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Hie Joo Ahn

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Heterogeneity in the Dynamics of Disaggregate Unemployment

Hie Joo Ahn [*] [†]
Federal Reserve Board

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Abstract

This paper explores the role that unobserved heterogeneity within an observed category plays in the dynamics of disaggregate unemployment and in the cross-sectional differences across individuals of the duration of unemployment spells. The distribution of unobserved heterogeneity is characterized as a mixture of two distributions with each mean and weight determined by the inflows and outflows of workers with unobserved types H and L, which are identified based on the nonlinear state-space model of Ahn and Hamilton (2016). I found that the contribution of each factor to the dynamics of disaggregate unemployment differs by observed category. The inflow of type L workers is the most important factor in the majority of demographic groups in the business-cycle frequency. I identify permanent job loss to be the observable characteristic most closely associated with the type L attribute. A simple model of heterogeneity based on two unobserved types can explain more than 50 percent of the cross-sectional dispersion in completed-duration spells after the Great Recession, while observed heterogeneity makes only a minor contribution.

Keywords: unemployment dynamics, unobserved heterogeneity, genuine duration dependence, state space model, extended Kalman filter, Great Recession

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[†]E-mail: hiejoo.ahn@frb.gov

Introduction

During the Great Recession, the average duration of unemployment reached its highest level since World War II, and it rose even further after the recession was over. To identify the source of this increase and sluggish recovery, economists have looked at the relationships between observable characteristics of unemployed individuals that are captured by the data—such as gender, age, education, occupation, and industry—and those individuals' durations of unemployment.[1] They have found that the share of long-term unemployment reached a record-high level in almost every observable-characteristic-based group, and that compositional shifts across groups in the unemployment seem to explain little of the observed increase in average duration of unemployment. This observation has led some to conclude that the rise in unemployment duration is driven by aggregate factors that affect many workers in a similar way.

This approach, however, overlooks heterogeneity within a group with similar observable characteristics—a crucial factor in understanding the dynamics of disaggregate unemployment. For example, among men who are high-school graduates, those who have a shorter duration of unemployment are more likely to exit unemployment than those who have been unemployed longer (Figure 1).[2] This phenomenon in which unemployed workers become less likely to exit unemployment status as they stay unemployed longer, often referred to as the "negative duration dependence of unemployment hazards," is a strikingly consistent feature across disaggregated groups of unemployed individuals over time.

What accounts for this phenomenon? There are two possible explanations. The first is

[1] See, for example, Aaronson, Mazumder, and Schechter (2010), Elsby, Hobijn, and Sahin (2010), Bachmann and Sinning (2012), Sahin, Song, Topa and Violante (2012), Barnichon and Figura (2013), Hall (2014), Hall and Schulofer-Wohl (2015), Kroft, Lange, Notowidigdo, and Katz (2016) and Krueger, Cramer and Cho (2014).

[2] The plotted value for $px_{t+1}^{4.6}$ was calculated from

$$px_{t+1}^{4.6} = \frac{U_{jt}^4 + U_{jt}^5 + U_{jt}^6 - U_{j,t+1}^5 - U_{j,t+1}^6 - U_{j,t+1}^7}{U_{jt}^4 + U_{jt}^5 + U_{jt}^6}$$

for U_{jt}^n the number of men with a high-school diploma who have been unemployed n months at t. Other magnitudes were constructed analogously from the raw data on U_{jt}^n using CPS micro data.

dynamic sorting due to individual characteristics that are not well captured in the data. If some individuals with given observed characteristics who are newly unemployed at time t have an intrinsically lower probability of exiting unemployment than others who share the same observable characteristics, the former individuals will make up a larger fraction of the unemployed for s months at time $t+s$ as a necessary consequence of dynamic sorting. As a result, the long-term unemployed would have a lower probability of exiting unemployment than the short-term unemployed. The second explanation is genuine duration dependence (hereafter, GDD), which means that the experience of being unemployed for a longer period of time changes the characteristics of a fixed individual. For example, Kroft, Lange, and Notowidigdo (2013) and Eriksson and Rooth (2014) use audit studies to show that employers may discriminate against those who have been unemployed longer, which is often referred to as unemployment scarring, or negative GDD. As a consequence, the longer a worker stays unemployed, the less likely to get a job that worker becomes. However, Farber, Silverman, and von Wachter (2015) also use an audit study and find that there is no relationship between employer callback rate and job applicants' duration of unemployment, once heterogeneity of job applicants is well controlled for.

The first explanation suggests that increased inflows of job losers who have particularly low probabilities of exiting unemployment because of unobserved individual attributes would be responsible for the rise in long-term unemployment within a group that shares certain observable characteristics. This further implies that the compositional variation of unobserved heterogeneity among newly unemployed individuals with the same observable characteristics could be an important element in the rise in average duration of unemployment and its sluggish recovery. The second explanation suggests that an overall fall in the probabilities of exiting unemployment could be the key factor in the dramatic rise of long-term unemployment within a group with similar observable characteristics. As unemployed people become less likely to find a job during recessions, they are more exposed to unemployment scarring, which could make them stay unemployed even longer. Which factor is more important in the cyclical dynamics of disaggregate unemployment? Furthermore, how much do observed and unobserved heterogeneity determine the differences across individuals in the duration of completed unemployment spells? These are the questions that I attempt to answer in this paper.

This paper explores heterogeneity within groups of individuals who share various observable characteristics. I assume that newly unemployed individuals are one of two unobserved types—type H, with high exit probability, and type L, with low exit probability—within a group of people who all have the same observed characteristics. The numbers of newly unemployed individuals and the unemployment continuation probabilities of both types vary over time. In addition, I assume an individual's probability of staying unemployed the following month changes depending how long she has been unemployed. I also allow limited time variation in the GDD based on the unemployment rate. Ahn and Hamilton (2016) show that in this setup, the identification of unobserved heterogeneity is achieved from the dynamic accounting identity of unemployment, and they use the approach to analyze aggregate unemployment dynamics in the U.S. In this paper, I apply the approach to specific subcategories based on observable characteristics and analyze the role of worker's unobserved heterogeneity in the cross-sectional dispersion of completed durations of unemployment over time, something no previous studies have attempted to do. To rigorously investigate the role of unobserved heterogeneity, I construct a dataset of unemployed individuals by duration using the Current Population Survey (CPS) micro data.

In studies of unemployment hazards, it is common to assume that the distribution of unobserved heterogeneity is time-invariant.[3] This paper distinguishes itself from the literature in that the distribution of unobserved heterogeneity is characterized as a mixture of two

[3]See, for example, Elbers and Ridder (1982), Heckman and Singer (1984 a,b,c), Ridder (1990), Honoré (1993) and Alvarez, Borovičková and Shimer (2015). Honoré (1993) shows that the effect on individual unemployment hazards of unobserved heterogeneity and GDD is identified without parametric assumptions on the distribution of unobserved heterogeneity, if we can observe two non-employment spells for each individual. However, Honoré (1993)'s identification is based on the assumption that the individual unobserved heterogeneity of two different periods is identical. Hougard (1987) stresses that the assumption is too restrictive even in a multiple-spell model, as the corresponding spells do not necessarily concern the same state.

distributions, with each mean and weight of the distribution varying over time.[4] The distribution of unobserved heterogeneity is likely to change over business cycles if a recessionary shock has an asymmetric effect on workers. Suppose, for example, there is a negative productivity shock on workers whose differences in skills are not fully captured by the characteristics observed by the econometrician. As firms demand fewer workers with those skills, the share of those workers among the unemployed will go up. In the presence of a reallocational friction, the distribution of market tightness across skill groups will change substantially, as the dispersion of market tightness becomes larger and the probability density of the group facing low market tightness increases.[5] This feature is not allowed in a model that assumes a time-invariant distribution of unobserved heterogeneity. Now suppose that the troubled workers are dispersed among many observed categories, we will then witness a similar rises in long-term unemployment across many groups. In this case, an economist who does not consider possible changes in the distribution of unobserved heterogeneity might conclude that the common rise in long-term unemployment is driven by an aggregate shock that affects workers in a similar way, even though it is driven by a sector-specific shock that has a disproportionate influence on a certain group of workers.

This paper contributes to the literature on the dynamics of unemployment (Baker, 1982; Fujita and Ramey, 2006, 2009; Fujita, 2011; Elsby, Michaels, and Solon, 2009; Shimer, 2012; Hornstein, 2012; Ahn and Hamilton, 2016). Except for Ahn and Hamilton (2016) and Hornstein (2012), these studies do not consider unobserved heterogeneity and GDD in their analyses, so their ability to explain the variation in the distribution of unemployment

[4]Van den Berg and van Ours (1996) allow the distribution characterizing unobserved heterogeneity to change over time. Their main focus is to non-parametrically identify the contribution of unobserved heterogeneity to the unemployment hazards of individuals using an idea similar to the dynamic accounting identity. This paper is distinguished from theirs in that the identification scheme based on the dynamic accounting identity is incorporated into a complete dynamic statistical model of unemployment that allows me to analyze the role of unobserved heterogeneity in the dynamics of disaggregate unemployment and the cross-sectional dispersion of unemployment duration. In addition, I allow limited time-variation in genuine duration dependence, while they assume that the pattern of genuine duration dependence does not change over time.

[5]Lise and Robin (2013) also characterize the time-varying distribution of market tightness in their equilibrium model of an on-the-job search.

duration is limited, as demonstrated in Section 1. This paper is also related to the strand of research that studies the rise of unemployment during the Great Recession (Aaronson, Mazumder, and Schechter, 2010; Elsby, Hobijn, and Sahin, 2010; Sahin, Song, Topa and Violante, 2012; Barnichon and Figura, 2013; Hall, 2014; Hall and Schulofer-Wohl, 2015; Kroft, Lange, Notowidigdo, and Katz, 2016; Krueger, Cramer and Cho, 2014). This paper's innovation to that literature comes from investigating the role of unobserved heterogeneity within an observed category. I find that heterogeneity not well captured by observable characteristics of unemployed individuals is crucial to the path of unemployment observed during the Great Recession.

This paper is closest to Ahn and Hamilton (2016) and Hornstein (2012), but distinguishes itself from them for the following reasons. First, Ahn and Hamilton do not consider observable worker characteristics, so they are silent about how observables and unobservables interact and impact unemployment dynamics. By investigating unobserved heterogeneity within an observed category, I can map the observable characteristics that are most likely to constitute the key unobserved attributes. Second, Ahn and Hamilton focus on the aggregate dynamics of unemployment, while the main focus of this paper is the role of unobserved heterogeneity in the dynamics of disaggregate unemployment and the cross-sectional dispersion of unemployment duration.

Meanwhile, Hornstein (2012) also applies the dynamic accounting identity to disaggregated data—including age, industry, and occupation—using minimum-distance estimation, but his model is under-identified, as discussed in Ahn and Hamilton (2016). In addition, like the previous literature on unemployment dynamics, Hornstein also uses an arbitrary de-trending procedure to analyze the degree to which the inflows and outflows of workers with unobserved heterogeneity explains the volatility of the unemployment rate in the business-cycle frequency. However, it has been noticed that the results could be sensitive to the choice of de-trending filters (Fujita and Ramey, 2009; Shimer, 2012). This is because the unemployment rate is highly serially-correlated and possibly nonstationary, so its variance may not be well defined. Given this dynamic nature of the unemployment rate, the analytic methods adopted in the previous studies may not help us to decompose how much each flow accounts for the variability of unemployment in the short and long term in a robust way. By contrast, the empirical approach of this paper is free from this problem. The complete dynamic statistical model presented in this paper characterizes unemployment using non-stationary processes of which the innovations driving the processes have well-defined variances. Therefore, regardless of the stationarity of the underlying process, the model presented in this paper generates a forecast of unemployment at any forecasting horizon, with well-defined distribution for forecast errors.[6] This feature allows us to compute how much a shock on each factor explains the variance of unexpected changes in unemployment at any frequency. Lastly, like Ahn and Hamilton (2016), Hornstein (2012) also did not consider the implication of unobserved heterogeneity for the cross-sectional dispersion of completed unemployment duration spells.[7]

I find that in every group of unemployed individuals with the same observable characteristic, substantial heterogeneity exists in their unemployment continuation probability both in normal and recessionary periods. During the Great Recession, the number of newly unemployed type L workers and their continuation probabilities increased dramatically in most of the categories, which resulted in the ubiquitous rise in long-term unemployment to unprecedentedly high levels across different groups of unemployed individuals. In the majority of demographic groups, type L inflows are the major driver of unemployment dynamics in the business cycle frequency. This suggests that compositional changes of unobserved heterogeneity among the inflows are crucial to the cyclical fluctuations of disaggregate unemployment. I offer interpretations of type L individuals based on various individual characteristics. The one observable characteristic that seems most closely associated with type L workers is reason for unemployment. I find that type L individuals who are permanently

[6] This feature is shown in den Haan (2000), and is also discussed in Ahn and Hamilton (2016).

[7] In addition, in this paper, the GDD is allowed to have a non-monotonic pattern that is not considered in Hornstein (2012).

separated from their previous employers without notice of recall account for almost half of the total newly unemployed type L individuals.[8] They are the key driver of countercyclical fluctuations in type L inflows.[9] Likewise, reason for unemployment is also the observed category that exhibits the largest difference in the unemployment dynamics. The importance of permanently separated workers in type L inflows illustrates the main reason for thinking about unobserved heterogeneity as a dynamic process. The difficulty that an individual has in finding a job is associated with changing economic conditions that give job losers dim prospects of returning to their previous employers, such as firm bankruptcy, replacement of certain workers with automation or outsourcing, and so on.

The unobserved heterogeneity that is crucial to the dynamics of disaggregate unemployment is also important in explaining the cross-sectional dispersion of completed-duration spells. The two unobserved types, H or L, account for around 40 percent of the dispersion across individuals, on average, between 1980 and 2007. The importance of unobserved types becomes greater after the Great Recession, accounting for more than 50 percent of the dispersion in 2011 when the average duration of unemployment reached record-highs. By contrast, observed heterogeneity plays a very limited role, explaining less than 10 percent of the variance on average. This empirical result suggests we should take into account unobserved heterogeneity of unemployed individuals to fully understand the distribution of

[8] Note that I am not claiming that permanent job loss is neither sufficient nor necessary condition for an unemployed individual type L. Although permanent job loss is highly associated with recall, this does not necessarily mean that the compositional variation across workers unemployed for different reasons for unemployment can explain the rises in the unemployment and the average duration of unemployment during recessions, while the increased share of type L workers among newly unemployed individuals can. A recent study by Fujita and Moscarini (2015) is closely related to the findings of this paper, and implies that the type L attribute could be closely linked to recall. They show that those who do not get recalled from the previous employer tend to have lower job-finding probabilities than others, and those who do not get recalled from the previous employer are found more often among permanently separated workers, but at the same time about 20% of permanent job losers become eventually recalled by their last employer. They further argue that whether an individual is eventually recalled to the previous employer or not has an implication on unemployment dynamics different from reason for unemployment.

[9] Bednarzik (1983) finds that permanent job losers tend to experience longer duration of unemployment than others. Elsby, Michaels, and Solon (2009) also argue that the contribution of inflows and outflows to the fluctuations of unemployment differs substantially by reason for unemployment. Fujita and Moscarini (2013) claim that job losers who don't get recalled to the previous employer are less likely to find a job than the others. Hall and Schulhofer-Wohl (2015) argue that reason for unemployment is an important individual characteristic to consider in measuring the aggregate matching efficiency.

completed unemployment duration and its changes.

This paper is organized as follows. Section 1 illustrates the key evidence justifying why we should consider heterogeneity within an observed category to understand unemployment dynamics. Section 2 presents the model and the empirical methods. Section 3 documents the empirical results. Section 4 demonstrates the contribution of inflows and outflows of each type of worker to the dynamics of disaggregate unemployment. In Section 5, how much observed and unobserved heterogeneity explains the difference across individuals in the completed duration spells is explored.

1 Why heterogeneity within an observed category?

Why is it important to consider heterogeneity within an observed category when thinking about the rise of unemployment and average duration of unemployment during recessions? I present simple accounting exercises to demonstrate that models of unemployment dynamics that do not consider heterogeneity within a group that shares observable characteristics are limited in their ability to match the distribution of unemployment duration.

Consider an economy in which unemployed individuals are identical and so have the same probability of exiting unemployment at $t+1$, conditional on having been unemployed at t. In this economy, the number of those unemployed for n months at t, denoted U_t^n, is determined by how many people become newly unemployed at $t-n+1$ and by the history between $t-n+1$ and t of probabilities to stay unemployed next month conditional on being unemployed in the current month. Let U_t be the total number of unemployed individuals at t. The probability of continuing to be unemployed at t conditional being unemployed at $t-1$, p_t, is calculated from

$$p_t = \frac{U_t - U_t^1}{U_{t-1}}, \tag{1}$$

where U_t^1 is the number of newly unemployed individuals in month t. Using U_t^1 and p_t, we can calculate the number unemployed for n months, $\hat{U}_t^n$ for $n = 1, 2, 3, ..., N$, as follows:

$$
\begin{aligned}
\hat{U}_t^1 &= U_t^1. \\
\hat{U}_t^2 &= U_{t-1}^1 p_t \\
\hat{U}_t^3 &= U_{t-2}^1 p_{t-1} p_t \\
&\cdots \\
\hat{U}_t^N &= U_{t-N+1}^1 \prod_{h=2}^{N} p_{t-N+h}.
\end{aligned} \tag{2}
$$

$\hat{U}_t^n$ is the number of people who have been unemployed for n consecutive months from $t-n+1$ to t, when every unemployed individual faces the same probability to continue to be unemployed next month in month t, p_t. With $\hat{U}_t^n$'s for $n = 1, 2, ..., N$, we can calculate the mean and standard deviation of unemployment duration in progress at t in the economy when everyone has the same probability of continuing to be unemployed. In Figure 2, Panel A shows the predicted mean duration (solid red line) and the actual mean duration of CPS (dashed blue line), and Panel B plots the predicted standard deviation (solid red line) and the standard deviation of unemployment duration computed directly from the CPS micro data (dashed blue line) from 1978 to 2013. On average, the predicted mean is 68 percent of the observed mean duration, and the predicted standard deviation is 44 percent of the standard deviation of unemployment duration in CPS micro data.[10] The substantially smaller predicted values imply that the distribution of unemployment duration and its variation over time cannot be correctly described without taking heterogeneity in the

[10] I calculated the variance of unemployment duration in progress using the CPS micro data. Until 1993, the duration was top-coded at 99 weeks. After 1993, the durations were recorded up to 124 weeks, and the top code was raised to 5 years in 2011. The share of people who report a duration longer than 99 weeks is small after 1993. In addition, even after CPS survey respondents are allowed to report a duration up to 5 years, observations between 2 and 5 years are relatively sparse. For time-series consistency and tractability in the analyses, I assume that the maximum duration of unemployment is 2 years, which is likely to understate the variance of ongoing unemployment duration slightly. I convert the unemployment duration in weeks into months and calculate the moments of duration distribution.

unemployment continuation probabilities into account.

Now suppose that workers differ only by observable characteristics. Let p_{jt} denote the unemployment continuation probability at t of individuals with observable characteristic j (group j) for $j = 1, 2, 3, ..., J$. The variable, p_{jt}, is calculated from

$$p_{jt} = \frac{U_{jt} - U^1_{jt}}{U_{j,t-1}},$$

where U_{jt} is the total number of unemployed individuals in group j and U^1_{jt} is the number of newly unemployed individuals in group j at t. As the observable characteristics, we consider gender, age, education, industry, occupation, and reason for unemployment. In this economy, the number of people in group j who are unemployed for n months, $\hat{U}^n_{jt}$ for $j = 1, 2, 3, ..., J$, is determined by

$$\hat{U}^n_{jt} = U^1_{j.t-n+1} \prod_{h=2}^{n} p_{j,t-n+h}. \tag{3}$$

With $\hat{U}^n_{jt}$ for $n = 1, 2, ..., N$, we can recover the distribution of ongoing duration of group j. Hence, the aggregate distribution of unemployment duration in progress is calculated from

$$\hat{U}^n_t = \sum_{j=1}^{J} \hat{U}^n_{jt}. \tag{4}$$

Using $\hat{U}^n_t$ in equation (4), we can also predict the mean and standard deviation of unemployment duration in this economy. In Figure 2, the predicted moments are compared with the actual moments observed in the data. If we take reason for unemployment as the observed category, for example, the predicted mean duration (dashed fuchsia line in Panel A) is 73 percent of the actual mean, and the predicted standard deviation (dashed fuchsia line in Panel B) is 51 percent, on average between 1978 and 2013. By Jensen's inequality, the mean and variance become larger or remain at the same levels as we consider finer gradations of heterogeneity in the model.[11] The predicted first and second moments are slightly

[11] To illustrate the intuition, suppose that the economy is in a steady state. Let W_j be the fraction of

larger than those simulated under the assumption that all the unemployed individuals are homogeneous. Although we consider different observed characteristics in varying levels of detail, meaningful improvement is not achieved in fitting the distribution of unemployment duration in progress to what is observed in the data.

Now consider an economy in which unemployed individuals who share the same observable characteristics have different unemployment continuation probabilities. I postulate that the probability of continuing unemployment for a current unemployed individual, $p_{jt}(\tau)$, is a function of duration, τ, because of either cross-sectional heterogeneity, GDD, or both. Suppose that $p_{jt}(\tau)$ can be written into the following form

$$p_{jt}(\tau) = \exp(-\exp(d_{jt}^{\tau})),$$

where d_{jt}^{τ} is a cubic function of τ

$$d_{jt}^{\tau} = \delta_{jt}^{0} + \delta_{jt}^{1}\tau + \delta_{jt}^{2}\tau^{2} + \delta_{jt}^{3}\tau^{3}.$$[12][13]

Suppose, for simplicity, that the economy is in the steady-state. Then $\hat{U}_{jt}^{n}$ is written as follows,

$$\hat{U}_{j}^{n} = w_j p_j(1)....p_j(n-1). \quad (5)$$

As in Ahn and Hamilton (2016), given observations on the numbers of individuals unem-

unemployed individuals with characteristic j among total unemployment. Then the average exit probability from unemployment, p, is calculated from $p = \sum_{j=1}^{J} W_j p_j$. Let D be the mean duration in progress that is predicted from equation (2). D can be also written into $D = m(p)$, where $m(\cdot)$ is a convex function of its arguments. Likewise, the mean duration in progress of unemployed individuals with characteristic j, D_j, is written as $D_j = m(p_j)$. The mean duration predicted by equation (4) is $D^J = \sum_{j=1}^{J} W_j D_j$. By Jensen's inequality, it then follows that $D \leq D^J$. The extension to the dynamic case is straightforward.

[12] The double-exponential function is a convenient way of implementing a proportional hazard specification to guarantee a positive hazard, and it is also adopted in Katz and Meyer (1990).

[13] Since I have five data points—the numbers unemployed for 1, 2–3, 4–6, 7–12 months, and longer than 1 year—a maximum of four parameters in d_{jt}^{τ} can be identified.

ployed for 1, 2-3, 4-6, 7-12 months, and longer than 1 year, we can solve for $\delta_j^0, \delta_j^1, \delta_j^2$ and δ_j^3 and recover $p_j(\tau)$.

Figure 3 plots $1 - p_j(\tau)$, the paths of the average exit probabilities over the duration of unemployment during 2003:M01-2007:M11 and 2007:M12-2013:M12. Panel A shows the exit probabilities of men aged 25–44 with some college education or an associate degree. Panel B shows the exit probabilities of women aged 16–24 with high school education or less. The patterns of paths are different over business cycle phases and between different groups. There are three interesting features. First, the exit probabilities exhibit a non-monotonic U-shape along the duration of unemployment, decreasing up to one year of duration and increasing after one year. The decreases in the exit probabilities up to one year of duration are commonly observed in different groups and in different time periods. This finding suggests that either dynamic sorting due to unobserved heterogeneity or negative GDD plays an important role in the exit probabilities of this duration group. Meanwhile, the increases in the exit probabilities after one year of duration also imply that workers who are unemployed longer than 1 year evidently are subject to positive GDD. The long-term unemployed might become more likely to leave the labor force out of discouragement or to find a low-paying job due to financial difficulty, as they stay longer unemployed, which I will refer to as motivational effects.[14] Second, the exit probabilities are lower after the beginning of the Great Recession than during the non-recessionary period. This evidence suggests the possibilities that either the average probabilities of exiting unemployment fell, or the share in the inflows of those who are less likely to leave the unemployment status due to unobserved individual characteristics rose after the Great Recession began. Lastly, there are substantial differences between groups in the shape of exit probabilities over duration of unemployment and how the paths change over time. The difference suggests that the importance of unobserved heterogeneity and GDD in the duration dependence of unemployment hazards differs by observable characteristics of

[14] The turnaround in duration dependence might be associated with unemployment insurance benefits. As the long-term unemployed exhaust their unemployment insurance benefits, they have less incentive to continue to stay unemployed, so could become more likely to stop searching for a job.

unemployed individuals.

As highlighted in previous research, distinguishing between the effects of unobserved heterogeneity and GDD on the unemployment hazards is challenging, and depends critically on the assumptions for identification. In previous studies, the methods of identification and estimation of the parameters characterizing the distribution of individual unobserved heterogeneity and GDD have often been designed to be applicable to the data available for the study (see, for example, Elbers and Ridder, 1982; Heckman and Singer, 1984a; van den Berg and van Ours, 1996; Alvarez, Borovičková and Shimer, 2015) The goal of this paper is to analyze the contribution to the dynamics of disaggregate unemployment of inflows and outflows of workers with unobserved attributes using the time series of the number of individuals who have been looking for work for 1 month, 2-3 months, 4-6 months, 7-12 months, and longer than 1 year for people grouped according to a variety of observable characteristics. I assume that there are two types of workers, type H and L, in group j.[15] Type H workers have a high probability of exiting unemployment, and type L workers have a low exit probability. The inflows and outflows of workers with unobserved types in group j are dynamic variables that change every month. To capture a possible non-monotonic pattern of unemployment exit probabilities over the duration of unemployment, I use a nonlinear function to characterize GDD that differs by observable characteristic j.[16] Lastly, following the previous research studying variation in GDD depending on the business-cycle phases, or the labor market slack (see, for example, Vishwanath, 1989; Lockwood, 1991; Blanchard and Diamond, 1994; Acemoglu, 1995; Ljunqvist and Sargent, 1998; and Kroft, Lange, and Notowidigdo, 2013), I assume that there are two regimes for GDD—a low- and high-unemployment-rate regime—but that the shape or magnitude of the GDD does not change within a regime.[17]

[15] Ham and Rea (1987), van den Berg and van Ours (1996), and van den Berg and van der Klaauw (2001) tested the number of types to characterize the distribution of unobserved heterogeneity, and found that the data used for their empirical analysis is best described by two types.

[16] Kerchkoffs, De Neubourg and Palm (1994), and van den Berg and van Ours (1996) found nonmonotonic GDD in the data from the Netherlands and the U.S., respectively.

[17] According to the employment screening models (Vishwanath 1989; Lockwood 1991), the duration of

Given this set of assumptions, Ahn and Hamilton (2016) demonstrated that we can identify the inflows and outflows of workers with two unobserved types and the parameters governing the GDD. To provide the intuition of identification, suppose that the economy is in the steady-state. Assume first that there is no GDD. Let w_j^L and w_j^H be the number of newly unemployed type L and H workers. The sum of w_j^L and w_j^H is U_j^1. Let p_j^L, and p_j^H be the probabilities of newly unemployed type L and H workers to continue to be unemployed next month. Then we can solve for w_j^L, w_j^H, p_j^L, and p_j^H using $U_j^1, U_j^{2.3}, U_j^{4.6}$ and $U_j^{7.12}$, since we have four unknowns and four observations. Suppose in addition that the exit probabilities are influenced by GDD, and that it is a linear function of τ characterized by one parameter. Then, we can further identify the GDD parameter along with w_j^L, w_j^H, p_j^L, and p_j^H using the five values $U_j^1, U_j^{2.3}, U_j^{4.6}, U_j^{7.12}$, and $U_j^{13.+}$. Now assume that we observe $U_j^1, U_j^{2.3}, U_j^{4.6}, U_j^{7.12}$, and $U_j^{13.+}$ in two different periods. We can solve for w_j^L, w_j^H, p_j^L, and p_j^H in each period, and use two remaining data points to characterize GDD. As we consider data from more periods, we could have a more general functional form for GDD. In fact, we use $U_{jt}^1, U_{jt}^{2.3}, U_{jt}^{4.6}, U_{jt}^{7.12}$, and $U_{jt}^{13.+}$ for every date t. Therefore, we can allow modest variation over time in the parameters governing GDD.[18]

I use the steady-state examples to illustrate the intuition of identification. The model that is used in the empirical exercise is a fully dynamic statistical model, which allows us to make inferences on the inflows and outflows of workers with unobserved types at each point in time from the variation in the distribution of unemployment duration. I formulate the statistical model of dynamic accounting identity in the next section.

unemployment is a signal of unobserved worker productivity, and negative duration dependence becomes weaker in slack markets as the spell length is less indicative of unobservable worker characteristics. Meanwhile, ranking models (Blanchard and Diamond 1994; Moscarini 1997) emphasize that applicants for a given position are less likely to face competition from applicants with shorter durations, so negative duration dependence is stronger in tight labor markets. Stock-flow search models (Coles and Smith 1998) also predict the negative duration dependence becomes greater during economic recessions, as workers become discouraged more and search less hard over time. In addition, changes in the eligibility of unemployment insurance benefits could also alter the pattern of GDD as suggested by Meyer (1990) and Katz and Meyer (1990a,b).

[18] More details on the identification are found in Ahn and Hamilton (2016).

2 Model and Estimation

The model is a variant of a state space model that casts the dynamic accounting identity of unemployment developed by Ahn and Hamilton (2016). The key difference from their baseline specification is that the model here is estimated with disaggregated data that contains various observable characteristics of unemployed individuals, such as gender, age, education, industry, occupation, and reason for unemployment. This feature of the model allows us to analyze how unemployment dynamics differs by observed characteristic of unemployed individuals and how much observed heterogeneity and unobserved types account for the cross-sectional dispersion of completed unemployment duration spells.

The measurement equation is the following. Let w_{jt}^{H} and w_{jt}^{L} denote the number of people of type H and L respectively who are newly unemployed at time t. The number of individuals with observable characteristic j who have been unemployed less than one month, U_{jt}^{1}, is expressed by

$$U_{jt}^{1} = w_{jt}^{H} + w_{jt}^{L}. \tag{6}$$

I assume that for unemployed individuals in group j who have already been unemployed for τ months as of time $t-1$, the fraction who will still be unemployed at t is given by

$$p_{jt}^{z}(\tau) = \exp[-\exp(x_{jt}^{z} + d_{j\tau}^{g_t})] \quad \text{for } z = H, L. \tag{7}$$

x_{jt}^{z} is a time-varying parameter influencing the unemployment exit probability for all workers of type z in group j regardless of their duration, and it captures cross-sectional heterogeneity in the unemployment continuation probabilities between the two types.

The term $d_{j\tau}^{g_t}$ captures the effect from GDD. In Section 1, I illustrated from the steady-state example the possibility that non-linearity exists in the relations between the probability of exiting unemployment and the duration of unemployment, as well as the possibility that the pattern of GDD could change over business-cycle phases. To incorporate these possibilities into the model flexibly, I use a linear spline for $d_{j\tau}^{g_t}$ with breaks at $\tau = 6$ and 12. In addition, the parameters have two regimes, whether or not the unemployment rate is above 6.5%. For months t when the unemployment rate is lower than 6.5 percent, I set $g_t = 0$, while $g_t = \mathrm{E}$ when the unemployment rate is 6.5 percent or higher.[19][20] I use the 6.5 percent of unemployment rate as the threshold of changes in regime, since it is likely to be an indicator of labor market slack.[21] Lastly, I set $d_{j\tau}^{g_t}$ to be constant as $\tau \geq 24$, assuming that those who have been unemployed for 2 years or longer are largely the same in their exit probabilities of exiting unemployment.

The functional form of $d_{j\tau}^{g_t}$ is as follows,

$$d_{j\tau}^{g_t} = \begin{cases} \delta_{j1}^{g_t}(\tau - 1) & \text{for } \tau < 6 \\ \delta_{j1}^{g_t}[(6-1)-1] + \delta_{j2}^{g_t}[\tau - (6-1))] & \text{for } 6 \leq \tau < 12 \\ \delta_{j1}^{g_t}[(6-1)-1] + \delta_{j2}^{g_t}[(12-1)-(6-1)] + \delta_{j3}^{g_t}[\tau - (12-1)] & \text{for } 12 \leq \tau < 24 \\ \delta_{j1}^{g_t}[(6-1)-1] + \delta_{j2}^{g_t}[(12-1)-(6-1)] + \delta_{j3}^{g_t}[(24-1)-(12-1)] & \text{for } 24 \leq \tau \end{cases},$$

where δ_{j1}^0, δ_{j2}^0, and δ_{j3}^0 govern the GDD when the unemployment rate is lower than 6.5

[19] Previous theoretical as well as empirical research argues that a change in GDD is associated with the labor market slack (Vishwanath 1989; Lockwood 1991; Blanchard and Diamond 1994; Acemoglu 1995; Moscarini 1997; Ljungqvist and Sargent 1998). Kroft, Lange, and Notowidigdo (2013) show that the callback rates from potential employers drop, if the unemployment rate is equal to or higher than 8.8 percent. I estimated the specification with 8.0 percent and 8.8 percent as the threshold unemployment rate, but it did not change the results significantly.

[20] Meyer (1990), and Katz and Meyer (1990a,b) show that unemployed individuals tend to accelerate exiting unemployment right before they exhaust their UI benefits. In normal times, the maximum duration of unemployment is 6 months. In states where the unemployment rate is higher than 6.5 percent, the UI benefits are extended up to 52 weeks. This suggests that the possibility that the pattern of GDD could change around the time when an unemployed individual has been unemployed for 6 months and 1 year. The two breaks could also capture this possibility. The possible connection between the UI benefits and GDD also implies that the GDD could change, whether or not the unemployment rate is higher than 6.5%.

[21] I use 6.5 percemt of unemployment rate as the proxy for the labor market slack for the following reasons: (1) the maximum duration of unemployment insurance benefits is automatically extended beyond 26 weeks in a state where the unemployment rate is 6.5 percent or higher; (2) the maximum level of CBO's natural rate of unemployment is 6.3 percent; (3) unemployment rate near 6.5 percent was the threshhold noted in the Fed's guidance in December 2012.

percent, whereas they become $\delta^E_{j1}, \delta^E_{j2}$, and δ^E_{j3} when the unemployment rate is greater than or equal to 6.5 percent. Positive valules of $\delta^{g_t}_{jh}$ for $h = 1, 2, 3$ mean that workers are more likely to exit unemployment, while negative values imply that individuals are less likely to exit unemployment as their spell proceeds over the relevant duration ranges.

Let $P^z_{jt}(k)$ be the fraction in group j of individuals of type z who were unemployed for one month or less as of date $t-k$ and are still unemployed at t. Then, $P^z_{jt}(k)$ is written as a product of monthly fractions $p^z_{j,t-j+h}(h)$ for $h = 1, 2, ..., j$ as follows

$$P^z_{jt}(j) = p^z_{j,t-j+1}(1)p^z_{j,t-j+2}(2)...p^z_{jt}(j). \tag{8}$$

Note that the individuals who have been unemployed for two to three months at t are those who become newly unemployed at time $t-1$ and look for a job at t, or those who become newly unemployed at $t-2$ and continue to look for a job at $t-1$ and t. Thus, the number of those who have been unemployed for between 5 and 14 weeks (or 2–3 months), $U^{2.3}_{jt}$, is written as follows

$$U^{2.3}_{jt} = \sum_{z=H,L} \left[w^z_{j,t-1} P^z_{jt}(1) + w^z_{j,t-2} P^z_{jt}(2) \right]. \tag{9}$$

Likewise, the number of those who have been unemployed for between 15 and 26 weeks (or 4–6 months, denoted $U^{4.6}_{jt}$), 27 and 52 weeks ($U^{7.12}_{jt}$), and longer than 52 weeks ($U^{13.+}_{jt}$) are

$$U^{4.6}_{jt} = \sum_{z=H,L} \sum_{k=3}^{5} \left[w^z_{j,t-k} P^s_{jt}(k) \right] \tag{10}$$

$$U^{7.12}_{jt} = \sum_{z=H,L} \sum_{k=6}^{11} \left[w^z_{j,t-k} P^z_{jt}(k) \right] \tag{11}$$

$$U^{13.+}_{jt} = \sum_{z=H,L} \sum_{k=12}^{47} \left[w^z_{j,t-k} P^z_{jt}(k) \right]. \tag{12}$$

I terminate the calculations after 4 years of unemployment.[22]

[22] In the CPS questionnaire, the duration of unemployment longer than 99 weeks is recorded in the category

I further assume that each data point, $U_{jt}^{1}, U_{jt}^{2.3}, U_{jt}^{4.6}, U_{jt}^{7.12}$ and $U_{jt}^{13.+}$, is observed with measurement error, $r_{jt}^{1}, r_{jt}^{2.3}, r_{jt}^{4.6}, r_{jt}^{7.12}$ and $r_{jt}^{13.+}$, respectively. Consequently, the measurement equation is as follows,

$$\begin{aligned}
U_{jt}^{1} &= w_{jt}^{H} + w_{jt}^{L} + r_{jt}^{1} \\
U_{jt}^{2.3} &= \sum_{z=H,L} \left[w_{j,t-1}^{z} P_{jt}^{z}(1) + w_{j,t-2}^{z} P_{jt}^{z}(2) \right] + r_{jt}^{2.3} \\
U_{jt}^{4.6} &= \sum_{z=H,L} \sum_{k=3}^{5} \left[w_{j,t-k}^{z} P_{jt}^{s}(k) \right] + r_{jt}^{4.6} \\
U_{jt}^{7.12} &= \sum_{z=H,L} \sum_{k=6}^{11} \left[w_{j,t-k}^{z} P_{jt}^{z}(k) \right] + r_{jt}^{7.12} \\
U_{jt}^{13.+} &= \sum_{z=H,L} \sum_{k=12}^{47} \left[w_{j,t-k}^{z} P_{jt}^{z}(k) \right] + r_{jt}^{13.+}.
\end{aligned}$$

We can arrive at the likelihood function for the observed data by assuming that the vector of measurement errors $r_{jt} = [r_{jt}^{1}, r_{jt}^{2.3}, r_{jt}^{4.6}, r_{jt}^{7.12}, r_{jt}^{13.+}]$ is independent Normal,

$$r_{jt} \sim N(0, R_j),$$

$$\underbrace{R_j}_{5\times5} = \begin{bmatrix} (R_j^{1})^2 & 0 & 0 & 0 & 0 \\ 0 & (R_j^{2.3})^2 & 0 & 0 & 0 \\ 0 & 0 & (R_j^{4.6})^2 & 0 & 0 \\ 0 & 0 & 0 & (R_j^{7.12})^2 & 0 \\ 0 & 0 & 0 & 0 & (R_j^{13.+})^2 \end{bmatrix},$$

where R_j^{1}, $R_j^{2.3}$, $R_j^{4.6}$, $R_j^{7.12}$, and $R_j^{13.+}$ are the standard deviations of $r_{jt}^{1}, r_{jt}^{2.3}, r_{jt}^{4.6}$, $r_{jt}^{7.12}$, and $r_{jt}^{13.+}$, respectively.

Let me turn to the state equation of the state space model. Let ξ_{jt} be the vector

"longer than 99 weeks" through 1993. I assume that the maximum duration of unemployment existing in this economy is 4 years. Assuming 2 or 3 years as the maximum duration does not change the result.

$[w^L_{jt}, w^H_{jt}, x^L_{jt}, x^H_{jt}]'$, and ϵ_{jt} be the vector $[\epsilon^{Lw}_{jt}, \epsilon^{Hw}_{jt}, \epsilon^{Lx}_{jt}, \epsilon^{Hx}_{jt}]'$. The assumption that the latent factors evolve as random walks would be written as

$$\underbrace{\xi_{jt}}_{4\times1} = \xi_{j,t-1} + \underbrace{\epsilon_{jt}}_{4\times1} \tag{13}$$

$$\underbrace{\epsilon_{jt}}_{4\times1} \sim N(\underbrace{0}_{4\times1}, \underbrace{\Sigma_j}_{4\times4})$$

$$\underbrace{\Sigma_j}_{4\times4} = \begin{bmatrix} (\sigma^w_{jL})^2 & 0 & 0 & 0 \\ 0 & (\sigma^w_{jH})^2 & 0 & 0 \\ 0 & 0 & (\sigma^x_{jL})^2 & 0 \\ 0 & 0 & 0 & (\sigma^x_{jH})^2 \end{bmatrix},$$

where $\epsilon^{Hw}_{jt}, \epsilon^{Lw}_{jt}, \epsilon^{Hx}_{jt}$ and ϵ^{Lx}_{jt} are the innovation terms that drive the dynamics of $w^H_{jt}, w^L_{jt}, x^H_{jt}$ and x^L_{jt}, respectively.[23] A random walk is a general approach of modeling time-varying latent variables. It is also found to pick up structural changes in the data (Baumeister and Peersman, 2013). Random walk specifications allow the inflows and continuation probabilities to track structural breaks in the CPS duration data—which might come from the 1994 redesign of the questionnaire, changes in the definition of words, changes in the classification of industries and occupations, and so on—and then to move on after the break to adapt to whatever comes next.[24]

Since the measurement equations (6)-(12) are a function of $\{\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47}\}$, the

[23] The shock could be contemporaneously correlated and can be captured with a factor structure of Σ_j. The latent variables estimated with a factor structure in Σ_j are not so much different from the estimates of the current model. Ahn and Hamilton (2016) also found that imposing a factor structure did not change the results.

[24] It has been noticed in the literature of unemployment dynamics that the CPS redesign in 1994 understates the number of individuals unemployed for 1 month. Researchers have used a factor to adjust upward the size of newly unemployed individuals. In this paper, I do not attempt to do the adjustment, because it is very difficult to come up with a credible adjustment factor for each group. Considering that increasing the number of newly unemployed individuals raises the importance of inflows, I essentially take a conservative route to make the argument for the importance of inflows.

joint distribution of ξ_{jt}'s from $t-47$ to t should be captured in the state equation as follows,

$$\underbrace{\begin{bmatrix} \xi_{jt} \\ \xi_{j,t-1} \\ \xi_{j,t-2} \\ \vdots \\ \xi_{j,t-46} \\ \xi_{j,t-47} \end{bmatrix}}_{192\times1} = \underbrace{\begin{bmatrix} \underbrace{I}_{4\times4} & \underbrace{0}_{4\times4} & 0 & 0 & ... & 0 & 0 & 0 \\ I & 0 & 0 & 0 & ... & 0 & 0 & 0 \\ 0 & I & 0 & 0 & ... & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & ... & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & ... & I & 0 & 0 \\ 0 & 0 & 0 & 0 & ... & 0 & I & 0 \end{bmatrix}}_{192\times192} \underbrace{\begin{bmatrix} \xi_{j,t-1} \\ \xi_{j,t-2} \\ \xi_{j,t-3} \\ \vdots \\ \xi_{j,t-47} \\ \xi_{j,t-48} \end{bmatrix}}_{192\times1} + \underbrace{\begin{bmatrix} \underbrace{\epsilon_{jt}}_{4\times1} \\ \underbrace{0}_{4\times1} \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}}_{192\times1}, \qquad (14)$$

where I and 0 denote a (4×4) identity and zero matrix.

Our system takes the form of a nonlinear state space model in which the measurement equation is nonlinear in the latent variables of interest. The extended Kalman filter is used to form the likelihood function for the observed data and form an inference about the unobserved latent variables. The model has 15 parameters to estimate for each group j, namely the diagonal terms in the variance matrices Σ_j and R_j and the parameters governing GDD, δ^0_{j1}, δ^0_{j2} , δ^0_{j3}, δ^E_{j1}, δ^E_{j2} and δ^E_{j3}. The system of equations is estimated with maximum likelihood. Inference about historical values for ξ_{jt} corresponds to full-sample smoothed inferences, denoted $\hat{\xi}_{jt|T}$.[25]

2.1 Data

I use CPS micro data to construct the numbers of people who have observed characteristic j and have been unemployed for 1 month, 2–3 months, 4–6 months, 7–12 months, and longer than 1 year. The observations for month t are collected in the vector $[U^1_{jt}, U^{2.3}_{jt}, U^{4.6}_{jt}, U^{7.12}_{jt}, U^{13.+}_{jt}]'$ for t running from January 1976 through December 2013. For the baseline model, each value of j summarizes the individual's age (broken down into

[25] More details about the estimation are found in the Appendix.

the three categories: 16–24, 25–44, and over 45), three categories of education (high school education or less, some college or associate degree, or college degree), and gender (male or female). This generates a total of 18 possible categories, though given limited numbers in some cells, I pool the second two education categories together for men or women aged 16–24 and 45 and over, for a total of 14 different values of j.[26] For extensions beyond the baseline case, I repeat the analysis with the data broken down by five different reasons for unemployment, eight different industries, or four different occupations.[27] Further details on data construction can be found in the appendix.

3 Empirical results

3.1 Baseline: Gender, age, and education

The smoothed estimates for the continuation probabilities of type H and L individuals within each group j are plotted in Figure 4. There are three distinct features. First, substantial unobserved heterogeneity exists in the continuation probabilities within every group in normal and recessionary periods. Average type L continuation probabilities (reported in row 2 of Tables 3 and 4) are between 0.74 and 0.95. Average type H continuation probabilities (row 3) are between 0.34 and 0.48. Second, the continuation probabilities of type H and L workers go up during recessions. Notably, the continuation probabilities of both types reach their highest levels during the Great Recession and remain elevated three years

[26] The 14 groups that are considered for the baseline case are (1) men/age 16–24/high school education or less; (2) men/age 16–24/some college, associate degree, or college degree; (3) men/age 25–44/high school education or less; (4) men/age 25–44/some college or associate degree; (5) men/age 25–44/college degree; (6) men/age 45 or over/ high school education or less; (7) men/age 45 or over/some college, associate degree, or college degree; (8) women/age 16–24/high school education or less; (9) women/age 16–24/some college, associate degree, or college degree; (10) women/age 25–44/high school degree or less; (11) women/age 25–44/some college or associate degree; (12) women/age 25–44/college degree; (13) women/age 45 or over/high school education or less; and (14) women/ age 45 or over/some college, associate degree, or college degree.

[27] I used the same occupation classification that Jaimovich and Siu (2012) used to construct the employment of four occupational groups (routine-manual, routine-cognitive, nonroutine-manual, nonroutine-cognitive). The occupation classification begins from 1983. Due to this reason, the sample period of duration data broken down by the four different occupations is from January 1983 to December 2013.

into the recovery in most of the groups. In addition, despite sharing the common cyclicality, the dynamics of continuation probabilities are different between types and across groups. For example, among men aged 25 to 44 with a high school education or less, type H probability recovers close to the pre-recession level, but their type L probability stays elevated three years after the Great Recession is over. Meanwhile, both type H and L continuation probabilities of women in the same age and education group remain elevated during the post-recession period.

Figure 5 plots smoothed estimates for the inflows of type H and L individuals in each group. As documented in the first rows of Tables 3 and 4, type L individuals make up a small portion of inflows and represent, on average, 4 to 36 percent of the newly unemployed across all groups. Despite the small share of inflows, type L newly unemployed individuals are an important factor in determining the size of long-term unemployment, as they have higher unemployment continuation probabilities. In addition, type L inflows exhibit stronger counter-cyclicality than type H inflows do. Therefore, the share of type L workers among the newly unemployed of each group goes up during recessions. The Great Recession is distinguished from previous recessions in that the inflows of type L workers, as well as their share among newly unemployed individuals, reached their highest levels in most of the groups.

Looking at the individual groups in more detail, the share and the cyclical fluctuations of type L individuals in the inflows differ substantially by demographic characteristic. The type L share of the inflows is higher among older and more highly educated individuals. Particularly, type L inflows show stronger counter-cyclicality among workers aged 25 to 44 who have some college education or an associate degree than other groups. Meanwhile, the type L share is lower and type L inflows exhibit more subdued counter-cyclical fluctuations among younger and less-educated workers (aged 16 to 24 with a high school diploma or less education). However, the average numbers of type L newly unemployed people in both groups are not so much different, as the number of newly unemployed individuals aged 16 to 24 with lower education is much larger in the first place.

It is notable that both the type L share of inflows and their continuation probabilities rise dramatically during the Great Recession in most of the categories. This explains why we observe the sharp increase in the average duration of unemployment and the share of long-term unemployment in every corner of the economy, as discussed in previous studies (Hall, 2014; Kroft, Lange, Notowidigdo, and Katz, 2016; and Krueger, Cramer, and Cho, 2014). Unlike the conclusions of Kroft et al. (2014) and Krueger et al. (2014) that compositional variations in the unemployment of worker heterogeneity played a limited role in the rise of long-term unemployment during the Great Recession, the empirical results suggest that the changes in the composition of type L workers in the disaggregate unemployment was crucial to the rise of long-term unemployment during the Great Recession and its recovery phase.[28]

Unobserved heterogeneity is also important in the low-frequency dynamics of unemployment. Abraham and Shimer (2002) claim that the population aging and the increased job-attachment of women explain the upward trend in average duration of unemployment accompanied by the secular decrease in the incidence of unemployment. The empirical results of this paper suggest that these secular changes are also closely related to unobserved heterogeneity. Among workers aged 16 to 24 who have a high-school education or less, the type H inflows decrease throughout the sample period, while the type L inflows remain around the same level. Meanwhile, both type H and L newly unemployed individuals aged 45 and over show upward trends. This suggests that the aging of the population is associated with the low-frequency dynamics of unemployment mainly through the secular decrease in the number of newly unemployed individuals who are type H among young and less-educated workers. In addition, it is notable that there is an upward trend in the type H continuation probabilities among women aged 16 to 44 whose education level is lower than college graduation. This might reflect that type H workers of this group are likely to be those female workers whose labor force attachment has increased over time. They might

[28]This point is investigated further using the historical decomposition in Section 4.2.

have become to stay unemployed longer to look for a job instead of leaving the labor force to, for instance, take care of their children, which also has contributed to the rising trend in the average duration of unemployment. In sum, the secular changes in the type H inflows of young and less-educated workers and the type H continuation probabilities of women aged lower than 45 who are not college graduates suggest that structural development in the labor market, such as demographic changes and increased labor force attachment of women, have asymmetric effects on workers with unobserved types, and this is an important source of the upward trend in the average duration of unemployment as well as the downward trend in the inflows to unemployment in the U.S. labor market.

The parameter estimates of GDD are reported in Tables 1 and 2. Many of the parameters of GDD are not statistically significant. Figure 6 illustrates the pattern of GDD with the path of average type L continuation probabilities by months spent in unemployment. The results imply a nonmonotonic pattern for GDD in most groups, with small positive GDD operating up to 6 months, negative GDD between 7-12 months in unemployment, and somewhat strong positive GDD setting in after 1 year.[29] This result is consistent with the U-shape unemployment hazards demonstrated in the steady-state examples in Section 2. In addition, the pattern and size of GDD do not change dramatically given a change in the level of unemployment rate. However, it is commonly observed in the majority of groups that when the unemployment rate is above 6.5 percent, unemployed individuals tend to leave the unemployment status slightly slower until around 1 year, but exit faster after 1 year than they do when the unemployment rate is below 6.5 percent.

[29] Different researchers have produced evidence of both negative and positive GDD using different methods and data sets. Kroft, Lange, and Notowidigido (2013), Kroft, Lange, Notowidigdo, and Katz (2016), Faberman and Kudlyak (2014), and Eriksson and Rooth (2014) all found evidence consistent with negative GDD, while Katz (1986) and Katz and Meyer (1990a,b) found evidence of positive genuine duration dependence attributable to eligibility for unemployment insurance. Kerchkoffs, De Neubourg and Palm (1994) and van den Berg and van Ours (1996) found nonmonotonic GDD in data from the Netherlands and the U.S., respectively.

3.2 Who are likely to be type L?

What could the observable characteristics that constitute type L attributes be? We can answer this question by looking at what observed characteristics is a newly unemployed type L individual most likely to have, and in which unemployment category is an unemployed individual most likely to be type L? In this section, I make use the baseline breakdown of unemployed workers by gender, age, education, and a number of other observable characteristics such as industry, occupation, and reason for unemployment to try to develop a richer description of some of the observed attributes that type L workers share.

The key result is summarized in Table 9. Particularly, I focus on the recent period from 2000:M01 to 2013:M12.[30] In the baseline breakdown, education is the single most important attribute distinguishing newly unemployed type L workers from a typical unemployed individual. For an average month t, more than half of the newly unemployed type L individuals have a high school education or less (see row 2 of Table 9). Actually, this group accounts for 63 percent of the total number of newly unemployed individuals (row 2). In other words, although less-educated individuals account for a large share in type L inflows, this can be more than accounted for by the fact that less-educated individuals are more likely to become unemployed in the first place. Overall, in the baseline break by gender, age and education, we do not observe a distinct group that takes a particularly large share in type L inflows as shown in Figure 7.

I next repeated the analysis while grouping individuals into eight different industries in which they had previously been employed. A quarter of newly unemployed type L workers are likely to have previously worked in the construction or manufacturing industries, compared with the 21 percent of all unemployed individuals who worked in those industries (see row 4 of Table 9). This simply reflects the fact that newly unemployed workers of any type are likely to have come disproportionately from this sector. I also applied the model to four different occupation categories. Unemployed workers who previously had routine-manual

[30] The summary statistics of the full sample period (1979:M12-2013:M12) are reported in Tables 3-8.

occupations take a slightly larger share among type L newly unemployed individuals, 39 percent, than they do among those who become newly unemployed, 32 percent (see row 5 of Table 9). However, there are no striking differences in the observed occupations of newly unemployed type L and H individuals.

Finally, I looked at five different reasons for unemployment: workers on temporary layoffs, permanent job losers, job leavers, re-entrants, and new entrants to the labor force.[31][32] 43 percent of newly unemployed type L workers are likely to have indicated "permanent separation" as their reason for becoming unemployed, while only about 22 percent of newly unemployed individuals report that they are permanent job losers (see row 6 of Table 9). The share of permanent job losers in type L inflows has increased over time. The average share between 1979M12 and 2013M12 is 38 percent (see row 5 of Table 9) lower than the recent average between 2000:M01 and 2013:M12, 43 percent. The share of type L workers in the inflows is higher among permanent job losers than is observed in groups with other reasons for unemployment as reported in the second row of Table 9. The type L share in the inflows is the second largest among workers on temporary layoff. However, their type L continuation probability is lower than that of workers who give other reasons for unemployment, and similar to the level of type H continuation probability of permanent job losers particularly during the Great Recession.

In addition, I present the composition of total type L inflows in Figure 8. The contribution of workers who were permanently separated from their previous jobs to the increase in inflows of type L workers during a typical recession is particularly striking. Most of the counter-cyclical fluctuations in total type L inflows is driven by type L permanent

[31] Permanent separations include permanent job losers and persons who completed temporary jobs. The separate series, permanent job losers and persons who completed temporary jobs, are publicly available from 1994, but their sum (permanent separations) is available back to 1976.

[32] Before 1994, the CPS questionnaire did not ask the survey respondents who indicates "layoff" as their reason for unemployment whether they have an expectation of recall or not. After 1994, questions were added to determine if survey respondents reported to be on layoff did in fact have an expectation of recall - that is, had they been given a specific date to return to work or, at least, had they been given an indication that they would be recalled within the next 6 months. However, this change in survey questionnaire in 1994 did not cause a structural break in the time series data used for the estimation.

job losers. Cyclically related inflows from the construction-manufacturing industries and routine-manual occupations are also dramatic, but they are not as unique to type L individuals as the inflows of permanent job losers are. To summarize, involuntary permanent separation appears to be the observable characteristic that is most closely associated with type L individuals.

The importance of permanently separated workers in the type L inflows illustrates a key reason for thinking about unobserved heterogeneity as a dynamic process. Although it is common in the micro literature to think of unobserved heterogeneity as a fixed characteristic of a given worker, these results suggest that the difficulty an individual has in obtaining a job is very much tied to changing economic conditions and labor demand, such as bankruptcy of the previous employer or possession of skills that are no longer in demand.

4 Dynamics of disaggregate unemployment

4.1 Variance Decomposition

The empirical results show that during economic recessions the share of type L individuals in the inflows as well as their continuation probability rise in most of the observed categories, and this could have contributed to the sharp increase in the long-term unemployment, and consequently the unemployment among workers with different characteristics. Which factor, inflows and continuation probabilities, is more important in the dynamics of disaggregate unemployment? In this section, I attempt to answer this question by applying the variance decomposition for the dynamic accounting identity developed by Ahn and Hamilton (2016) to the estimates of group j. Similarly to the variance decomposition of linear VAR, this method measures how much each shock contributes to the mean-squared error (MSE) of an s-period-ahead forecast of a magnitude of interest.[33] As a byproduct, we can also identify which is the key observable characteristic that is most closely associated with type L attributes.

[33] Details on the derivation are found in Appendix.

Uncertainty surrounding the type L inflow is likely to be the most crucial factor accounting for the variance of unemployed group with the key observable characteristic, while the type H inflow is likely to be the main component explaining the variance of other groups.

The state space model for the dynamic accounting identity of unemployment can be used to forecast the unemployment of group j s-period-ahead at t. Let $y_{j,t+s}$ be the the vector $[U^{1}_{j,t+s}, U^{2.3}_{j,t+s}, U^{4.6}_{j,t+s}, U^{7.12}_{j,t+s}, U^{13.+}_{j,t+s}]'$, and $\hat{y}_{j,t+s|t}$ be the forecast of $y_{j,t+s}$ made at t. If we linearize the measurement equations, the forecast error can be written as

$$y_{j,t+s} - \hat{y}_{j,t+s|t} = \sum_{l=1}^{s} [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})] \varepsilon_{j,t+l}, \tag{15}$$

where $\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})$ is a (5×4) matrix of coefficients that are functions of $\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}$. The MSE matrix that captures the s-period-ahead forecast of $y_{j,t+s}$ is

$$\begin{aligned} & E(y_{j,t+s} - \hat{y}_{j,t+s|t})(y_{j,t+s} - \hat{y}_{j,t+s|t})' \\ = & \sum_{l=1}^{s} [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})] \Sigma_j [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})]' \\ = & \sum_{l=1}^{s} \sum_{m=1}^{4} \Sigma_j^m [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) e_m][\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) e_m]' \end{aligned}$$

for e_m, column m of the (4×4) identity matrix, and Σ_j^m, the row m, column m element of Σ_j. Thus, the contribution of innovations of type L workers' inflows (the first element of $\varepsilon_{jt} = (\varepsilon_{jt}^{Lw}, \varepsilon_{jt}^{Hw}, \varepsilon_{jt}^{Lx}, \varepsilon_{jt}^{Hx})')$ to the MSE of the s-period-ahead linear forecast error of group j's unemployment, $\iota_5' y_{jt}$, is given by

$$\iota_5' \sum_{l=1}^{s} \Sigma_j^1 [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) e_1][\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) e_1]' \iota_5 \tag{16}$$

where ι_5 denotes a (5×1) vector of ones. Equation (16) is evaluated at the smoothed inferences $\{\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}\}$, and then takes the average value across all dates t in the sample. This gives us an estimate of the contribution of the type L workers' inflows to unemployment fluctuations of group j over a horizon of s months:

$$q_{s,1}^{j} = T^{-1}\sum_{t=1}^{T}\iota_5{}'\sum_{l=1}^{s}\Sigma_j^1[\Psi_{sl}(\hat{\xi}_{jt|T},\hat{\xi}_{j,t-1|T},...,\hat{\xi}_{j,t-47+s|T})e_1][\Psi_{sl}(\hat{\xi}_{jt|T},\hat{\xi}_{j,t-1|T},...,\hat{\xi}_{j,t-47+s|T})e_1]'\iota_5.$$

Consequently, the ratio of the first factor's contribution to the MSE of predicting unemployment of group j at horizon s is measured with $q_{s,1}^{j}/\sum_{m=1}^{4}q_{s,m}^{j}$.[34]

Figures 10 shows the contribution of each factor to the MSE in predicting unemployment as a function of the forecasting horizon by gender, age, and education. How much uncertainty about future inflows and continuation probabilities of type H and L workers matters in forecasting unemployment s-period ahead differs significantly based on the observable characteristics of unemployed individuals. For most demographic groups, type L inflows are found to be the most important factor in cyclical unemployment dynamics. In particular, type L inflows are the major driver of the cyclical variation in unemployment among men whose education level is higher than high school graduation and women younger than 45. Meanwhile, type L continuation probabilities are the crucial factor among women aged 45 and over, and men aged 45 and over who are high-school graduates or have a lower level of education. In addition, type H inflows and continuation probabilities explain most of unemployment fluctuations throughout different frequencies in the group of women aged 16-24.

Figures 11, 12 and 13 show the variance decompositions by reason for unemployment, occupation, and industry. The observed category that exhibits the largest difference is reason for unemployment. As shown in Figure 11, Type L inflow is the major driver of the unemployment dynamics of permanent job losers, while type H workers are crucial in the unemployment dynamics of workers on temporary layoffs, job leavers, and new entrants to the labor force. This finding again confirms the finding that type L attribute is closely

[34] The contribution of GDD to the variance of unemployment is not separately considered for two reasons. First, the change in GDD is assumed to be deterministic in the model. Second, the consequence of changes in GDD to the unemployment dynamics in the disaggregate level is negligible as shown in the historical decompositions demonstrated in the next section.

associated with permanent job loss.

Looking at this in more detail, type L inflows are the most important source of uncertainty in forecasting the unemployment of permanent job losers. When a forecaster predicts the unemployment of this group one- to- two- years ahead, which is business-cycle frequency in a spectral decomposition, more than 60 percent of MSE is associated with the uncertainty of type L inflows.[35] Meanwhile, the uncertainty of type L continuation probability is the most critical factor in predicting the unemployment of reentrants to the labor force for all forecasting horizons. Type L inflows and continuation probability together account for more than 80 percent of the MSE associated with two-year-ahead forecasts of unemployment of permanent job losers and reentrants to the labor force.

Meanwhile, type H inflows are the most important factor in predicting unemployment for workers on temporary layoffs, job leavers, and new entrants to the labor force throughout the forecasting horizons, while the type L contribution is small. Uncertainty about type H inflows explains more than 70 percent of the MSE in predicting unemployment of these groups three months ahead, and more than 50 percent of the MSE associated with two-year-ahead forecasts.[36] Type H inflows and continuation probabilities together account for between 60 and 70 percent of the MSE in predicting the unemployment of these groups in the business-cycle frequency.

It is notable that among workers who experienced involuntary separation, the unemployment dynamics of workers on temporary layoff are quite different from those of permanent job losers. This result implies that whether a job loser gets recalled or not could be an important source of heterogeneity in the unemployment dynamics, as claimed by Fujita and Moscarini (2013). In addition, there is a substantial difference between those who enter the

[35] The error of forecasting unemployment between one- and- two- years ahead comes critically from the uncertainty around when the next recession will begin or the current recession ends. The MSE associated with two-year-ahead forecasts is closely related to what some researchers refer to as the "business cycle frequency."

[36] The importance of type H inflows in the unemployment dynamics of job leavers suggests that type H inflows in this group could be associated with churning of which the crucial component is quits (Lazear and Spletzer, 2012).

labor force for the first time and those who left the labor force and come back. Reentrants to the labor force could be those who had difficulty getting a job, possibly because of permanent job loss, and then left the labor force out of discouragement. Type L continuation probabilities are important in their dynamics, since they could have inherited type L characteristics associated with the circumstance of job loss before they left the labor force.

4.2 Historical Decomposition

Using the model, we can further analyze how much each component, inflows and outflows of type H and L workers, and GDD, contributed to the changes in unemployment of different groups during a certain period of time, which is analogous to the historical decomposition of linear VAR.

Let $\hat{y}^o_{j,t+s|t}$ be the level of unemployment at $t+s$ predicted on the basis of history of inflows and outflows of type H and L workers in group j up to t=2007:M11, $\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}$, with the assumption that the path of GDD operating in November 2007 will continue to influence the unemployment hazards between t and $t+s$. Since the unemployment rate in November 2007 is 4.7%, the magnitude of GDD is characterized by the parameter estimates, $\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}$ and $\hat{\delta}^0_{j3}$. $y^o_{j,t+s|t}$ can be written as follows,

$$\hat{y}^0_{j,t+s|t} = c_s(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T} | \hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3}), \ \forall s,$$

where $c_s(\cdot)$ is the sum of five equations in the dynamic accounting identity.

Let $\hat{y}_{j,t+s|t}$ be the level of unemployment at $t+s$ predicted on the basis of $\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}$, and the full information on the path of GDD between t and $t+s$. $y_{j,t+s|t}$ is written as follows,

$$
\begin{aligned}
\hat{y}_{j,t+s|t} &= c_s(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3}), \quad \text{if } ur_{t+s} < 6.5\% \\
&= c_s(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^E_{j1}, \hat{\delta}^E_{j2}, \hat{\delta}^E_{j3}), \quad \text{if } ur_{t+s} \geq 6.5\%,
\end{aligned}
$$

where ur_{t+s} is the unemployment rate at $t+s$.

Then, the unemployment of group j at time $t+s$ can be approximated as follows,

$$
\begin{aligned}
& y_{j,t+s} - \hat{y}^0_{j,t+s|t} \\
\simeq\ & (\hat{y}_{j,t+s|t} - \hat{y}^0_{j,t+s|t}) + \sum_{l=1}^{s}[\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3})]\hat{\varepsilon}_{j,t+l|T} \\
& + \sum_{l=1}^{s}[\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}) - \Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3})]\hat{\varepsilon}_{j,t+l|T},
\end{aligned}
\tag{17}
$$

where $\hat{\varepsilon}_{j,t+l|T} = \hat{\xi}_{j,t+l|T} - \hat{\xi}_{j,t+l-1|T}$. $\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3})$ denotes the (5×4) matrix of coefficients that are functions of inflows and outflows of type H and L workers in group j up to t=2007:M11, $\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}$, and the parameters characterizing the GDD, $\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}$ and $\hat{\delta}^0_{j3}$.[37]

The first term in the right-hand side of equation (17) captures how much the variation in GDD changes the unemployment rate of group j, given the initial condition of flows. The second term is the contribution of shocks on type H and L workers in group j between t and $t+s$ with no changes in the GDD. The third term captures the magnitude of contribution from interactions between changes in GDD and the flows of workers with unobserved types.

[37] $\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T})$ is the vector of coefficients with the full information on the path of genuine duration dependence between t and $t+s$ as follows,

$$
\begin{aligned}
\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}) &= \Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3}), \quad \text{if } ur_{t+s} < 6.5\% \\
&= \Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^E_{j1}, \hat{\delta}^E_{j2}, \hat{\delta}^E_{j3}), \quad \text{if } ur_{t+s} \geq 6.5\%.
\end{aligned}
$$

The contribution of changes in GDD between $t+1$ and $t+s$ to the deviation of the level of unemployment at $t+s$ from the value predicted on the basis of initial conditions at t is estimated from

$$\iota_5{}'[\hat{y}_{j,t+s|t} - \hat{y}^0_{j,t+s|t}]. \tag{18}$$

The contribution of shocks to w^L_{jt}, for example, is estimated from

$$\iota_5{}'\sum_{l=1}^{s}[\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3})]e_1\hat{\varepsilon}'_{j,t+l|T}e_1. \tag{19}$$

Likewise, the total contribution of shocks on unobserved flows between $t+1$ and $t+s$ interacted with changes in GDD to the unemployment is estimated from

$$\iota_5{}'\sum_{l=1}^{s}[\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}) - \Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}|\hat{\delta}^0_{j1}, \hat{\delta}^0_{j2}, \hat{\delta}^0_{j3})]\hat{\varepsilon}'_{j,t+l|T}. \tag{20}$$

Figure 14 shows the contribution of each component to the realized unemployment rate during the Great Recession and its recovery phase by gender, age and education. The solid line (labeled Ubase) in each panel is $y^0_{j,t+s|t}$. In the majority of groups, changes in inflows of type L individuals (whose contribution indicated by the starred red curves) were the most important factor in the rise of unemployment during the Great Recession consistent with the result of variance decomposition. This again suggests that compositional changes of unobserved heterogeneity among the newly unemployed individuals with certain observable characteristics were crucial in the ubiquitous rises of disaggregate unemployment during the recession. Particularly, the importance of type L inflows was more prevalent among men than women. The second most important factor was type L continuation probability (whose contribution indicated by the blue curves with circles). It is notable that the sluggish recovery of unemployment after the end of recession is explained by the sustained high levels in type

L continuation probabilities in many groups. Meanwhile, the contribution to unemployment of changes in GDD (indicated by the difference between the solid line, $\hat{y}^0_{j,t+s|t}$, and the lower dotted line, $\hat{y}_{j,t+s|t}$, and labeled GDD) is small, and that of interaction between changes in GDD and flows (indicated by the difference between the solid line and the dashed dotted line, equation (20), and labeled Interaction) is even smaller, which overall raises the total unemployment less than 0.2 percentage point during the Great Recession.[38]

Figure 15 shows the contribution of each component to the realized unemployment rate by reason for unemployment during the Great Recession. Type L inflows was the key factor in the increased unemployment of permanent job losers, whereas type L continuation probability was the major driver of the rise in unemployment of reentrants to the labor force. Both type L inflows and outflows were of equal importance in the unemployment of new entrants to the labor force. Meanwhile, the rise of temporary job losers' unemployment is mainly explained by type H inflows. The unemployment of voluntary job leavers rose a bit in the first half of the recession, but fell in the later part of the recession. It is notable that all four factors contributed to the rise, but the drop was driven mostly by type H inflows. Consistent with the results of variance decomposition, the contribution of each factor to changes in unemployment during the Great Recession shows the most difference, if we disaggregate the unemployment data by reason for unemployment.

5 Distribution of completed duration spells

In this section, I analyze how much of the differences across newly unemployed individuals in any given month in how long it will take before they complete their unemployment spell can be explained on the basis of their observed characteristics and unobserved types. Since we have the full information on the number of newly unemployed individuals with the two unobserved types in group of observable characteristic j and their paths of unemployment

[38] This result suggests that changes in GDD do not affect significantly the contribution of inflows and outflows to the unemployment dynamics, which justifies the variance decomposition of the previous section.

continuation probabilities over time, we can use simulations to recover the distribution of completed-duration spells of those who become newly unemployed in month t, and compute how much observed and unobserved heterogeneity accounts for the variance of distribution.

Let n_{mt} be the completed duration spell of individual who becomes unemployed in month t. If we let $Var(n_{mt})$ be the unconditional variance of completed-duration spells of individual m who becomes newly unemployed in month t, $Var(n_{mt})$ is decomposed into the following:

$$Var(n_{mt}) = \underbrace{Var[E(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{observed characteristics}}} + \underbrace{E[Var(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{within} \\ \text{observed characteristic.}}}. \tag{21}$$

The first term in the right-hand side is the dispersion explained by the difference among observed groups, and the second term captures the average dispersion within each group. The $Var(n_{mt}|O_m = j)$ can be further decomposed into

$$Var(n_{mt}|O_m = j) = \underbrace{Var[E(n_{mt}|O_m = j, Q_m = s)|O_m = j]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{unobserved types}}} + \underbrace{E[Var(n_{mt}|O_m = j, Q_m = s)|O_m = j]}_{\substack{\text{heterogeneity} \\ \textit{within} \\ \text{unobserved type}}}. \tag{22}$$

The first term in equation (22) captures the dispersion of average completed-duration spells explained by the difference between two unobserved types, and the second term is the average dispersion within each type.

By plugging equation (22) into equation (21), we have the full decomposition of the distribution of completed duration spells as follows:

$$
\begin{aligned}
Var(n_{mt}) &= \underbrace{Var[E(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{observed characteristics}}} + \underbrace{E[Var\{E(n_{mt}|O_m = j, Q_m = s)|O_m = j\}]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{unobserved types}}} \\
&+ \underbrace{E[E\{Var(n_{mt}|O_m = j, Q_m = s)|O_m = j\}]}_{\text{idiosyncrasy}} . \qquad (23)
\end{aligned}
$$

The first component in equation (23) is the variance that is accounted for by the difference in completed duration spells across individuals with different observed characteristics. The second term is the amount explained by differences in the average completed-duration spells of type H and L workers. The last term is the remaining MSE, resulting from idiosyncratic differences across individuals that are not captured by either observed characteristics or unobserved types.

Figure 16 displays the result of this decomposition for every month between 1980:M01 and 2011:M12. Whether an individual is type H or L explains around 40 percent of variance of completed duration spells on average. By contrast, observed characteristics of unemployed individuals only account for less than 10 percent on average.[39] The contribution of unobserved types to the cross-sectional dispersion of completed-duration spells increases to above 50 percent in the year 2011, when the long-term unemployment reached the post-WWII era's record-high level. The overall result suggests that differences in observable characteristics of unemployed individuals play little role in accounting for the cross-sectional dispersion of completed-duration spells, and that the two unobserved types that are crucial in the dynamics of disaggregate unemployment are much more important in the distribution of completed unemployment duration.

[39] I used five reasons for unemployment for the breakdown of observable characteristics for this exercise. I also used 14 gender-age-education categories, but this explains less of the variance than reason for unemployment does.

6 Conclusion

In this paper, I investigate unobserved heterogeneity within an observed category of unemployment. I estimate the inflows and outflows of workers with unobserved types who share the same observable characteristics. With the estimates, I analyze their roles in the dynamics of disaggregate unemployment and the cross-sectional dispersion of completed-duration spells of unemployment over time.

The key findings are as follows. In a given unemployed category with certain observable characteristics, substantial heterogeneity across individuals still exists in their exit probabilities from unemployment. It is commonly found across different groups that both the share of type L workers in the inflows and the unemployment-continuation probabilities of both types of workers go up during recessions. The two unobserved types explain around 50 percent of the cross-sectional dispersion of completed-duration spells after the Great Recession, while observed heterogeneity plays a very limited role. The importance of inflows and outflows of type H and L workers in the disaggregate dynamics of unemployment differs by observed category. I find that when we break the data down by reason for unemployment, the contribution of each factor exhibits the most difference. Permanent job loss is the job characteristic most closely associated with the type L attributes. The importance of permanent job loss explains why we should think about unobserved heterogeneity as a dynamic process. Not only the certain characteristics of job searchers but also the demand for them jointly contributes to the unobserved heterogeneity that is crucial in understanding the unemployment dynamics. This is in stark contrast to the literature on unemployment hazards that assumes that unobserved heterogeneity is a fixed characteristic of a given individual that does not change over time.

I conclude the paper by briefly discussing some of the policy implications based on the empirical findings. The characteristics that make an individual more likely to remain unemployed for long periods are determined before an individual becomes unemployed. Once they become unemployed, people with particular attributes or circumstances are likely to stay unemployed for longer durations regardless of the recovery of other parts in the economy. This suggests expansionary policy measures might have a limited ability to reduce the unemployment duration, insofar as policies cannot change the intrinsic characteristics of unemployed individuals, have limitations to boost demand for a certain group of workers. It further implies that we need to exert effort in reducing the number of workers separating from firms as well as enhancing the reemployment prospect of job seekers.

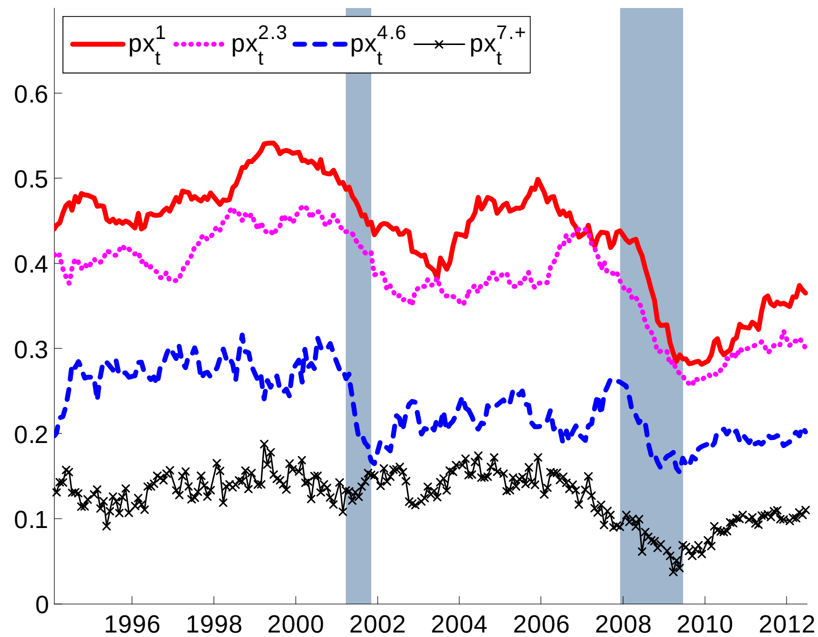
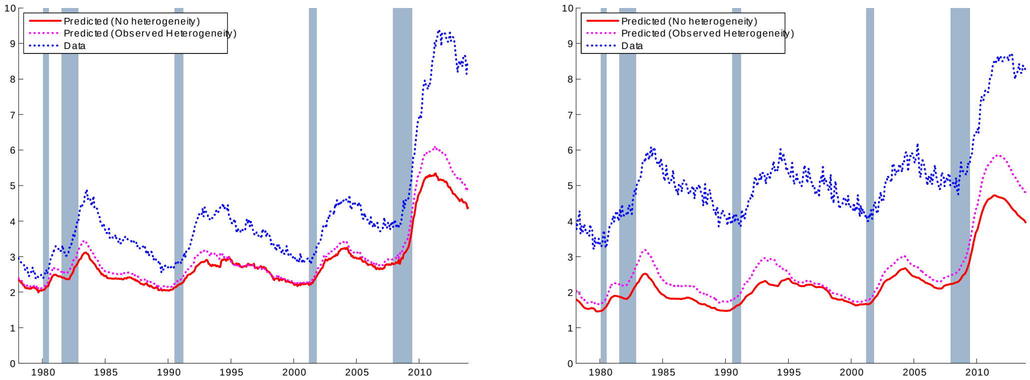
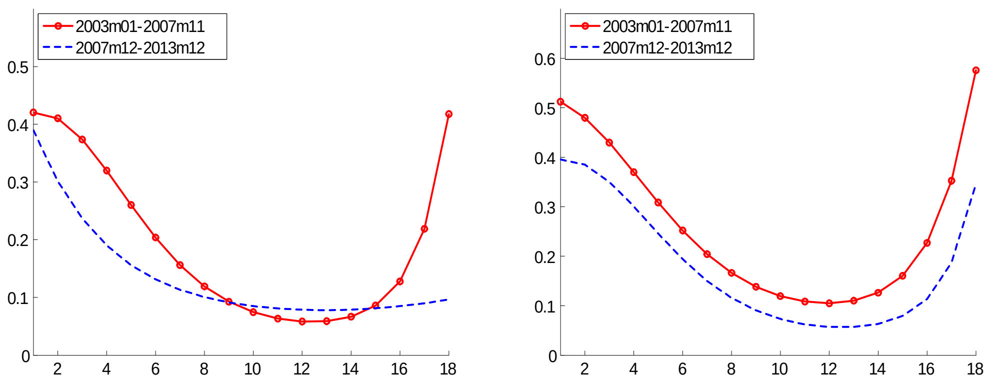


Figure 1. Exit probability from unemployment by duration for men with high school diploma, 1994:M06-2012:M06. px_t^1 denotes exit probability for those who have been unemployed for just one month in month t, $px_t^{2.3}$ for those who have been unemployed for 2-3 months, and so on. The 12 month moving averages are plotted to filter out seasonality and measurement errors. Source: author's calculation.



Panel A: Predicted Mean Panel B: Predicted Standard deviation

Figure 2. Mean and standard deviation of distribution of unemployment duration in progress predicted from equation (1)-(3), and the actual mean and standard deviation computed from CPS micro data. Shaded areas denote NBER recessions. Source: author' calculation.



Men, 25-44, Some college/Associate degree   Women, 16-24, High school or less

Figure 3. Fitted path of exit probability from unemployment as a function of duration based on constant-parameter pure duration dependence specification. Notes to Figure 3. Horizontal axis shows duration of unemployment in months and vertical axis shows probability that individual leave the unemployment status the following month. Curves denote predicted values from the 5-parameter pure GDD model fit to 2003:M01-2007:M12 historical average values (line with dots) and for values since 2007:M12 (dashed line).

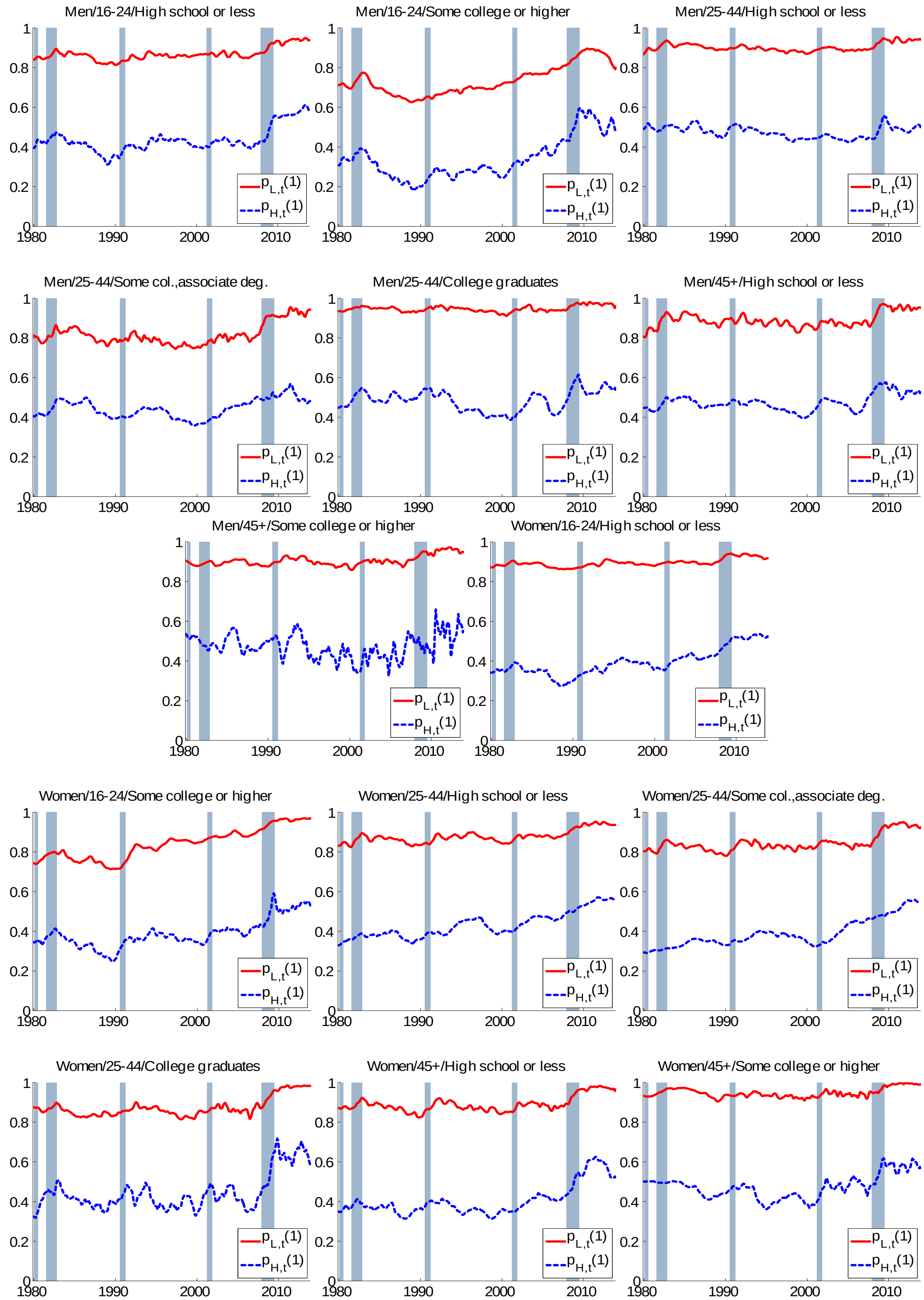


Figure 4. Probability that a newly unemployed worker of each type will still be unemployed the following month ($\widehat{p}^{z}_{jt|T}$ for $z = L, H$) by gender, age and education. Shaded areas denote NBER recessions.

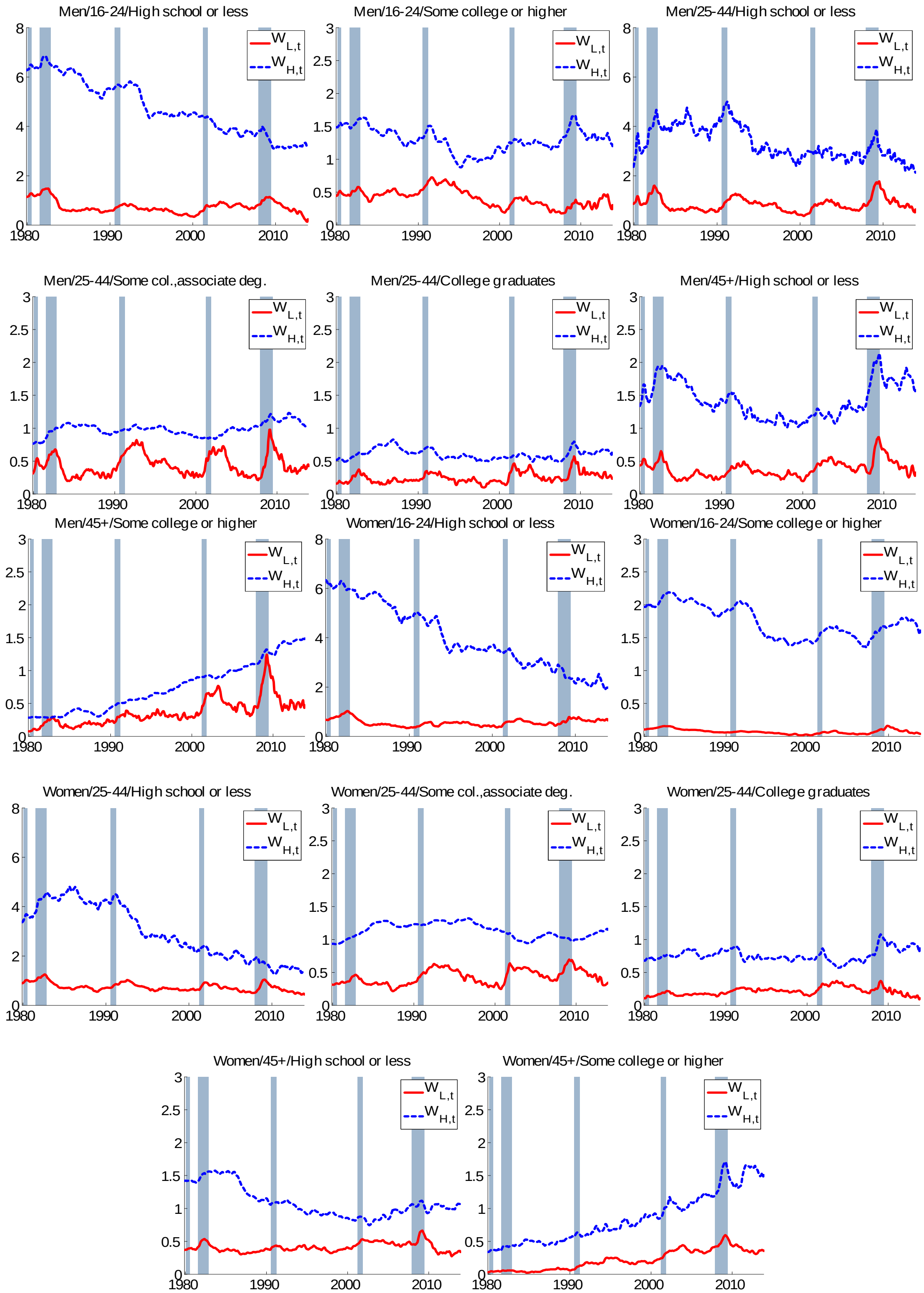


Figure 5. Number of newly unemployed workers of each type ($\widehat{w}^z_{jt|T}$ for $z = L,H$) by gender, age and education. Units are in hundred thousands. Shaded areas denote NBER recessions.

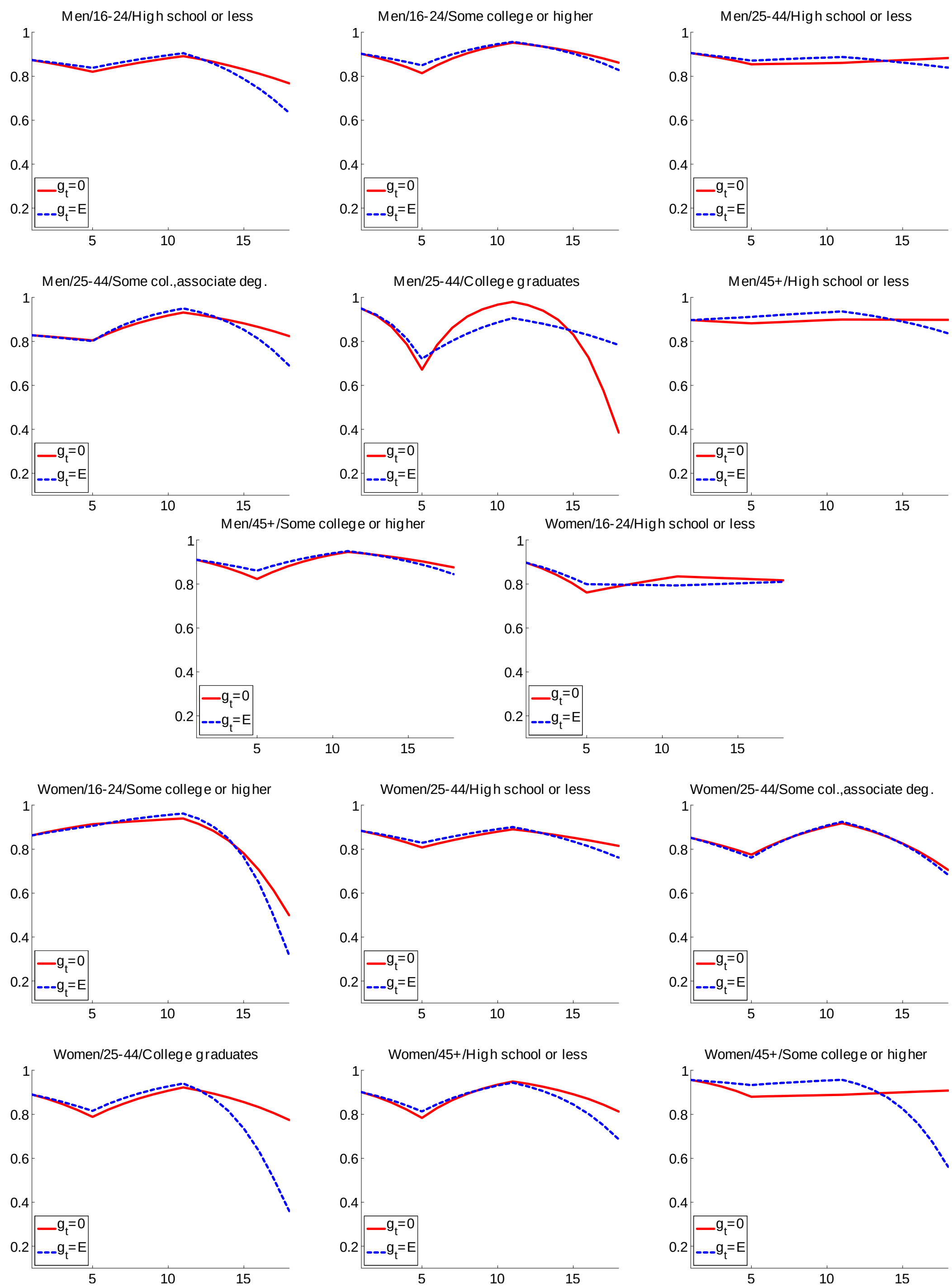


Figure 6. Estimates of GDD by gender, age and education. Plot of the path of average type L continuation probabilities over τ, months spend in unemployment. Solid line when $g_t = 0$. Dashed line when $g_t = E$. I only report the effect of GDD on the continuation probabilities for type L workers for most horizons. This is because the effect on long-horizon continuation probabilities for type H workers are empirically irrelevant, since the probability that type H workers would be unemployed for more than 12 months is so remote. $(0.5^{12} = 2.4 \times 10^{-4})$

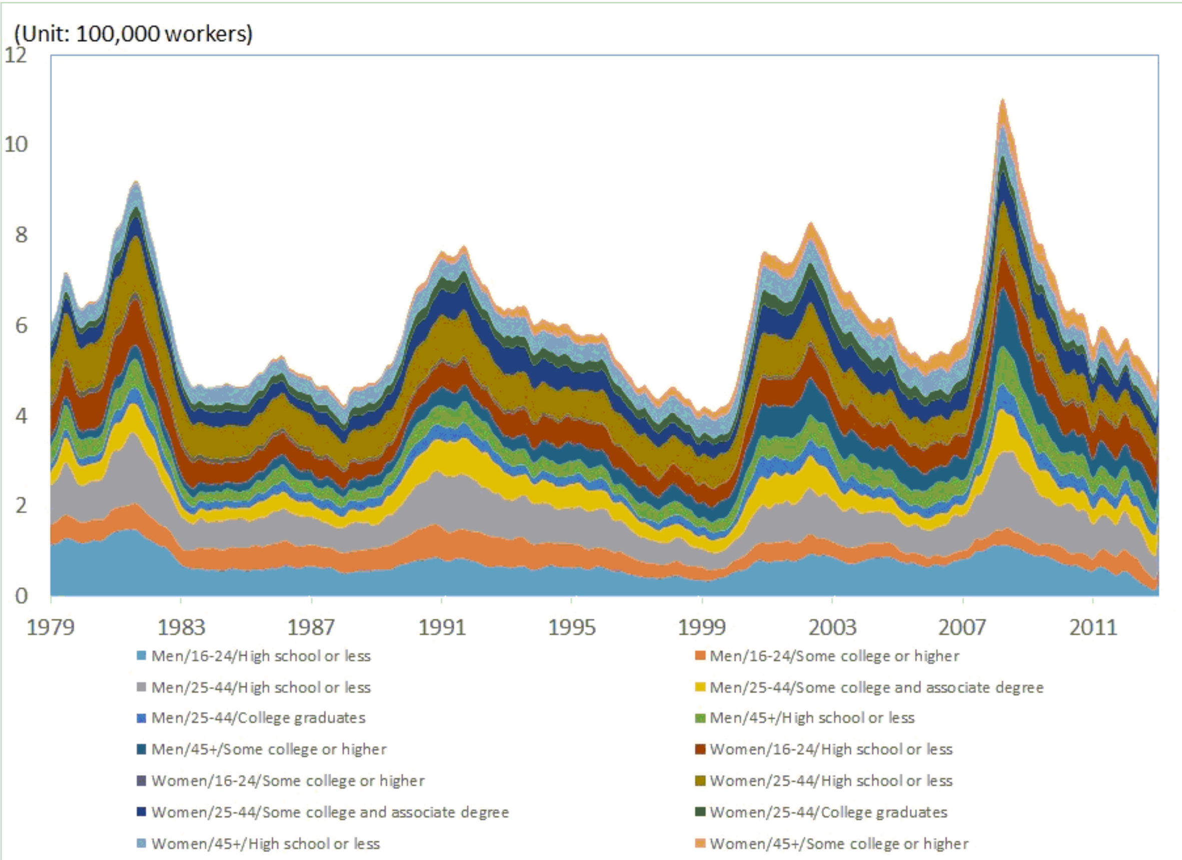


Figure 7. Composition of total type L inflows by gender, age and education

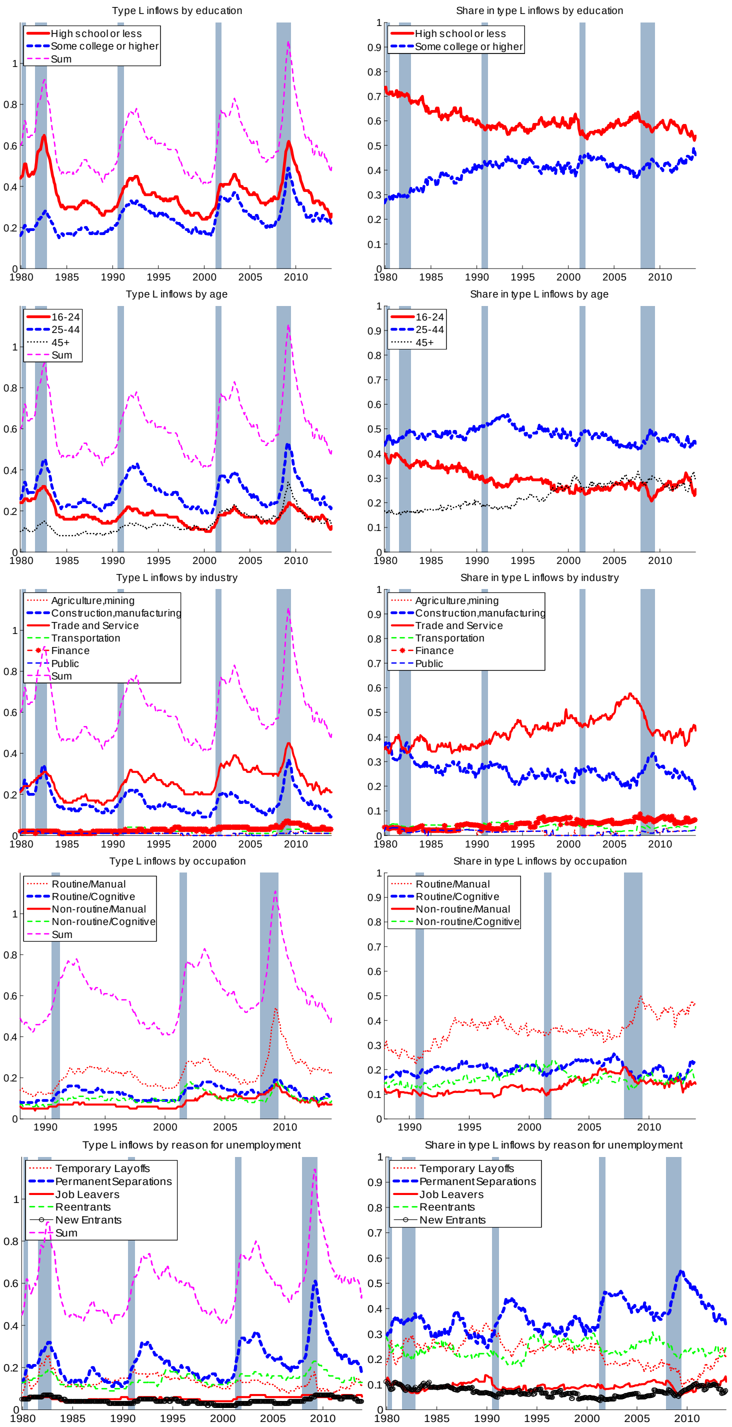


Figure 8. Size and share of type L individuals of each group by education, age, industry, occupation and reason for unemployment. Units for the inflows are in millions.

Notes to Figure 8. Type L inflows by industry and occupation does not exactly add up to the total type L inflows, because type L individuals who do not have previous work experience are not considered. However, the difference is small and does not change the result qualitatively.

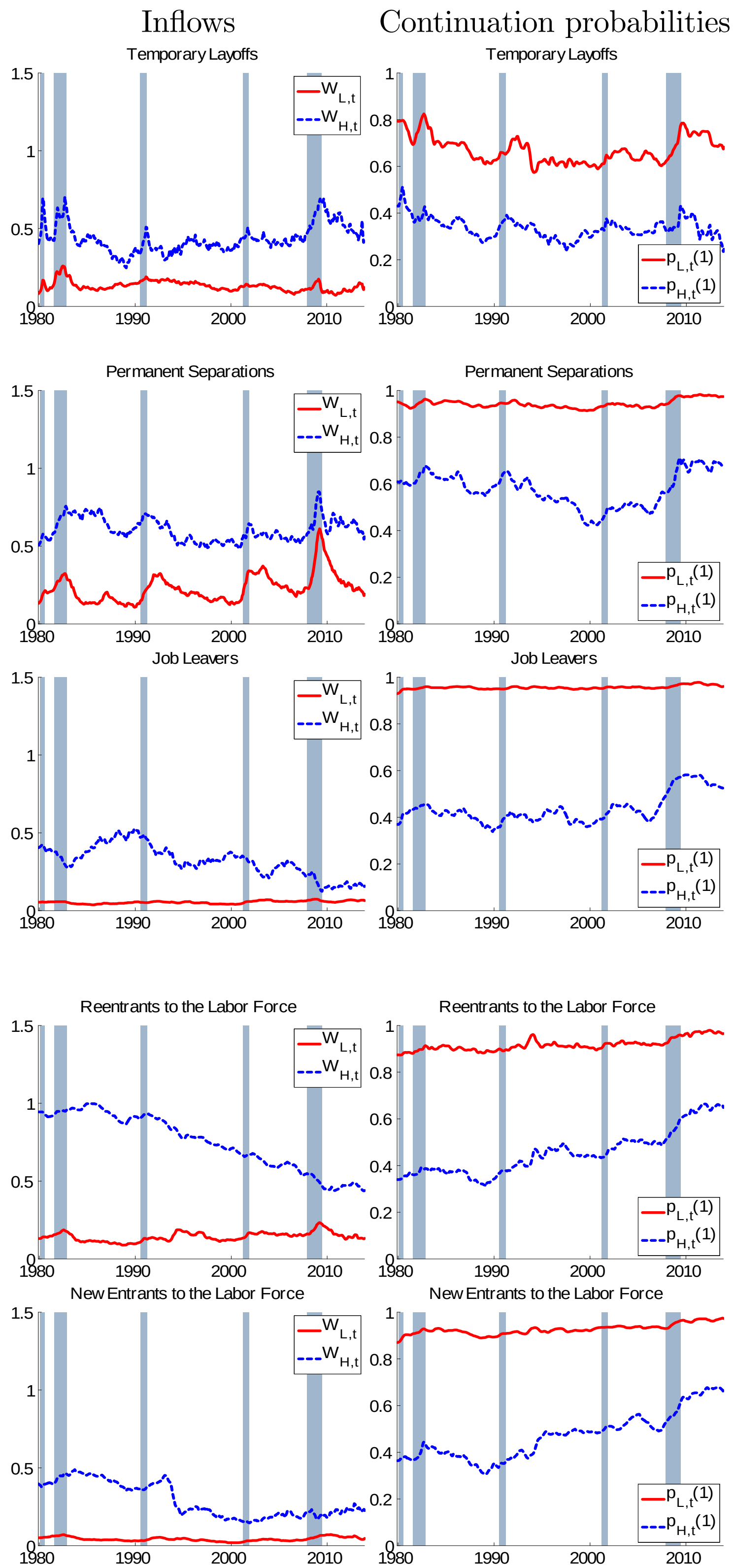


Figure 9. Inflows and continuation probabilities of type H and L by reason for unemployment. Units for the inflows are in millions.

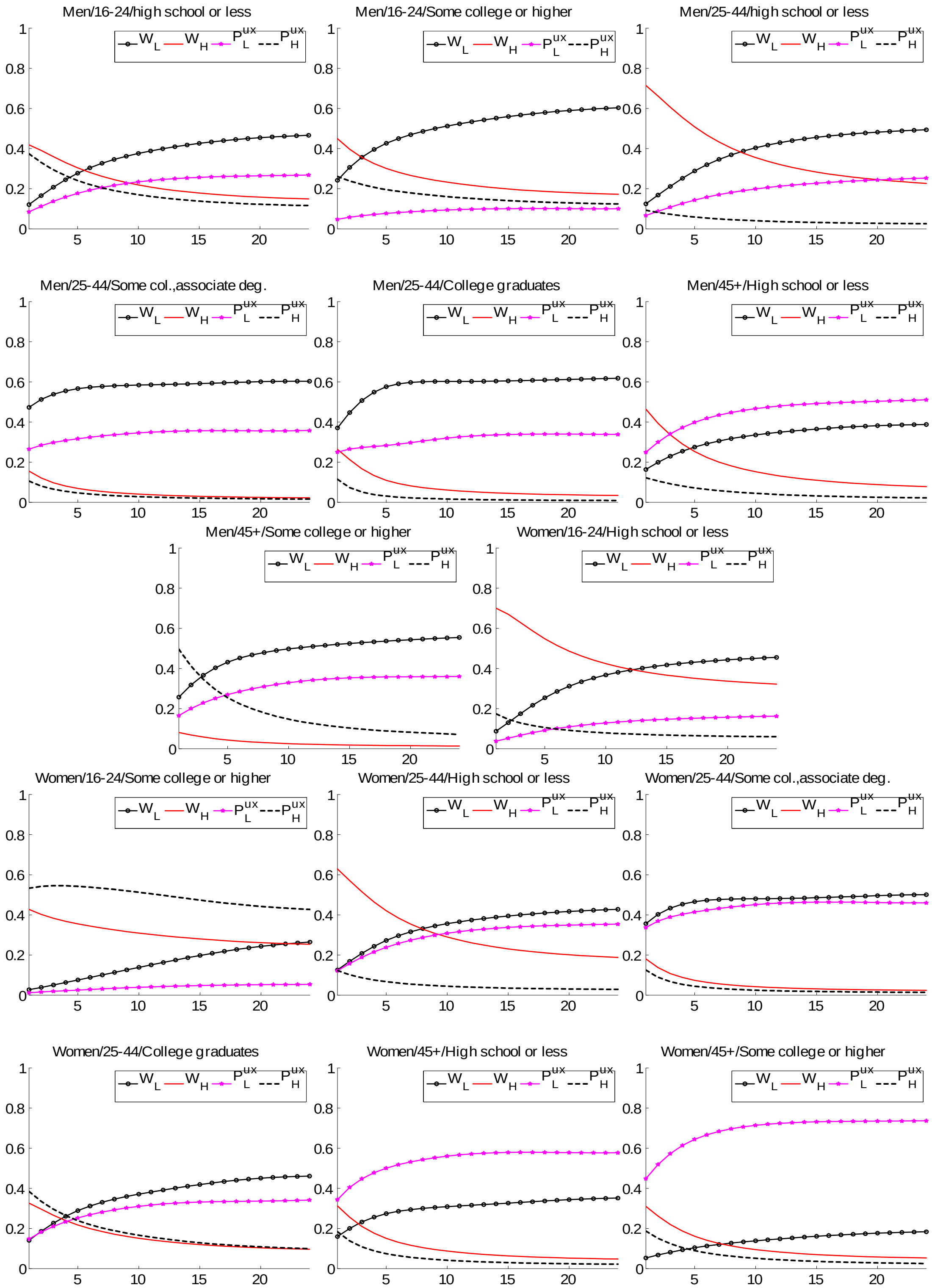


Figure 10. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by gender, age and education

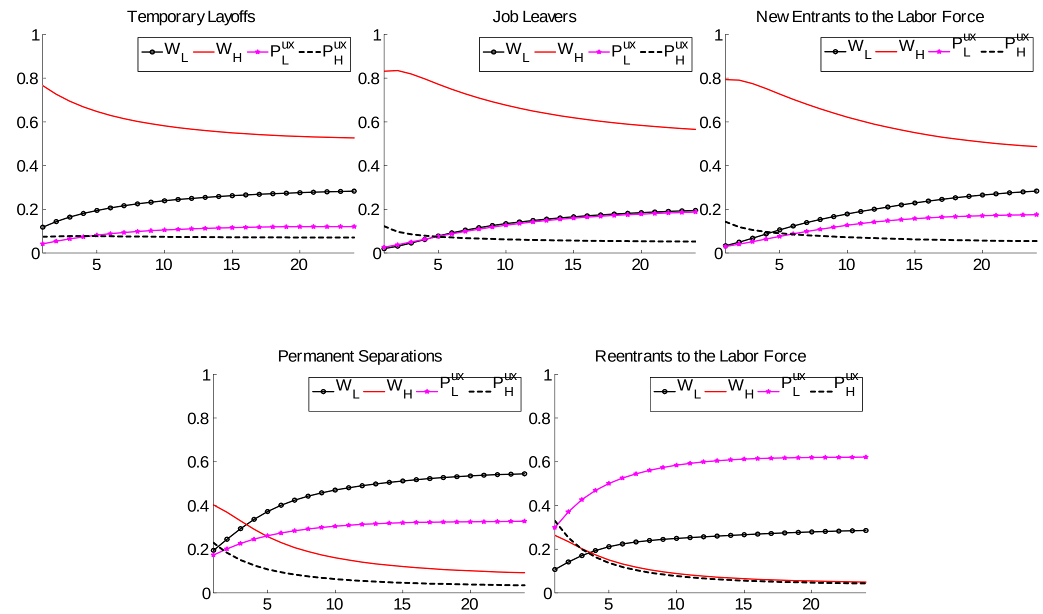


Figure 11. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by reason for unemployment

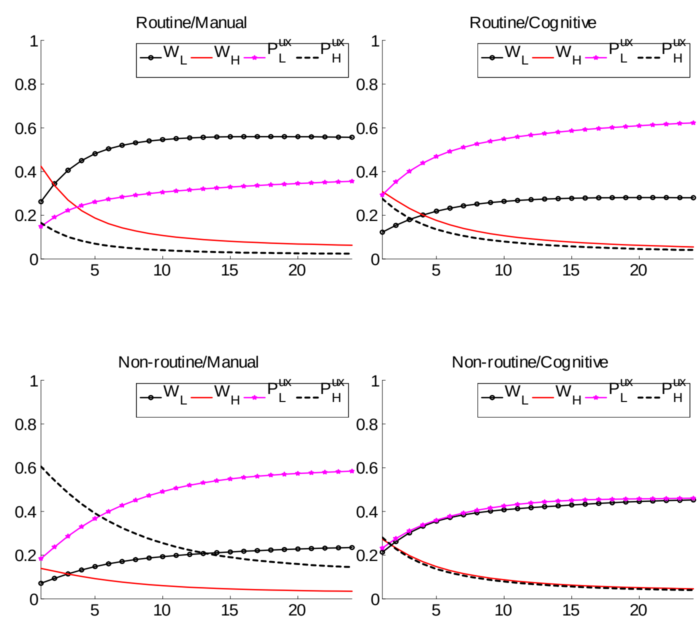


Figure 12. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by occupation

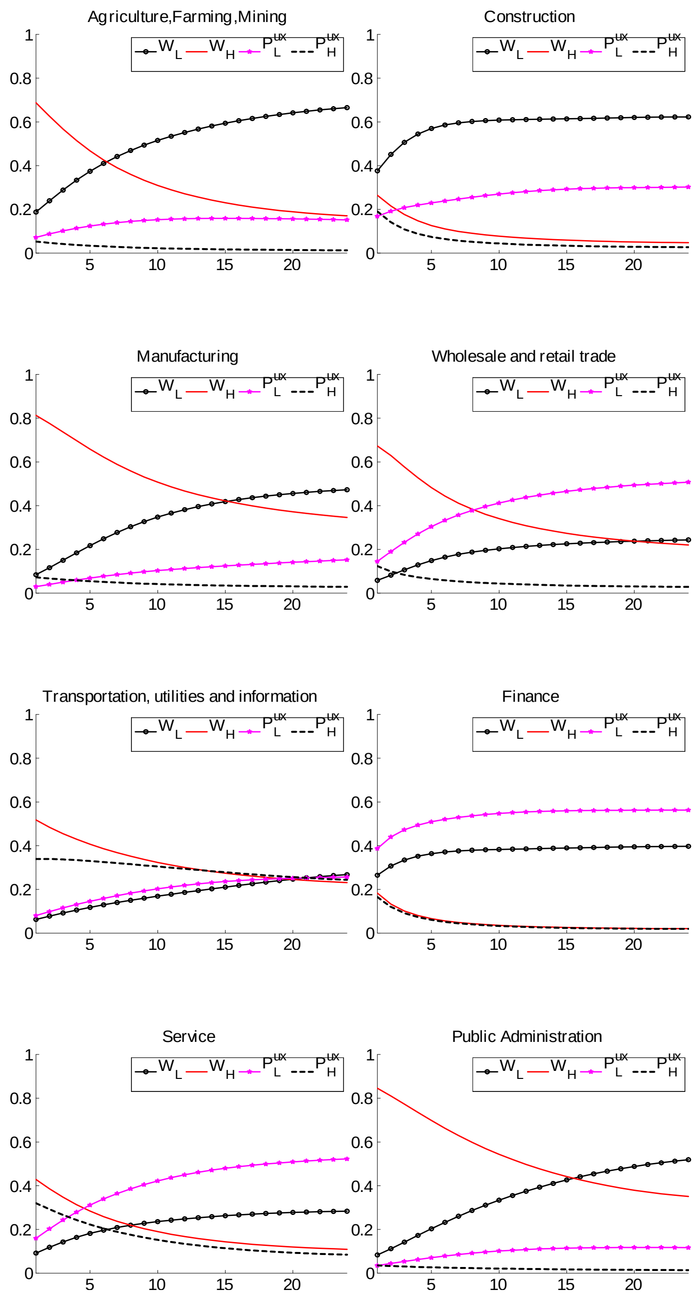


Figure 13. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by industry. The first industry includes agriculture, forestry, fishing, farming and mining industries.

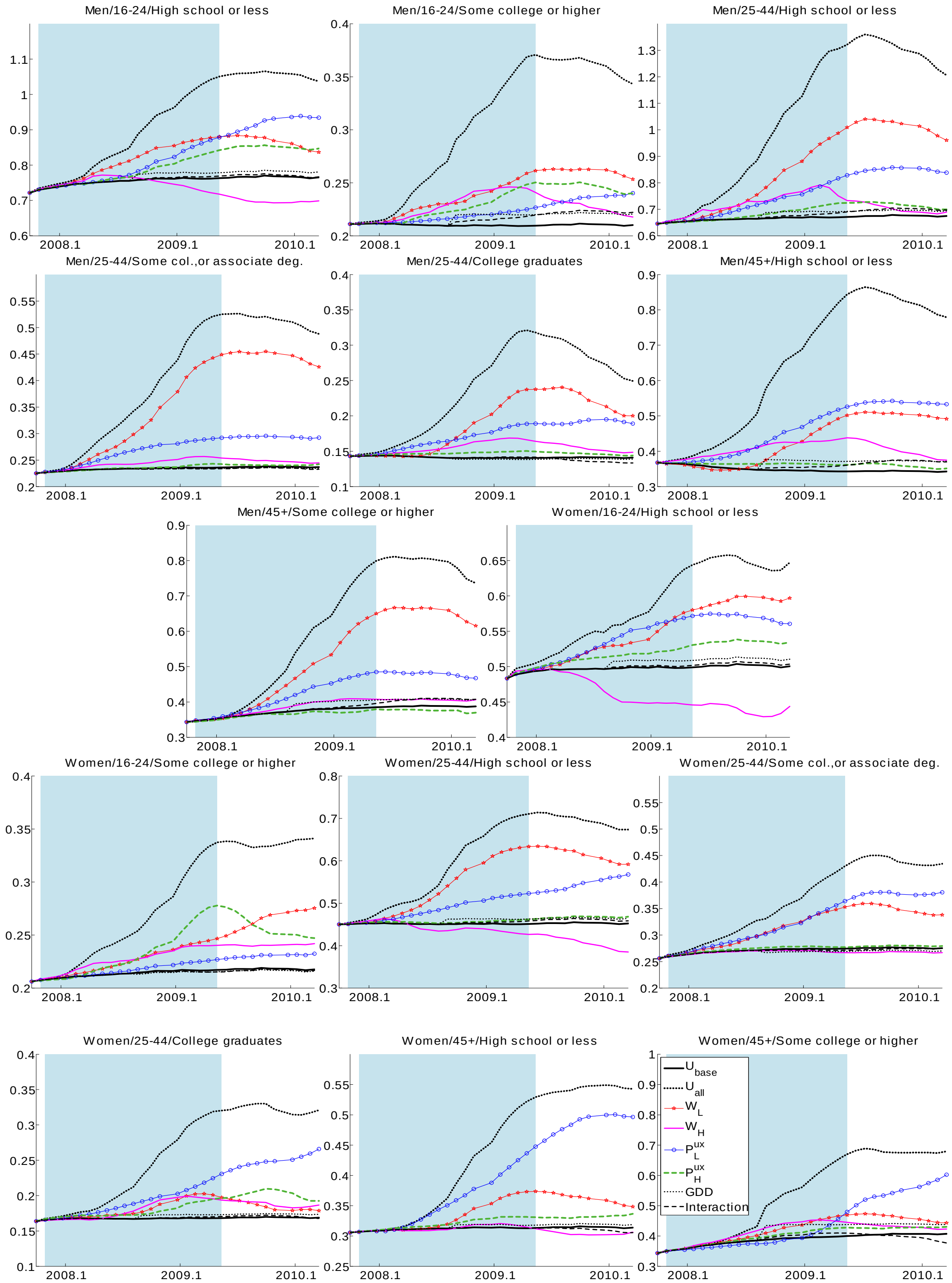


Figure 14. Historical decomposition of Great Recession by gender, age and education. Note to Figure 14. The lines denote predicted shares out of the total labor force. Units are %. Shaded area denotes the NBER recession.

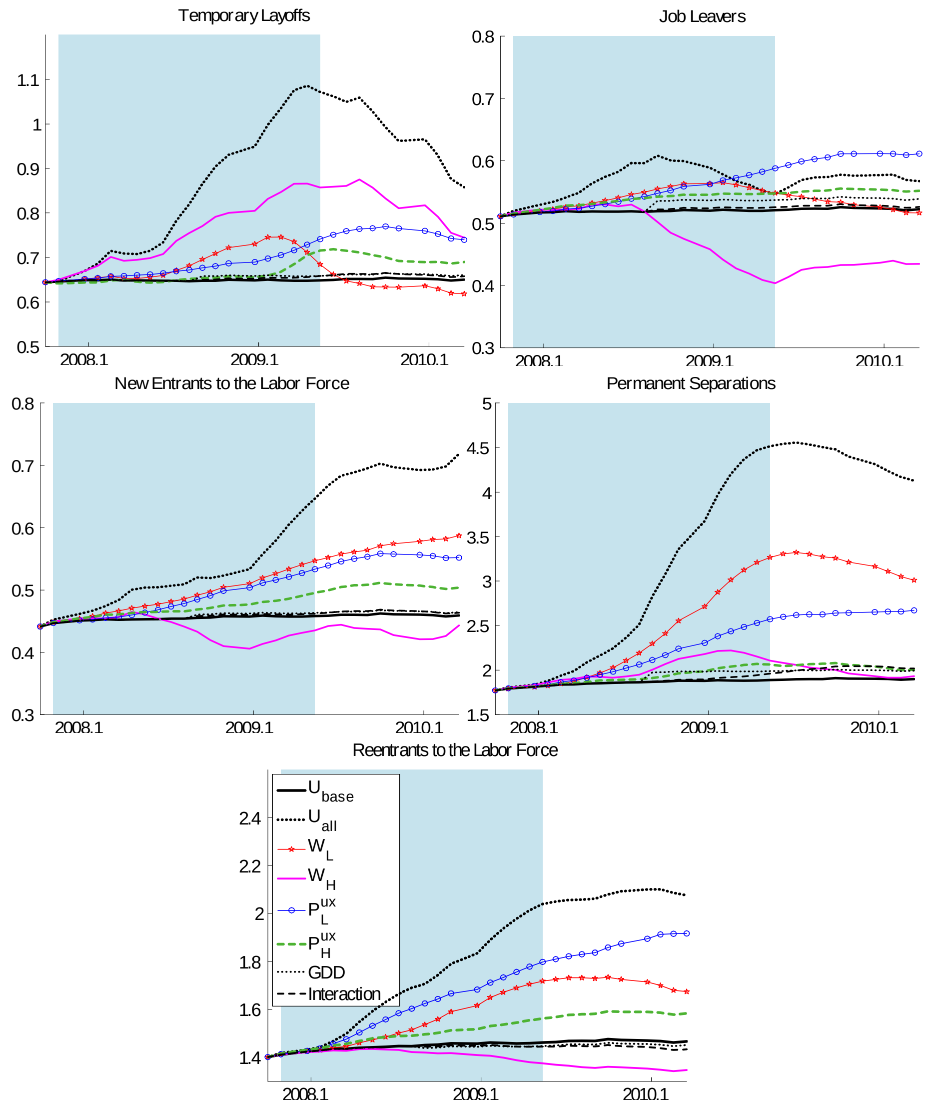


Figure 15. Historical decomposition of Great Recession by reason for unemployment. Note to Figure 15. The lines denote predicted shares out of the total labor force. Units are %. Shaded area denotes the NBER recession.

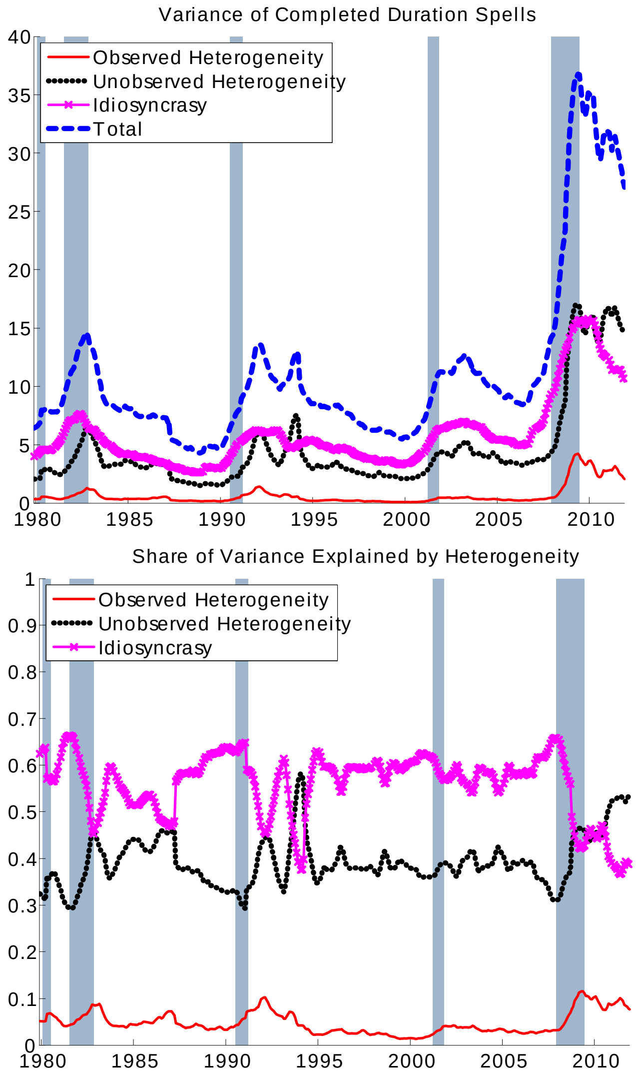


Figure 16. Amount of variance of the completed duration spells of unemployment across individuals accounted for by observed and unobserved heterogeneity. Panel A: Level. Panel B: Share out of total variance.

Table 1. Parameter estimates for the baseline model (Male)

Education	High school			College			
				Some/Graduate	Some	Graduate	Some/Graduate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
σ^w_{jL}	0.0053***	0.0077***	0.0402***	0.0367	0.0543***	0.0497***	0.0347***
	(0.0018)	(0.0011)	(0.0073)	(0.0246)	(0.0122)	(0.0105)	(0.0057)
σ^w_{jH}	0.0099***	0.0186***	0.0678***	0.0501*	0.0311	0.0279***	0.0293***
	(0.0021)	(0.0036)	(0.0128)	(0.0292)	(0.0230)	(0.0108)	(0.0107)
σ^x_{jL}	0.0702***	0.0725***	0.1368***	0.0461**	0.1000	0.0972**	0.1229**
	(0.0274)	(0.0160)	(0.0362)	(0.0226)	(0.1070)	(0.0462)	(0.0574)
σ^x_{jH}	0.0329***	0.0306***	0.0357***	0.0540*	0.0395	0.1237***	0.0544
	(0.0064)	(0.0087)	(0.0102)	(0.0309)	(0.0655)	(0.0490)	(0.0343)
R^1_j	0.0342***	0.0276***	0.1811***	0.2107***	0.1862***	0.1605***	0.1277***
	(0.0020)	(0.0021)	(0.0088)	(0.0108)	(0.0138)	(0.0114)	(0.0066)
$R^{2.3}_j$	0.0305***	0.0285***	0.1759***	0.1542***	0.1580***	0.1237***	0.1310***
	(0.0015)	(0.0016)	(0.0108)	(0.0109)	(0.0210)	(0.0089)	(0.0081)
$R^{4.6}_j$	0.0187***	0.0212***	0.1383***	0.1014***	0.1220***	0.1119***	0.0889***
	(0.0009)	(0.0012)	(0.0080)	(0.0069)	(0.0093)	(0.0073)	(0.0053)
$R^{7.12}_j$	0.0168***	0.0194***	0.1319***	0.0813***	0.1078***	0.1247***	0.0947***
	(0.0009)	(0.0011)	(0.0075)	(0.0047)	(0.0085)	(0.0080)	(0.0057)
$R^{13.+}_j$	0.0126***	0.0174***	0.1378***	0.0750***	0.0961***	0.1071***	0.0674***
	(0.0008)	(0.0011)	(0.0125)	(0.0076)	(0.0161)	(0.0086)	(0.0048)
δ^0_1	0.0953***	0.1160***	0.0365***	0.0858	0.0353	0.1257*	0.5091***
	(0.0312)	(0.0442)	(0.0103)	(0.0811)	(0.1566)	(0.0742)	(0.0854)
δ^0_2	-0.0911	-0.0080	-0.0288	-0.3397**	-0.1864	-0.2331***	-0.4931***
	(0.1160)	(0.0881)	(0.0410)	(0.1732)	(0.2688)	(0.0974)	(0.1327)
δ^0_3	0.1195	-0.0258	0.0025	0.4255	0.1435	0.1559*	0.5473***
	(0.1193)	(0.0820)	(0.0486)	(0.3158)	(0.2397)	(0.0803)	(0.2087)
δ^E_1	0.0660	0.0826**	-0.0400	0.0149	0.0393	0.0750	0.4596***
	(0.0477)	(0.0399)	(0.0314)	(0.0637)	(0.1123)	(0.0647)	(0.0743)
δ^E_2	-0.0946	-0.0253	-0.0575	-0.2076	-0.2443	-0.2405***	-0.2000***
	(0.1017)	(0.0583)	(0.0419)	(0.1343)	(0.1407)	(0.0629)	(0.0674)
δ^E_3	0.2171***	0.0558	0.1430***	0.2417*	0.2838***	0.2332***	0.1290**
	(0.0670)	(0.0612)	(0.0539)	(0.1289)	(0.1131)	(0.0575)	(0.0655)
No.Obs.	409	409	409	409	409	409	409
Log-L	4650.27	4406.50	585.37	1288.58	950.75	984.25	1498.77

Notes to Table 1. White (1982) quasi-maximum-likelihood standard errors in parentheses.

Table 2. Parameter estimates for the baseline model (Female)

Education	High school			College			
				Some/Graudate	Some	Graduate	Some/Graudate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
σ^w_{jL}	0.0037***	0.0450***	0.0243***	0.0094	0.0321***	0.0182***	0.0237***
	(0.0007)	(0.0056)	(0.0045)	(0.0146)	(0.0067)	(0.0049)	(0.0070)
σ^w_{jH}	0.0105***	0.1005***	0.0339***	0.0371***	0.0229***	0.0438***	0.0361***
	(0.0015)	(0.0174)	(0.0123)	(0.0098)	(0.0066)	(0.0121)	(0.0141)
σ^x_{jL}	0.0500***	0.0676***	0.0967***	0.1000	0.0776***	0.2178	0.1221
	(0.0114)	(0.0171)	(0.0216)	(0.7257)	(0.0201)	(0.1649)	(0.0948)
σ^x_{jH}	0.0248***	0.0249***	0.0425**	0.0391***	0.0283***	0.0528**	0.0803***
	(0.0051)	(0.0058)	(0.0143)	(0.0170)	(0.0124)	(0.0259)	(0.0264)
R^1_j	0.0295	0.2918***	0.1723***	0.2122***	0.1861***	0.1545***	0.1437***
	(0.0015)	(0.0158)	(0.0082)	(0.0104)	(0.0092)	(0.0150)	(0.0068)
$R^{2.3}_j$	0.0218**	0.2269***	0.1541***	0.1450***	0.1587***	0.1340***	0.1259***
	(0.0011)	(0.0123)	(0.0082)	(0.0077)	(0.0082)	(0.0079)	(0.0068)
$R^{4.6}_j$	0.0148	0.1866***	0.1186***	0.0988***	0.1117***	0.1146***	0.0834***
	(0.0010)	(0.0095)	(0.0059)	(0.0058)	(0.0054)	(0.0063)	(0.0055)
$R^{7.12}_j$	0.0132	0.1524***	0.1010***	0.0787***	0.1096***	0.1202***	0.0849***
	(0.0007)	(0.0082)	(0.0050)	(0.0080)	(0.0082)	(0.0084)	(0.0065)
$R^{13.+}_j$	0.0100***	0.1217***	0.1036***	0.0584***	0.0874***	0.0999***	0.0719***
	(0.0006)	(0.0074)	(0.0067)	(0.0107)	(0.0079)	(0.0124)	(0.0083)
δ^0_1	0.2304***	0.1348	0.2138***	-0.1220***	0.1154	0.2623***	0.1775***
	(0.0512)	(0.2062)	(0.0782)	(0.0260)	(0.1254)	(0.0660)	(0.0664)
δ^0_2	-0.0680	-0.1018	-0.2576***	-0.0623	-0.1821**	-0.0144	-0.1791
	(0.0588)	(0.0908)	(0.0604)	(0.6962)	(0.0885)	(0.1602)	(0.1448)
δ^0_3	0.0159	0.0812	0.1977***	0.3442	0.2010*	-0.0282	0.1641
	(0.0664)	(0.0680)	(0.0709)	(0.5492)	(0.1164)	(0.1303)	(0.1974)
δ^E_1	0.1816***	0.1027	0.1725***	-0.1008***	0.1315	0.1076	0.1395***
	(0.0436)	(0.1819)	(0.0592)	(0.0320)	(0.1097)	(0.0658)	(0.0531)
δ^E_2	0.0052	-0.0985*	-0.2126***	-0.1560	-0.2072***	-0.0766	-0.1992***
	(0.0418)	(0.0519)	(0.0786)	(0.6783)	(0.0514)	(0.0740)	(0.0530)
δ^E_3	-0.0135	0.1317	0.2676***	0.4883***	0.2259***	0.3693	0.4011***
	(0.0479)	(0.0972)	(0.1105)	(0.1163)	(0.0699)	(0.2511)	(0.1318)
No.Obs.	409	409	409	409	409	409	409
Log-L	5174.92	212.82	1044.56	1463.10	1102.18	1057.23	1533.57

Notes to Table 2. White (1982) quasi-maximum-likelihood standard errors in parentheses. (1) Age 16-24/High school graduates and less than high school, (2) Age 16-24/ Some college, associate degree and college graduates, (3) Age 25-44/ High school graduates and less than high school, (4) Age 25-44/ Some college and associate degree (5) Age 25-44/ College graduates, (6) Age 45 and over/ High school graduates and less than high school, (7) Age 45 and over/ Some college, associate degree and college graduates. White (1982) quasi-maximum-likelihood standard errors in parentheses.

Table 3. Average type L share and continuation probability (Men, 1979:M12-2013:M12)

Education	High school			College			
				Some/graduate	Some	Graduate	Some/graduate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
Type L share in inflows	0.13	0.20	0.21	0.24	0.31	0.36	0.29
Type L continuation prob.	0.87	0.90	0.89	0.74	0.82	0.88	0.95
Type H continuation prob.	0.44	0.48	0.47	0.34	0.44	0.45	0.48
Share in total L inflows	0.12	0.14	0.06	0.07	0.07	0.07	0.04
Share in total inflows	0.17	0.13	0.06	0.05	0.05	0.04	0.03

Table 4. Average type L share and continuation probability (Women, (1979:M12-2013:M12)

Education	High school			College			
				Some/graduate	Some	Graduate	Some/graduate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
Type L share in inflows	0.12	0.20	0.27	0.04	0.28	0.20	0.22
Type L continuation prob.	0.90	0.88	0.89	0.84	0.84	0.95	0.87
Type H continuation prob.	0.39	0.43	0.41	0.39	0.39	0.47	0.45
Share in L inflows	0.09	0.12	0.07	0.01	0.07	0.04	0.03
Share in total inflows	0.14	0.11	0.05	0.06	0.05	0.04	0.03

Table 5. Key characteristic of type L inflows (1979:M12-2013:M12)

Key characteristic	Fraction in w_L	Fraction in $w_L + w_H$
Men	57%	52%
Age 25-44	48%	42%
High school or less	60%	66%

Table 6. Average type L share and continuation probability by industry (1979:M12-2013:M12)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type L share in inflows	0.15	0.27	0.18	0.19	0.17	0.28	0.16	0.15
Type L continuation prob.	0.91	0.87	0.91	0.91	0.83	0.87	0.86	0.92
Type H continuation prob.	0.52	0.44	0.49	0.45	0.51	0.35	0.46	0.53
Share in L inflows	0.01	0.14	0.12	0.19	0.04	0.05	0.23	0.01

Notes to Table 6. Only those who report their previous industry are taken into account in computing the share of each group in the total type L inflows. Newly unemployed individuals who does not have previous industry are not considered. (1) Agriculture, forestry, fishing, farming and mining, (2) Construction, (3) Manufacturing, (4) Wholesale and retail trade, (5) Transportation, (6) Finance, (7) Service, (8) Public Administration. The shares in L inflows does not add up to 1, since unemployed individuals who do not have previous work experience are not considered.

Table 7. Average type L share and continuation probability by occupation (1987:M12-2013:M12)

	(1)	(2)	(3)	(4)
Type L share in inflows	0.22	0.19	0.15	0.27
Type L continuation prob.	0.88	0.90	0.88	0.90
Type H continuation prob.	0.33	0.47	0.45	0.53
Share in L inflows	0.37	0.20	0.13	0.16

Notes to Table 7. Only those who report their previous occupation are taken into account in computing the share of each group in the total type L inflows. Newly unemployed individuals who does not have previous occupations are not considered. (1) Routine/manual occupation, (2) Routine/cognitive occupation, (3) Non-routine/manual occupation, (4) Non-routine/cognitive occupation. The shares in L inflows does not add up to 1, since unemployed individuals who do not have previous work experience are not considered.

Table 8. Average type L share and continuation probability by reason for unemployment (1979:M12-2013:M12)

	Temp.Layoff	Perm.Sep.	Job Leavers	Re-entrants	New entrants
Type L share in inflows	0.23	0.27	0.15	0.16	0.13
Type L continuation prob.	0.67	0.94	0.96	0.92	0.93
Type H continuation prob.	0.34	0.58	0.44	0.46	0.47
Share in L inflows	0.22	0.38	0.09	0.24	0.07

Table 9. Key characteristic of type L inflows (2000:M01-2013:M12)

Key characteristic	Fraction in w_L	in $w_L + w_H$
Age-Gender-Education		
- High school diploma or less	58%	63%
Industry		
- Wholesale, retail trade and service	46%	53%
- Construction and manufacturing	25%	21%
Occupation		
- Routine/Manual	39%	32%
Reason for unemployment		
- Permanent separation	43%	22%

Appendix

A. Data

The CPS micro data used for the construction of a data set of the number of individuals unemployed for a duration of less than 5 weeks, between 5 and 14 weeks, between 15 and 26 weeks, between 27 and 52 weeks, and for longer than 52 weeks categorized by each individual characteristic are publicly available at the NBER website (http://www.nber.org/data/cps_basic.html). Since the CPS is a probability sample, each individual is assigned a unique weight that is used to produce the aggregate data series.

The category for individual characteristics that I consider for the baseline case is as follows: (1) men/aged 16–24/high school education or less; (2) men/aged 16–24/some college, associate degree, or college degree; (3) men/aged 25–44/high school education or less; (4) men/aged 25–44/some college or associate degree; (5) men/aged 25–44/college degree; (6) men/aged 45 and over/high school education or less; (7) men/aged 45 and over/some college, associate degree, or college degree; (8) women/aged 16–24/high school education or less; (9) women/aged 16–24/some college, associate degree, or college degree; (10) women/aged 25–44/high school education or less; (11) women/aged 25–44/some college or associate degree; (12) women/aged 25–44/college degree; (13) women/aged 45 and over/high school education or less; (14) women/aged 45 and over/some college, associate degree, or college degree.

I also consider five categories for reason for unemployment: (1) temporary layoffs, (2) permanent separations (including other separation and temporary job ended), (3) job leavers, (4) reentrants, and (5) new entrants. I consider eight categories for industry: (1) agriculture, forestry, fishing, farming, and mining; (2) construction; (3) manufacturing; (4) wholesale and retail trade; (5) transportation, utilities, and information; (6) finance; (7) service; and (8) public administration. And I consider four categories for occupation: (1) routine/manual occupation, (2) routine/cognitive occupation, (3) non-routine/manual occupation, and (4) non-routine/cognitive occupation.

It is well known that the CPS redesign in 1994 understates the number of individuals unemployed for one month and could have subsequently affected the size of longer-duration groups after 1994. I do not take into account the possible effect of the 1994 redesign on the distribution of unemployment duration for two reasons. First, the goal of this paper is to explain the observed distribution of unemployment duration. Although the data is observed with possible measurement errors, correcting the measurement errors in each group is beyond the scope of this paper. Second, the main interest of this paper is not the relative importance of inflows and outflows in the unemployment dynamics, for which the correction of short-term unemployment for the 1994 redesign could be important, as mentioned by Elsby, Michaels, and Solon (2009) and Shimer (2012).

B. Estimation Algorithm

The state space model can be summarized as

$$\begin{aligned} x_{jt} &= Fx_{j,t-1} + \epsilon_{jt} \\ y_{jt} &= h(x_{jt}) + r_{jt} \end{aligned}$$

for $x_{jt} = (\xi'_{jt}, \xi'_{j,t-1}, ..., \xi'_{j,t-47})'$, $E(\epsilon_{jt}\epsilon'_{jt}) = \Sigma_j$ and $E(r_{jt}r'_{jt}) = R_j$. The function $h(.)$ as well as elements of the variance matrices R_j and Σ_j depend on the parameter vector $\theta_j = (\delta^0_{j1}, \delta^0_{j2}, \delta^0_{j3}, \delta^E_{j1}, \delta^E_{j2}, \delta^E_{j3}, R^1_j, R^{2.3}_j, R^{4.6}_j, R^{7.12}_j, R^{13.+}_j, \sigma^{Lw}_j, \sigma^{Hw}_j, \sigma^{Lx}_j, \sigma^{Hx}_j)'$. The extended Kalman filter (e.g., Hamilton, 1994b) can be viewed as an iterative algorithm to calculate a forecast $\hat{x}_{j,t+1|t}$ of the state vector conditioned on knowledge of θ_j and observation of $Y_{jt} = (y'_{jt}, y'_{j,t-1}, ..., y'_{j1})'$ with $P_{j,t+1|t}$ the MSE of this forecast. With these we can approximate the distribution of y_{jt} conditioned on $Y_{j,t-1}$ as $N(h(\hat{x}_{jt|t-1}), H'_{jt}P_{jt|t-1}H_{jt} + R_j)$ for $H_{jt} = \partial h(x_{jt})/\partial x'_{jt}|_{x_{jt}=\hat{x}_{jt|t-1}}$ from which the likelihood function associated with that θ_j can be calculated and maximized numerically. The forecast of the state vector can be updated using

$$\hat{x}_{j,t+1|t} = F\hat{x}_{jt|t-1} + FK_{jt}(y_{jt} - h(\hat{x}_{jt|t-1}))$$

$$K_{jt} = P_{jt|t-1}H_{jt}(H'_{jt}P_{jt|t-1}H_{jt} + R_j)^{-1}$$

$$P_{j,t+1|t} = F(P_{jt|t-1} - K_{jt}H'_{jt}P_{jt|t-1})F' + Q_j.$$

A similar recursion can be used to form an inference about x_{jt} using the full sample of available data, $\hat{x}_{jt|T} = E(x_{jt}|y_{jT}, ..., y_{j1})$ and these smoothed inferences are what are reported in any graphs in this paper.

For the initial value for the extended Kalman filter, we calculated the values that would be implied if pre-sample values had been realizations from an initial steady state, estimating the (4×1) vector $\bar{\xi}_{j0}$ from the average values for $\bar{U}^1_j, \bar{U}^{2.3}_j, \bar{U}^{4.6}_j, \bar{U}^{7.12}_j$ and $\bar{U}^{13.+}_j$ over January 1976 - December 1979 using the method described in Section 1.1 of Ahn and Hamilton (2016) given the GDD parameter estimated from the average values for $\bar{U}^1_j, \bar{U}^{2.3}_j, \bar{U}^{4.6}_j, \bar{U}^{7.12}_j$ and $\bar{U}^{13.+}_j$ over December 1979 - December 2013. Our initial guess was then $\hat{x}_{j1|0} = \iota_{48} \otimes \bar{\xi}_{j0}$ where ι_{48} denotes a (48×1) vector of ones. Diagonal elements of $P_{j1|0}$ determine how much the presample values of ξ_{jl} are allowed to differ from this initial guess $\hat{\xi}_{jl|0}$. For this we set $E(\xi_{jl} - \hat{\xi}_{jl|0})(\xi_{jl} - \hat{\xi}_{jl|0})' = c_0 I_4 + (1 - l)c_1 I_4$ with $c_0 = 10$ and $c_1 = 0.1$.[40] The value for

[40] Exceptions are men aged 16-24 whose education level is higher than high school diploma, and women in the same age and education category. For these groups, I set $c_0 = 1$, but it still a large variance for each initial value.

c_0 is quite large relative to the range of $\xi_{jt|T}$ over the complete observed sample, ensuring that the particular value we specified for $\hat{x}_{j1|0}$ has little influence. For $k < l$ we specify the covariance[41] $E(\xi_{jl} - \bar{\xi}_{j0})(\xi_{jk} - \bar{\xi}_{j0})' = E(\xi_{jk} - \bar{\xi}_{j0})(\xi_{jl} - \bar{\xi}_{j0})'$. The small value for c_1 forces presample ξ_{jl} to be close to ξ_{jk} when l is close to k, again consistent with the observed month-to-month variation in $\hat{\xi}_{jt|T}$.

C. Derivation of linearized variance

The state equation $\xi_{j,t+1} = \xi_{j,t} + \varepsilon_{j,t+1}$ implies

$$\begin{aligned} \xi_{j,t+s} &= \xi_{jt} + \varepsilon_{j,t+1} + \varepsilon_{j,t+2} + \varepsilon_{j,t+3} + \cdots + \varepsilon_{j,t+s} \\ &= \xi_{jt} + u_{j,t+s}. \end{aligned}$$

Letting $y_{jt} = (U_{jt}^{1}, U_{jt}^{2.3}, U_{jt}^{4.6}, U_{jt}^{7.12}, U_{jt}^{13.+})'$ denote the (5×1) vector of observations for date t, our model implies that in the absence of measurement error y_{jt} would equal $h(\xi_{jt}, \xi_{j,t-1}, \xi_{j,t-2}, ..., \xi_{j,t-47})$ where $h(\cdot)$ is a known nonlinear function. Hence

$$y_{j,t+s} = h(u_{j,t+s} + \xi_{jt}, u_{j,t+s-1} + \xi_{jt}, ..., u_{j,t+1} + \xi_{jt}, \xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}).$$

We can take a first-order Taylor expansion of this function around $u_{j,t+l} = 0$ for $l = 1, 2, ..., s$,

$$y_{j,t+s} \simeq h(\xi_{jt}, ..., \xi_{jt}, \xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) + \sum_{l=1}^{s} [H_l(\xi_{jt}, \xi_{jt}, ..., \xi_{jt}, \xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})] u_{j,t+s+1-l}$$

for $H_l(\cdot)$ the (5×4) matrix associated with the derivative of $h(\cdot)$ with respect to its lth argument. Using the definition of $u_{j,t+l}$, this can be rewritten as

$$y_{j,t+s} \simeq c_s(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}) + \sum_{l=1}^{s} [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})] \varepsilon_{j,t+l} \tag{24}$$

from which (15) follows immediately.

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[41] In other words,

$$P_{1|0} = \begin{bmatrix} c_0 I_4 & c_0 I_4 & c_0 I_4 & \cdots & c_0 I_4 \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + c_1 I_4 & \cdots & c_0 I_4 + c_1 I_4 \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + 2c_1 I_4 & \cdots & c_0 I_4 + 2c_1 I_4 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + 2c_1 I_4 & \cdots & c_0 I_4 + 47c_1 I_4 \end{bmatrix}.$$

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