

NBER WORKING PAPER SERIES

WHAT CAUSES LABOR TURNOVER TO VARY?

Edward P. Lazear
Kristin McCue

Working Paper 24873
<http://www.nber.org/papers/w24873>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2018, Revised December 2018

Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. James Spletzer contributed to an earlier version of this paper. All results have been reviewed to ensure that no confidential information is disclosed. We thank Lucia Foster and John Haltiwanger for comments on the earlier version.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2018 by Edward P. Lazear and Kristin McCue. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

What Causes Labor Turnover To Vary?
Edward P. Lazear and Kristin McCue
NBER Working Paper No. 24873
July 2018, Revised December 2018
JEL No. E24,J0,J6,J63,M50,M51

ABSTRACT

Most turnover reflects churn, where hires replace departures. Churn varies substantially by employer, industry and worker characteristics. For example, leisure and hospitality turnover is more than double that of manufacturing. In the LEHD (QWI) data, permanent employer differences account for 36% of the variation in churn. The cost of churn is proxied by the mean wage and the benefit by the variance in wages. QWI and JOLTS data confirm predictions that high mean wage labor markets experience less churn and high wage-variance ones experience more churn. Additionally, less educated, younger and male workers have higher separation and churn rates.

Edward P. Lazear
Graduate School of Business
Stanford University
Stanford, CA 94305
and Hoover Institution
and also NBER
lazear@stanford.edu

Kristin McCue
U.S. Census Bureau
CES/2K130E
4600 Silver Hill Rd
Washington DC 20233-6300
kristin.mccue@census.gov

The Quarterly Workforce Indicators (QWI) and Job Openings and Labor Turnover Survey (JOLTS) data reveal stark differences in turnover rates across industries. For example, turnover rates in leisure and hospitality are more than double those in manufacturing. The source data for the QWI statistics—the Longitudinal Employer Household Dynamics (LEHD) microdata—show large differences across individual employers as well. In the LEHD sample, employer fixed effects account for 36% of the variation in turnover rates, implying that permanent differences in employer-specific turnover rates are an important part of variations in the labor market.

Turnover may come about because employers grow and shrink, but more frequently because workers leave voluntarily to move to a better job or are terminated and need to be replaced. The explanation of hiring and separation patterns across employers and industries that is emphasized here relates to this replacement hiring or “churn” rather than hiring for expansion or separation for contraction. In the LEHD data, churn accounts for over two-thirds of hiring and separations, so it is necessary to understand why churn varies to understand turnover.¹

¹ Churn accounts for the majority of hiring and separation as has been shown in prior literature and as is documented below at the employer level using the LEHD. Because the churn and reallocation process occurs primarily among the younger workers who are a small fraction of the total employed, hire and separation rates may decline in a major recession by many times the rate at which total employment declines. There already exists a literature that documents the empirical relation of churn to total hiring. Early papers that lay the groundwork for the empirical logic employed below are Davis and Haltiwanger (1992), Hamermesh, Hassink and Van Ours (1996) and Albaek and Sorensen (1998). They examine the proportion of hires that occur in firms with decreasing or constant employment, added to the separations in firms with expanding employment. Burgess, Lane and Stevens (2000, 2001) focus directly on churn hiring as a proportion of the total. The authors make the point that most job flows are accounted for by churn. Picot, Heisz and Nakamura (2000) perform a similar exercise using Canadian data. Abowd, Corbel and Kramarz (1999) use French data to examine the relation of skill level to hiring and separation and find simultaneous entry and exit is a decreasing function of skill level.

Churn is defined at the level of the employer and is a hire that replaces a separation. For example, if an employer hires seven workers and separates five, then five of the hires are churn and two reflect expansion. If alternatively, an employer hires five and separates seven, then five of the hires are churn and the two surplus separations reflect contraction. Thus, churn is defined formally as the minimum of hires and separations by the employer in a given time period.

Figure 1 shows the distribution (kernel density) of employer-average churn rates across the 13 million sample employers. The modal employer has churn rates equal to about 3% per quarter, but there is large variation in employer-specific turnover rates. A significant fraction of employers have quarterly churn rates that are below 1% and another substantial portion have churn rates that are above 15% of their workforces.

Some turnover differences can be explained by observable worker characteristics, but much cannot. Although turnover and specifically separation rates vary substantially by worker demographic characteristics with older, more educated and female workers having the lowest rates, those factors do not explain much of the difference in churn rates at the employer level. Even after accounting for composition of the workforce at a given employer, most of the employer differences in turnover rates remain. These findings are akin to those on wages. Standard human capital variables enters as theory predicts, but worker (and firm) unexplained fixed effects account for the bulk of variation in wages across workers. Just as is the case in the wage literature, the goal is to explain differences in turnover using standard economic variables that proxy the costs and benefits of moving workers from one job to another and then to recognize that important unexplained employer-specific variation remains.

The existence of churn in the cross-section pattern of hires and separations derive from the primary role of turnover in an economy, namely, to move workers to their highest valued use.

The idea dates back at least four decades, captured in the labor market matching approach of Jovanovic (1979). Because workers have skills that are more valuable to one firm than another and because some of these skills may be most effectively used by a firm other than the one in which the worker is currently employed, a reshuffling is often necessary.²

Moving workers from one firm to another is costly, but carries the benefit of raising the worker's productivity by the difference between the expected value of the worker in a new firm and the actual value of the worker in the current firm. The costs and benefits vary by employer, by industry and by more narrowly-defined worker type. The empirical analysis uses workers as the unit of analysis to examine separation rates and employers as the unit of analysis to examine churn, since churn can only be defined in the context of a hiring unit. (Churn is hiring for replacement and whether a worker was hired for replacement or expansion cannot be known at the worker level.) In the worker based analysis, workers are assigned to one of 17,632 "labor markets" based on their gender, age, education, industry and state of residence. The variables that proxy costs and benefits explain about 28% of the variation in separations rates in these labor markets. The inclusion of industry, demographic and employer effects increases the proportion explained to 65%, most of this resulting from the inclusion of industry effects.

Churn, which is an employer-level concept, behaves as predicted by the model, but the amount of quarterly variation in churn rates is less well explained by the variables of interest than are worker-level separation rates. Although churn rises in benefits and declines in cost of churn, a small fraction of employer-level variation in churn rates is explained by the two proxy

² An alternative reason for sorting is that workers have specific preferences over jobs independent of productivity and monetary considerations.

variables, even including demographic and industry variables. Rather, 36% of the variation is a result of unobserved idiosyncratic employer fixed effects.

The model formalized below uses the standard notion that hiring and separation move workers to their most efficient use, taking into account the cost of turnover. A worker is hired away from a firm when the expected value of the worker at a new firm exceeds the value to the current employer by more than the transaction cost of moving. Put differently, but equivalently in equilibrium, a firm separates a worker when that worker's productivity is lower than the expected productivity of a new hire, net of hiring costs.

There are three main findings. First, churn allocates workers to higher productivity uses. Specifically, when the benefit to mobility is highest, as proxied by the variance in wages and when the cost of mobility is lowest, as proxied by the mean wage, churn rates are also highest. Second, observable characteristics, such as education and age, are also correlated with churn rates. Most obviously, employers with young workers experience more churn than those with older workers. The value of moving young workers, for whom a large fraction of the career remains, to high productivity jobs is higher than the value of moving old workers. Jobs for less educated workers and those dominated by males also have more churn. Third, even after accounting for observable and unobservable differences in the types of workers that are employed, persistent differences in churn rates across employers remain. The unexplained, but persistent employer effects and not workforce composition, account for much of cross-employer variation in churn.

I. The Model

The model is standard efficient sorting and where hiring and separation allocate workers to their most productive uses. Separation is modeled to be efficient and the theory abstracts from the distinction between quits and layoffs.³ The purpose is instead to emphasize the role of churn in allocating workers to their highest valued use. A model of efficient matching is sufficient, although perhaps not necessary, to generate the observed behavior. The essential idea is that mobility occurs because a worker is worth more elsewhere and the market responds to differences in productivity by offering higher wages in their more productive uses.

The structure is of the standard overlapping-generations type. The model is highly stylized but captures the essence of sorting and churn. It reflects a reality in which workers join the labor force when young, retire when old and seek to find the most suitable employment in the middle. That is what is modeled in a two-period setting.

Specifically, in every period, N workers are born and each lives for two periods. There are two firms, i and j , each employing half of the labor force in expectation. Each firm faces the same distribution of worker productivity. A worker's productivity in firm i is V_i and in firm j is V_j . V_i and V_j are defined as

$$(1) \quad V_i = V + \varepsilon_i \quad \text{and} \quad V_j = V + \varepsilon_j$$

where ε_i and ε_j are i.i.d., each being governed by the density and distribution functions $f(\varepsilon)$ and $F(\varepsilon)$, respectively.⁴

³ As modeled, separation is efficient, so the difference between a quit and layoff seems vacuous. As economists know, a layoff can be turned into a quit by adjusting the wage appropriately and vice versa. See McLaughlin (1991), who was among the first to investigate the distinction between quits and layoffs. The empirical work focuses on total separations, since the LEHD data has no information on quits versus layoffs.

⁴ At this point, V could be assumed to be equal to zero, but it will be useful to allow it to take on other values later to consider expansion, contraction and business cycle effects.

A worker's productivity is unknown at the time of employment. In expectation, half of the young cohort of workers starts at i and half at j . After one period, productivity at the current firm is known, but productivity in the other firm remains unknown because ε_i and ε_j are independent.

The cost of hiring, which includes unworked time in moving from i to j , is given by η . Efficient separation for workers at i implies that a middle-aged worker, i.e., one who has worked one period, should leave i and move to j when the expected output at j , net of hiring cost, exceeds V_i , or when

$$(2) \quad V + \varepsilon_i < E(V_j) - \eta .$$

Using (1), the condition for efficient separation can be written as

$$(2') \quad \varepsilon_i < -\eta .$$

Analogous conditions hold for those who start at j and consider a move to i .

The probability that a middle-aged worker is separated is therefore $F(-\eta)$. Consequently, in each period, N workers retire and $N F(-\eta)$ workers separate because their output at their current firm is lower than the expected output, net of turnover costs, at the alternate firm. The expected number of separations in any period is then

$$(3) \quad S = N (1 + F(-\eta)) .$$

Consider firms' replacement hiring. Each period N workers retire, creating N job openings. At the same time, $N F(-\eta)$ of the middle-aged workers separate from their firms creating another $N F(-\eta)$ job openings. The number of workers available to be hired consists of

N new entrants to the labor market, plus the $N F(-\eta)$ middle-aged workers who separated from their firms. The number of job openings equals the number of workers available for hire and, absent frictions, the number of hires is therefore

$$(4) \quad H = N (1 + F(-\eta)) = S .$$

Hiring occurs to replace workers who separate. The condition in (2), that workers separate when their expected productivity, net of turnover costs, is greater elsewhere than at the current firm, is equivalent to stating that separation occurs to make room for a worker who is expected to be better than the incumbent. A firm chooses to hire for replacement when the incumbent is less productive than the expected value of the replacement, net of turnover costs, or when

$$V + \varepsilon_i < E(V_i) - \eta .$$

Because $E(V_i) = V$, the condition is

$$\varepsilon_i < -\eta ,$$

which is the same as (2'). One can think of hiring as occurring to replace departing workers or of separation as occurring to make room to hire better workers. They are equivalent. Both phenomena reflect movement of labor to a more efficient use and it is variations in η and in $F(\varepsilon)$ that drive both.⁵

It follows immediately from equation (4) that

⁵ To be accurate, it should be noted that the number hired and separated in the economy is a random variable, not a deterministic number. As a consequence, there will always be some amount of non-matching, leaving some vacancies and unemployed workers.

$$(5) \quad \frac{\partial H}{\partial \eta} = \frac{\partial S}{\partial \eta} = -N f(-\eta)$$

which is negative. As is intuitive, an increase in the cost of hiring, η , leads to a decrease in the number of hires and separations. This works through a decrease in churn of middle-aged workers.

Equations (4) and (5) describe the primary features of the labor market. Hires equal separations both for the labor force as a whole and for each particular firm. The model is one of pure churn, where all firms remain at their initial size. The amount of hiring and separation depends on the cost of turnover, η and on the shape of the productivity distribution function, $F(\epsilon)$. Industries or firms with a high η should exhibit less churn. The empirical work below analyzes how churn varies across individual and job characteristics that proxy for the cost of hiring. Additionally, because the amount of mobility at middle age equals $N F(-\eta)$, the shape of the productivity distribution $F(\epsilon)$ also determines mobility. As discussed in more detail below, a fatter lower tail to the distribution implies more churn.⁶

Labor Market Efficiency

It is useful to ask whether the mobility described in the last section is consistent with market equilibrium. In particular, the existence of a turnover cost, η , means that an alternative firm is at a disadvantage relative to the current firm. Given the wedge created by turnover costs, it is useful to ask whether the equilibrium wage offer distribution creates the possibility of inefficient separation? Despite the turnover cost, the equilibrium wage will always be such that turnover is efficient and as described by the model.

⁶ The efficient separations model and the resulting separation probability $F(-\eta)$ are not new, but novel here is a focus on how the distribution of productivity affects the probability of separation.

For inefficient separation to occur, it would be necessary either for the equilibrium wage to be too low to retain the worker when retention is efficient or for the equilibrium wage to be so high that the firm chooses to fire the worker when he should be retained. As shown formally in the Appendix, the following three statements hold.

1. A worker never quits when it is socially efficient to stay at the current firm.
2. The firm never terminates a worker when retaining the worker is socially efficient.
3. Separations always occur when the worker is more valuable at the alternative firm than at the current one.

II. Empirical Analysis

The primary focus of the empirical analysis is on explaining cross-industry, employer and worker-type differences in turnover rates. However, the evidence on the time-series relationships described in the last section is straightforward so the analysis begins with an examination of published aggregate hires and separations data and its variations over time. There are two sources of such data for the United States: the Job Openings and Labor Turnover Survey (JOLTS) and the Quarterly Workforce Indicators (QWI).

JOLTS is a monthly survey of 16,000 establishments that has collected data on hires, separations and job openings since December 2000.⁷ The analysis here uses quarterly data created from the monthly JOLTS statistics, restricted to the private sector, with a time series that begins in 2001:Q1.

⁷ For information on the JOLTS, see <http://www.bls.gov/jlt/>.

The QWI statistics are derived from the Longitudinal Employer Household Dynamics (LEHD) microdata, which are used in subsequent sections of this paper. The LEHD is a longitudinally linked employer-employee dataset created by the U.S. Census Bureau as part of the Local Employment Dynamics federal-state partnership. The state partners provide quarterly Unemployment Insurance (UI) wage records and the Quarterly Census of Employment and Wages (QCEW) establishment data and the database is also enhanced by the Census Bureau with information about the worker (age, gender and education) and the firm (firm age and firm size) from other Census data sources. Abowd, et al. (2009) provide a thorough description of the source data and the methodology underlying the LEHD data. The analysis in this section uses quarterly measures of hires and separations from the Quarterly Workforce Indicators (QWI) statistics.⁸ The time series available in the QWI (and the LEHD micro data) varies across states. The data used here are private sector data from 29 states that have information available from at least 1998:Q2 forward.⁹

Cross-Industry Differences in Turnover Rates

Figure 2 plots industry hire and separation rates from the published JOLTS and QWI data, where each industry's data point is the hires and separation rate averaged across quarters.¹⁰ The scatterplot makes clear that there are high turnover industries and low turnover industries. The leisure and hospitality industry has the highest hires and separation rates in each data source,

⁸ See <http://lehd.ces.census.gov/data/#qwi>

⁹ The 29 states in our sample are CA, CO, FL, GA, HI, ID, IL, IN, KS, LA, MD, ME, MN, MO, MT, NC, ND, NJ, NM, NV, PA, RI, SC, SD, TN, TX, VA, WA and WV. These 29 states account for about 65 percent of national employment.

¹⁰ The public use JOLTS and QWI data are aggregated to 12 industries: Mining, Construction, Manufacturing, Wholesale Trade, Retail Trade, Transportation and Utilities, Information, Financial Activities, Professional and Business Services, Education & Health Services, Leisure and Hospitality Services and Other Services. Averages are computed over the quarters in common to both data: 2001:Q1 – 2014:Q2.

whereas manufacturing has the lowest hires and separation rates in each data source. Not surprisingly, the scatterplot also shows that each industry has its thirteen-year average hire rate approximately equal to its thirteen-year average separation rate, which is necessary if the industry is not undergoing major expansion or contraction.¹¹

Table 1 reports the industry-specific average quarterly hires and separation rates from Figure 2, along with the industry-specific time series correlation between hires and separations from both the JOLTS and the QWI public use data. It is evident that hires and separations are positively correlated within each industry in each data source.¹² Industries with high hiring rates also have high separations rates.

The evidence in Table 1 and Figure 2 shows that the hire rates and the separation rates are positively correlated across industries. Table 1 also reveals that hire and separation rates are correlated within industries over time. A given industry is either hiring many workers and separating many workers or hiring relatively few workers and separating relatively few. That holds for each of the 12 industries with the possible exception of mining, which accounts for a small part of employment.

Employer-Level Hires, Separations and Churn: Evidence from the LEHD Microdata

¹¹ If the industry were the proper unit of analysis for churn, this would imply that turnover is primarily churn. But churn is appropriately determined at the level of the firm so the analysis of churn, which is most germane to the labor reallocation issue, is done below at the employer level.

¹² Indeed, the industry level conclusion was established years ago by Davis, Haltiwanger and Schuh (1996), who showed that more than 90 percent of job reallocation is within 4-digit manufacturing industries rather than across industries.

The empirical analysis continues with an examination of churn in the LEHD microdata, which provide information on hires and separations for individual employers. These data include establishment-level measures of employment, payroll, industry and location.¹³

As discussed above, churn is the minimum of hires and separations at the employer level. Figure 3 presents the seasonally adjusted time series of quarterly hires and separations from the QWI, along with churn measured using the LEHD microdata for the same set of states and time period. The LEHD data used here has 4.8 billion employee-quarter observations and 341 million firm-quarter observations. Subsets of these data are used below to perform the LEHD calculations. Table 2 contains the summary statistics for both employee-quarter unit of analysis variables and for employer-quarter unit of analysis variables.

Between the 2001 and 2007 recessions, the quarterly hire and churn rates were roughly constant at 24.9 percent and 17.1 percent, respectively. These statistics imply that 71 percent of all quarterly hiring was churn, that is, hiring associated with replacing separated workers and in the quarters following the 2007-2009 recession, 66 percent of quarterly hiring is churn.¹⁴ The

¹³ In most states, information about the part of a multi-location firm in which an individual works is maintained at a more aggregate level than establishment. Typically, this is a grouping of a firm's establishments within a state that operate in the same industry. The LEHD database includes imputed links that assign workers to specific establishments within that grouping, but the imputations generally assume that workers remain at the same location for the duration of their spell with their employer. When an employee stays with a multi-location firm but switches workplaces, that should count as a separation and hire at the establishment level, but not at the firm level. Since with-in firm moves will be understated in the LEHD data, hires and separations in this analysis should be thought of as being measured at the state/industry level for multi-location employers—a unit referred to here as “employer”, rather than firm or establishment.

¹⁴ It is not possible to define churn over a period shorter than a quarter using LEHD data, as a quarter is the time unit over which the data are reported. Using this definition, offsetting hires and separations within the quarter are defined as churn. A monthly accounting would, we believe inappropriately, define these as expansion and contraction hiring. If a firm experiences separations in one month followed by an equal number of hires in the next, the quarterly definition counts that as churn, whereas a monthly definition would count it as separation for contraction followed by hires for expansion. Which is right? Hiring for expansion means that an employer continues to hire at a level that exceeds separation for a significant period of time. Hiring that exceeds separation for more than a quarter is—

interpretation is that roughly two-thirds of separations are replaced by a new hire during the same quarter.¹⁵

This is reinforced by further statistical evidence in Table 3, which presents OLS regressions of the employer-level hire rates on the employer-level separation rate. The sample used in Table 3 has over 340 million employer-quarter observations (roughly five million employers in each of the 69 quarters 1998:Q2 – 2015:Q3). The first specification in Table 3 estimates a simple one-variable regression of the employer-level hire rate on the employer-level separation rate. The coefficient is .9395 (with a clustered and employment-weighted standard error of .0191). This estimated coefficient declines only slightly when controls are added for time (column 2) and for industry (column 3). Column (4) of Table 3 includes employer fixed effects. The estimated coefficient in this specification is .9048, which implies that intertemporal variation in the hiring rate is similar to the separation rate for the typical employer. In quarters when an employer's separation rate is high, its hiring rate is also high and vice-versa. These findings are consistent with earlier work, as already noted.

Churn Decreases in the Mean and Increases in the Variance of the Wage

If hiring is primarily for the purpose of replacement as is the case when turnover is allocative, then any factor that increases the cost of turnover on the hiring or firing side results in

appropriately-- counted as hiring for expansion by the LEHD quarterly definition . Similarly, separation that exceeds hiring over at least the quarter is not counted as churn by the LEHD quarterly definition, which is also appropriate

¹⁵ Using the JOLTS microdata, Lazear and Spletzer (2012) report that variations in churn account for the bulk (79 percent) of total hiring *change* during the 2007-09 recession, which is slightly greater than the proportion that would be predicted given churn's share of total hiring.

less churn and lowers both hire and separation rates. Conversely, any factor that increases the benefits from a worker moving to a higher valued use increases churn.

The time cost associated with job search is likely to be a major component of turnover costs, which implies that high wage workers face larger turnover costs than low wage ones for any given amount of time spent looking for a job.¹⁶ Even job search that occurs while an individual is currently working requires time. The empirical implication is that η is higher and mobility lower in jobs that have higher average wages because the time cost of moving from one job to another is increasing in the wage.

The issue is more complex because there is likely to be a correlation between η , the cost of relocating and the value of relocating. It might be relatively cheap for low skilled workers to relocate because forgone earnings are low and the amount of time necessary to find an equivalent or better job is short. For more specialized workers, searching for work carries with it a higher cost per unit of time, but also a greater return to finding a job to which the worker is well-suited. The firm-specific match component is likely to matter more for skilled workers, implying that the gains from sorting are correlated with the cost of search.

Consequently, it is useful to examine the effect of heterogeneity on the benefit from mobility. Heterogeneity relates to the shape of the $f(\varepsilon)$ density, which provides the ingredients for determining the expected gain associated with a move from one job to another. Recall equation (1):

$$(1) \quad V_i = V + \varepsilon_i \quad \text{and} \quad V_j = V + \varepsilon_j$$

¹⁶ Those with higher time costs will economize on search, but the cost of search still rises with the wage, even if total expenditures on search do not. High wage workers are likely to search while on the job, but that still diminishes either productive work time or leisure, each of which has higher marginal value to high wage workers.

where ε_i and ε_j are i.i.d. Also, from (2), a move occurs only when $\varepsilon_i < -\eta$. The change in and productivity for movers is given by the expected gain from a move, which is

$$E(V + \varepsilon_j - V - \varepsilon_i \mid \varepsilon_i < -\eta) - \eta,$$

or

$$\text{Expected gain from move} = E(-\varepsilon_i \mid \varepsilon_i < -\eta) - \eta$$

Equivalently,

$$\text{Expected gain from move} = \frac{1}{F(-\eta)} \int_{-\infty}^{-\eta} -\varepsilon f(\varepsilon) d\varepsilon - \eta$$

because ε_j is independent of ε_i and has an expectation of zero. ¹⁷

It is true under quite general conditions (for example, well-behaved symmetric distributions) that an increase in spread in the distribution also implies an increase in separation probabilities.

To see this, consider two distributions $F(\varepsilon)$ and $H(\varepsilon)$. Define x^* such that $F(x^*)=H(x^*)$. Let the distributions be such that $h(x^*) < f(x^*)$ and that there is a single crossing in the region where $x < x^*$ at $x=A$, so $f(A)=h(A)$ at $A < x^*$. Assume further that $\eta > x^*$.¹⁸ An example is shown in Figure 4. A distribution with higher spread is defined as one for which the height of the density function at x^* is lower and for which the value of the c.d.f.s are equal at x^* . (For example,

¹⁷ If workers receive all the rents from the match, then the change in productivity would also equal the change in wages, but the goal here is to describe mobility so wage changes are not investigated. Nor is this assumption essential. The qualitative implications of what follows is invariant to having the rents shared in some given proportion between workers and firms.

¹⁸ This is natural if $x^*=0$, but this is not necessary. It is also plausible because x is the productivity of the entire population most of whom have minimal or negative productivity in most jobs. Few who work as plumbers would have much value as economics professors and the converse is also true.

normal and distributions with different variances but the same mean and uniform distributions with different variances and the same mean satisfy the conditions.)

Separation probabilities are higher if the distribution of is $H(\varepsilon)$ than if it is $F(\varepsilon)$ for any given η . If $-\eta < A$, then it is clear that $H(-\eta) > F(-\eta)$, which means that separation probabilities are higher with $h(x)$ than with $f(x)$ because $h(x) > f(x)$ for $x < A$. For $A < -\eta < x^*$ (for example, $-\eta$ '

in figure 4), $H(-\eta) > F(-\eta)$. This follows because

$$H(-\eta) = H(x^*) - \int_{-\eta}^{x^*} h(x) dx,$$

$$F(-\eta) = F(x^*) - \int_{-\eta}^{x^*} f(x) dx,$$

$$H(x^*) = F(x^*)$$

and

$$f(x) > h(x) \quad \forall \quad A < x < x^*$$

Consequently, separations rise when the spread in the underlying distribution increases.

To the extent that the standard deviation of wages proxies spread as defined here, the implication is that turnover should be increasing in the standard deviations of wages. As long as some of the match-specific rent is shared with the workers, it is reasonable to assume that the wage distribution is increasing in the spread of the distribution of the match-specific component,

ε .¹⁹

It is certainly true that components other than the match-specific value might also affect the wage spread. Underlying observed worker heterogeneity, independent of the match component, is likely to be reflected in wage spread as well. For example, even if all employers were identical, there might be more heterogeneity among college graduates than among high

¹⁹ Without a specific model of rent sharing, it is impossible to say how much of the observed distribution of wages reflects the underlying distribution. The assumption here is that the standard deviation of the observed distribution is highly correlated with the standard deviation of the true productivity distribution across markets.

school graduates (or vice versa). To deal with this, worker groups are defined narrowly so as to remove observable and measurable sources of heterogeneity.

The two interpretations of the model influence the empirical work. The model can be viewed from the perspective of the individual – a worker separates when the alternative wage, net of moving costs, is higher than the wage that is received at the current employer. This occurs when $\varepsilon_i < -\eta$. For this interpretation, workers are defined by their labor markets, which is the gender-age-education-industry-state specific cell.

The alternative interpretation is at the employer level. Employers separate workers and hire a new worker to replace the separated one when the expected value of the new worker, net of hiring costs, exceeds the productivity of the incumbent. This occurs when $\varepsilon_i < -\eta$, which is the same condition. Consequently, the empirical analysis is done at both the worker and employer levels. Each is informative and the results obtained are reinforcing. The employer level regressions speak directly to the issue of churn, that is, separations replaced by hires at a given employer to improve productivity.²⁰ The information that a worker separates from an employer can be obtained at the worker level, but in order to know whether that separation reflects a reallocation of labor (churn) instead of a contraction, it is necessary to know what happened to the number of hires and separations at the specific employer from which the worker separated. The employer-based regressions determine how churn varies with the costs and benefits of efficient sorting of workers.

²⁰ One could think of an industry as a “firm,” which hires for the purpose of expansion, contraction or replacement, but the industry is not the decision making unit. Churn is best defined in the context of the employer or even small units like a department within a firm.

The empirical implications neither require nor test efficient matching. Although churn is modeled as facilitating the efficient allocation of labor, churn could just as well be a result of rent seeking and the implications would remain. For example, suppose that a worker's productivity were the same at two employers i and j , but that employer j used a rent-splitting algorithm that favored workers more than did employer i . Were a worker to receive an offer from employer j , she would leave employer i , vacating a position and leaving an open slot. Churn would result, even though the move had no effect on productivity. Furthermore, the likelihood of moving would still depend on the cost of moving, again related to the wage level and on the value of moving, related to the variance in wages across employers.

Worker-Based Analysis

The analysis is done first at the worker level, using the actual log earnings distribution, with corrections for worker heterogeneity. The theory has assumed for simplicity that all individuals are homogeneous. But at the empirical level, it is necessary to drop this simplifying assumption. For example, neither the talent nor the wage distribution of teenagers is the same as the talent or wage distribution of college educated middle-aged persons. To account for these differences, assume that an individual's labor market in a given quarter can be defined by the gender, age, education, industry and state of residence of that individual. Within that market, the distribution of ε is assumed to be the same. This stratification generates 17,632 different cells each quarter and each cell is allowed to have its own wage distribution. The mean and standard deviation of the wage distribution for a given cell are measured in each quarter using log full-

quarter earnings of all individuals with the same gender, age group, education, industry and state.²¹

The worker level test of the theory takes a labor market, i.e., a cell, as the unit of analysis. The theory predicts that cells with a low mean wage and a high standard deviation of wages should experience the highest turnover because the representative worker in that cell has low costs of search and high expected value from moving. The mean and the standard deviation of the individual's relevant log earnings distribution are the key explanatory variables in the job separation regressions. Because this is the mean for an industry-demographic cell, it is not reflecting the fact that workers who draw high wages are less likely to move because they have already found a good match. Although that can be true at the individual level, it is not true for a cell that is determined exogenously, not on the basis of wage, but on the basis of location, industry and demographic characteristics.

Table 4 reports the results from job separation regressions. Workers younger than 25 or older than 64 are excluded from the sample. There are about 1.15 million observations in this quarter-worker-type data set.²² All specifications include year and quarter. Observations are weighted by cell employment and standard errors are clustered at the 17,632 worker-type level.

²¹ There are 2 genders, 4 age groups, 4 education categories, 19 industries and 29 states. Thus potentially 17,632 earnings distributions are created for every quarter in the dataset (1998:Q3 – 2014:Q1) though some are not populated. Some technical details warrant mentioning. First, the quarterly earnings microdata have been Winsorized at 99% of the state-year-quarter distribution to control for outliers that do affect the mean and the standard deviation. Second, all earnings measures are in real terms (2011:Q4=100) and in natural logs. And third, only “full quarter earnings” are used in the calculation, where full quarter earnings are the quarterly earnings for an individual who works for the current employer in both the previous and the following quarter. The LEHD does not have measures of hours or weeks worked and this full quarter earnings restriction assumes that the individual works for the employer all 13 weeks of the quarter. The education variable is imputed for the majority of individuals.

²² Restricting to age 25-64 and full-quarter jobs drops the sample of individual-quarter observations to 3.21 billion. There are potentially 1,163,712 labor markets, or cells, in this sample: 2 genders, 4 age groups, 4 education categories, 19 industries, 29 states and 66 quarters of “full quarter” data (1998:Q2 – 2014:Q3). The average cell has roughly 2800 individuals.

The dependent variable is the proportion of workers who separate from their job during a specific quarter in that particular demographic cell.

The results in Table 4 conform to the theoretical predictions. All specifications imply that there is a strong negative relation of job separation to log earnings. The finding is consistent with the prediction that the higher is the time cost of search, the lower is the likelihood of turnover. Also as predicted, there is a positive relation of job separation to the variance in log earnings, reflecting higher potential benefit from a move. The regression results support the view, expressed by the theory, that separations are related in the expected direction to the costs of and benefits from mobility. As the wage rises, the cost of turnover rises and separation becomes less common. Additionally and less easily explained by other theories, is that as the standard deviation of log earnings rises, the benefit from turnover rises and turnover is more common.

The estimated effects are reasonable. The mean of the full quarter separation rate is .103.²³ Using the column (3) estimates, a one standard deviation increase in the average market log earnings reduces expected turnover by .018, ($.0378 \times .455 = .017$), which is about 17% of the average separation rate. A one standard deviation increase in the standard deviation of the log earnings of the cell in which the worker is situated increases turnover by .0046, ($.0229 \times .212 = .0049$), which is about 5% of the average separation rate.²⁴ The explanatory power rises considerably when demographic and industry controls are included (for example, compare column 1 with an R-squared of .28 with column 3 with an R-squared of .43). This suggests that the mean and variance of wages measure costs and benefits of turnover, but only imperfectly

²³ See Table 2 for sample summary statistics.

²⁴ If the average wage and variance in wage are poor proxies for the costs of and benefits to turnover, this would have the effect of lowering explanatory power and biasing the estimated coefficients toward zero. The errors-in-variables bias toward zero might account for the relatively small magnitudes of the coefficients.

because other observable factors continue to be strong determinants of separation. It is not surprising, for example, that the young (the left out category) have higher separation rates than other groups because the value of moving to a higher productivity job is greatest when young. The specifications that include observables related to gender, age and education do not undo the predicted the effects of the unobservables (as reflected in mean and standard deviation of the wage) on separation. The effects of observables on separation rates is intuitive and interesting. Most important is that the sorting story emphasized here is one that operates on unobservables and that the results with respect to unobservables are robust to the inclusion of observable demographic characteristics.

Employer-Based Analysis

Churn is a concept that makes sense only at the employer level, where workers are hired to replace separating workers.²⁵ The stylized model gives no explicit consideration to ex ante worker observable heterogeneity. In reality, nothing requires that the employer hire only one type of worker. Each employer typically hires workers of different skills and occupations. For example, a large consulting firm has MBA consultants, but also hires support staff that may include clerical

²⁵ Actually needed is that the unit that hires/separates is an ongoing concern, which continues beyond the single worker's employment horizon. The entity could be a firm, an establishment or even a department. Required is that the entity can hire to replace departing workers. Churn cannot be defined for a worker because a worker cannot hire and replace himself and whether his hire is for expansion or churn cannot be determined without examining the hiring entity.

workers, IT specialists, artistic design people, writers and editors and building facilities managers and workers. The workers in the different categories are in no way substitutes for one another and they sell their labor in separate labor markets. Consequently, there is not one labor market from which an employer buys labor, but many, each reflecting the idiosyncrasies of their labor types. In recognition of this fact, workers at each employer are categorized into one of 32 different types. This is based on the same kind of partition as used in the worker-based analysis, but involves many fewer than the 17,632 markets used above for table 4 because neither industry nor state of employment differs among workers for a given employer.²⁶

For each of the employers in the sample, there are up to 32 types of workers, each of which has a hire, separation and churn rate for every quarter. For example, an employer might have 100 slots generally occupied by young male high-school graduates and another 300 slots generally occupied by middle-aged female college graduates. If the churn rate among the first group is .2 and among the second is .1, then the employer churn rate is $(100/400)(.2) + (300/400)(.1) = .125$.

Before calculating an aggregate churn rate for the employer, churn rates in each of the separate job cell categories are used as dependent variables and are regressed on the mean and standard deviation of the wage within that cell type. That is, the dependent variable is the quarterly churn rate for a given employer for the group of workers in one of the 32 different labor markets. Thus, there are up to 32 observations per time period for each employer so the unit of

²⁶ In the LEHD, all employers are headquartered in one and only one state and are assigned to one and only one industry. The 32 categories are formed from 2 genders, 4 education groups and 4 age groups.

analysis is an employer-worker-type-quarter.²⁷ There are a total of 1.306 billion observations overall, comprising labor markets, employers and quarters.

The results of the employer-based analysis are contained in table 5. Column 2 is the regression that most directly fits the theory. The churn rate within each cell depends negatively on the mean wage and positively on the standard deviation of wage within cell. This is what the theory predicts and is in line with the results obtained in the worker-based analysis on separation. Column 3 performs the same analysis, but adds observable demographic variables. They matter, but they do not alter the effects of the mean wage and standard deviation of the wage within the cell, again consistent with the theory that relates to the unobservable as opposed to the observable factors. Columns 4 through 6 simply add industry dummies to the regressions. In column 7, employer fixed effects are added, which control for employer-specific tendencies to have churn rates that are higher or lower than the within labor market group average.

The demographic effects reported in table 5 are of interest themselves. Just as was the case for the worker based analysis in table 4, jobs and by extension employers that employ more educated workers experience less churn. All coefficients on the education groups are negative and the comparison is to those with less than high school. Additionally, in the regressions that control for industry, the pattern is monotonic, with the most educated jobs having the lowest churn rates. Similarly, jobs that employ young workers (the left out category being the labor market for those less than 35 years old) have the highest churn. Finally, jobs that are held by female workers have lower turnover rates.

²⁷ The firm may not have employed workers from every market in every period, in which case there are fewer than 32 observations per firm per period.

Using the results from table 5, it is possible to estimate an employer level churn rate for each of the employers' 32 types of workers in each of the quarters of the data. The specifications in table 5 allow an estimated churn rate for each of the 1.306 billion cells where the cell is defined by the employer, the quarter and the labor type. To get the estimated employer level churn rate for any given quarter, it is simply necessary to compute a weighted average of the churn rates where the weights reflect the importance of the 32 different labor markets for a given firm in a specific quarter, just as in the example above with two worker types above.

Given the estimated churn rates, it is now possible determine the relative importance of the various factors in explaining variations in churn across employers. Table 6 reports the results of analysis. The basic approach is to regress the actual churn rates for each employer on the estimated churn rate, where the estimate is based on one of the columns in table 5.

To understand this, consider the entry of 0.020 in the upper left of table 6. Column 1 of table 5 has only the mean wage as an independent variable and does not control for NAICS. That regression allows one to compute an estimated churn rate for each labor market for each quarter for each employer. As discussed above, the estimated employer churn rate in any given quarter is then the weighted average of the estimated churn rates in the employer's 32 labor markets for that employer. The R-squared value of 0.020 is what is obtained from regressing the actual overall churn rate for the employer on the estimated churn rate for the employer computed by a weighted average of predicted labor-market specific churn rates based on column 1 of table 5. The unit of observation is then an employer-quarter of which there are approximately 265 million.

This is repeated throughout table 6, but using different columns as the estimates. The second row of the first column of table 6 reports the r-squared that is obtained by regressing the

actual employer churn rate in each quarter on the predicted churn rate where the prediction is based on the regression in table 5, column 2. The third row reports the r-squared based on predictions that include demographic variables associated with the labor markets from which the employer hires. Adding demographics to predict labor-market specific churn rates as estimated in column 3 of table 5 about doubles the r-squared, but the r-squared remains low at .03. It is only when employer fixed effects are added to the regression of actual on predicted churn rates that the r-squared moves and then substantially to .42. The second column of table 6 performs the same analysis but uses predicted churn values from table 5, columns 4-6, which include NAICS sector dummies. The sector dummies boost the r-squared values, but once again, it is only when the employer fixed effects are added that the r-squared is substantial.

The most important inference drawn from table 6 is that 36% of the total variation in churn rates for the 265 million employer-quarter observations is explained by employer fixed effects. This is an important result because it documents that employers differ in a consistent way in their churn behavior. As stated in the introduction, there is wide variation in churn rates across employers that was reported in figure 1. Not only are employer fixed effects important, but the average quarterly churn rates across firms vary from almost none to over 16%, as estimated by the kernel density in figure 1. Even after accounting for differences in the types of workers that firms employ, there remain large persistent differences in firm turnover rates. Some employers experience chronically high churn while others see almost no churn in ways that are not explained by industry or the nature of the labor markets from which they draw.

Because these data cannot discern the nature of the separation, it is impossible to determine why employers differ so substantially in their churn experience. It is possible that

employers differ in the types of workers that they employ that is not captured by the demographic variables. It is also possible the mean and variance in wages do not fully capture the costs of or benefits to search. Possibly, some employers encourage more churn, either implicitly or explicitly. For example, an employer that had a comparative advantage in training workers, but not in using them would hire workers, train them and then see them move to other employers. At this point, these remain conjecture, but the fact that the permanent components of turnover rates vary so substantially across employers is a result worthy of attention.

Beyond the differences in churn rates across employers, the employer-based analysis provides a number of findings. First, churn rates at firms do respond as predicted. When the costs of turnover are higher, as measured by the log mean wage of the labor group in question, churn is lower. When the benefits of turnover are higher, as measured by the standard deviation of the log mean wage of the labor group, churn is higher. Additionally, demographic factors affect churn beyond that captured by the mean and standard deviation of the wage. It is unsurprising that observables are correlated with churn. More important is that the predictions of the sorting view, namely that the mean wage and standard deviation of the wage should correlate negatively and positively, respectively, with churn, is invariant to the inclusion of observables.

III. Conclusion

Analysis based on the LEHD reveals that churn rates vary enormously across employers. Some of the differences among employers reflect the characteristics of the workers whom they employ. For example, young workers have higher turnover rates than old and employers with young workers naturally have higher churn rates than those with old workers. Some employer

variation reflects industry differences. Churn rates in manufacturing are less than half those in retail. Additional variation is picked up by the variables prescribed by the model. Employers that use highly idiosyncratic labor experience greater churn than those using more standardized labor. The predictions operate especially well at the worker level, where demographic and industry differences also are strongly related to worker separation.

At the employer level, even accounting for all observable differences, most of the employer-related churn variation remains. Unexplained, but persistent employer effects, account for much of cross-employer variation in churn in the QWI (LEHD) data. Specifically, about 36% of the variation in churn rates across firms is captured by employer fixed effects as compared with 7% accounted for by differences in the compositions of their workforces.

Theory predicts that churn reflects moving workers to more productive uses. Unobservable employer-worker productivity difference associated with a particular match are revealed over time and generate efficiency-enhancing labor market mobility. The prediction is that workers who have low costs of moving and high benefits from moving should be more likely to separate from their firms during their careers. Analogously, there should be more labor churn among employers of highly idiosyncratic workers.

The cost and benefit of churn are measurable in the LEHD and are proxied by the mean and standard deviations in log wages. The benefit of moving a worker from the current firm to a new one depends on the magnitude of the initial job mismatch. When a worker is poorly suited to the current employer, the benefit from getting a new draw on employment is greater. The worker is likely to benefit by moving to another firm and the firm is likely to benefit by hiring a replacement. The cost depends on the value of the worker's time. The results, using both worker

and employer as units of analysis, confirm the theoretical predictions. Those workers or jobs for which the cost of mobility, as proxied by the average wage, is high experience lower churn rates. Those workers or jobs for which the benefit to mobility, as proxied by the variance in wages, is high experience higher churn rates.

Additional results are noteworthy. Observable differences across workers correlate with both separation rates at the worker level and churn rates at the employer level. Younger workers, less educated and male workers have higher separation rates, and the jobs and firms that employ them experience have more churn.

References

- Abowd, J., Corbel, P., & Kramarz, F. 1999. "The Entry and Exit of Workers and the Growth of Employment." *Review of Economics and Statistics* 81(2), 170-187
- Albaek, K., & Sorensen, B. E. 1998. "Worker Flows and Job Flows in Danish Manufacturing, 1980-91." *Economic Journal* 108(451), 1750-71.
- Anderson, Patricia M. and Bruce Meyer. 1994. "The Extent and Consequences of Job Turnover." *Brookings Papers on Economic Activity*.
- Bentolila, Samuel & Bertola, Giuseppe. 1990. "Firing Costs and Labour Demand: How Bad Is Eurosclerosis?" *Review of Economic Studies*, 57(3), 381-402.
- Burgess, S., Lane, J., Stevens, D. 2000. "Job flows, worker flows and churning." *Journal of Labor Economics* 18(3), 473-502.
- Burgess, S., Lane, J., Stevens, D. 2001. "Churning dynamics: an analysis of hires and separations at the employer level." *Labour Economics* 8(1), 1- 14.
- Davis, Steven J., R. Jason Faberman and John Haltiwanger. 2006. "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links." *Journal of Economic Perspectives*, 20(3), 3-16.
- Davis, Steven J., R. Jason Faberman and John C. Haltiwanger. 2012. "Labor Market Flows in the Cross Section and over Time." *Journal of Monetary Economics* 59(1): 1-18.
- Davis, Steven J. and John Haltiwanger. 1992. "Gross Job Creation, Gross Job Destruction and Employment Reallocation." *Quarterly Journal of Economics* 107(3), 819-863.
- Davis, S.J., Haltiwanger, J.C. and Schuh, S., 1998. *Job Creation and Destruction*. MIT Press Books.
- Fujita, S. and Moscarini, G., 2013. "Recall and Unemployment. National Bureau of Economic Research Working Paper No. W19640.
- Hamermesh, D.S., Hassink, W. H. J., Van Ours, J.C. 1996. "Job Turnover and Labor Turnover: A taxonomy of Employment Dynamics." *Annales d.Economie et de Statistique* 41-42, 21-39.
- Hyatt, Henry R. and James R. Spletzer. 2013. "The Recent Decline in Employment Dynamics." *IZA Journal of Labor Economics*, Vol. 2, No. 5, 2013, pp. 1-21.

Jovanovic, Boyan. 1979. "Job Matching and the Theory of Turnover." *Journal of Political Economy* 87(5), 972-990.

Lazear, Edward P. 1990. "Job security provisions and employment." *Quarterly Journal of Economics* 105(3), 699-726.

Lazear, Edward P. and Kathryn L. Shaw (eds). 2009. *The Structure of Wages: An International Comparison*. Chicago: University of Chicago Press.

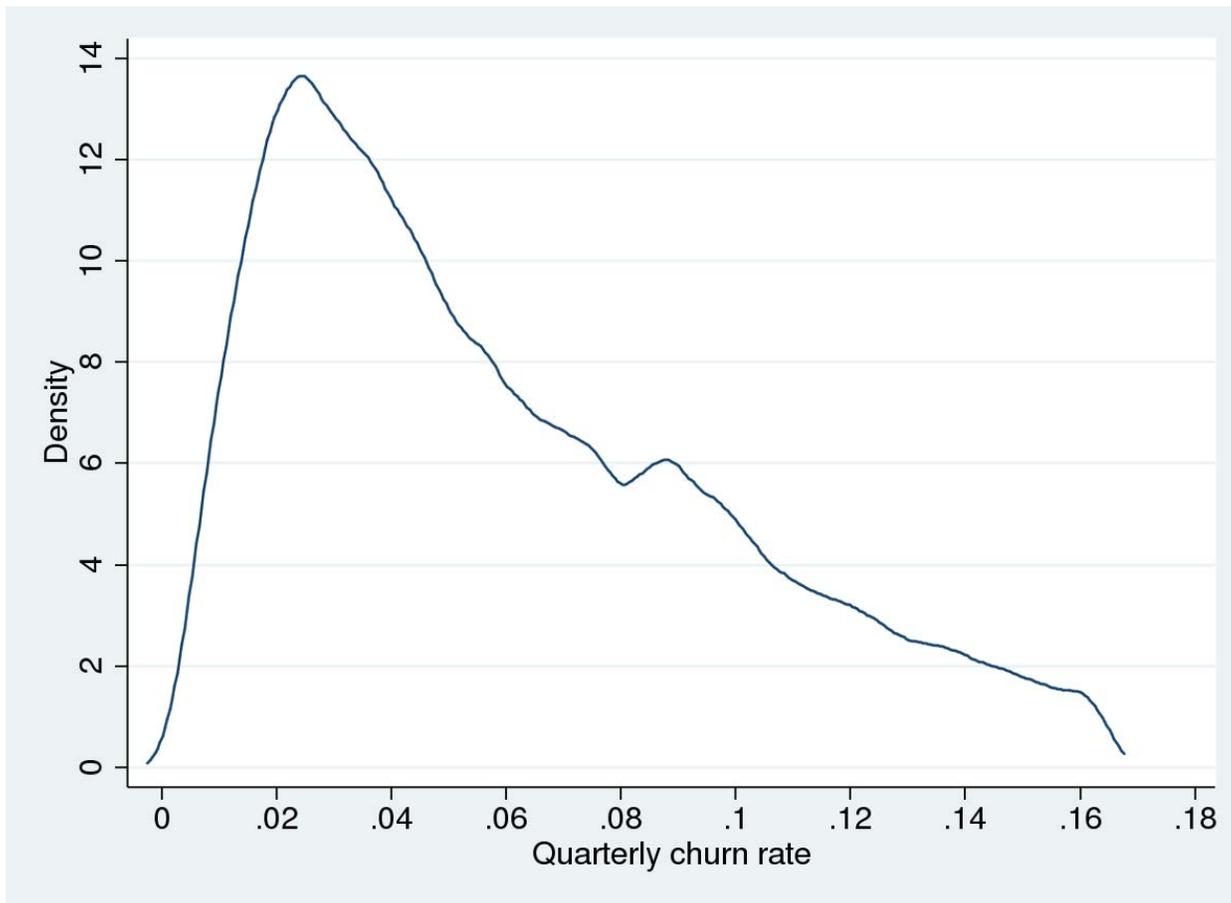
Lazear, Edward P. and James R. Spletzer. 2012. "Hiring, Churn and the Business Cycle." *American Economic Review Papers and Proceedings* 101(3) 575-579.

McLaughlin, Kenneth. 1991. "A Theory of Quits and Layoffs with Efficient Turnover." *Journal of Political Economy* 99(1) 1-29.

Moulton, Brent R. 1990. "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units." *The Review of Economics and Statistics* 72(2) 334-338.

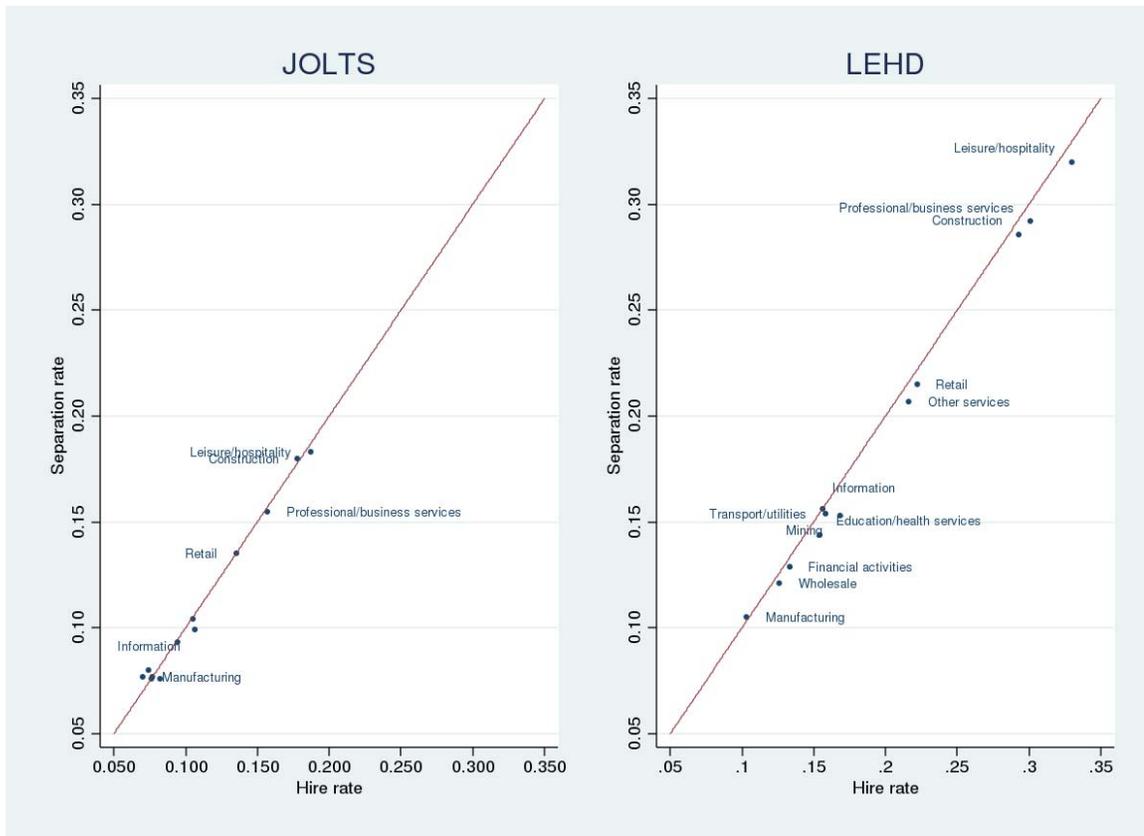
Picot, Garnett andrew Heisz and Alice Nakamura. 2000. "Were the 1990s Labour Markets Really Different?" *Policy Options*, July-August.

Figure 1: Kernel Density of employer average churn rates



Notes: Figure gives kernel density estimates of the employment-weighted distribution of employer average quarterly churn rates. To protect confidential data, the bottom and top 5% of the distribution are not included in the estimates. The denominator for the quarterly rate is the average of beginning of quarter and end of quarter employment. Churn rates exclude jobs that both begin and end in the same quarter. Averages are calculated based on data for the private sector in 29 states over the period 1998q2-2015q1.

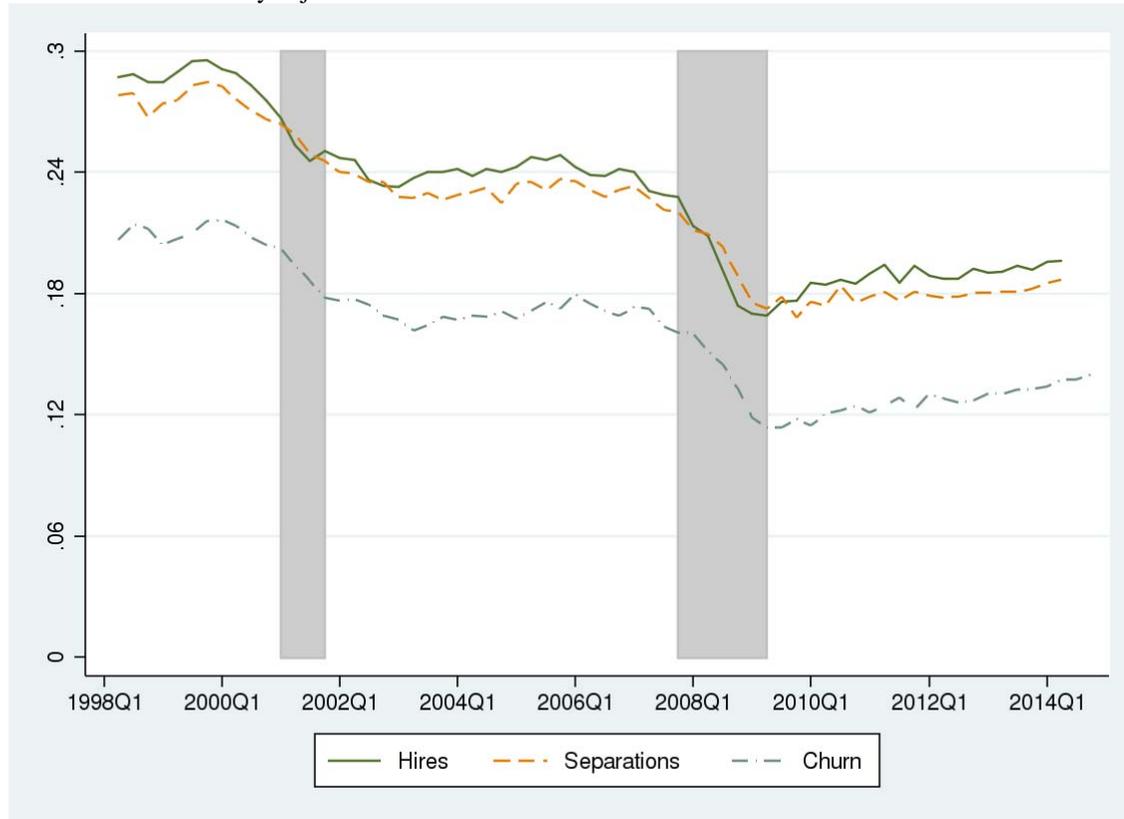
Figure 2: Quarterly Hires and Separation rates, by Industry
JOLTS Data (left panel), Averages 2001:Q1 – 2014:Q3
QWI Data (right panel), Averages 2001:Q1 – 2014:Q3



Source: Authors' calculations from Job Openings and Labor Turnover Survey (JOLTS) and LEHD Quarterly Workforce Indicators (QWI) statistics. JOLTS monthly statistics converted to a quarterly frequency. LEHD statistics are employment-weighted averages of QWI statistics for 29 states. Both sets of statistics are for the private sector and have been seasonally adjusted by the authors.

Figure 3: Quarterly Hires, Separations and Churn Rates
QWI and LEHD Data, 1998:Q2 – 2015:Q1

LEHD microdata for 29 states, private sector.
Each series is seasonally adjusted.



Source: Churn rates based on authors' calculations from private-sector LEHD microdata for 29 states. Hire and separation rates are based on QWI statistics.

Figure 4: Two Hypothetical Wage Densities

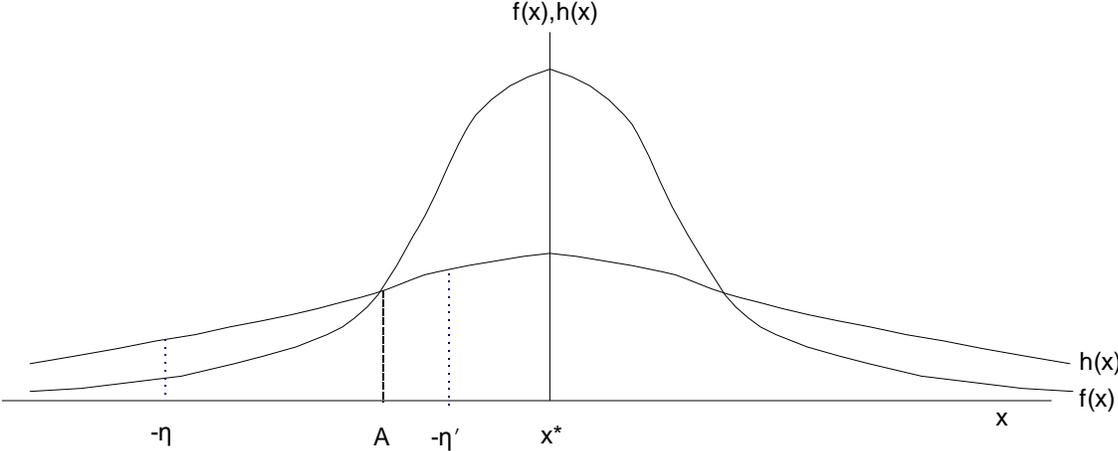


Table 1: Quarterly Hires and Separation Rates, by Industry

Industry	JOLTS 2001Q1-2014Q2			QWI 2001Q1-2014Q2		
	Average hire rate	Average separation rate	Time series correlation	Average hire rate	Average separation rate	Time series correlation
Mining and logging	0.106	0.099	0.029	0.168	0.153	0.476
Construction	0.178	0.180	0.583	0.293	0.286	0.869
Manufacturing	0.070	0.077	0.451	0.103	0.105	0.724
Wholesale trade	0.076	0.076	0.761	0.126	0.121	0.918
Retail trade	0.135	0.135	0.931	0.222	0.215	0.982
Transport, warehousing, utilities	0.094	0.093	0.670	0.158	0.154	0.894
Information	0.074	0.080	0.780	0.156	0.156	0.713
Financial activities	0.077	0.077	0.859	0.133	0.129	0.933
Professional and business services	0.157	0.155	0.853	0.301	0.292	0.982
Education and health services	0.082	0.076	0.954	0.154	0.144	0.987
Leisure and hospitality	0.187	0.183	0.977	0.330	0.320	0.992
Other services	0.105	0.104	0.891	0.216	0.207	0.989
Private, non-farm	0.118	0.117	0.861	0.216	0.209	0.973

Source: Authors calculations based on Bureau of Labor Statistics national JOLTS statistics and Census Bureau QWI statistics for 29 states. JOLTS monthly data were converted to a quarterly frequency. All data are for the private sector and were seasonally adjusted by the authors.

Table 2: Sample summary statistics

	Samples			
	All jobs		Full-quarter jobs	
Rates	Mean	Std Dev	Mean	Std Dev
Hire Rate	0.238	1.304	0.102	0.066
Separation Rate	0.254	1.317	0.103	0.184
Churn Rate	0.165	1.267	0.052	0.089
Worker characteristics				
Log full-quarter earnings			8.80	0.738
Cell mean log full-quarter earnings			8.80	0.455
Standard deviation of log full-quarter earnings in cell			0.827	0.212
Female			0.47	
Age			42.5	10.1
Education categories				
Less than HS			0.134	
HS graduate			0.273	
Some college			0.317	
College graduate			0.276	
Years of education			13.5	0.97
Sample sizes				
Number of job/quarters included		4.79B		3.27B
Number of employer/quarters included		340.9M		265.7M
Number of cell/quarters				1.15M

Notes: All jobs sample includes all private-sector job/quarters at employers with at least one employee at either the beginning or end of the quarter in our sample of 29 states, over the period 1998q2-2015q1. Full-quarter jobs sample includes the subset of full-quarter jobs held by those aged 25-64 over the period 1998q2-2014q3. A job is classified as full-quarter in quarter t if the individual has earnings with that employer in quarters $t-1/t+1$. For some analyses, the full-quarter sample of jobs is classified into cells based on quarter, state, industry sector, 10-year age groups, education categories and gender. All statistics are employment weighted.

Table 3: Regressions of Hire Rate on Separation Rate

	(1)	(2)	(3)	(4)
Separation rate	0.9395*** (0.0191)	0.9593*** (0.0131)	0.9390*** (0.0194)	0.9048*** (0.0250)
Intercept	0.0001 (0.0048)	-0.0050 (0.0033)	0.0002 (0.0049)	0.0089 (0.0064)
Fixed effects:				
Year*quarter	No	Yes	No	No
Industry (2-digit NAICS sector)	No	No	Yes	No
Employer	No	No	No	Yes
R-squared	0.9000	0.9177	0.9000	0.9031

Source: LEHD microdata for private sector in 29 states. Standard errors in parentheses. Dependent variable is the ratio of hires in current quarter over the average of the count of employees at the beginning and the end of the quarter. All regressions are employment weighted. Sample size is 340.9M employer-quarter observations. Standard errors are clustered at the employer level.

Table 4: Job Separation Regressions, LEHD Full-quarter jobs

	(1)	(2)	(3)	(4)	(5)	(6)
Mean wage	-0.0369*** (0.0009)	-0.0352*** (0.0010)	-0.0378*** (0.0012)	-0.0244*** (0.0008)	-0.0245*** (0.0008)	-0.0111*** (0.0012)
Standard deviation of wage		0.0129*** (0.0023)	0.0229*** (0.0033)		-0.0147*** (0.0016)	0.0133*** (0.0012)
Female			-0.0169*** (0.0009)			-0.0028*** (0.0006)
35-44			-0.0242*** (0.0012)			-0.0267*** (0.0006)
45-54			-0.0377*** (0.0011)			-0.0397*** (0.0006)
55-64			-0.0426*** (0.0011)			-0.0413*** (0.0006)
High school grad			-0.0086*** (0.0015)			-0.0095*** (0.0008)
Some College			-0.0074*** (0.0015)			-0.0112*** (0.0008)
College grad			-0.0021 (0.0017)			-0.0136*** (0.0011)
Intercept	0.4281*** (0.0084)	0.4027*** (0.0093)	0.4547*** (0.0121)	0.3553*** (0.0076)	0.3684*** (0.0079)	0.2668*** (0.0104)
Fixed effects:						
Year*quarter	Yes	Yes	Yes	Yes	Yes	Yes
NAICS sector	No	No	No	Yes	Yes	Yes
Employer	No	No	No	No	No	Yes
R-squared	0.275	0.278	0.430	0.538	0.540	0.655

Source: LEHD microdata for private sector in 29 states, 1998Q2-2014Q3. Unit of observation is a state/quarter/ industry/age/ gender/ education cell. All regressions are weighted by cell employment and include year and quarter dummies. Sample size is 1.15M cell quarter observations. Dependent variable is the cell share of individuals leaving a full-quarter job in the next quarter. Regressions in columns 4-6 include dummies for the 19 NAICS sectors included in the sample. Standard errors (in parentheses) are clustered at the cell level. * p<0.05, **p<0.01, *** p<0.001

Table 5: Churn Regressions, including within-employer variation across labor market groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean wage	-0.0189*** (0.0002)	-0.0171*** (0.0002)	-0.0163*** (0.0007)	-0.0111*** (0.0003)	-0.0111*** (0.0003)	-0.0014*** (0.0005)	0.0037*** (0.0003)
Standard deviation of wage		0.0140*** (0.0015)	0.0233*** (0.0021)		-0.0061*** (0.0026)	0.0133*** (0.0026)	0.0041*** (0.0004)
High school grad			-0.0047*** (0.0002)			-0.0048*** (0.0002)	-0.0019*** (0.0001)
Some College			-0.0045*** (0.0004)			-0.0062*** (0.0003)	-0.0027*** (0.0001)
College grad			-0.0041*** (0.0006)			-0.0095*** (0.0005)	-0.0059*** (0.0002)
35-44			-0.0142*** (0.0002)			-0.0157*** (0.0002)	-0.0142*** (0.0001)
45-54			-0.0222*** (0.0003)			-0.0234*** (0.0002)	-0.0211*** (0.0001)
55-64			-0.0295*** (0.0003)			-0.0288*** (0.0003)	-0.0253*** (0.0001)
Female			-0.0086*** (0.0003)			-0.0010*** (0.0003)	0.0003*** (0.0001)
Intercept	0.1999*** (0.0019)	0.1723*** (0.0030)	0.1804*** (0.0071)	0.1744*** (0.0033)	0.1799*** (0.0027)	0.1021*** (0.0053)	0.0209*** (0.0023)
Fixed effects:							
Year*quarter	Yes						
NAICS sector	No	No	No	Yes	Yes	Yes	No
Employer	No	No	No	No	No	No	Yes
R-squared	0.008	0.009	0.017	0.025	0.026	0.032	0.191

Source: LEHD microdata for private sector in 29 states, 1998Q2-2014Q3. Unit of observation is a group of an employer's workers defined by worker age, gender and education groups as defined in Table 4. All regressions are weighted by group employment. Sample size is 1.306 billion employer/group/quarter observations. Dependent variable is the quarterly churn rate for a labor-market group at a particular employer. The sample includes 19 NAICS sectors. Standard errors (in parentheses) are clustered at the employer level. Clustered standard errors for columns 3-7 could not be estimated on the full sample with available computational resources. The standard errors in those columns were computed using a random half-sample, which should over estimate the true standard errors.

Table 6: R-squares from regression of actual employer churn rate on predicted churn rate using Table 5 models

Variables included	No sector controls	Sector dummies
Mean wage	0.020	0.057
Mean and standard deviation of wage	0.021	0.058
Mean and standard deviation of wage and demographics	0.032	0.064
Mean and standard deviation of wage, demographics and fixed effects	0.424	0.424

Appendix

Three statements on efficient separation are proved here.

1. A worker never quits when it is socially efficient to stay at the current firm.

Proof: First consider whether the wage can be so low that the worker quits even when it is inefficient to do so. Inefficient separation is defined as separation when $V + \varepsilon_i > V + E(\varepsilon_j) - \eta$ or when $\varepsilon_i > -\eta$. Now, the current firm is always willing to pay up to $V + \varepsilon_i$. An alternative firm j can never pay more than $V - \eta$. For firm j to offer enough to attract the worker, it would have to be the case that $V - \eta > V + \varepsilon_i$ or that $\varepsilon_i < -\eta$, which only happens when separation is socially optimal

2. The firm never terminates a worker when retaining the worker would be socially efficient.

Proof: The alternative firm will pay no more than $V - \eta$ and the current firm will retain the worker as long as productivity exceeds the wage, which means the current firm will pay up to $V + \varepsilon_i$. For the wage to be so high that the firm would fire the worker, it would have to be the case that $V - \eta > V + \varepsilon_i$ or that $\varepsilon_i < -\eta$ which violates the definition of inefficient separation.

3. Separations always occur when the worker is more valuable at the alternative firm than at the current one.

Proof: A separation is efficient when $\varepsilon_i < -\eta$. The maximum wage that the current firm can pay is $V + \varepsilon_i$. An alternative firm can pay up to $V - \eta$. Thus, a worker will quit whenever the outside wage exceeds the maximum current wage or whenever $V - \eta > V + \varepsilon_i$, which is the same as whenever $-\eta > \varepsilon_i$. But if $-\eta > \varepsilon_i$, then separation is efficient by (2'). Thus, a competitive labor market ensures efficient turnover even when hiring cost