution</td>
<td>$\frac{N_t}{D_t} \left( \frac{\Sigma n_{it} y_{it-1} - \tilde{y}_t}{N_t} \right)$</td>
<td>0.144</td>
<td>0.018</td>
<td>0.126</td>
</tr>
<tr>
<td>Avg. Growth</td>
<td>$\Sigma n_{it} y_{it-1} - \tilde{y}_t$</td>
<td>-1.953</td>
<td>-1.107</td>
<td>-0.846</td>
</tr>
<tr>
<td>Exiters from Emp. Contribution</td>
<td>$\frac{R_t}{D_t} \left( \frac{\Sigma r_{it} y_{it-1}}{R_t} - \tilde{y}_t \right)$</td>
<td>0.043</td>
<td>0.019</td>
<td>0.024</td>
</tr>
<tr>
<td>Avg. Growth</td>
<td>$\Sigma r_{it} y_{it-1} - \tilde{y}_t$</td>
<td>3.930</td>
<td>1.449</td>
<td>2.482</td>
</tr>
</tbody>
</table>

Notes: Regressions of the changes in the components were run on percentage point changes in the unemployment rate with season dummies and a time trend. Earnings and wages series are presented in 2014 constant dollars. All point estimates are for the eleven state dataset and are multiplied by 100 to reduce the number of significant digits.

other employer $\left( \frac{\Sigma n_{it} \Delta y_{it}}{2} \right)$ are procyclical, the contribution of new hires from nonemployment $\left( \frac{N_t}{D_t} \left( \frac{\Sigma n_{it} y_{it-1}}{N_t} - \tilde{y}_t \right) \right)$ is not. This finding confirms that the composition of the labor market does vary over time and is cyclical, preventing aggregate measures of earnings and wage changes from properly capturing cyclicity.

We moreover see that the magnitude for the correlations of the contributions differs from those of the average growth subcomponents. The contribution of job stayers to aggregate earnings growth is only ten percent smaller than their average growth in earnings due to the fact that most employees in any given quarter are job stayers. Their employment share $\left( \frac{1}{2} \left( \frac{S_t}{D_t} + \frac{S_{t-1}}{D_{t-1}} \right) \right)$ does not vary substantially over time and is always between 85 percent and 91 percent. In contrast, the contribution of new hires from another employer is drastically different in magnitude from their average earnings change. While they see large increases in earnings, their contribution is not as big as that of job stayers due to their tiny employment share.14 Similarly, the contributions of new hires from nonemployment $\left( \frac{N_t}{D_t} \left( \frac{\Sigma n_{it} y_{it-1}}{N_t} - \tilde{y}_t \right) \right)$ and incumbent workers exiting employment $\left( \frac{R_t}{D_t} \left( \frac{\Sigma r_{it} y_{it-1}}{R_t} - \tilde{y}_t \right) \right)$ have lower

14We find the contribution of employer-to-employer transitions to the wage growth of the continuously employed is in excess of 20 percent. This is somewhat larger than findings from a related exercise done by Devereux and Hart (2006), who find employer-to-employer transitions account for less than a tenth of the cyclical wage growth of the continuously employed. Our LEHD data for the U.S. shows a higher rate of employer-to-employer transitions as well as a larger degree of excess cyclicality of new hire wages than their data for the U.K.
magnitudes than their differences between their respective average earnings and $\tilde{y}_t$.

Since our accounting method is a decomposition, we can recover the overall growth in earnings and wages by summing the contributions of all worker types. While job stayers and new hires from another employer contribute positively to the aggregate, new hires from nonemployment and incumbent workers exiting employment subtract from the overall. In fact, we find that about 25 percent of the combined increase in average earnings for the former is offset by the net contribution of the latter. This finding suggests job stayers, and not new hires, account for most of the cyclicality in the growth of aggregate earnings and wages. We further explore the sources of overall growth in the next section.

While we use $\bar{y}_t$ to generically denote average earnings, hours, or wages, it is important to point out that growth in aggregate earnings is additive in wages and hours. That is, we can define earnings growth as $\Delta \bar{e}_t = \Delta \bar{w}_t + \Delta \bar{h}_t$, where $e_t$ denotes earnings, $w_t$ denotes wages, and $h_t$ denotes hours. Table 3 allows us to examine the cyclical properties of hours and wages and their role in explaining average earnings growth. We find only a small drop in aggregate earnings growth (denoted by $\Delta \bar{y}_t$) when the unemployment rate increases. A one percentage point rise in the unemployment rate causes average earnings to decline by 0.546 percent. Comparing the first column with the second and third, we find more than 40 percent of this is accounted for by changes in average hours and the remainder by changes in average wages. However, this finding varies by worker type. While the contributions of job stayers and new hires from nonemployment are predominantly driven by changes in average wages, the contribution of new hires from another employer are equally accounted for by changes in average hours and wages.

4 Sources of Aggregate Earnings Growth

In the previous section, we analyzed measures of cyclicality for earnings and wages in the U.S. between 1996 and 2016. However, growth in earnings and wages varied during this time period, with increases in the late 1990s being substantially larger than those observed more recently in 2015. Daly and Hobijn (2016) first explore the cyclicality of earnings and wages under different labor market conditions and argue it is largely weak in aggregate data due to workers entering and exiting employment. They find workers who enter employment receive lower wages than those who exit, resulting in a wage gap that masks sustained wage growth in the intensive margin and leads to acyclical wage aggregates. We likewise examine the time series of average earnings and wage growth and the contributions of
each worker type. Given our finding in the previous section that much of the excess cyclicality of new hire wages observed in the literature can be explained by match effects, we also expand on the work of Daly and Hobijn (2016) and attempt to determine the extent to which match quality, rather than time varying factors like the unemployment rate and other observable characteristics, accounts for growth in aggregate earnings and wages.

### 4.1 Time Series Analysis By Worker Type

Figures 1 and 2 display average earnings and wages growth in our eleven state dataset as well as the contributions made by each worker type. In Figure 1, we see that overall average earnings (solid line) increased in most quarters of the late 1990s before entering a period of sluggish growth where gains slowed to just above zero at the start of the 2001 recession. They then fell by up to -0.9 percent per quarter during the Great Recession, with signs of a recovery first appearing in 2014 when quarterly increases reached 0.8 percent. Decomposing this into contributions associated with each worker type, we find those of job stayers and new hires are procyclical while that of exiters is countercyclical. Job stayers contribute gains as high as 0.9 percent during expansions and losses up to 0.6 percent during and after contractions. Meanwhile, the contribution of new hires from another employer (dash-dot line) consistently adds 0.1 percent to 0.5 percent each quarter. While the quarterly contribution of new hires from nonemployment (long dash line) subtracts 3.1 percent to 4.0 percent, much of it is offset by incumbent workers exiting employment who positively contribute 2.7 to 3.4 percent each quarter. On net, the nonemployment margin ends up reducing quarterly average earnings growth by 0.3 percent to 0.7 percent. As a result, we find the contributions of new hires from nonemployment and exiters offsets much, but not all, of the gains associated with new hires from employment. Figure 2 tells a similar story for wages and confirms the finding in Daly and Hobijn (2016). The key take-

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15 Another way to represent the decomposition would be to exhaustively graph earnings, wages, and employment shares for each worker type. These elements are available in Appendix D.

16 Recall that all results in this paper are presented in logs. Results in levels are similar and are available upon request.

17 Daly and Hobijn (2016) consider a different measure of job change than employer-to-employer transitions. Specifically, they measure job change as a respondent reporting change from one industry and occupation code to a different 3-digit Census industry or occupation code in linked outgoing rotation groups of the CPS. Thus, the annual job transition rate in their analysis is about 54 percent (we calculate this transition rate by diving two shares found on page 7 of Daly and Hobijn (2016): the 48 percent of job changers by the 89 percent of continuously employed). They find similar wage changes for continuously employed workers who do and do not make so-defined job transitions, which may better capture results for task-level changes than employer changes. In contrast, the annual employer-to-employer transition rate from the March CPS is at most 16 percent, see Hyatt (2015). See Stewart (2007) for a discussion of differences between these employment transition concepts.
away of Figures 1 and 2 is that average earnings growth are driven by a dynamics process of labor market entry, on the job employment transitions, and eventual exit. Those dynamics tend to mostly offset each other in the aggregate resulting in aggregate earnings growth patterns that largely follow the earnings growth of job stayers. The story for wages is similar albeit less strong since there is wedge between overall wage growth and growth of job stayers. This difference in growth rates of earnings and wages is attributed to hours paid.

We can also use equation (4) to examine the contribution of wages and hours separately to aggregate earnings growth. A key finding of our decomposition is the existence of an hours job ladder that matters at least as much as a job ladder for wages. This is seen in looking at the contribution of hours and wages to overall earnings growth of new hires in Figure 3. Workers changing employers are associated with gains in hours comparable to those of wages, meaning their earnings increases may be equally well explained by moves to jobs with greater hours as those with higher wages. It also implies the existence of a job ladder where workers leave jobs with limited hours to take ones that offer more hours. While a discussion of the mechanisms responsible for an active job ladder in hours is beyond the scope of this paper, our finding does imply the existence of frictions or adjustment costs that make changing hours within a job more costly for a worker than moving to a job with a preferred hours schedule. This finding echoes work on rigidities that restrict hours choice by Altonji and Paxson (1986) and Chetty et al. (2011).

4.2 Time Series Analysis of Persistent and Transitory Sources

To get a better understanding of the extent to which earnings and wages for new hires and incumbent workers move because of persistent or transitory factors, we now present time series data that reveal how the average effects of covariates change and account for aggregate earnings and wage growth over time. Since these factors have already been estimated in our regression analysis, we first-difference our regression equation (1) and aggregate each regression component over all workers. We can then estimate the cyclicality of the average effects of these covariates while controlling for compositional changes in our dataset.

For new hires from another employer, we express their average growth in earnings, hours, and wages as:

\[
\frac{\sum_i q_{it} \Delta y_{it}}{Q_t} = \frac{\sum_i q_{it} \Delta x_{it} \hat{\beta}}{Q_t} + \frac{\sum_i q_{it} \Delta l_{it} \hat{\gamma}}{Q_t} + \frac{\sum_i q_{it} \Delta \hat{\alpha}}{Q_t} + \frac{\sum_i q_{it} \Delta \hat{\epsilon}}{Q_t}
\] (5)
Figure 1: Decomposition of Growth in Average Earnings

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Earnings series are presented in 2014 constant dollars. Shaded areas indicate recessions. Overall indicates average change. See text for details.
Figure 2: Decomposition of Growth in Average Wages

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Wages series are presented in 2014 constant dollars. Shaded areas indicate recessions. Overall indicates average change. See text for details.
Figure 3: Contribution of New Hires: Wages and Hours

(a) New Hires from Another Employer

(b) New Hires from Nonemployment

Notes: All series are log series that have been seasonally adjusted and Henderson-filtered using x12. Wage series are presented in 2014 constant dollars. Shaded areas indicate recessions.
where $\Delta x_{it} = x_{it} - x_{it-1}$ is the change in the vector of observable characteristics from time $t-1$ to time $t$ with parameter $\hat{\beta}$, $\Delta l_{it} = l_{it} - l_{it-1}$ is the analogous change in the unemployment vector $l_{it} = [u_{it} q_{it} u_{it} n_{it} u_{it}]$ with parameter vector $\hat{\gamma} = [\gamma_1 \gamma_2 \gamma_3]'$, $\Delta \hat{\alpha}_{it} = \hat{\alpha}_{it} - \hat{\alpha}_{it-1}$ is the change in estimated match effects, and $\Delta \hat{\epsilon}_{it} = \hat{\epsilon}_{it} - \hat{\epsilon}_{it-1}$ is the change in the estimated residual.

For new hires from nonemployment, we compare their earnings with those of all other workers and obtain the following relationship for their average growth:

$$
\left( \frac{\sum n_{it} y_{it-1}}{N_t} - \bar{y}_t \right) = \left( \frac{\sum n_{it} x_{it-1}}{N_t} - \bar{x}_t \right) \hat{\beta} + \left( \frac{\sum n_{it} l_{it-1}}{N_t} - \bar{l}_t \right) \hat{\gamma} + \left( \frac{\sum n_{it} \hat{\alpha}_{it-1}}{N_t} - \bar{\alpha}_t \right) + \left( \frac{\sum n_{it} \hat{\epsilon}_{it-1}}{N_t} - \bar{\epsilon}_t \right)
$$

where $\bar{x}_t$ is a row vector of average observable characteristics, $\bar{l}_t$ is a row vector of average unemployment rates interacted with worker type, $\bar{\alpha}_t$ is an average of fitted match effects, and $\bar{\epsilon}_t$ is an average of fitted residuals. The average of each element, generically denoted by $\bar{g}_t$, is

$$\bar{g}_t = \frac{S_t}{S_t + Q_t} \left( \frac{\sum q_{it} (g_{it} + g_{it-1})}{2S_t} \right) + \frac{Q_t}{S_t + Q_t} \left( \frac{\sum q_{it} (g_{it} + g_{it-1})}{2Q_t} \right).$$

For incumbents exiting employment, we have the following relationship for average growth:

$$
\left( \frac{\sum r_{it} y_{it-1}}{R_t} - \bar{y}_t \right) = \left( \frac{\sum r_{it} x_{it-1}}{R_t} - \bar{x}_t \right) \hat{\beta} + \left( \frac{\sum r_{it} u_{it-1}}{R_t} - \bar{u}_t \right) \hat{\gamma} + \left( \frac{\sum r_{it} \hat{\alpha}_{it-1}}{R_t} - \bar{\alpha}_t \right) + \left( \frac{\sum r_{it} \hat{\epsilon}_{it-1}}{R_t} - \bar{\epsilon}_t \right).
$$

We can do the same for job stayers and express their average change, weighted by their average share, as follows:

$$
\frac{\sum s_{it} \Delta y_{it}}{S_t} = \frac{\sum s_{it} \Delta x_{it} \hat{\beta}}{S_t} + \frac{\sum s_{it} \Delta l_{it} \hat{\gamma}}{S_t} + \frac{\sum s_{it} \Delta \hat{\epsilon}_{it}}{S_t}
$$

Note that, by construction, stayers never have any change in match effects (since they are constant for any employer-employee combination), so the contribution of match effects for stayers is zero throughout the time series.

We now combine our first differenced regression equations with their corresponding employment shares. For new hires from another employer, each term in equation (5) is multiplied by $\frac{Q_t}{S_t} \cdot \frac{Q_{t-1}}{S_{t-1}}$ and
is then plotted in Figure 4. Likewise for new hires from nonemployment, equation (6) is multiplied by $\frac{N_t}{D_t}$ and the time series are shown in Figure 5. Equation (7) for incumbents exiting employment is multiplied by $\frac{R_t}{D_t}$ and the time series are shown in Figure 6. Lastly, for stayers, equation (8) is multiplied by $\frac{S_t}{D_t} + \frac{S_{t-1}}{2}$ and the time series are shown in Figure 7. Note that each figure has a panel for earnings and wages and the corresponding total contribution line (solid lines) is taken from Figures 1 and 2, respectively.

In Panel 4(a), we see new hires from another employer (solid line) offer gains to total earnings change that are as high as 0.5 percent during expansions and as low as 0.1 percent during and after contractions. Their quarterly contribution is consequently positive throughout the time series and amounts to roughly 0.4 percent in the average quarter. Of the model covariates, it appears to be predominantly driven by match effects (dotted line), whose contribution is also consistently above zero and explains 52.5 percent to 95.1 percent of the variation. Interestingly, match quality explains a substantially higher percentage of the contribution of new hires from another employer during periods of economic growth than it does during recessions. These gains are slightly offset by the unemployment contribution (short dash line), which captures any transitory excess cyclicality of new hires from another employer and ranges from -0.4 percent to -0.1 percent. While changes associated with other observable characteristics (long dash line) are typically increases, they are essentially zero in magnitude. Lastly, changes attributed to the residual (dash-dot line) are roughly the same in magnitude as those associated with the unemployment rate but are generally positive. Results for growth in wages are shown in Panel 4(b) and similarly indicate that match quality are key for new hires from another employer.

Panel 5(a) shows the contribution of new hires from nonemployment (solid line) and finds it is negative and has a persistent offsetting effect on growth in aggregate earnings. These losses range from -4.0 percent to -3.1 percent and, like new hires from another employer, are closely tracked by the contribution of match effects (dotted line), which account for 72.8 percent to 80.0 percent of their level and intertemporal movement. Contributions associated with other model covariates play much smaller roles. The unemployment rate (short dash line) has a generally negative effect as low as -0.3 percent, reflecting the transitory excess sensitivity of new hires from nonemployment to the unemployment rate. Since we do not allow for the excess sensitivity of these workers to the unemployment rate in equation (1), they look more like other workers during recessions via this channel. Other observable characteristics (long dash line) subtract consistent losses that vary from 0.7 percent to 1.0 percent in
Figure 4: New Hires from Another Employer: Regression-Based Decomposition

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Earnings and wage series are presented in 2014 constant dollars. Shaded areas indicate recessions. Total indicates the total contribution of employer-to-employer transitions. See text for details.
magnitude. Meanwhile, changes attributed to the residual (dash-dot lines) are generally positive but are small, ranging from zero to 0.1 percent. We obtain similar results for wages in Panel 5(b).

Lastly, we consider how earnings for stayers evolve in Panel 7(a). Match effects (dotted line) do not contribute to earnings growth of job stayers by construction. We find the unemployment rate and observable characteristics do not capture the variability found in the total contribution line. The unemployment rate adds 0.2 percent to 0.4 percent to earnings growth during expansions but subtracts 0.1 percent to 0.7 percent during recessions. Meanwhile, changes in observable characteristics contribute positively, by up to 0.4 percent, due to factors like job tenure and age which increase over time and are associated with earnings increases. Combined, these two factors poorly approximate the time variation of the earnings contribution of job stayers to the overall growth rate. By contrast, the residual, which necessarily includes anything not captured in equation (1), exhibits substantial cyclicality relative to the other series. In magnitude, it is mostly negative from 0.0 percent to 1.0 percent and more than offsets the earnings increases associated with changes in the unemployment rate and other observable characteristics. In fact, residual factors drive the exceptional earnings growth of job stayers in the late 1990s and 2015. During these time periods the residual contribution becomes positive in magnitude.18

These results provide further insights into the source of aggregate earnings growth. We find the employer-employee match effect component predominantly drives the contributions of new hires, leaving other time varying factors with substantially smaller roles. This suggests that when workers start jobs after a period of nonemployment, they tend to move to jobs that offer low earnings and wages and are more likely to obtain gains in wages by transitioning to a job with another employer than by remaining with their employer. New hires from nonemployment are consequently workers at the bottom of the job ladder while new hires from another employer are workers moving out of these entry-level jobs almost as soon as they enter them. These results support the Topel and Ward (1992) argument that earnings growth experienced by job changers is driven by workers moving up the job ladder. However, when accounting for overall earnings and wage growth, we note that the direct contribution of job stayers accounts for a remarkably large share of the aggregate growth rate.

18An exhaustive attempt to model wage regressions is beyond the scope of this paper. It is worth pointing out that the residual represents features of the process not captured in the empirical specification in equation (1). The residual is persistently negative for most of the time series—except during growth episodes of the 1990s and 2015. This persistent negative contribution most likely reflects the fact that we only allow returns to job tenure to increase and do not have a corresponding “time from exit” series. Furthermore, there may be labor productivity growth or nonlinearities in the effect of the unemployment rate.
Figure 5: New Hires from Nonemployment: Regression-Based Decomposition

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Earnings and wage series are presented in 2014 constant dollars. Shaded areas indicate recessions. Total indicates the total contribution of nonemployment transitions. See text for details.
Figure 6: Exiters: Regression-Based Decomposition

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Earnings and wage series are presented in 2014 constant dollars. Shaded areas indicate recessions. Total indicates the total contribution of nonemployment transitions. See text for details.
Figure 7: Job Stayers: Regression-Based Decomposition

Notes: All series are log series that have been seasonally-adjusted and Henderson-filtered using x12. Earnings and wage series are presented in 2014 constant dollars. Shaded areas indicate recessions. Total indicates the total contribution of stayers. See text for details.
While the source of this growth appears not to be driven by transitory factors, we leave it to future research to quantify the sources of gains among job stayers.

5 Conclusion

We use matched employer-employee data to investigate how the recent slowdown in the job ladder relates to sluggish wage and earnings growth in the U.S. from 2000 to 2014. To do so, we first employ a linear regression specification to capture match effects and differences in earnings and wage cyclicality among new hires and incumbent workers. We then aggregate these individual-level transitions through an accounting framework that decomposes changes in average earnings, hours, and wages into growth for job stayers, employer-to-employer transitions, and nonemployment transitions. We investigate the cyclical properties of these more aggregated series compared to our individual-level findings. Ultimately, we integrate our regression estimates into our decomposition to distinguish between transitory and persistent factors in the evolution of average earnings, hours, and wages.

We have several important findings. First, we attribute any excess cyclicality of new hire wages compared to incumbent workers largely to the permanent component of wages that persists through a match quality effect and not the transitory effect of new hires that disappears after one quarter. Moreover, we find mixed evidence of excess cyclicality among new hires compared to incumbent workers once we account for these match quality effects. We interpret this as limited evidence of sticky wage contracts that are staggered across time and updated at the start of an employment spell.

Second, the employer-to-employer transitions at the aggregate level have a limited ability to explain overall earnings growth. The findings of Topel and Ward (1992) have been used to link cyclical employer-to-employer transitions to aggregate earnings growth, and, more recently, authors such as Davis and Haltiwanger (2014), Molloy, Smith, and Wozniak (2014), and Hyatt and Spletzer (2016) have applied this reasoning to understand the consequences of the historic drop in post-2000 employment transition rates. However, we find increases from employer-to-employer transitions mostly just offset the contribution of nonemployment transitions, which tend to lower average earnings, hours, and wages. Direct gains via employer-to-employer transitions are thus distinctly secondary to indirect mechanisms that might link the earnings growth of job stayers to those of employer-to-employer transitions. Such mechanisms may include efficiency wages that reduce employee turnover (Salop, 1979) or job offers that are not taken but lead to increases in labor compensation (Postel-Vinay and
Third, we show the importance of changes in wages that occur within particular employer-employee matches. Daly and Hobijn (2016) recently proposed that the primary driver of aggregate real wage growth is the “intensive margin,” made up of the continuously employed whose gains during expansions tend to be offset by the nonemployment “extensive margin,” especially by new hires from nonemployment who earn much less than incumbents. Our results highlight that this offsetting effect is concentrated among a subset of the continuously employed: workers who change employers. Further analysis shows how the job ladder links these two margins: new hires from nonemployment start with relatively low match effects and move to better matches via employer-to-employer transitions. The surprisingly small overall contribution of the cyclical job ladder to growth in earnings, hours, and wages highlights the importance of job stayers, whose relatively modest changes end up determining most of the aggregates.

Finally, we find wage growth is not the key determinant of worker decisions to change employers. Most economic models of on-the-job search focus on wages and make the reasonable assumption that workers prefer jobs offering higher wages. Our analysis shows that, in addition to wage increases, many of these transitions are made to obtain a match with a preferred hours allocation. This is consistent with the existence of frictions within job matches that restrict the feasible choice of hours (Altonji and Paxson, 1986). We conclude that abstracting from an hours choice in the on-the-job search literature following Burdett (1978) and Jovanovic (1979) is a significant limitation.

In summary, we propose a framework that incorporates several different methods that measure how earnings and wages evolve over time: the earnings growth accounting of Topel and Ward (1992), the extensive vs. intensive margins of Daly and Hobijn (2016), and the Gertler and Trigari (2009) match effects extension of the Bils (1985) wage-unemployment specification. Taking it to the data, we find these channels account for only a small part of the earnings and wage stagnation in the U.S. from 2000 to 2014. The large increases in earnings in the late 1990s and 2015 are driven by job stayers, in a way that is mostly unrelated to changes in the unemployment rate. What mechanisms account for the large estimated residual that we obtain when the earnings of job stayers surge? We hope this paper provides motivation for future work and perhaps a set of moments that can be used to estimate formal models.

19Models such as Menzio and Shi (2011), Lise and Robin (2017), and Moscarini and Postel-Vinay (2017c) may prove helpful starting points for assessing the direct vs. indirect effects of the employer-to-employer transition rate on earnings and wages over the business cycle.
References


Appendices

A Definitions

This appendix provides definitions of employment and earnings concepts used in this paper and follows the notation in Abowd et al. (2009), Hahn et al. (2017), and Hyatt et al. (2017). Let $w_{ijt}$ denote earnings for individual $i$ from employer $j$ in time $t$. If an individual has reported earnings from an employer in a given quarter and $w_{ijt} > 0$, then we infer the individual worked for the employer at some point during the quarter of interest and call this employer-employee combination a job.

A.1 Basic Employment Concepts

Following Hyatt et al. (2017), we consider the subset of jobs that span two consecutive quarters. Formally, these are:

$$b_{ijt} = \begin{cases} 1, & \text{if } w_{ijt-1} > 0 \text{ and } w_{ijt} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

Moreover, we only allow workers to have at most one job per quarter. Since LEHD administrative records lack employment start and end dates, we cannot distinguish between a worker holding multiple jobs and a worker transitioning between jobs in a given quarter. We therefore determine where workers are earning the most and call this the dominant job. Formally, this is:

$$d_{ijt} = \begin{cases} 1, & \text{if } b_{ijt} = 1 \text{ and } w_{ijt} + w_{ijt-1} > w_{ikt} + w_{ikt-1} \forall k \\ 0, & \text{otherwise.} \end{cases}$$

We then compare dominant employers across quarters and identify when a job transition has occurred.

For the study of earnings, it is also useful to introduce the concept of full quarter jobs. Full quarter jobs span three consecutive quarters, such that:

$$f_{ijt} = \begin{cases} 1, & \text{if } w_{ijt-1} > 0 \text{ and } w_{ijt} > 0 \text{ and } w_{ijt+1} > 0 \\ 0, & \text{otherwise.} \end{cases}$$
For these jobs, we assume employees worked the entire middle quarter and use total earnings from that quarter as their quarterly earnings rate.

We can now define four employment concepts: job stayers, employer-to-employer transitions, incumbent workers exiting to nonemployment, and new hires from nonemployment. We can also define earnings associated with these concepts. Note that while all full quarter jobs are consecutive quarter jobs, not all consecutive quarter jobs are full quarter jobs. We therefore restrict our employment concepts to subsets where full quarter earnings are available for times $t - 1$ and $t$ for job stayers and employer-to-employer transitions, time $t$ for workers exiting employment, and time $t - 1$ for workers entering employment.

A.1.1 Job Stayers

Job stayers are workers who do not change employers and thus have the same dominant job in times $t$ and $t + 1$. Formally,

$$s_{ijt} = \begin{cases} 
1, & \text{if } d_{ijt} = 1 \text{ and } d_{ijt+1} = 1 \\
0, & \text{otherwise.} 
\end{cases}$$

Since job stayers are employed by the same employer in times $t - 1$, $t$, and $t + 1$, they at minimum have full quarter earnings observations in time $t$.

A.1.2 Employer-to-Employer Transitions

Workers undergoing an employer-to-employer transition exhibit a change in dominant job, moving from an old dominant job in time $t$ to a new dominant job in time $t + 1$. Note that in time $t$, they are receiving earnings from both jobs, suggesting they separated from the old employer and started employment with the new employer in the same quarter. Hyatt et al. (2017) consequently refer to these transitions as “within-quarter” employer-to-employer transitions. For this paper, we consider the subset of these transitions where full quarter earnings are available for both the old and new
dominant job. Formally, our employer-to-employer transitions are those where:

\[
q_{ijkt} = \begin{cases} 
1, & \text{if } d_{ijt} = 1 \text{ and } d_{ikt+1} = 1 \\
& \text{and } f_{ijt-1} = 1 \text{ and } f_{ikt+1} = 1 \\
& \text{and } j \neq k \\
0, & \text{otherwise}.
\end{cases}
\]

A.1.3 Nonemployment Transitions

There are two types of nonemployment transitions. If a worker had a dominant job in time \( t \) but not in time \( t+1 \), then the worker transitioned from employment to nonemployment. Likewise, if a worker does not have a dominant job in time \( t \) but does in time \( t+1 \), then the worker transitioned from nonemployment into employment during time \( t \). For this analysis, we consider the subset of nonemployment transitions that have full quarter earnings observations.

Incumbent workers exiting employment in time \( t \) are those where:

\[
r_{ijt} = \begin{cases} 
1, & \text{if } d_{ijt} = 1 \text{ and } f_{ijt-1} = 1 \\
& \text{and } d_{ilt+1} \neq 1 \forall l, \\
1, & \text{if } d_{ijt} = 1 \text{ and } f_{ijt-1} = 1 \\
& \text{and } d_{ikt+1} = 1 \text{ and } f_{ikt} = 0 \text{ and } f_{ikt+1} = 0 \\
0, & \text{otherwise}.
\end{cases}
\]

New hires from nonemployment into employment in time \( t \) have full quarter earnings when:

\[
n_{ikt} = \begin{cases} 
1, & \text{if } d_{ikt+1} = 1 \text{ and } f_{ikt+1} = 1 \\
& \text{and } d_{ilt} \neq 1 \forall l \\
1, & \text{if } d_{ijt} = 1 \text{ and } f_{ijt-1} = 1 \\
& \text{and } d_{ikt+1} = 1 \text{ and } f_{ikt} = 0 \text{ and } f_{ikt+1} = 0 \\
0, & \text{otherwise}.
\end{cases}
\]

A.2 Earnings

Since the data do not include employment start or end dates, we do not know if earnings were received for work completed throughout the entire quarter or simply a portion of it. We therefore rely on a “full quarter” earnings concept that underlies the published LEHD data; see Abowd et al. (2009), Hahn et al. (2017), and Hyatt et al. (2017). When jobs span three consecutive quarters, we assume employees
worked the entire middle quarter and take the total earnings from that quarter to be their quarterly earnings rate. All data are winsorized at the 99th percentile.

When both quarters in a consecutive quarter pair have full quarter earnings, we use the average of the two as earnings for that job. Otherwise, if only one has full quarter earnings, then we use that quarterly earnings rate. Earnings are therefore defined as follows:

$$e_{ikt} = \begin{cases} \frac{w_{ikt} + w_{ikt+1}}{2}, & \text{if } d_{ikt} = 1 \text{ and } f_{ikt} = 1 \text{ and } f_{ikt+1} = 1 \\ w_{ikt}, & \text{if } d_{ikt} = 1 \text{ and } f_{ikt} = 1 \text{ and } f_{ikt+1} = 0 \\ w_{ikt+1}, & \text{if } d_{ikt} = 1 \text{ and } f_{ikt} = 0 \text{ and } f_{ikt+1} = 1 \\ 0, & \text{otherwise.} \end{cases}$$

This helps to ensure symmetry. Consider the following example. For a job stayer in time $t$ whose dominant job spans four quarters from time $t - 2$ to time $t + 1$, we calculate earnings change from time $t$ to time $t + 1$ as the difference between the average of full quarter earnings from times $t$ and $t - 1$ and the average of full quarter earnings from times $t + 1$ and $t$. Since full quarter earnings for time $t$ cancel, earnings change ends up being the difference in full quarter earnings between quarters $t + 1$ and $t - 1$, divided by two. Now, take the case of an employer-to-employer transition where the old job spans from time $t - 2$ to time $t$ and the new job spans from time $t$ to time $t + 2$. Earnings change is equal to the difference between the full quarter earnings for the new job in time $t + 1$ and the old job in time $t - 1$. Both calculations thus use full quarter earnings from the same quarters to estimate earnings growth, despite being for different types of employment transitions.

Finally, we note that each definition presented in this section has an hours and a wage analog, which we do not list here to save space and avoid redundancy. To calculate wages, each positive earnings measure is divided by hours.

## B Hours Imputation

For observations without hours data in our eleven state dataset, we impute hours values using models estimated on our four states dataset, which has data on hours paid between 1994 and 2016. The underlying microdata starts in 1994, but since we use a two year measure of job tenure in our imputation, we omit the first two years from our analysis so our hours imputation is not biased. Models are estimated separately for each worker type $c$ and are simulated from the posterior predictive distribution of parameters. Imputed values of hours are then drawn, see Rubin (1987).
The model takes the following form:

\[ h_{itc} = Z_{itc} \sigma_Z^c + M_{itc} \sigma_M^c + G_{itc} \sigma_G^c + Q_{itc} \sigma_Q^c + \mu_{itc}^c \]

where \( h_{itc} \) denotes log hours for worker \( i \) of worker type \( c \) at time \( t \). The matrix \( Z_{itc} \) is a vector of worker-specific demographics (i.e. sex, age, age-squared, level of completed education, race, and tenure) with marginal effects \( \sigma_Z^c \), \( M_{itc} \) is a vector of employer characteristics (i.e. industry group, firm age group, and firm size category) and worker earnings (and earnings-squared and earnings-cubed) with marginal effects \( \sigma_M^c \), \( G_{itc} \) is a vector of geography characteristics (i.e. the number of average hours worked and the unemployment rate in the employer’s state) with marginal effects \( \sigma_G^c \), \( Q_{itc} \) is a vector of quarter characteristics (i.e. quarter dummies and the number of Fridays in quarter with a lead and a lag) with marginal effects \( \sigma_Q^c \), and \( \mu_{itc}^c \) is an i.i.d. error term. All continuous variables are defined in logs.

Point estimates from a diagnostic regression are provided in Table B1, where \( c \) is defined over stayers, employer-to-employer transitions, and new hires from nonemployment, for exposition. The regressions estimated in the model are done on a finer level of disaggregation before any averaging detailed in Appendix A is done. Disaggregated regressions are not reported here since our three worker types already show evidence of substantial explanatory power.

Our hours imputation does have some limitations. We do not allow for state-fixed effects that account for systematic differences in hours across states beyond those accounted for by observable explanatory variables, such as worker demographics and firm characteristics. Furthermore, if states have idiosyncratic components that have an effect on cyclical fluctuations on earnings, hours, and wages, then these components are magnified here. In Appendix C, we further evaluate the quality of our hours imputation by comparing our average hours and wages series with those available from other sources.
Table B1: Hours Imputation - Point Estimates

<table>
<thead>
<tr>
<th></th>
<th>Stayers</th>
<th>Emp-to-Emp.</th>
<th>Entrants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings</td>
<td>11.50***</td>
<td>6.789***</td>
<td>11.72***</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.392)</td>
<td>(0.225)</td>
</tr>
<tr>
<td>Earnings²</td>
<td>−1.060***</td>
<td>−0.519***</td>
<td>−1.074***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.045)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Earnings³</td>
<td>0.032***</td>
<td>0.012***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Tenure</td>
<td>−0.015***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Age</td>
<td>−0.006***</td>
<td>−0.010***</td>
<td>−0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Age²/1000</td>
<td>0.054***</td>
<td>0.095***</td>
<td>0.063***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>State Avg. Hours Worked</td>
<td>−0.006***</td>
<td>−0.006***</td>
<td>−0.006***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>State Unemployment Rate</td>
<td>−0.004***</td>
<td>−0.001</td>
<td>−0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Quarter</td>
<td>0.000***</td>
<td>−0.002***</td>
<td>−0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Quarter²/1000</td>
<td>0.003***</td>
<td>0.012***</td>
<td>0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>No. of Fridays</td>
<td>0.005***</td>
<td>−0.001</td>
<td>−0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>R²</td>
<td>0.599</td>
<td>0.667</td>
<td>0.727</td>
</tr>
</tbody>
</table>

Notes: Variables included in the diagnostic regression but not in the table above are dummy variables for worker demographics (i.e. sex, race, and level of completed education) as well as destination firm characteristics (i.e. industry group, firm age group, and firm size category).
C Comparability of LEHD Earnings, Hours, and Wages to Other U.S. Data Sources

Figure C1 shows the trend in earnings for our eleven state dataset and compares it with other series available from the Current Employment Statistics (CES), the CPS, the Employer Cost of Employee Compensation Survey (ECEC), and the Quarterly Census of Employment and Wages (QCEW). While there are notable differences among them, all trend upward and exhibit sharp gains during the late 1990s.\(^{21}\) Our series (solid line) shows higher levels of wage and salary compensation from employers than others do, with the exception of the ECEC’s total compensation line (dash-dot-dot line), which includes employee benefits like health insurance and is therefore greater on a per-worker basis, and the LEHD Quarterly Workforce Indicator (LEHD QWI) line (long dash-dot-dot line). At the same time, it tracks both the Average Weekly Wage (QCEW) (long dash-medium dash line) and LEHD QWI series fairly closely.\(^{22}\) This suggests the differences seen in the figure can generally be attributed to differences in data sources and tabulation strategies. We additionally ran correlations between all of the series and two cyclical indicators, the real GDP and the unemployment rate, and find our earnings series is moderately procyclical. In contrast, the Average Weekly Wages and LEHD QWI series are much more procyclical while the other series are nearly acyclical or even slightly countercyclical. See Table C1.

In Figure C2, we present our imputed hours series from our eleven state dataset alongside hours series available from the CES and CPS\(^ {23}\). We also include our non-imputed hours series from our four state dataset, which starts in 2011Q3 since hours data for our four state dataset are only complete beginning in that quarter. Overall, our imputed hours series (solid line) appears to be comparable to the three outside hours series between 2000 and 2014. It lies consistently above the CES line (dash line) and below the two CPS lines (dotted and dash-dot lines) and exhibits similar behaviors, with all series indicating that hours remained constant until the Great recession when they declined. While the

\(^{21}\) Differences among earnings series have been noted by Abraham, Spletzer, and Stewart (1998) as well as Champagne, Kurmann, and Stewart (2017).

\(^{22}\) We expect our series to be most similar to the Average Weekly Wage series (QCEW) created as part of the Quarterly Census of Employment and Wages program and the Average Monthly Earnings series from LEHD’s QWI (LEHD QWI). All three rely on QCEW data and use universe-level, employer-reported total wage and salary payments calculated from administrative records. Differences primarily lie in the types of jobs included in the average. The QCEW series counts jobs where workers are employed during the week of the 12th in the third month of the quarter while the LEHD QWI series includes all jobs that span at least three consecutive quarters. Our series is essentially a subset of the latter as it includes all dominant jobs that span at least three consecutive quarters.

\(^{23}\) The CPS hours series is created from microdata available from IPUMS (Flood et al., 2017).
Table C1: Correlations - Earnings

<table>
<thead>
<tr>
<th>Source</th>
<th>Series</th>
<th>Real GDP</th>
<th>Unemp. Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEHD 11 State</td>
<td>Avg Quarterly Earnings</td>
<td>0.280</td>
<td>-0.268</td>
</tr>
<tr>
<td>LEHD QWI</td>
<td>Avg Monthly Earnings</td>
<td>0.755</td>
<td>-0.519</td>
</tr>
<tr>
<td>QCEW</td>
<td>Avg Weekly Wages</td>
<td>0.629</td>
<td>-0.355</td>
</tr>
<tr>
<td>CES</td>
<td>Avg Weekly Earnings</td>
<td>0.018</td>
<td>0.053</td>
</tr>
<tr>
<td>CPS</td>
<td>Median Weekly Earnings</td>
<td>-0.180</td>
<td>0.313</td>
</tr>
<tr>
<td>ECEC</td>
<td>Wages and Salary</td>
<td>-0.148</td>
<td>0.192</td>
</tr>
<tr>
<td>ECEC</td>
<td>Total Compensation</td>
<td>-0.131</td>
<td>0.172</td>
</tr>
</tbody>
</table>

Notes: Real GDP is the first difference of the log of the seasonally-adjusted and Henderson-filtered real GDP and is presented in 2014 constant dollars. Unemployment Rate is the first difference of the log of the seasonally-adjusted national unemployment rate. Correlations with these cyclical indicators were calculated using the first difference of the logs of the seasonally-adjusted and Henderson-filtered earnings series from 1996Q1 to 2015Q4. All earnings series are presented in 2014 constant dollars.

CES, CPS (Full-Time), and CPS lines exhibit larger drops in hours than our imputed hours series, all show a slight recovery in hours after 2010. After 2014, our imputed series shows a sharp gain in hours while the other lines are mostly flat. We believe this difference is not related to the quality of our hours impute since our non-imputed series (dash-dot-dot line) also increases at a similar rate. Correlations between these hours series and the cyclical indicators are presented in Table C2 and show the CES and CPS series are highly procyclical while the CPS (Full-Time) and our imputed hours series are much less so.

Table C2: Correlations - Hours

<table>
<thead>
<tr>
<th>Source</th>
<th>Series</th>
<th>Real GDP</th>
<th>Unemp. Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEHD 11 State</td>
<td>Avg Quarterly Hours</td>
<td>0.193</td>
<td>-0.289</td>
</tr>
<tr>
<td>LEHD 4 State</td>
<td>Avg Quarterly Hours</td>
<td>-0.235</td>
<td>-0.102</td>
</tr>
<tr>
<td>CES</td>
<td>Avg Weekly Hours</td>
<td>0.602</td>
<td>-0.679</td>
</tr>
<tr>
<td>CPS</td>
<td>Avg Total Hours</td>
<td>0.351</td>
<td>-0.356</td>
</tr>
<tr>
<td>CPS</td>
<td>Hours Worked Last Week</td>
<td>0.689</td>
<td>-0.722</td>
</tr>
</tbody>
</table>

Notes: Real GDP is the first difference of the log of the seasonally-adjusted and Henderson-filtered real GDP and is presented in 2014 constant dollars. Unemployment Rate is the first difference of the log of the seasonally-adjusted national unemployment rate. Correlations with these cyclical indicators were calculated using the first difference of the logs of the seasonally-adjusted and Henderson-filtered hours series from 1996Q1 to 2015Q4.

Figure C3 shows our imputed wage series from our eleven state dataset as well as other wage series available from the CES and ECEC. Also included is our non-imputed wage series from our four state dataset, again only starting in 2011Q3 when hours data begin to be complete. Our imputed wage
Figure C1: Trends in Average Compensation and Earnings in the U.S., 1996-2015

Notes: All series are presented in 2014 constant dollars and have been seasonally adjusted and Henderson-filtered using x12. Shaded areas indicate recessions. CES indicates the Current Employment Statistics’ average weekly earnings series for production and nonsupervisory employees in the private sector, multiplied by 13. CPS indicates the Current Population Survey’s median usual weekly earnings series for full-time wage and salary workers in all industries and occupations who are 16+ years old, multiplied by 13. ECEC WS indicates the Employer Costs of Employee Compensation Survey’s cost per hour worked (wages and salaries) series of all private industry employees for all occupations, multiplied by 13 and 34.5. ECEC Comp. indicates the Employer Costs of Employee Compensation Survey’s cost per hour worked (total compensation, including wages and salaries and benefit compensation) of all private industry employees for all occupations, multiplied by 13 and 34.5. QCEW indicates the Bureau of Labor Statistics’ average monthly earnings series of all employees in the private sector, multiplied by 13. LEHD QWI indicates the LEHD Quarterly Workforce Indicators’ average monthly earnings series of employees with stable jobs, (i.e. worked with the same firm throughout the quarter), multiplied by 3. LEHD 11 State indicates the average earnings series from our eleven state dataset.

series (solid line) is similar to the others in the figure, with all lines suggests wages rose during the
late 1990s and were subsequently flat. While the other series show a slight increase in wages during the Great Recession, our imputed series suggests wages remained roughly the same. However, all lines do display a small rise in wages at the end of the time series. Our imputed series is substantially higher than the others, with the exception of the ECEC’s total compensation line (dash-dot line),
Table C3: Correlations - Wages

<table>
<thead>
<tr>
<th>Source</th>
<th>Series</th>
<th>Real GDP</th>
<th>Unemp. Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEHD 11 State</td>
<td>Avg Quarterly Wages</td>
<td>0.364</td>
<td>-0.260</td>
</tr>
<tr>
<td>LEHD 4 State</td>
<td>Avg Quarterly Wages</td>
<td>0.254</td>
<td>-0.099</td>
</tr>
<tr>
<td>CES</td>
<td>Avg Hourly Earnings</td>
<td>-0.285</td>
<td>0.355</td>
</tr>
<tr>
<td>ECEC</td>
<td>Hourly Cost of Wages and Salaries</td>
<td>-0.148</td>
<td>0.192</td>
</tr>
<tr>
<td>ECEC</td>
<td>Hourly Cost of Compensation</td>
<td>-0.131</td>
<td>0.172</td>
</tr>
</tbody>
</table>

Notes: Real GDP is the first difference of the log of the seasonally-adjusted and Henderson-filtered real GDP and is presented in 2014 constant dollars. Unemployment Rate is the first difference of the log of the seasonally-adjusted national unemployment rate. Correlations with these cyclical indicators were calculated using the first difference of the logs of the seasonally-adjusted and Henderson-filtered wage series from 1996Q1 to 2015Q4. All wage series are presented in 2014 constant dollars.

but it is similar in level to our non-imputed series (dash-dot-dot line) suggesting our hours impute is functioning well. Correlations in Table C3 between these wage series and the cyclical indicators reveal our imputed and non-imputed series are procyclical while those from the CES and ECEC are countercyclical.
Figure C3: Trends in Average Wages in the U.S., 1996-2015

Notes: All series are presented in 2014 constant dollars and have been seasonally adjusted and Henderson-filtered using x12. Shaded areas indicate recessions. CES indicates the Current Employment Statistics’ average hourly earnings series for production and nonsupervisory employees in the private sector, multiplied by 13. ECEC WS indicates the Employer Costs of Employee Compensation Survey’s cost per hour worked (wages and salaries) series of all private industry employees for all occupations, multiplied by 13. ECEC Comp. indicates the Employer Costs of Employee Compensation Survey’s cost per hour worked (total compensation, including wages and salaries and benefit compensation) of all private industry employees for all occupations, multiplied by 13. LEHD 11 State indicates the average earnings series from our eleven state dataset. LEHD 4 State indicates the average non-imputed wage series from our four state dataset. This series begins in 2011Q3, when the hours data for the four state dataset begins to complete.
D Earnings and Employment Shares Over Time by Transition Type

Average quarterly earnings at times $t-1$ and $t$ are also presented by worker type in Figure D1. This earnings data is the basis of our analysis, which mostly focuses on the change in average log earnings from time $t-1$ to time $t$. Job stayers in times $t-1$ (dash line) and $t$ (solid line) have the highest average earnings and exhibit incremental increases from time $t-1$ to time $t$. These gains are smallest during economic downturns (indicated by shaded areas). The next to highest earnings levels are associated with employer-to-employer transitions in time $t$ (dotted line). These earnings tend to be markedly higher, about $3,000 more, than earnings for the same workers in time $t-1$ (dash-dot line). The remaining lines show earnings of incumbent workers exiting employment (dash-dot-dot line) and new hires from nonemployment (long dash-medium dash line). Earnings of exiters in time $t-1$ tend to be about $500 greater than earnings of new hires from nonemployment in time $t$, which can be attributed to tenure and composition effects. Figure D2 shows the same time series in logs instead of levels. We also include corresponding figures for hours and wages in Figures D3 and D4 as well as Figures D3 and D4, respectively.

We also plot a time series of shares of worker types over the past two decades in Figure D7. The decomposition presented in our paper is a transformation of average log earnings shown in Figure D2 and employment shares shown in this figure. We see employment is generally dominated by job stayers. In the late 1990s, this group of workers made up roughly 90 percent of employment. Their share subsequently increased by about 1 percent. The share jumped again by 2 percent to 93 percent during the Great Recession. It has gradually declined from that peak in 2010 to 91 percent at the end of our timeseries. Meanwhile, the share of employer-to-employer transitions slowly declined from 3 percent in the late 1990s to a low of 1.7 percent after the Great Recession. It has subsequently returned to levels seen before the 2001 recession and is approximately 3 percent again. The shares of new hires from nonemployment and incumbent workers exiting employment started at roughly 6-7 percent of employment in the beginning of the time series but have decreased, mostly during recessions, to just under 6 percent.\textsuperscript{24}

\textsuperscript{24}The shares of workers with full quarter earnings in times $t-1$ and $t$, i.e. job stayers and employer-to-employer transitioners, vary depending on whether employment at time $t-1$ or time $t$ is used as the denominator. In the U.S., employment typically grows from time $t-1$ to time $t$, so shares by worker type, and consequently contributions to the aggregate, change in a quarter even though the numerator remains the same. To better understand this, consider job stayers. When employment grows, the number of job stayers in time $t$ remains the same but their share is lower when
Figure D1: Average Quarterly Earnings for Stayers and Transitioners in the U.S., 1996-2015

Notes: All series are presented in 2014 constant dollars and are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.

the denominator is employment in time \( t \) compared to employment in time \( t-1 \). In Figure D7, we see the solid line is generally lower than the dotted line. This is similarly the case, although to a far smaller degree, for employer-to-employer transitions.
Notes: All series are presented in 2014 constant dollars and are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.
Figure D3: Average Quarterly Hours for Stayers and Transitioners in the U.S., 1996-2015

Notes: All series are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.
Figure D4: Average Quarterly Log Hours for Stayers and Transitioners in the U.S., 1996-2015

Notes: All series are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.
Figure D5: Average Quarterly Wages for Stayers and Transitioners in the U.S., 1996-2015

Notes: All series are presented in 2014 constant dollars and are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.
Figure D6: Average Quarterly Log Wages for Stayers and Transitioners in the U.S., 1996-2015

Notes: All series are presented in 2014 constant dollars and are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions.
Figure D7: Share of Employment Transitions, 1996-2015

Notes: All series are seasonally-adjusted and Henderson-filtered using x12. Shaded areas indicate recessions. Stayers Share at Time $t - 1$ indicates the number of job stayers divided by employment in time $t - 1$. Stayers Share at Time $t$ indicates the number of job stayers divided by employment in time $t$. Emp-to-Emp. Share at Time $t - 1$ indicates the number of employer-to-employer transitions divided by employment in time $t - 1$. Emp-to-Emp. Share at Time $t$ indicates the number of employer-to-employer transitions divided by employment in time $t$. Exiters Share at Time $t - 1$ indicates the number of incumbent workers exiting employment divided by employment in time $t - 1$. Entrants Share at Time $t$ indicates the number of new hires from nonemployment divided by employment in time $t$. 
E Additional Results

E.1 First-Difference Regression Estimates

We now briefly compare our basic regression results to those found in the existing literature. A first difference specification following Bils (1985) and is commonly found in the literature. Estimated coefficients for this specification are found in Table E1. A survey of previous studies by Pissarides (2009) concludes the wages of new hires decline by three percent for every one percentage point increase in the unemployment rate. We find wages respond from 2.2 percent ($= 2.0 + 0.2$) to 3.2 percent ($= 2.7 + 0.5$), which aligns with the literature using first difference specifications. There are fewer reference points for how hours respond to the unemployment rate but we find it is in the range of 1.3 percent to 4.4 percent. Since the change in earnings is approximately the sum of the response of hours and wages, it is larger than both.
Table E1: First-Difference Earnings, Hours, and Wages Regressed on the Unemployment Rate

<table>
<thead>
<tr>
<th></th>
<th>Earnings</th>
<th>Hours</th>
<th>Wages</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Four States</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job Stayers ($\gamma_1$)</td>
<td>-0.007***</td>
<td>-0.004***</td>
<td>-0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>New Hires from Another Employer ($\gamma_2$)</td>
<td>-0.029***</td>
<td>-0.009***</td>
<td>-0.020***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>New Hires from Nonemployment ($\gamma_3$)</td>
<td>-0.060***</td>
<td>-0.040***</td>
<td>-0.020***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Observations (Millions)</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.026</td>
<td>0.016</td>
<td>0.010</td>
</tr>
</tbody>
</table>

|                         |          |       |       |
| **Eleven States**       |          |       |       |
| Job Stayers             | -0.007*** | -0.002*** | -0.005*** |
|                         | (0.000)  | (0.000) | (0.000) |
| New Hires from Another Employer ($\gamma_2$) | -0.051*** | -0.024*** | -0.027*** |
|                         | (0.001)  | (0.002) | (0.002) |
| New Hires from Nonemployment ($\gamma_3$) | -0.045*** | -0.018*** | -0.027*** |
|                         | (0.001)  | (0.001) | (0.001) |
| Observations (Millions) | 29.0     | 29.0  | 29.0  |
| $R^2$                   | 0.019    | 0.002 | 0.001 |

Notes: Regressions were run using two analysis datasets. The top set of results are from regressions using non-imputed, disaggregated earnings, hours, and wages data from our four state dataset. The bottom set of results are from regressions using non-imputed, disaggregated earnings data and mostly imputed, disaggregated hours and wages data from our eleven state dataset. Earnings and wages series are presented in 2014 constant dollars. See text for specification details.