Labor Reallocation, Employment, and Earnings: Vector Autoregression Evidence

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Abstract. We present time series evidence for the USA 1993–2013 on the relationship between labor reallocation, employment, and earnings using a vector autoregression framework. We find that an increase in labor market churn by 1 percentage point predicts that employment will increase by 100,000–560,000 jobs, lowering the unemployment rate by 0.05–0.25 percentage points. Job destruction does not predict changes in employment but a 1 percentage point increase in job destruction leads to an increase in unemployment 0.14–0.42 percentage points. We find mixed results on the relationship between labor reallocation rates and earnings.

1. Introduction

The US labor market exhibits a considerable amount of job and worker reallocation. Employers are continually entering and exiting the market, which is itself expanding and contracting, while workers are at the same time beginning and ending jobs. The rate at which these transitions occur have many well-known cyclical properties. During expansions, job creation rises as new businesses enter and incumbents expand, whereas during contractions job destruction rises as businesses exit and incumbents contract. Hires and separations in the US economy occur much more frequently than is necessary to reallocate jobs across employers. Excess reallocation, called labor market churn, is procyclical and increases along with other measures of the health of the labor market.[1] A number of studies including Davis and Haltiwanger (2014), Hyatt and Spletzer (2013), and Molloy *et al.* (2016) present evidence that measures of aggregate labor reallocation have declined dramatically since the start of the millennium, and may also done so in previous decades. But whether and how job reallocation and churn affect other labor market outcomes and the economy as a whole remains unknown, despite increasing interest from researchers and policymakers.[2]

In this paper, we provide empirical evidence on the consequences of changes in labor reallocation through both job reallocation and churn. Job reallocation includes two

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components: job creation, which measures employment growth through establishment entry and expansion, and job destruction, which measures employment losses through establishment exit and contraction. These two measures capture the rate at which jobs are being moved across employers, see Davis *et al.* (1996). By churn we mean those worker movements into and out of establishments that is not necessary to explain their entry and growth, see Burgess *et al.* (2000). Many of these movements reflect employer-to-employer transitions that do not affect employment directly, and which are quickly replaced. Total worker reallocation (all hires and separations) is given by the sum of job reallocation and (twice) churn.[3]

We take advantage of new data sources that permit the measurement of labor market churn for recent decades. Specifically, we use national-level data from the Quarterly Workforce Indicators from the Longitudinal Employer-Household Dynamics (LEHD) program at the US Census Bureau, see Abowd and Vilhuber (2011). These provide data on labor reallocation (job creation, job destruction, and churn), employment, and average earnings for 1993.Q2 to 2013.Q4. In addition to these, we use data on output (Gross Domestic Product, or GDP), the price level (the Consumer Price Index, or CPI), and the unemployment rate. We also use two additional sources to measure the earnings level: the Current Employment Statistics (CES) and the Current Population Survey (CPS). We consider the relationship between labor reallocation, employment, and earnings in a vector autoregressive (VAR) model. This framework allows us to measure when movements in aggregate measures are immediately followed by changes in other aggregate measures, and assess to what extent one set of variables impacts the forecast performance of other variables. When such a forecast impact is non-negligible, the variable is said to Granger (1969) cause movements in another variable. We also implement a novel test whether relationships between variables can safely be omitted. This parameter selection technique assesses whether variables in the VAR affect each other on the basis of overall model fit.

This paper contains empirical estimates of the relationship between labor reallocation and other labor market and economic measures. We find that an increase in labor market churn by 1 percentage point predicts that, in the next quarter, employment will increase by 100,000–560,000 jobs, lowering the unemployment rate by 0.05–0.25 percentage points.[4] Job destruction does not predict future changes in employment but a 1 percentage point increase in job destruction leads to an increase in future unemployment 0.14–0.42 percentage points. We also find mixed evidence on the relationship between labor reallocation rates and earnings, with some specifications indicating that a 1 percentage point increase to either job destruction or churn leads to increased earnings of <2 per cent. We also present estimates of the relationship that labor reallocation has with output and inflation.

Our empirical findings can be used to assess the relative importance of proposed mechanisms that govern the relationship between labor reallocation, employment, and earnings. Models such as Mortensen and Pissarides (1994) capture the effects of changes in the aggregate state of the economy on unemployment and how it is lowered through job creation increased through job destruction. Job ladder models such as Barlevy (2002) propose that, during expansions, a higher rate of voluntary worker separations to take better jobs may lead to improved job match or employer quality and therefore higher earnings. In contrast, evidence on the returns to job tenure and the theory of firm-specific human capital provide mechanisms through which higher rates of labor reallocation may be associated with lower earnings. Most of the empirical evidence that has been used to evaluate these models has been through moment matching exercises that parameterize a structural model, or from reduced-from empirical studies that highlight the existence of particular mechanisms. Our estimation strategy does not assume any particular model of the labor market, which makes it unlike structural models: our VAR is purely data driven (Sims, 1980). These features imply that our framework is more similar to reduced-form studies, although our VAR estimation allows for a richer set of relationships between variables.

Our findings show how labor reallocation rates affect the health of the labor market. Consistent with most models of unemployment in the labor market, we find that increases in output indeed Granger cause increases in job creation and churn, but we find only limited evidence that labor reallocation affects aggregate output. We also find evidence that churn predicts increases in job creation, which is consistent with models in which firms engage in replacement hiring, as firms replace workers that are lost to other employers through poaching, leading to a 'vacancy chain.' We find mixed evidence on the relationship between labor reallocation and earnings, but our findings in which churn leads to increased earnings are consistent with job ladder models of the labor market, which provide two channels for churn to affect earnings: the direct effect of improved match quality, as well as increases in worker bargaining power. Our models do not find a significant relationship between churn and output, which is consistent with the bargaining power channel dominating. Our findings on job destruction are consistent with labor market models in which low-quality matches are 'cleansed' during downturns. We find no evidence that suggests that increases in labor reallocation lead to material earnings reductions, which implies that lower levels of firm-specific human capital implied by increases in such measures do not have first-order effects on earnings.

This paper also provides a methodological contribution in which we propose and implement a novel method for testing hypotheses in a VAR. As is well-known, in conducting hypothesis tests in which there is a single dependent variable of interest, it is usually unknown *ex ante* whether different variables affect each other and therefore their effects should be included in the analysis as control variables, and this is also true in a setting in which there are multiple dependent variables that potentially determine each other. We, therefore, propose and implement a multivariate Wald test appropriate to our VAR framework for changes in the goodness of fit from adding additional relationship into our analysis. Given that this method rules out about half of the potential relationships among our variables of interest, it provides significant clarity to our analysis. It also adds substantial precision to the remaining parameter estimates. And for interested readers, we always provide conventional (unrestricted) VAR estimates for comparison.

Our empirical findings, and especially our tests for joint multivariate significance, can assist in the interpretation of previous empirical findings. Studies such as Davis and Haltiwanger (2014), Hyatt and Spletzer (2013), and Molloy *et al.* (2016) consider the causes and consequences of different labor reallocation measures in separate empirical specifications. However, if changes in one labor reallocation measure leads to changes in another, then failure to include or control for multiple measures can lead to omitted variable bias in the analysis of labor reallocation. Given that we find that the innovations to each of job creation, job destruction, and churn largely do not predict innovations in the others, this implies that the conventional framework for analyzing the effects of labor reallocation rates is usually without issue.[5] However, we do find evidence that churn leads to increases in job creation. Therefore, failure to control for churn in a time series analysis of job creation may lead to inadvertent attribution of the effects of churn to job creation: since job creation is a byproduct of churn, then an empirical finding, e.g., that job creation leads to wage growth may not be due to job creation's role in productivity-enhancing job reallocation, but may be because churn leads to more bargaining power for workers and therefore higher wages.

Furthermore, our estimation provides context to the ample evidence that job reallocation and especially churn evolve procyclically in tandem with many other measures of the health of the labor market such as labor force participation and wage growth.[6] These empirical regularities of course suggest a relationship between these variables, but the existence and direction of any causality has continued to be an open question. We find that only changes in the price level and output lead to changes in employment reallocation rates, and the labor market outcomes that are more conventionally of interest to policymakers such as unemployment, employment, and wage growth have at most a very small role in determining labor reallocation rates. The evidence suggests that employment reallocation affects employment and earnings rather than the reverse (although, as noted above, results are more mixed for earnings). The effects of churn seem to be especially important for how we understand unemployment over the business cycle. For example, in the 2007–09 recession, churn dropped by 8 percentage points, whereas the unemployment rate increased by 5 percentage points. Our estimates suggest that this decline in churn can explain 0.4–2 percentage points of that increase.

The main benefit of using a VAR framework for analysis of labor reallocation is its ability to capture dynamic relationships between macroeconomic aggregates. We document complex relationships between churn and employment, as well as between reallocation and earnings. Such relationships are difficult to pin down precisely in the reduced-form studies that constitute most of the empirical literature on labor reallocation. We also view our framework as a purely data-driven approach that can help motivate future structural estimation of the labor market. Churn appears to play a key role in increases in employment and potentially also earnings. Future structural work can help explore the ability of theoretical mechanisms to produce such relationships, and provide moments that the estimation of such models might target.

The paper proceeds as follows. In Section 2, we review the theory and empirical evidence on job reallocation and churn. In Section 3, we provide a description of our data. In Section 4, we describe our econometric methodology. In Section 5, we present the empirical results and relate them to the predictions of the models of the labor market. A brief conclusion follows in Section 6.

2. Theory and evidence on job reallocation and churn

This section reviews economic theory and empirical evidence on job reallocation and churn. Several classes of models make predictions about the implications of job reallocation and churn on other labor market outcomes such as employment, unemployment, and earnings. Although elements of all such theories surely play a role in determining economic outcomes, our empirical analysis of economic aggregates clarifies whether a particular mechanism has a substantial effect on the labor market as a whole.

2.1 Models of job creation and destruction

The standard reference in the theory of job creation and destruction is Mortensen and Pissarides (1994). This is a model of business cycles in which better aggregate states of the economy (e.g., higher GDP growth) lead firms to post vacancies that lead to job creation, and recessions lead to job destruction through firm exit decisions. In this framework, job creation will lower the unemployment rate, whereas job destruction will raise the unemployment rate. In Mortensen and Pissarides (1994) and other variants that include job-specific 'match quality,' during recessions it is the jobs with the lowest match quality that will be destroyed. This leads to another prediction, that job destruction may increase average earnings, although this is not an unambiguous prediction in this class of models because in economic downturns the wage rate generally declines.[7]

Empirical evidence is consistent with productivity-enhancing effects of job creation and job destruction. Studies such as Foster *et al.* (2001) have found that, within given industries, more productive businesses expand, whereas less productive ones contract, and that entering businesses are more productive than the exiting firms that they replace. There is also evidence that more productive firms are also higher paying, see Abowd *et al.* (2005) and Dunne *et al.* (2004), so this reallocation may move jobs from lower paying to higher paying firms, and also it seems plausible that job destruction events may lead to countercyclical earnings growth.

This set of models generally lacks predictions about churn. That is because a theoretical analogue for churn requires more of a notion of firm size than is included in most such models.[8] It also requires that some job moves not result in changes in the size of firms or establishments, which is easiest to conceptualize in a framework that includes on-the-job search, which we describe in the next section.

2.2 *Job ladders and on-the-job search*

Models of on-the-job search make predictions about the relationship between job reallocation, churn, employment, and earnings, and this represents the main theory of churn in macroeconomics. Barlevy (2002) demonstrates that in an environment with on-the-job search and heterogeneous match quality, separations to unemployment will feature similar cleansing effects as those found in Mortensen and Pissarides (1994). However, since on-the-job search moves workers from worse to better (and higher paying) matches, recessions have a 'sullying effect.' In models where firms can make counter-offers, rejected offers also contribute to procyclical wage growth in addition to the direct effect of procyclical improvements in job match quality on wages, see Lise and Robin (2017). If increased levels of churn lead to increases in match quality, both earnings and output should increase. However, if increased churn influences earnings primarily through increasing worker bargaining power, it could lead to earnings increases without a large effect on output.

Models of on-the-job search, therefore, suggest that greater levels of churn should be associated with earnings increases. This seems plausible because both churn and earnings growth are procyclical. There is also substantial empirical evidence from microdata that such worker movements across employers lead to earnings increases. Topel and Ward (1992) documented that the earnings changes associated with job change account for about one-third of the cumulative earnings increase for young men. Hahn *et al.* (2017) provide more recent evidence that the earnings changes associated with job change are procyclical and also lead to earnings increases in the aggregate economy. Haltiwanger *et al.* (2018) provide evidence that worker movements from low-paying to higher paying firms is procyclical and translate into earnings increases for those affected workers. Faberman and Justiniano (2015) show that quits and earnings growth are both procyclical, and Karahan *et al.* (2017) provide evidence that employer-to-employer transitions are associated with earnings growth using state-level regressions.

Some models of on-the-job search also feature replacement hiring and vacancy chains. In a framework such as Schaal (2017), the loss of a worker who is poached leads the firm to post a vacancy. This is a natural consequence of a framework in which there is an optimal firm size given the firm's production technology. If on-the-job search and poaching leads to such vacancy chains, then increases in churn may lead to increases in job creation and employment. Davis and Haltiwanger (2014) provide evidence that higher levels of labor reallocation are associated with higher levels of employment using state-level instrumental variable regressions.

2.3 Returns to tenure and firm-specific human capital

Although models of on-the-job search and job ladders lead to the prediction that churn will lead to earnings increases, there is an alternative strand of the labor economics literature that would seem to suggest that job destruction and churn might lead to earnings losses. The theory of firm-specific human capital, see Lazear (2009), suggests that, when workers separate from their jobs, they lose some productivity that was inherent in that employer–employee match. The standard theory suggests that the amount of such firm-specific human capital should grow over time, consistent with empirical findings on the returns to tenure at a specific employer. Studies such as Jacobson, Lalonde, and Sullivan (1993) have shown that earnings drop by more than 20 per cent, even several years after job loss. Davis and von Wachter (2011) argue that it is difficult for models in style of Mortensen and Pissarides (1994) to generate earnings losses of this magnitude, and so this mostly empirical literature provides a strong alternative reference point on the relationship between wages and job destruction.

These models provide a mechanism for increasing job reallocation and churn to lower average earnings. If employment instability leads to losses of firm-specific human capital, then we would expect to see job destruction and labor market churn lead to lower average earnings. Hyatt and Spletzer (2016) provide evidence that median job tenure is countercyclical as during recessions there are fewer new hires and therefore fewer jobs of low duration. Models of the returns to job tenure suggest that it increases over time and therefore should be at its lowest point at the start of a new job, and so these countercyclical increases in job tenure could lead to increases in average earnings. However, Hyatt and Spletzer (2016) find that even though there are empirical returns to tenure throughout the past couple of decades, it has changed over time to such an extent that increased job tenure has not led to aggregate earnings increases.

The recent work of Daly and Hobijn (2016) and Hahn *et al.* (2017) have recently documented a channel for countercyclical wage and earnings growth that is understood in part based on returns to job tenure. These studies provide evidence that workers leaving employment for nonemployment (i.e., including retirees) tend to earn more than workers leaving nonemployment for employment (i.e., including young people looking for work for the first time). During expansions, as employment increases, by definition the number of employment entrants exceeds the number of employment exiters, and so employment growth leads to lower average earnings via this nonemployment margin. Therefore, we may expect to see increases in job creation be associated with a lower the level of average earnings because of an influx of low-earning new entrants.

2.4 Summary of model predictions

Economic models of the labor market lead to a number of predictions on the causes and consequences of job reallocation and churn, which are not necessarily consistent across models. We summarize these as follows:

1. Job creation is a natural consequence of economic expansion, and should be associated with increases in employment and decreases in unemployment as workers fill these new jobs. Job creation may be associated with lower average earnings since workers entering new jobs lack firm-specific human capital (i.e., have not accumulated returns to tenure).
2. In labor market search models, job destruction is a consequence of worsening economic conditions. If recessions cleanse away matches that are of low quality, leading to earnings increases. On the other hand, increased job destruction may lead to earnings decreases if it leads average job duration to decline, leading to an employed population with less firm-specific human capital. Job destruction may naturally lead to reductions in employment and increases in unemployment.
3. Churn is viewed either as a vehicle for moving workers up a job ladder or, alternatively, as an indication of employment instability. If the former channel dominates, churn may lead to earnings increases, although if the latter does then increasing churn would lower average job tenure and therefore lead to earnings decreases. Churn may lead to increases in employment and job creation if employer-to-employer transitions lead to vacancy chains.

The empirical work that follows clarifies which of these mechanisms matter for the labor market as a whole.

3. The data

3.1 Economic measures

We use quarterly data job creation, job destruction, and churn at a national level for 1993.Q2 through 2013.Q4. We are interested in the impact of these variables on earnings, employment, and unemployment. Of secondary interest are GDP and the price level, which are included as controls.[9] In what follows, we provide an overview of the economic measures used in the analysis. For additional details and specific steps in the data preparation, see Appendix S1.

3.1.1 Labor reallocation measures. Definitions of labor reallocation measures are as follows for a particular time interval t (year, month, etc.). We can count the number of individuals employed at the beginning of that quarter ($empbeg_t$) and also at the end of that quarter ($empend_t$). Hires ($hires_t$) are employer–employee relationships that begin during quarter t (i.e., did not exist in time $t-1$). Separations ($seps_t$) are employer–employee relationships that end in period t (i.e., do not exist at the end of quarter t). Job creation (jc_t) measures the net hires at establishments that enter (all employees that appear in time t, i.e., all hires) or gain employment (i.e., hires in excess of separations). Job destruction (jd_t) measures the net separations at establishments that exit (all employees that appear in time t separate) or contract (i.e., separations in excess of hires).

These four series exhibit strong seasonal movements, which mask the underlying trend and cyclical movements; for this reason, we will focus upon seasonally adjusted data where additive outliers have been removed. Before discussing these procedures, we note that these labor series have an element of redundancy — the following identity is a stylized economic fact, and moreover is numerically true (up to rounding errors):

$$hires_t - seps_t = jc_t - jd_t = empend_t - empbeg_t \tag{1}$$

for all times t.[10] Given the empirical validity of [1], it would be a fallacy to include all the four variables for hires, separations, job creation, and job destruction in a model, as this would generate multicollinearity problems and yield a nonidentifiable model.[11] Now, with the definition of churn ($churn_t$) as

$$churn_t = hires_t - jc_t, \tag{2}$$

it follows from [1] and [2] that

$$seps_t = jd_t + churn_t. \tag{3}$$

So [3] indicates that separations should be eliminated from the data; we will henceforth focus upon churn, job creation, and job destruction.[12]

3.1.2 Employment and unemployment. We are chiefly interested in the impact of these three variables upon earnings, employment, and unemployment.[13] Following Abowd and Vilhuber (2011), employment is from the LEHD Quarterly Workforce Indicators and is defined as

$$emp_t = \frac{empend_t + empbeg_t}{2}. \tag{4}$$

The unemployment rate comes from the Bureau of Labor Statistics, and measures the frequency with which people aged 16 and over are available for work and have looked for work in the last 4 weeks. The denominator for this rate is the sum of those people aged 16 and over who are employed plus those who are unemployed (i.e., the labor force).

3.1.3 Earnings. Finding a suitable proxy variable for the concept of earnings presents several choices. Economists tend to focus attention on real earnings, defined as nominal earnings normalized by the inflation rate. The LEHD database offers one such real earnings series, but we also consider sources from the CES and the CPS as well, as sensitivity checks for our analysis. These data sources have substantial differences that have been the subject of many studies, discussed in Abraham *et al.* (1998) and Champagne and Kurmann (2017). We also wish to highlight trends in earnings in the LEHD data, which is an administrative records source. Average earnings in the LEHD data have recently been considered by Hahn *et al.* (2017), Hyatt and Spletzer (2017) and Karahan *et al.* (2017).

3.1.4 Other aggregate measures. In addition, we consider the variables of the price level as measured by the CPI, as well as output measured by real GDP; see Appendix S1. These are included primarily as control variables.

3.2 Signal extraction

Our main variables of interest are job creation, job destruction, churn, earnings, and employment. Other variables of secondary interest are the unemployment rate, the CPI, and GDP, which we utilize to examine the robustness of the identified economic relationships. Each series is subject to anomalous effects, generating extreme values and idiosyncratic noise. Therefore, our models will involve standard techniques to identify and control for level shifts, seasonality, and other data anomalies. The principal goal of analysis is to determine whether certain variables Granger-cause other variables, and we apply standard VAR methods (Lütkepohl, 2007) in our empirical analysis.

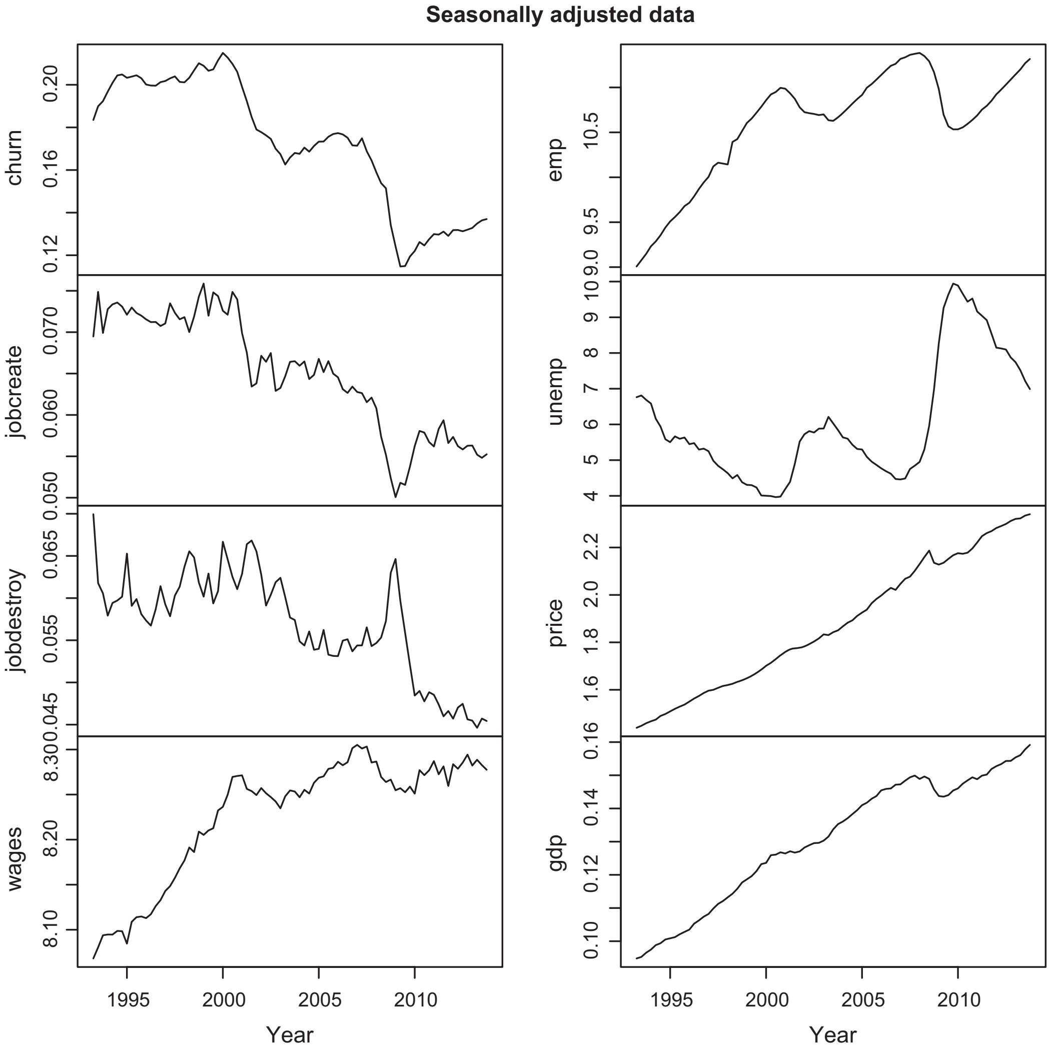
3.2.1 Seasonal adjustment. The raw data must be seasonally adjusted, because we are not interested in Granger-causality of seasonal movements. Moreover, we argue that the data should be detrended, so that long-term co-movements do not produce spurious correlations between the variables. Ideally, a single latent component model involving seasonal, trend, and cyclical structures should be fitted. However, we are able to obtain adequate and statistically defensible results by proceeding in three stages. First, we seasonally adjust each series individually (and account for outliers and other fixed effects) using X-13ARIMA-SEATS (U.S. Census Bureau, 2016). Second, we remove long-term trend movements via application of the HP high-pass filter. The output can be viewed as the stationary cyclical component (although idiosyncratic noise will also be included). Third, we model this estimated cycle with a VAR(1) model. We next provide a few details on each step.

Univariate seasonal adjustment is recognized to be adequate in most cases, with little added benefit to performing multivariate seasonal adjustment. We proceed to specify Reg ARIMA (Autoregressive Integrated Moving Average with Regression effects) for each of the eight series, allowing the X-13ARIMA-SEATS software to automatically determine a Box-Cox transform, identify additive outliers and level shifts, test for trading day effects, and select a seasonal ARIMA model from a suite of candidates. Details about these models and procedures, as well as the software X-13ARIMA-SEATS, can be found in U.S Census Bureau (2016). The identified model is used to forecast-extend the data, to which the X-11 moving average filters are applied. The resulting seasonal adjustment was checked for adequacy via several diagnostics.

The seasonally adjusted data, rescaled in some cases, are graphed in Figure 1. All residual diagnostics (i.e., Ljung–Box statistics) for the RegARIMA models were satisfactory, and autocorrelation diagnostics indicate that all dynamic seasonality was removed. Consistent with the evidence in Hyatt and Spletzer (2013), the labor reallocation series appear to have a trend decline. Job creation is distinctly lower in the recession years of 2008 and 2009, when job destruction is distinctly higher. Labor market churn has a clear ‘stair-step’ pattern with declines in the labor market downturns associated with the 2001 and 2007–2009 recessions and tepid rises afterwards. Earnings increases during the late 1990s, then is constant and mildly procyclical after the year 2000. Employment shows a similar pattern to earnings, with a sustained rise followed by a procyclical but essentially flat series after the year 2000. Unemployment rises when employment is lower. Finally, the price level and GDP expand throughout the 1990s and 2000s, with a noticeable downturn in each during the recession years 2008 and 2009.

3.2.2 Trend. The HP filter is quite popular among econometricians for decomposing seasonally adjusted data into long-term trend and business cycle. For quarterly data, the canonical choice of 1/1,600 for the signal-to-noise ratio parameter is recommended (Hodrick and Prescott, 1997). Failure to remove strong trend effects in the data will drive the VAR parameters toward the region of nonstationarity, as some of the seasonally

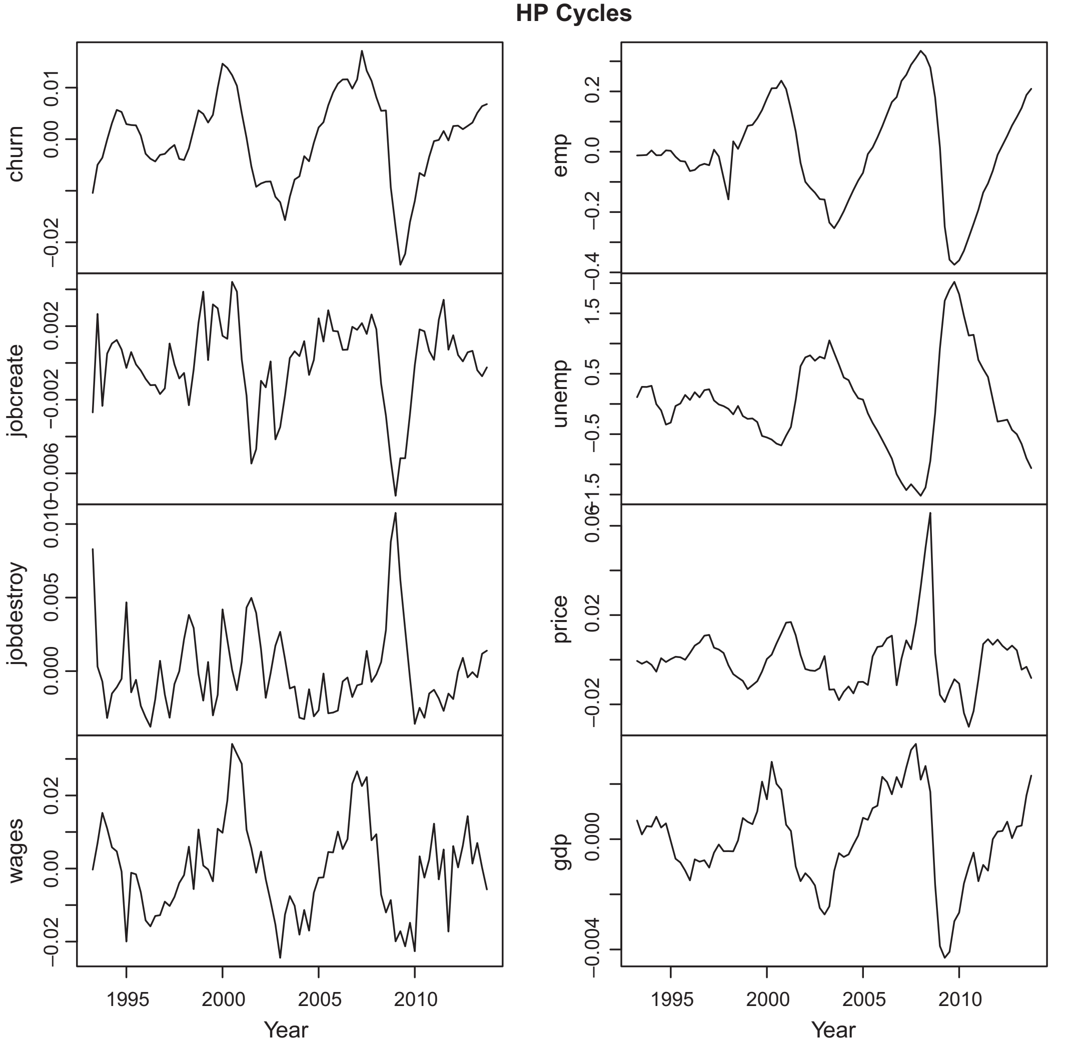
Figure 1. Seasonally adjusted data with additive outliers removed, 1993.Q2 through 2013.Q4. All data are in percentage points, with the following exceptions. Employment is in tens of millions, GDP is in hundreds of trillions, and average earnings are in logs.



adjusted series resemble a random walk, or autoregression with strong persistency. Of course, choice of the signal to signal-to-noise ratio (SNR) will have an impact on the cycle that is obtained: an SNR of zero will yield a straight line trend, whereas an SNR of infinity yields a cycle equal to zero identically.[14] Our choice of 1/1,600 for the finite-sample HP filter is *ad hoc*, but at least is consistent with current practice, and yields sensible results.[15]

The residual cycle estimates — which have mean zero, due to the HP-detrending — are given in Figure 2. These show clear co-movements among series; also observe the counter-acting movements of employment (emp_t) and unemployment ($unemp_t$).[16] It is precisely these series that enter directly into our VAR model, but there are a few things we can learn from these graphs directly. First, churn and GDP are remarkably similar after detrending. Second, the detrended employment and unemployment series are mirror images of each other, which is expected as the populace can be subdivided into three mutually exclusive categories: employed, unemployed, and not in the labor force. Finally, LEHD earnings appears procyclical and rather similar to churn and GDP.[17]

Figure 2. Cycles, 1993.Q2 through 2013.Q4. The cycles are computed by applying the HP high-pass filter with signal-to-noise ratio equal to 1/1,600 to the adjusted data.



4. Vector autoregression strategy

4.1 Standard (Unrestricted) VAR estimation

Having obtained the trend residual, or cycle, we proceed to modeling via the VAR methodology.[18] Standard diagnostics, such as residual autocorrelation plots, were utilized to assess goodness of fit, and indicated the adequacy of the order one VAR for these series.

It's important to assess the significance of the VAR coefficients, which can be done by utilizing their estimated standard errors, as discussed in Lütkepohl (2007). Granger-causality for a VAR model reduces to examination of the nonzero coefficients of the fitted model. Writing $\{x_t\}$ for the vector process for all the variables, the VAR(1) satisfies

$$x_t = \Phi x_{t-1} + \epsilon_t, \tag{5}$$

where $\{\epsilon_t\}$ is an independent and identically distributed sequence of random vectors of covariance matrix Σ. The individual entries of the matrix Φ are denoted Φ_{jk}. If some entry Φ_{jk} is significantly different from zero, we say that variable k Granger-causes variable j. Of course, this is a feedback system, so it could happen that variable one Granger-causes variable two, and variable two also Granger-causes variable one. To understand the impact of a single shock to this feedback system, it suffices to examine the infinite moving average representation of the process as a function of index (Lütkepohl, 2007). In the case of a VAR(1), one focuses upon the jkth entry of Φ^t as t increases from $t = 1$. Slow decay of such a sequence to zero indicates that the impact of variable k upon variable j is quite persistent.

4.2 Testing for variable significance in a multivariate setting

We raise the following question: given a collection of time series variables for which a VAR(1) model is a correct specification, when is it beneficial to include additional variables? The problem is central to this paper: we wish to obtain causal relations among churn, job creation, job destruction, earnings, and employment, but are concerned that the unemployment rate, price level, and GDP also merit inclusion. More generally, economics papers will feature analyses for certain sets of variables, and critics will wonder why other important or favored variables were omitted. How would the results change with the additional variables?

In regression analysis, such questions are quite natural and have long been solved; Greene (2007, Chapter 5) gives a discussion of specification tests, such as Wald and likelihood ratio. But vector regression can be viewed as a special case of multivariate regression, and the problem becomes more complicated, and is given only limited treatment in leading econometric texts on multivariate time series (e.g., Hamilton (1994) and Lütkepohl (2007)). In univariate regression, omission or inclusion of a covariate has an impact only upon a single regression equation, and thus the question can be treated with t-statistics or Wald statistics. In multivariate regression, the extension of the same strategy leads to the possibility of a covariate being included in some regression equations, but not in others; the covariate cannot be completely eliminated from the data analysis, unless it has no presence in any of the regression equations.

If an upper triangular or lower triangular block of Φ is equal to zero, it follows that the corresponding columns indicate a subset of variables that *do not* Granger-cause those variables corresponding to the rows of zeros. A further interpretation of a zero upper triangular block (and the lower triangular block, by flipping the argument) is that the latter collection of series can be omitted from the model, if interest is focused upon the former batch of series. For example, letting y_t denote the vector of churn, job creation, job destruction, earnings, and employment, and with z_t denoting the vector of unemployment, price, and GDP, a zero upper triangular block in Φ would indicate that the latter three control variables can be eliminated from the model.

One way to proceed, is to refit the VAR model with parameter constraints, by constraining any entries of Φ to be zero if their t-statistic is sufficiently small. Then one could examine the upper triangular blocks of Φ, and see whether any of these blocks are completely zero. The goodness of fit test described proceeds by fitting the constrained VAR with a particular upper triangular block set to zero, and checks to see whether the Whittle likelihood (Taniguchi and Kakizawa, 2000) is significantly worsened by this restriction. Another method is to utilize a Wald statistic for all the estimated coefficients in an upper triangular block. The first method requires one to re-estimate the VAR model with insignificant coefficients constrained to be zero; this procedure works quite fast by utilizing the constrained Yule–Walker formulas of McElroy and Findley (2015).

In what follows, we will refer to the version of the model in which we set parameters equal to zero via a Yule–Walker test as our ‘restricted model,’ whereas conventional VAR estimation is called our ‘unrestricted model.’ We employ custom R code to estimate the parameters via an extension of the Yule–Walker method that allows for parameter restrictions, see McElroy and Findley (2015). For additional details of this estimation method, see Appendix S2.

5. Results

5.1 Baseline findings using LEHD earnings data

5.1.1 Small model. The basic relationships between our variables of interest are shown in Table 1, which shows the VAR parameter estimates for churn, job creation, job destruction, LEHD earnings, and employment. We can see that some relationships are statistically significant, whereas others are not. For example, increases in churn predict (Granger-cause) job creation, LEHD earnings, and employment ratio. Increases in employment Granger-cause decreases in churn and job creation and increases in job destruction. The relationships appear to be dominant diagonal: all five variables are positive and statistically significant, so innovations in each variable predict increases future increases in that variable. The parameter estimates are all less than one, which is a rough indication that the system is stationary.[19] Of the three labor reallocation measures and the two labor market outcomes of interest, churn appears most persistent: an change in churn is followed by a change in churn that is about 97 per cent its size, although we are not able to rule out a parameter estimate of one. This is much more persistent than job creation and job destruction, where innovations are followed by changes in a similar direction with 5–67 per cent, and 11–63 per cent of its magnitude, respectively.[20] There is a very strong impact of churn on employment: a one percentage point increase in churn is

Table 1. Small model, no parameter restrictions

	Effect of				
Effect on	**Churn**	**JC**	**JD**	**Earnings**	**Emp**
Churn	0.966*** (0.114)	0.289 (0.310)	−0.119 (0.194)	0.042 (0.039)	−0.011** (0.005)
JC	0.204*** (0.057)	0.360** (0.153)	0.083 (0.096)	0.017 (0.019)	−0.010*** (0.002)
JD	−0.079 (0.078)	−0.146 (0.210)	0.370*** (0.132)	−0.001 (0.026)	0.009*** (0.003)
Earnings	0.639** (0.292)	1.259 (0.789)	1.266** (0.495)	0.510*** (0.099)	−0.019 (0.012)
Emp	5.102*** (1.504)	4.458 (4.069)	−2.225 (2.552)	0.616 (0.510)	0.693*** (0.062)

Notes: Variables are Churn, Job Creation (JC), Job Destruction (JD), LEHD Earnings, and Employment (Emp). Standard errors in parentheses.
*,**,*** Statistical significance at the 10%, 5%, and 1% level, respectively.

associated with an increase in employment of 210,000–930,000. Churn also Granger causes increases in earnings: a one percentage point increase in earnings increases the earnings level by about 0.06–1.22 per cent. Employment affects churn: an increase in employment by one million is associated with a 0.1–2.1 percentage point decline in churn, and a similar decline of 0.6–1.4 percentage points is found for job creation.

The restricted model increases the precision of estimates by setting relationships that do not affect the model's goodness of fit to be equal to zero. Estimates are reported in Table 2, and there are a few things to note here. First, not all the remaining relationships are statistically significant: there is an imprecise relationship between job destruction and LEHD earnings, the exclusion of which significantly reduces the fit of the model. Although the fit is imprecise, the sign of the relationship is positive, and, indeed, in other specifications this relationship turns out to be positive and significant. All other relationships included in the restricted version of the model were statistically significant in the unrestricted case. The signs of the point estimates all agree with the unrestricted model. Furthermore, the precision of the remaining estimates increases, which is quite natural given that the number of parameters to be estimated is fewer in this case. The additional precision of the estimates leads to lower confidence intervals for the effects of the different labor market measures on each other. The estimated persistence of churn is even more tight around 1, with the size of the effect estimated to be 95–120 per cent rather than 74–119 per cent in the unrestricted model.[21] A 1 percentage point increase in churn leads to a 0.11–0.26 percentage point increase in job creation, an increase in employment of 600,000–950,000 and a 0.18–0.77 increase in earnings. Increases in employment of 1 million lead to a 0.6–1.8 percentage point decline in churn, a decline in job creation of 0.3–1.1 percentage points, and an increase in job destruction of 0.2–0.6 percentage points.

Our estimates show that an increase in employment Granger-causes decreases in job creation and churn, and increases job destruction. This may be surprising, but is a logical consequence of the fundamental relationships between the data elements. Increased employment in one period predicts increased employment in the next, but by far less — only about 63 per cent of the employment growth in the previous period. Job creation and job destruction must sum to the change in employment, by definition. Therefore, if the level of the change in employment is less than that of the previous period, either job creation must be lower, job destruction must be lower, or both. Indeed, the estimates suggest that both factors are at play. Churn does not have a similar deterministic relationship with employment as do job creation and destruction, but appears to move with employment

Table 2. Small model, with parameter restrictions

Effect on	Effect of: Churn	JC	JD	Earnings	Emp
Churn	1.076*** (0.061)	0[a] (0)	0[a] (0)	0[a] (0)	−0.012*** (0.003)
JC	0.186*** (0.039)	0.240*** (0.091)	0[a] (0)	0[a] (0)	−0.007*** (0.002)
JD	0[a] (0)	0[a] (0)	0.523*** (0.071)	0[a] (0)	0.004*** (0.001)
Earnings	0.478** (0.148)	0[a] (0)	0.377 (0.318)	0.497*** (0.090)	0[a] (0)
Emp	7.739*** (0.883)	0[a] (0)	0[a] (0)	0[a] (0)	0.629*** (0.045)

Notes: Variables are Churn, Job Creation (JC), Job Destruction (JD), LEHD Earnings, and Employment (Emp). Standard errors in parentheses.
[a]Relationship is constrained to be equal to zero.
*,**,*** Statistical significance at the 10%, 5%, and 1% level, respectively.

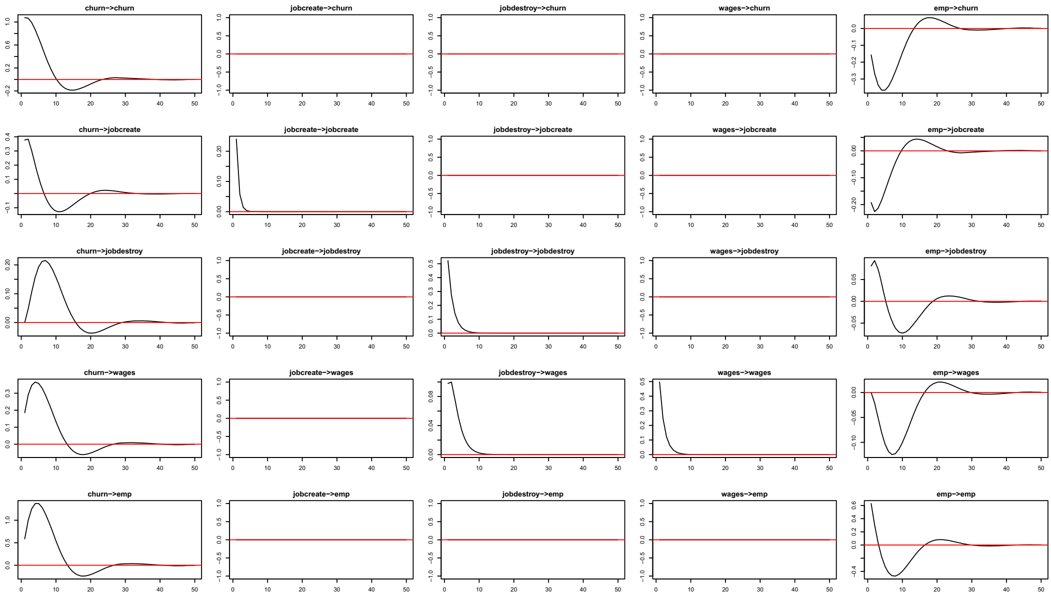
and so is lower when employment growth is only 63 per cent of what it was in the previous quarter.

In order to characterize how this estimated system will respond in total to innovations in each of these measures, we present impulse response charts in Figure 3. These take into consideration how the measures respond to the shock in the one via the direct effects of the parameter estimates and the secondary effects caused by other variables. For example, the restricted model did not include any direct effect of employment on LEHD earnings. However, because a shock to employment Granger-causes decreases in churn and increases job destruction, each of which has its own effect on LEHD earnings, there can be an effect on earnings. These impulse response plots show what the overall impact of all primary and secondary relationships is. In the case of the overall effect of an increase in employment, there is initially zero effect (the first period's effects are determined only by primary relationships). But there is a negative impact on earnings over the 5 years (20 quarters), reducing it by −0.1 per cent per quarter about 2 years after the increase, all of which is due to secondary channels. On the other hand, an increase in churn leads to a substantial increase in earnings. A one standard deviation increase in churn has an initial period effect of 0.19 and increases to about 0.36 after a year.

There is more to learn from Figure 3. The only labor reallocation rate that affects employment as shown in Table 2 is churn. Because (aside from churn itself) only employment Granger-causes churn, and likewise only churn Granger-causes employment (aside from employment itself), innovations to these measures affect each other. Furthermore, churn and employment both Granger-cause job creation, and employment Granger-causes job destruction, so shocks to churn and employment Granger-cause changes to job creation and job destruction. In contrast, LEHD earnings do not Granger-cause changes in any other series, and so a one log point shock to LEHD earnings affects only itself and dissipates over time. Job destruction affects LEHD earnings, but because LEHD earnings do not Granger-cause changes in other series, the effect of an increase in job destruction begins at its initial level of 0.523 and dissipates to 0.523^t by quarter t.

These initial estimates yield some insights concerning the labor market models we summarized in Section 2. We found that increases in churn leads to strong increases in job creation and employment. This is consistent with the predictions of job ladder models that include a vacancy chain component. When firms lose workers due to churn, they seek to replace at least some them, and so when firms that are at the top of the ladder expand,

Figure 3. Impulse-response functions for cycle components, 1993. Q2 through 2013.Q4.



the firms will post vacancies to replace these jobs. The process of replacing workers who voluntarily quit may take some time. The VAR framework does not summarize the estimates from contemporaneous effects (in our framework, those that occur in the same quarter) but rather the correlated lag. Especially in small establishments, poaching losses that are not refilled immediately can appear as job destruction events in the contemporaneous quarter but as job creation in the next or some future quarter. Our results suggest that poaching losses associated with churn lead to replacement hiring in the next quarter that accounts for 10–25 per cent of churn. This range can provide a reasonable lower bound on the total effect of vacancy chains: each job move associated with churn in turn creates at least a tenth of a job.

Increases in churn are associated with increased earnings, although the range is rather large: even in the restricted model, a 1 percentage point increase in churn increases earnings by 0.18–0.77 per cent. This evidence is consistent with earnings increases that occur as workers move up the job ladder, and more quickly when the rate of churn is higher. In the results that follow, the relationship between labor reallocation and earnings differs considerably across specifications, whereas churn leading to job creation and employment is more robust.

5.2 Full model

The next set of estimates come from the most general version of our model in Table 3 and its restricted analogue in Table 4. These estimates include the unemployment rate, the price level, and GDP as additional variables in the VAR. The estimated relationship among the five variables from Tables 1 and 2 plus the unemployment rate, the CPI, and GDP.[22]

Table 3. Full model, no parameter restrictions, using LEHD earnings

	Effect of							
Effect on	**Churn**	**JC**	**JD**	**Earnings**	**Emp**	**UR**	**Price**	**GDP**
Churn	0.793*** (0.118)	−0.109 (0.296)	−0.236 (0.183)	0.032 (0.037)	−0.014** (0.007)	−0.001 (0.002)	−0.093*** (0.031)	1.436** (0.558)
JC	0.171*** (0.059)	0.147 (0.148)	0.004 (0.092)	−0.001 (0.019)	−0.006** (0.003)	0.001 (0.001)	−0.044*** (0.016)	0.840*** (0.280)
JD	−0.057 (0.087)	0.011 (0.217)	0.439*** (0.134)	0.012 (0.027)	0.006 (0.005)	−0.001 (0.001)	0.041* (0.023)	−0.479 (0.410)
Earnings	0.560* (0.315)	0.499 (0.789)	1.081** (0.488)	0.427*** (0.100)	−0.001 (0.019)	0.009** (0.004)	−0.066 (0.083)	4.517*** (1.489)
Emp	1.951 (1.570)	4.378 (3.924)	−0.305 (2.428)	1.182** (0.495)	0.400*** (0.092)	−0.065*** (0.022)	0.508 (0.411)	10.430 (7.407)
UR	−10.767 (7.481)	−13.969 (18.697)	28.294** (11.568)	−4.202* (2.359)	1.169*** (0.440)	0.971*** (0.105)	1.264 (1.957)	−27.168 (35.299)
Price	−0.614* (0.349)	0.812 (0.872)	−0.602 (0.539)	0.135 (0.110)	0.007 (0.021)	−0.006 (0.005)	0.631*** (0.091)	0.506 (1.646)
GDP	0.024 (0.027)	0.023 (0.068)	−0.062 (0.042)	0.012 (0.009)	−0.002 (0.002)	−0.001*** (0.000)	−0.017** (0.007)	0.611*** (0.129)

Notes: Variables are Churn, Job Creation (JC), Job Destruction (JD), LEHD Earnings, Employment (Emp), Unemployment Rate (UR), Price Level, and GDP. Standard errors in parentheses.
*,**,*** Statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Full model, with parameter restrictions, using LEHD earnings

	Effect of							
Effect on	**Churn**	**JC**	**JD**	**Earnings**	**Emp**	**UR**	**Price**	**GDP**
Churn	0.840*** (0.077)	0[a] (0)	−0.114 (0.112)	0[a] (0)	−0.006 (0.004)	0[a] (0)	−0.095*** (0.023)	1.192*** (0.381)
JC	0.187*** (0.036)	0[a] (0)	0[a] (0)	0[a] (0)	−0.004** (0.002)	0.001 (0.001)	−0.049*** (0.013)	0.774*** (0.197)
JD	0[a] (0)	0[a] (0)	0.492*** (0.069)	0[a] (0)	0[a] (0)	0[a] (0)	0.055*** (0.016)	0[a] (0)
Earnings	0.511* (0.280)	0[a] (0)	0.890*** (0.341)	0.472*** (0.086)	0[a] (0)	0.010*** (0.003)	0[a] (0)	4.789*** (1.381)
Emp	3.291*** (1.165)	0[a] (0)	0[a] (0)	1.031** (0.408)	0.440*** (0.065)	−0.058*** (0.018)	0[a] (0)	9.266* (5.563)
UR	−15.213*** (5.042)	0[a] (0)	28.122*** (7.062)	−4.835*** (1.852)	1.081*** (0.318)	0.963*** (0.076)	0[a] (0)	0[a] (0)
Price	0.377*** (0.120)	0[a] (0)	0[a] (0)	0[a] (0)	0[a] (0)	0[a] (0)	0.654*** (0.074)	0[a] (0)
GDP	0[a] (0)	0[a] (0)	−0.088*** (0.024)	0.013** (0.006)	0[a] (0)	−0.001*** (0.000)	−0.019*** (0.005)	0.610*** (0.094)

Notes: Variables are Churn, Job Creation (JC), Job Destruction (JD), LEHD Earnings, Employment (Emp), Unemployment Rate (UR), Price Level, and GDP. Standard errors in parentheses.
[a]Relationship is constrained to be equal to zero.
*,**,*** Statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. VAR specifications, with alternative earnings measures

Effect on	**(1)**	**(2)**	**(3)**	**(4)**
Effect of Churn				
CES average earnings	0.112 (0.183)	0[a] (0)		
CPS median earnings			−0.301 (0.229)	0[a] (0)
Emp	5.395*** (1.492)	7.812*** (0.880)	5.210*** (1.519)	7.808*** (0.883)
Effect of job creation				
CES average earnings	−0.387 (0.525)	0[a] (0)		
CPS median earnings			0.399 (0.613)	0[a] (0)
Emp	4.258 (4.272)	0[a] (0)	6.625 (4.063)	0[a] (0)
Effect of job destruction				
CES average earnings	−0.068 (0.347)	0[a] (0)		
CPS median earnings			0.757* (0.405)	0.816*** (0.249)
Emp	−2.830 (2.821)	0[a] (0)	−0.997 (2.686)	0[a] (0)
Restricted	No	Yes	No	Yes

Notes: Standard errors in parentheses.
[a]Relationship is constrained to be equal to zero. The full set of parameter estimates for column (1) is presented in Appendix S5: Table E1, the full set of parameter estimates for column (2) is presented in Appendix S5: Table E2, the full set of parameter estimates for column (3) is presented in Appendix S5: Table E11, and the full set of parameter estimates for column (4) is presented in Appendix S5: Table E12.
*,**,*** Statistical significance at the 10%, 5%, and 1% level, respectively.

These additional variables yield relationships that were not included in the previous set of specifications. First, increases in churn are associated with increases in the CPI. A 1 percentage point increase in churn is associated with a 0.014–0.062 percentage point increase in the price level, and also a reduction in the unemployment rate by 0.05–0.25 percentage points (and the increase in employment is now only 100,000–560,000). However, increases in churn do not predict changes in aggregate output. Inclusion of these additional variables leads to job creation not having a persistent component. Job destruction now is associated with increases in earnings, although over a broad interval: a 1 percentage point increase in job destruction is associated with a 0.2–1.6 per cent increase in earnings. Job destruction also predicts future changes in the unemployment rate, with a 1 percentage point increase associated with a corresponding increase in the unemployment rate in the range of 0.14 percentage points to 0.42 percentage points.

These additional variables also predict some of our variables of interest. A 1 percentage point increase in the price level predicts a 0.5–1.4 percentage point decline in churn, a 0.23 to a 0.75 decline in job creation, and a 0.23–0.87 percentage point increase in job destruction. Increases in output predict increases in job creation and churn. A 1 trillion dollar increase in GDP is associated with an increase in churn of 0.43–1.95 percentage points and an increase in job creation of 0.38–1.17, but it does not Granger cause any change in job destruction.

These results have additional implications for what sort of models of the labor market are consistent with the empirical data. In most labor market search models, an improvement to aggregate conditions will increase output directly as well as lead to firms hiring workers. This is consistent with our findings, in which increases in output lead to greater hiring and churn. The finding that increases in churn are correlated with future reductions in the unemployment rate is also consistent with job ladder models that include replacement hiring and vacancy chains. The finding that increases in job destruction lead to increases in the unemployment rate is a standard prediction of labor market search models in the family of Mortensen and Pissarides (1994).[23] Consistent with the finding that increases in churn predict increases in job creation and employment, increases in churn predict lower unemployment, which is consistent with job ladder models in which vacancy chains lead to reductions in unemployment. The finding that churn affects earnings but not output (directly) suggests that any relationship between churn and earnings is driven by bargaining power rather than better job matches.[24]

These results also shed light on the cleansing effects of recessions. Controlling for additional economic conditions also now provides a specification in which we are able to reject zero for the effect of job destruction on earnings, and we find that increases in job destruction lead to increases in average earnings. This is consistent in which jobs with the lowest match quality are those that are destroyed during recessions, leaving only the higher productivity matches in which workers earn more.

The relationship between labor reallocation and the price level is also interesting. The main economic model that relates the price level to employment is the Phillips curve, in which inflation and unemployment have a negative relationship. We find an asymmetry in the direction of causality between employment and inflation. Increases in churn and job creation both predict increases in inflation, which is consistent with this standard model, but increases in inflation predict less employment growth and even job destruction. We also find that labor market churn increases the price level. Although there are not many models in which there is both on-the-job search and an inflationary component, and we so lack a model to provide guidance on what we should expect. We suggest that this is an important area for future research.

5.3 Measures of earnings

It is well-known that measures of employment from different data sources move together more strongly than measures of worker earnings, see Abraham *et al.* (1998) and Champagne and Kurmann (2017). Therefore, we estimate alternative VAR models in which we replaced LEHD earnings with CES average earnings for production and nonsupervisory workers, which is the longest continuously available earnings measure for the USA. We also substituted the CPS median earnings series for LEHD earnings. Selected parameter estimates are included as Table 5.[25]

The inclusion of these alternative earnings measures affects which labor reallocation measures Granger-cause increases in earnings. First, note that none of the labor reallocation measures seem to Granger-cause changes in the CES earnings series. This may be because the CES average earnings level is not as tied to aggregate employment reallocation as the economy-wide average earnings level is. Or, it may be because the CES earnings series is only for workers who are paid by the hour and excludes salaried workers. If earnings results are concentrated among more highly paid workers, then this too provides a mechanism which would be consistent with labor reallocation having little effect on the CES earnings series.

The CPS median earnings results are more consistent with the LEHD earnings results. Here, we find an effect of job destruction on CPS median weekly earnings for full-time workers that is similar in magnitude to the LEHD earnings results. Again, job destruction Granger-causes increases in earnings. However, churn is not found to Granger-cause changes in the CPS median weekly earnings series. Again, this may be due to the measures under consideration. If LEHD earnings increases are concentrated among more highly paid workers, then effects may not be found at the median although they may be so found among the higher end. If the positive Granger-causal effect of job destruction on earnings is truly due to cleansing, then it is plausible that this has an effect on the median earnings, which are closer to the lower tail affected by cleansing than high earners, who also have more dispersion.

6. Conclusion

We estimated a number of VAR models to assess the relationship between labor reallocation, employment, and earnings. Our estimates describe what economic variables Granger-cause each other: that is, the changes in one series predict changes that occur soon after in other series. Of particular interest was whether labor reallocation measures Granger-cause employment or earnings growth. We distinguish between three types of labor reallocation: job creation, job destruction, and churn. To provide guidance for the interpretation of our empirical findings, we survey the related economics literature on job reallocation and churn.

Increases in labor market churn predict increases in job creation and employment, as well as decreases in unemployment. This is consistent with models of job ladders with replacement hiring and vacancy chains. The evidence suggests that when employers lose workers through poaching, they replace at least some of them, and so poaching leads to employment growth. Because not all replacement hiring will occur in precisely the next quarter, our results put a lower bound on the amount of replacement hiring. Each hire that is a part of churn appears to create 0.1–0.25 additional hires in the next quarter. This evidence is also consistent with the findings of Davis and Haltiwanger (2014) that higher rates of labor reallocation are associated with employment growth.

Results on the relationship between employment reallocation rates and earnings are more mixed and vary by the earnings series we use. Job destruction and churn both Granger-cause increases in LEHD earnings. Churn does not have a strong relationship the CES earnings series or the CPS median weekly earnings of full-time workers. Job destruction is found to Granger cause increases in the CPS median weekly earnings but not the CES average earnings series. This provides mixed evidence on the cleansing effects of job destruction, and the role of churn in earnings growth. If the findings from the LEHD earnings series better reflect the underlying concepts of interest, then we should think of job destruction as cleansing and churn as earnings enhancing, consistent with the predictions of labor market search and job ladder models. Further research is needed to provide a more definitive answer to this question. Even if the job ladder leads to productivity-enhancing employment growth, this will not lead to earnings growth unless there is sufficient bargaining power of workers relative to firms.[26] The extent to which earnings increases from employer-to-employer transitions reflect improved match quality or higher worker bargaining power has been and remains an open question in the literature on on-the-job search. Our estimates of churn leading to increases in worker earnings while not affecting aggregate output are consistent with workers having more bargaining power in tighter labor markets.

There is no evidence that labor reallocation leads to lower earnings. Thus, the intuition from models of firm-specific human capital, and the consistent finding that job displacement leads to earnings reductions for affected workers, does not appear to have first-order implications for the evolution of economic aggregates. In other words, job reallocation and churn do not appear to lead to earnings-reducing employment volatility, at least in aggregate.

Overall, our analysis provides empirical evidence that is broadly consistent with recent contributions to models of labor market search with job ladders, especially the recent work of Schaal (2017). It is increasingly clear that churn leads to vacancy chains and replacement hiring, thus being an important mechanism in employment growth. Given that as of 2017, the rates of churn, job-to-job flows, and other measures of labor reallocation have not yet reached the levels seen prior to the 2001 recession, the low rates of post-2000 employment growth documented by Aaronson *et al.* (2014) and Acemoglu *et al.* (2016) might be explained by lower rates of churn. If churn were to increase to the levels seen in the late 1990s, the USA might exhibit stronger growth in employment than has been seen since the start of this millennium.

Notes

[1] See Abowd and Vilhuber (2011) and Burgess *et al.* (2000).

[2] Yellen (2014) notes that labor market flows provide information on the amount of slack in the labor market, and slack is important in judging where the economy is with regard to full employment. The Economic Report of the President (2015) notes that lower rates of labor market fluidity may lead to reduced earnings growth through two channels: a reduction due to fewer job changes, and reduced bargaining power on the current job as the threat of changing jobs decreases.

[3] We provide additional details about these measures and their relationship in Section 3.

[4] In summarizing our results, we state the 95% confidence intervals from our restricted VAR estimates using the full model, our preferred specification. Note that our unrestricted VAR estimates generally have point estimates of the same sign, but have much larger confidence intervals than the restricted VAR estimates.

[5] The results of our estimation might seem to justify omitting particular relationships from reduced-form specifications. We caution against this because our estimates of a zero relationship between macroeconomic aggregates may not generalize to other countries or time periods.

[6] See, among many others, Davis and Haltiwanger (2014), Faberman and Justiniano (2015), Hyatt and Spletzer (2013), and Molloy *et al.* (2016)

[7] Some models such as Bils *et al.* (2014) and Schoefer (2015) include wage rigidity as a means of solving the Shimer (2005) puzzle that in the standard Mortensen and Pissarides (1994) framework it is otherwise difficult to have a strong relationship between output and employment. Although these models have the implication that a higher earnings level may lead to lower employment and so less job creation, we caution against such a prediction for two reasons. First, wage rigidity implies the absence of a change, whereas the VAR strategy we employ later considers the correlation of innovations. Second, this model also predicts that wage growth will occur when the state of the economy expands and job creation increases and so the former effect would need to dominate the latter. In any case, the empirical evidence presented later does not suggest a relationship between earnings and job creation.

[8] As discussed further in the next subsection, Schaal (2017) is an important counterexample.

[9] Omitting relevant variables from a VAR model may indicate a direct causal relationship between two variables that otherwise would be described indirectly through the action of the omitted variable.

[10] See Burgess *et al.* (2000), Davis, Faberman, and Haltiwanger (2006), and Lazear and Spletzer (2012).

[11] In the setting of a stationary VAR process, such multicollinearity would manifest through a coefficient matrix of reduced rank.

[12] Hires and separations are defined at the establishment level in the LEHD and so within-company transfers across establishments in principle contribute to churn. However, among US states, only Minnesota requires employers to report such transfers, so within-company transfers are best measured in the LEHD data when a worker's transfer is across establishments that have different Unemployment Insurance accounts, for example, when a transfer is across states. Difficulty in measuirng within-company transfers means that establishment-level churn is slightly understated in the LEHD data.

[13] Note that employment and unemployment rates do not sum to unity, because there is a third component — those persons not in the labor force.

[14] McElroy (2008) discusses the relationship of SNR to cycle periodicity, which in the case of 1/1,600 is roughly 14 years.

[15] We also ran analyses, not reported here, with other values of the SNR parameter; 1/400 corresponds to a cycle period of 10 years. These different choices of the SNR tended to decrease the goodness of fit in the subsequent VAR model.

[16] For a step-by-step accounting of how we extract the signal from these data, see Appendix S3.

[17] This is consistent with the evidence in similar charts comparing the quit rate and earnings growth in Faberman and Justiniano (2015).

[18] One might consider the broader VARMA class, but the pure VAR is easier to interpret.

[19] Stationarity is enforced by Yule–Walker estimation, but is credible given the behavior of the cycles.

[20] Unless otherwise noted, ranges of estimates reflect 95% confidence intervals for parameter estimates.

[21] The parameter estimates for churn are often very close to, and sometimes in excess of, 1. We stress that this does not imply in itself that the system of equations is nonstationary, and in fact the eigenvalues for all estimates of our VAR(1) matrices are less than 1, which implies stability.

[22] We also included each additional variable separately for the robustness of the small model. For these additional results, see Appendix S4.

[23] The finding that increases in job destruction are associated with *future* increases in GDP suggests that there are non-contemporaneous effects may have implications for how discrete time implementations of such models should have employment and output sequenced. In other words, to match this moment may be necessary for job destruction events to occur at the end of a period after production takes place rather than at the start of the next period.

[24] Although churn does not affect output directly in Table 4, it does affect earnings, which in turn is associated with higher output. This indirect relationship is shown in Appendix S4: Figure D1, and an innovation in churn leads initially to an increase in output, followed by a decline in output that is similar in magnitude. Also, it is noteworthy that when we use alternative measures of earnings which are unaffected by churn, there is a usually statistically significant relationship between churn and output in Appendix S5: Tables E4, E10, E18, although Appendix S5: Table E20 provides an exception. Although our preferred specifications suggest that bargaining power drives any relationship between churn and wages, this additional evidence suggests that churn may also lead to productivity-enhancing match quality.

[25] For the full set of parameter estimates from all specifications, see Appendix S5.

[26] Bargaining power enters into labor market search models, but its incorporation is usually quite indirect and set exogenously for the purposes of calibration. However, a few recent studies carefully consider worker bargaining power as a parameter of interest in a model of on-the-job search, see, e.g., Cahuc *et al.* (2006).

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web-site.

Appendix S1. Data Details.
Appendix S2. Restricted VAR Estimation.
Appendix S3. Signal Extraction in Detail.
Appendix S4. Additional VAR Results with LEHD Earnings.
Appendix S5. Detailed Tables of VAR Results with Alternative Earnings Measures.