

A Unified Approach to Measuring u^*

Richard K. Crump* Stefano Eusepi† Marc Giannoni‡ Ayşegül Şahin§

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Abstract

This paper bridges the gap between two popular approaches to estimating the natural rate of unemployment, u_t^* . The first approach uses detailed labor market indicators such as labor market flows, cross-sectional data on unemployment and vacancies, or various measures of demographic changes. The second approach which comprises reduced form models and DSGE models relies on aggregate price and wage Phillips curve relationships. We combine the key features of these two approaches to estimate the natural rate of unemployment in the United States using both data on labor market flows and a forward-looking Phillips curve linking inflation to current and expected deviations of unemployment from its unobserved natural rate. We estimate that the natural rate of unemployment is around 4.0% toward the end of 2018 and that the unemployment gap is roughly closed. Identification of a secular downward trend in the unemployment rate, driven solely by the inflow rate, facilitates the estimation of u_t^* . We identify the increase in labor force attachment of women, decline in job destruction and reallocation intensity, and dual aging of workers and firms as the main drivers of the secular downward trend in the inflow rate.

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*Federal Reserve Bank of New York.

†University of Texas at Austin.

‡Federal Reserve Bank of Dallas.

§University of Texas at Austin.

1 Introduction

The unemployment rate in the United States peaked at 10.2% in October 2009. Since then, it has declined gradually, reaching below 4% for the first time in almost twenty years. A debate has arisen about how sustainable these low levels are and how monetary policy should respond. Starting with [Friedman \(1968\)](#) and [Phelps \(1967, 1968\)](#), academics and policymakers have endeavored to measure a sustainable level of unemployment and what implications deviations from this level have for price and wage inflation. This natural rate of unemployment, u_t^* , is broadly defined as the unemployment rate such that, controlling for supply shocks, inflation remains stable. u_t^* is thought to vary over time with changes in the economy such as demographic shifts, changes in the structure of the labor market, or technological advances.¹

There are two popular approaches to estimating u_t^* , in the literature. The first approach uses detailed labor market data such as changes in demographics ([Perry \(1970\)](#), [Summers \(1986\)](#), [Shimer \(1998\)](#), [Brauer \(2007\)](#), [Barnichon and Mesters \(2018\)](#)), labor market flows and job vacancies ([Blanchard and Diamond \(1989\)](#), [Daly, Hobijn, Şahin, and Valletta \(2012\)](#)), firms' recruiting intensity ([Davis, Faberman, and Haltiwanger \(2013\)](#)) or skills mismatch ([Şahin, Song, Topa, and Violante \(2014\)](#)). One potential limitation of this approach is the absence of information from inflation to infer u_t^* ; moreover, these measures are not additive as they cannot be considered as independent from each other and so they are not conclusive on the *level* of the natural rate of unemployment. Finally, there is the need for detailed datasets (to build mismatch indexes, for example) that are available only for the more recent period.

The second approach which comprises reduced form models ([Staiger, Stock, and Watson \(1997\)](#), [Laubach \(2001\)](#), [Orphanides and Williams \(2002\)](#)) and dynamic stochastic general equilibrium (DSGE) models ([Galí \(2011\)](#), [Gertler, Sala, and Trigari \(2008\)](#), [Galí, Smets, and Wouters \(2012\)](#)) relies mainly on price and wage Phillips curve relationships, together with model-specific assumptions on aggregate demand. This approach, in contrast, makes little use of detailed labor market information, and has been subjected to two sets of criticism. First, the natural rate estimates obtained from these models tend to be surrounded by a considerable degree of uncertainty, hampering their use for policy decisions. Second, the relationship between “economic slack” and inflation has

¹For example, in the face of a spike in unemployment during the Great Recession, the modest decline in inflation was, in part, attributed to increases in mismatch unemployment, decline in firms' recruiting intensity, the extension of unemployment benefits, and uncertainty in economic conditions. This time variation in u_t^* is reflected in the time series of forecasted longer-run unemployment observed in survey data and FOMC projections (see [Figure C.1](#) in the Supplemental Appendix).

been called into question since the financial crisis of 2007, as the strong rise in unemployment did not lead to a sizable and persistent decline in inflation.

We combine the key features of these two approaches and estimate u_t^* using a forward-looking Phillips curve linking inflation to current and expected deviations of unemployment from its *unobserved* natural rate. The estimation relies on two key pieces of information. First, we propose a measure of the secular trend in the unemployment rate obtained from separation (unemployment inflow) rates and job-finding (unemployment outflow) rates. We exploit the rich cross-sectional variation in the flow rates of different demographic groups to obtain an estimate of the trends. Our analysis of unemployment flows identifies the downward trend in the inflow rate as the main driver of the secular unemployment trend. The identification of such trends aids the measurement of the unobserved natural rate of unemployment. Second, we use survey-based professional forecasts to measure the term structure of inflation expectations, that is, the forward-looking component of the Phillips curve. We find that it is vital to account for the behavior of expectations to reconcile the observed behavior of inflation and slack over time consistent with [Del Negro, Giannoni, and Schorfheide \(2015\)](#) and [Carvalho, Eusepi, Moench, and Preston \(2017\)](#).

We estimate the natural rate of unemployment for the United States over the period 1960 to 2018. As of the third quarter of 2018, we estimate that u_t^* was around 4%; in particular, using only information from price inflation we estimate that u_t^* stood at 4.0% with a 68% confidence interval of 3.5% to 4.5%. When we add information from wage inflation the estimate shifts down slightly to 3.9% with associated confidence interval of 3.4% to 4.2%. We find that the unemployment gap was roughly closed by the end of 2018 as short-term inflation expectations have approximately converged toward their long-run mean. More generally, we find that the natural rate of unemployment, estimated using both price and wage inflation, was steady just below 6% in the 1960s, rose sharply in the 1970s to over 8% before falling steadily to below 5% in 2000. During the 2000s up until the Great Recession the natural rate of unemployment has been rangebound. In the Great Recession, we document a rise in u_t^* of about 1 percentage point relative to its pre-recession levels. We demonstrate that this estimate aligns surprisingly well with estimated contributions to the unemployment rate attributed to mismatch unemployment and the extension of unemployment benefits.

We trace the long-term decline in u_t^* over the last 40 years to a secular downward trend in the rate at which workers become unemployed (the inflow rate). The decline in the inflow rate reflects three important changes in the labor market: (1) the rise in participation and labor force attachment

of women which coincided with fewer labor force interruptions related to maternity and child birth and culminating in the closing of the gender unemployment gap; (2) the shift of the labor force from younger workers, who frequently become unemployed, to older workers, who are less likely to become unemployed; (3) the aging of firms, as older firms tend to have reduced rates of job destruction (layoffs and firings). The second and third changes are connected, and we refer to them as the *dual aging* of the U.S. economy, which has resulted in less job destruction and unemployment incidence in the labor market not only through a composition effect but also by reducing unemployment incidence (job destruction) for workers (firms) in all age groups. Dual aging stands out as the primary driver of the lower trend rate of unemployment especially in the last two decades. Together, these secular changes have reduced the overall flow rate into unemployment, and consequently, the unemployment rate itself.

The structure of the paper is as follows. Section 2 presents an overview of the paper and discusses its contributions relative to the extensive literature on the natural rate of unemployment. Section 3 estimates the secular trend of unemployment using detailed information for unemployment inflows and outflows by demographic groups. Section 4 introduces a simple forward-looking Phillips curve, discusses its theoretical underpinning, and details the estimation methodology. Section 5 presents the time series for the natural rate of unemployment, u_t^* , for the sample 1960–2018. Section 6 provides a quantitative evaluation of three factors in driving the trend decline in the unemployment inflow rate: increase in female labor force attachment; decline in job destruction and reallocation; and dual aging of workers and firms in the economy. Section 7 concludes.

2 Overview and Relation to the Literature

The object we seek to estimate is “the natural rate of unemployment,” u^* , which is defined as the unemployment rate such that, controlling for supply shocks, inflation remains stable.² While the relation between inflation and unemployment is a perennial topic in macroeconomics (Humphrey (1991)), the concept of the natural rate is often attributed to Friedman (1968) and Phelps (1967, 1968) and the notation u^* can be traced back to Phelps. As originally suggested by Friedman, u^* is generally assumed to vary over time possibly as a function of demographic shifts, changes in the structure of

²The extensive literature on the natural rate of unemployment used long run, frictional, average, equilibrium, normal, steady state, lowest sustainable, Hodrick-Prescott trend, NAIRU and the unemployment at full employment to refer to related, perhaps the same, object that we are trying to estimate. An insightful article by Richard Rogerson in 1997 entitled *Theory Ahead of Language in the Economics of Unemployment* discusses the confusion and uncertainty around the language used (Rogerson (1997)).

the labor market, or technological advances. Friedman in his 1968 Presidential address wrote *To avoid misunderstanding, let me emphasize that by using the term “natural” rate of unemployment, I do not mean to suggest that it is immutable and unchangeable. On the contrary, many of the market characteristics that determine its level are man-made and policy-made...Improvements in employment exchanges, in availability of information about job vacancies and labor supply, and so on, would tend to lower the natural rate of unemployment.*

Friedman clearly pointed out changes in labor supply behavior and efficiency of the matching process in the labor market arising from better matching technology as shifters of the natural rate. However, despite this key insight, an ongoing assumption of the time was that the natural rate was 4%, which caused policy makers to underestimate how tight the labor market was. Various influential papers in the inaugural issues of the Brookings Papers on Economic Activity in the early 1970s studied the rise in the *natural* rate of unemployment such as [Hall \(1970b\)](#), [Gordon \(1970b,a\)](#), [Perry \(1970, 1972\)](#), and [Schultze \(1971\)](#). These papers emphasized the role of the changing demographic structure of the economy and the importance of labor market flows in assessing the natural rate in real time. We expand on these enduring insights and estimate the secular trend of unemployment and integrate it into the New Keynesian Phillips curve.

Our point of departure is a simple decomposition of the unemployment rate,

$$u_t = \bar{u}_t + \underbrace{(u_t - u_t^*)}_{x_t} + \underbrace{(u_t^* - \bar{u}_t)}_{z_t}, \quad (1)$$

where \bar{u}_t is the *secular trend of unemployment* and u_t^* is the *natural rate*. The secular trend of unemployment, \bar{u}_t , captures the elements of the unemployment rate that are driven by slow-moving factors such as demographics and social change. The unemployment gap, x_t , measures the deviation of the observed unemployment rate from the natural rate and is the primary input to monetary policy considerations (e.g., the goal of maximum employment). The natural rate of unemployment is defined as the sum of the secular trend component and a cyclical component z_t . Conceptually, we would expect the natural rate of unemployment to converge to \bar{u}_t over time in the absence of shocks.

While it is tempting to use traditional filtering techniques to eliminate the higher-frequency fluctuations in the unemployment rate, we instead rely on rich cross-sectional variation in unemployment flow rates by demographic groups to assess the extent of the secular trend of unemployment, \bar{u}_t . We do so for multiple reasons: (i) the inherent asymmetry in the unemployment rate ([Montgomery,](#)

Zarnowitz, Tsay, and Tiao (1998), Hamilton (2005)) makes it challenging to directly estimate its secular, slow moving trend; (ii) the inflow/outflow dynamics of the unemployment rate—which is the source of the underlying asymmetry—by itself provides a better characterization of the evolution of the unemployment rate (Blanchard and Diamond (1990), Barnichon and Nekarda (2012), Şahin and Patterson (2013)) (iii) extensive cross-sectional information on these flow rates enables us to better distinguish and analyze the underlying common and group-specific trends.

In estimating the secular trend of unemployment, we allow trends of unemployment inflows and outflows to vary by age and gender. This follows a long-standing literature dating back to George Perry’s influential Brookings paper in 1970 which has recognized age and gender as the main demographic characteristics that need to be taken into account in assessing the natural rate unemployment. In particular, Perry (1970) suggested an adjustment to account for the rising share of teenagers and women in the labor force that is often referred to as the *Perry-adjusted* unemployment rate. This adjustment—which assigns a lower weight to the unemployment rate of demographic groups with lower hours and wages—has been used in the literature in estimation of the Phillips curve such as in Gordon (1982) and Summers (1986) and provides a basis for different measures of labor market underutilization such as U-1 and U-6. Shimer (1998) built on Perry (1970), Gordon (1982) and Summers (1986) and provided a critical evaluation of the underlying assumption of applying demographic adjustments to the unemployment rate: demographic shifts in the labor market only affect the aggregate unemployment rate through the changing labor force shares without affecting group-specific unemployment rates. Shimer (1998) argued that this assumption is adequate with respect to changes in the age structure but is violated when there are changes in educational attainment. More recently, Barnichon and Mesters (2018) revisited the demographic adjustment of the unemployment rate and proposed a new demographic adjustment based on gross flows data. We build on Barnichon and Mesters (2018) and examine the relationship between demographics and unemployment flows instead of focusing on the unemployment rate directly.

To connect inflation to the state of the labor market we employ a forward-looking Phillips curve linking inflation to expected inflation and the unemployment gap. Following Friedman (1968) and Phelps (1967, 1968) and building on the rational expectations school of thought in the 1970s (Sargent (1971), Lucas (1972)) it has become common to link the gap between the unemployment rate and a natural rate of unemployment to the inflation rate, through an expectations-augmented Phillips curve. According to this relationship, whenever the unemployment rate is equal to its natural rate,

inflation and inflation expectations should settle to their long-run value in the absence of supply shocks. For this reason, the natural rate of unemployment is sometimes called the non-accelerating inflation rate of unemployment (NAIRU).³ Moreover, for given unemployment, inflation, and an assumption about inflation expectations, this relation allows for the estimation of u_t^* . We utilize survey-based expectations of inflation at different horizons to provide noisy signals of true inflation expectations and impose that the secular trend act as an anchor for the natural rate although accommodating the possibility of persistent deviations.

A Phillips curve by itself is, however, not a panacea to estimate the natural rate of unemployment. Indeed, as many authors have emphasized, the estimates of the response of inflation to the unemployment gap in conventional backward-looking Phillips curves — that relate current inflation to a measure of economic slack and lags of inflation to proxy for inflation expectations — appear to have diminished substantially since the late 1980s (e.g., [Hall \(2011\)](#), [Ball and Mazumder \(2011\)](#)). This raises two issues. First, instability of key parameters of the Phillips curve render the estimate of u_t^* more difficult. Second, relatively flat Phillips curves may result in uncertain estimates of u_t^* .

Several authors (e.g., [Ball and Mazumder \(2011\)](#), [Hall \(2011\)](#), [Blanchard \(2016\)](#)) have also questioned the Phillips curve relationships on the grounds that the dramatic increase in the unemployment rate and the collapse in economic activity recorded during the Great Recession should have implied a very large drop in the inflation rate, or even deflation, in contrast to the relatively modest decline in inflation registered in the aftermath of the Great Recession. However, recent research has shown that while the criticism of backward-looking Phillips curves is well justified, it does not apply to forward-looking Phillips curves linking inflation to the unemployment gap and expectations of *future* inflation.⁴ For example, [Del Negro, Giannoni, and Schorfheide \(2015\)](#) show that a relatively standard monetary dynamic stochastic general equilibrium (DSGE) model with forward-looking expectations and financial frictions can account remarkably well for the joint evolution of inflation and economic activity during and following the Great Recession. This is because forward-looking agents in the model understand that monetary policy will be more accommodative in the future, the more activity contracts, thereby helping anchor inflation expectations. [Carvalho, Eusepi, Moench, and Preston \(2017\)](#) provide further evidence that it is possible to reconcile the observed behavior of inflation

³[Modigliani and Papademos \(1975\)](#) defined the noninflationary rate of unemployment (NIRU) as a rate such that, as long as unemployment is above it, inflation can be expected to decline and estimated it to be somewhat over 5.5% in 1975.

⁴Early derivations of the New Keynesian Phillips curve that features expectations of future inflation can be found in [Calvo \(1983\)](#), [Rotemberg \(1987\)](#), [Roberts \(1995\)](#), [Fuhrer and Moore \(1995\)](#), [Yun \(1996\)](#), [Goodfriend and King \(1997\)](#), [Rotemberg and Woodford \(1997\)](#), [Galí and Gertler \(1999\)](#), and [Sbordone \(2002\)](#).

with the level of slack during the crisis and its aftermath. In particular, they show that inflation expectations have remained “anchored” over that period, which has contributed to promoting price stability.

We build on this insight and use a forward-looking Phillips curve linking inflation to the unemployment gap and expectations of future inflation, which is based on the model of Galí (2011). Importantly, the forward-looking nature of this Phillips curve implies that inflation depends not only the contemporaneous unemployment gap but also the entire path of expected future unemployment gaps. This tighter link, along with data on inflation expectations at various horizons, coupled with the secular trend of the unemployment rate, helps us identify u_t^* .

Finally, our examination of the determinants of the secular trend in the unemployment rate links to the recent but growing literature on the decline in labor market dynamism. Worker and job reallocation have declined substantially in the recent decades, as initially documented by Davis, Haltiwanger, Jarmin, and Miranda (2006) and recently analyzed in Davis and Haltiwanger (2014) and Molloy, Trezzi, Smith, and Wozniak (2016). Our analysis links the decline in labor market fluidity to movements in the inflow rate and assesses its quantitative impact on the natural rate of unemployment.

3 Secular Trend in Unemployment

We estimate u^* in two steps. In the first step, described in this section, we extract the slow-moving trends in the inflow and outflow rates using a linear state-space model and obtain the unemployment rate trend \bar{u}_t . In the the second step, we combine this trend estimate, together with measures of price inflation, wage inflation, and inflation expectations to infer the natural rate of unemployment from a New-Keynesian Phillips curve.

It could be argued that, from a statistical standpoint, it is more efficient to estimate the unemployment trend and the natural rate jointly. Our choice reflects two main considerations. First, the current approach is simple to implement and transparent. Single step estimation would add significant complexity as it would require conducting inference with a nonlinear state space model of a reasonably large dimension (see equation (3) below). Second, as we argue in Section 6, the evolution of the unemployment secular trend is driven by forces such as changes in labor supply behavior reflecting social change or slow-moving demographic changes. This is broadly consistent with the assumption that \bar{u}_t evolves exogenously to the state of the business cycle or changes in

monetary and fiscal regimes during our sample period.

Section 3.1 introduces and summarizes the flow origins of the unemployment rate. Section 3.2 characterizes overall flows into and out of unemployment whereas Section 3.3 focuses on these flows for specific demographic subgroups. Finally, in Section 3.4, we introduce a state-space model to estimate the slow-moving components of the inflows and outflows to unemployment which maps directly to the slow-moving component of the unemployment rate.

3.1 Flow Dynamics of the Unemployment Rate

Our main premise is that the flow origins of unemployment rate movements help us better connect to the underlying drivers of unemployment fluctuations and trends. Therefore we start with the evolution of the unemployment stock from month t to month $t + 1$

$$dU/dt = s_t(L_t - U_t) - f_t U_t \quad (2)$$

where L_t denotes the labor force, s_t is the separation rate (inflow rate) to unemployment and f_t is the job-finding rate (outflow rate) from unemployment. While s_t is generally referred to as the separation rate and f_t as the job-finding rate, we will use the inflow-outflow terminology as in [Elsby, Michaels, and Solon \(2009\)](#) and [Elsby, Hobijn, and Şahin \(2010\)](#). This terminology creates a clear differentiation between s_t and f_t and employment-to-unemployment and unemployment-to-employment flow rates based on gross flows data computed using longitudinally matched monthly CPS microdata.

The unemployment rate, u_t is defined as the fraction of the labor force L_t that is unemployed, $u_t = U_t/L_t$. We follow [Shimer \(2005, 2012\)](#) and calculate the outflow probability F_t using the observation that

$$U_{t+1} - U_t = U_{t+1}^S - F_t U_t$$

where U_{t+1}^S is the number of unemployed who report having been unemployed for less than one month. Solving for F_t ,

$$F_t = 1 - \frac{U_{t+1} - U_{t+1}^S}{U_t}$$

which can be mapped into a Poisson outflow hazard rate

$$f_t = -\log(1 - F_t).$$

The idea behind this calculation is intuitive: individuals who reported being unemployed for less than one month were not in the unemployed pool in the previous month and therefore subtracting them out from this month’s unemployment pool leaves us with the unemployed who failed to exit unemployment between month t and month $t + 1$. Solving the differential equation (2) forward as in Shimer (2012), we can solve for the unemployment inflow rate s_t

$$U_{t+1} = \frac{(1 - e^{-[s_t+f_t]})s_t}{s_t + f_t}L_t + e^{-[s_t+f_t]}U_t.$$

Given the fast transitional dynamics of the unemployment rate in the U.S., as noted by Shimer (2005), Elsby, Michaels, and Solon (2009) and others, the unemployment rate is closely approximated by its flow steady-state value given by

$$\frac{s_t}{s_t + f_t}. \tag{3}$$

It is important to note that we focus on a two-state representation of unemployment where we do not explicitly differentiate between the source of unemployment inflows and destination of unemployment outflows following Shimer (2005, 2012), Hall (2005), Elsby, Michaels, and Solon (2009), Elsby, Hobijn, and Şahin (2010), Davis, Faberman, Haltiwanger, Jarmin, and Miranda (2010) and Şahin, Song, Topa, and Violante (2014). The inflow and outflow rates we use are estimated from CPS time series, rather than the longitudinally matched monthly CPS micro-data. This abstraction simplifies the framework and better connects to the literature on unemployment dynamics. While we maintain the two-state abstraction through Section 5, we explicitly consider the role of the participation margin for women when we examine the drivers of the trends in unemployment flows in Section 6.

3.2 Unemployment Inflows and Outflows

The Current Population Survey (CPS) provide us with monthly measures of stock of unemployment, short-term unemployment and labor force. We calculate monthly unemployment inflow and outflow hazard rates using the methodology described above and plot quarterly averages of monthly s_t and f_t for the 1976:Q1-2018:Q4 period in Figure 1.⁵ Visual examination of inflow and outflow rates confirms the findings of the earlier literature regarding the cyclical properties of these flows. The

⁵Supplemental Appendix B provides details on the data sources used in the paper.

inflow rate is characterized by sharp, short-lived spikes during recessions.⁶ The outflow rate from unemployment is strongly procyclical with persistent downswings during recessions.

Figure 1. Inflow and outflow rates.

This figure shows the unemployment inflow rate (left panel) and outflow rate (right panel) for the sample 1976Q1–2018Q4.

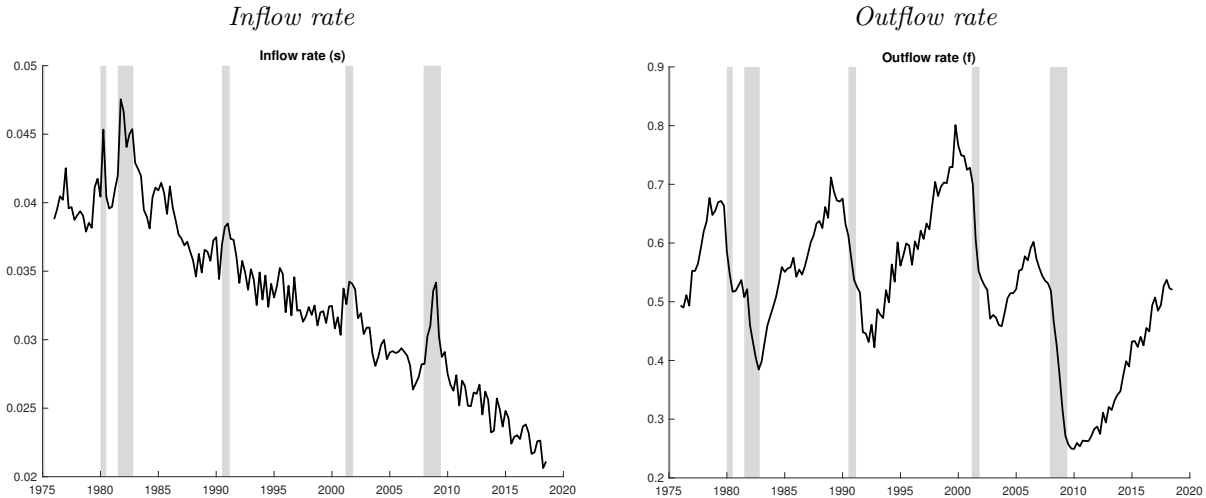


Figure 1 also reveals that these two flows that shape the evolution of the unemployment rate over time exhibit differential long-run trends. The inflow rate has a striking downward trend declining gradually to 0.02, half of its level preceding the twin recessions of the early 1980s. In contrast, there is less evident trending behavior in the outflow rate.

While it is tempting to use traditional filtering techniques to filter out the trends in the inflow and outflow rates, it is well known that the presence of a severe downturn—such as the Great Recession— at the end of the sample is likely to affect the estimate of the underlying trend. Instead we rely on rich cross-sectional variation in the flow rates to assess the extent of the trends. In addition, cross-sectional information allows us to analyze the underlying drivers of the trends in the flow rates.

3.3 Demographics of Unemployment Inflows and Outflows

We start with a visual examination of the flows by gender and age before we move on to our state-space setting to estimate the secular trends. Figure 2 summarizes the changes in the gender and age

⁶As emphasized by Shimer (2005, 2012) and Hall (2005), the response of the inflow rate was relatively muted during the mild recessions in 1990-91 and 2001. However, the inflow rate, without exception, exhibited sharp increases during severe recessions, including the most recent 2007-09 recession as emphasized by Elsbey, Hobijn, and Şahin (2010) and many others.

composition of the labor force from 1976 to 2018. With the rise in the female labor force participation rate, the labor force share of women increased to around 48 percent by 2000 and has stabilized. The age composition shifted from younger workers to prime-age workers as the baby boom cohort entered the labor force and gradually aged, with the share of prime-age workers peaking in the late 1990s. Since 2000, workers aged 55 and older constituted an increasing share of the labor force—this has come about not just because of the aging of the population but also because of the differential trend in labor force participation rates of younger and older workers.

Figure 2. Labor force shares.

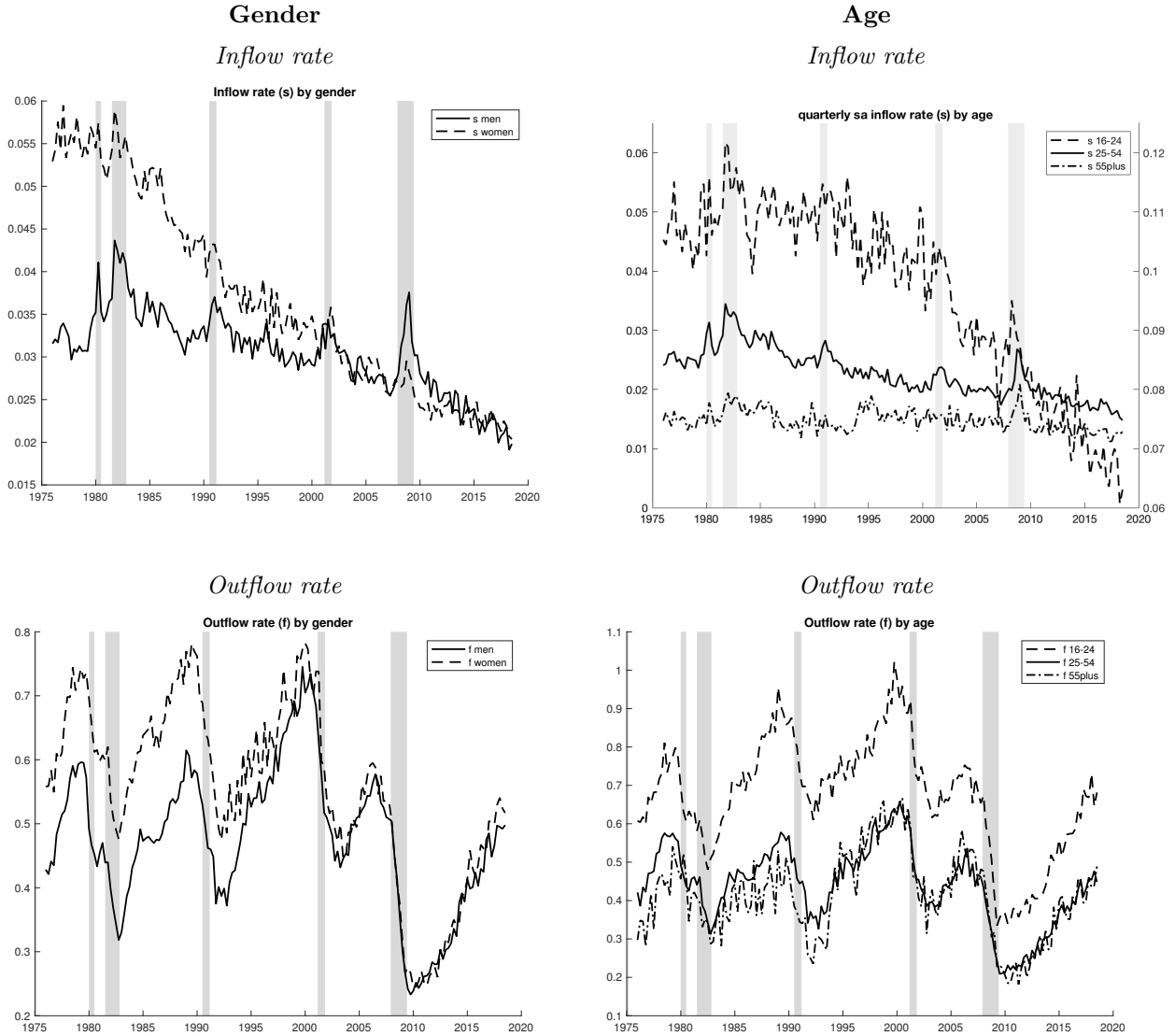
This figure shows the labor force shares by gender (left panel) and age (right panel) for the sample 1976Q1–2018Q4.



The left panels of Figure 3 reveal the drastic convergence of men and women both in terms of their unemployment inflow and outflow rates. A clear implication of this pattern is the disappearance of the gender unemployment gap as discussed in Shimer (1998) and Albanesi and Şahin (2018). While the inflow rate has a downward trend for both male and female workers, the downtrend is more pronounced for female workers in the earlier part of the sample. The right panels of Figure 3 shows the importance of age composition. Workers younger than 25 years old experienced an unemployment inflow hazard that was approximately five fold of those of the prime-age workers in early 1980s. The recent decades shows a partial convergence in their inflow rate as well as a decline in their shares.

Figure 3. Inflow and outflow rates by gender and age.

This figure shows inflow rates (top row) and outflow rates (bottom row) by gender (left panels) and by age (right panels).



3.4 Secular Trends in Unemployment Flows

In this section we estimate the slow-moving trend in the inflow and outflow rates. We build off of [Barnichon and Mesters \(2018\)](#) and cast these trends of job market flows as latent processes in a linear state-space setting (see also [Tasci \(2014\)](#), [Hornstein and Kudlyak \(2019\)](#)). Each flow is described by the following set of equations,

$$s_t^i = \theta_i^s \varphi_t^s + \tau_t^{s,i} + \epsilon_t^{s,i} \quad (4)$$

$$f_t^i = \theta_i^f \varphi_t^f + \tau_t^{f,i} + \epsilon_t^{f,i} \quad (5)$$

for $i = 1, \dots, 6$, our six demographic subgroups and we normalize one element of θ_i^s and θ_i^f to one. The individual flow rates are mapped into the aggregate rates s_t and f_t using a choice of weights giving

$$s_t = \sum_{i=1}^6 \omega_{it}^s s_t^i \quad \text{and} \quad f_t = \sum_{i=1}^6 \omega_{it}^f f_t^i. \quad (6)$$

We use as weights for the inflow rate each group's share in the employment and nonemployment pool since flows into unemployment originate from both employment and out of the labor force.⁷ For the outflow rate we use each group's share in the unemployment pool. The trends in the inflow and outflow rate evolve according to,

$$\tau_t^{s,i} = g_t^{s,i} + \tau_{t-1}^{s,i}, \quad g_t^{s,i} = g_{t-1}^{s,i} + \eta_t^{s,i} \quad (7)$$

$$\tau_t^{f,i} = \tau_{t-1}^{f,i} + \eta_t^{f,i}. \quad (8)$$

We assume that the slow-moving trend for the inflow rate, $\tau_t^{s,i}$, is characterized by an $I(2)$ process, to accommodate the apparent secular trend in these flows. The trend for the outflow rate, $\tau_t^{f,i}$, is instead a random walk. The common component, $\varphi_t \equiv (\varphi_{st}, \varphi_{ft})'$, follows a second-order vector autoregressive process:

$$\varphi_t^f = \phi_{11}\varphi_{t-1}^f + \phi_{12}\varphi_{t-1}^s + \phi_{13}\varphi_{t-2}^f + \phi_{14}\varphi_{t-2}^s + \zeta_t^f \quad (9)$$

$$\varphi_t^s = \phi_{21}\varphi_{t-1}^f + \phi_{22}\varphi_{t-1}^s + \phi_{23}\varphi_{t-2}^f + \phi_{24}\varphi_{t-2}^s + \zeta_t^s. \quad (10)$$

The common cyclical component, φ_t , accommodates joint business-cycle behavior between the inflow rate and outflow rate for each group. This allows us to capture the specific lead-lag relationship around business cycle turning points (see, e.g., [Fujita and Ramey \(2009\)](#), [Elsby, Hobijn, and Şahin \(2013\)](#)). Finally, the flow-specific components are the first-order autoregressive processes

$$\epsilon_t^{s,i} = \psi_i^s \epsilon_{t-1}^{s,i} + \varepsilon_t^{s,i} \quad (11)$$

$$\epsilon_t^{f,i} = \psi_i^f \epsilon_{t-1}^{f,i} + \varepsilon_t^{f,i}, \quad (12)$$

⁷Recall from Section 2 that s is the solution to a non-linear equation and unlike f , it is not linear in group-specific weights. In unreported results, we verify the using employment shares and a more complex weighting scheme that corrects for time aggregation does not alter our main findings. However, small differences can arise between the overall series computed using aggregate data and the series constructed as a weighted average.

representing idiosyncratic, possibly persistent, movements in the individual flow rates. The innovations $(\eta_t^{s,1}, \dots, \eta_t^{s,6}, \eta_t^{f,1}, \dots, \eta_t^{f,6}, \zeta_t^s, \zeta_t^f, \epsilon_t^{s,1}, \dots, \epsilon_t^{s,6}, \epsilon_t^{f,1}, \dots, \epsilon_t^{f,6})'$ are mutually independent, Gaussian random variables. The initial conditions $(\varphi_0, \varphi_{-1}, \epsilon_0^s, \epsilon_0^f)'$ are normally distributed with mean zero and unconditional variance implied by equations (9)–(12). Equations (4)–(6) represent the observation equations in the state-space model, and equations (7)–(12) are the transition equations. The model is estimated using Bayesian methods, utilizing the Gibbs sampler approach proposed in [Del Negro, Giannone, Giannoni, and Tambalotti \(2018\)](#)⁸ (see also [Carter and Kohn \(1994\)](#) and [Kim and Nelson \(1999\)](#)). We estimate the model using quarterly data on labor market flows for the sample 1960Q1 through 2018Q3. We focus on six demographic subgroups: the interaction of three age groups, 16 to 24, 25 to 54, and 55 and over with gender. Since individual flow rates are available only starting in 1976, we use aggregate flows for the remaining sample period, together with the weights, ω_{it}^s and ω_{it}^f , in order to estimate the unobserved trends for the entire sample.

The priors for the coefficients and variances of the VAR(2) common components have standard form

$$p(\text{vec}(\Phi)|\Sigma_\zeta) = \mathcal{N}(0, \Sigma_\zeta \otimes \Omega) \quad \text{and} \quad p(\Sigma_\zeta) = \mathcal{IW}(\kappa_\zeta, \Psi_\zeta), \quad (13)$$

where Φ is the autoregressive matrix corresponding to equations (9) and (10). The priors for the variance-covariance term of the innovations, Σ_ζ , is a fairly diffuse inverse Wishart with just enough degrees of freedom ($\kappa_\zeta = 4$) to have a well defined prior mean for the innovations to the VAR. For simplicity of exposition, in this subsection only, we work with the flow rates multiplied by one hundred. The choice of priors in equation (13) imply standard deviations of 0.45 and 1.4 for the innovations to φ_t^s and φ_t^f and also imply mutual independence of these innovations.

The prior for Φ is a standard Minnesota prior with the hyperparameter for the overall tightness $\lambda = 2$ (which regulates the matrix Ω); this parametrization reflects a relatively loose prior. We implement similar priors for the two first-order autoregressive processes described by equations (11) and (12). The prior on the innovations corresponds to an inverse-gamma with shape and scale parameters implying a diffuse prior consistent with a well defined mean.⁹ The prior mean delivers a standard deviation of 0.45 for innovations to ϵ_t^s and 1 for innovations to ϵ_t^f . The prior on the autocorrelation coefficient is normally distributed with zero mean and variance determined using the

⁸We thank the authors for helpful discussions and for sharing their code.

⁹The distribution has a shape parameter of 1.5 and scale parameters of 0.1 and 1 for ϵ_t^s and ϵ_t^f respectively.

same parametrization with $\lambda = 2$ as in the VAR Minnesota prior. Also in this case, the prior is fairly diffuse. Finally, the priors on the innovations in the trend variables, $\tau_t^{s,i}$ and $\tau_t^{f,i}$, have inverse-gamma distributions. The parameters are chosen to guarantee a well defined mean and deliver a standard deviation at the mean prior of 0.1 for the innovation to the trend in the outflow rate and of 0.01 to the innovation of the inflow rate.¹⁰ The priors on the loadings θ^s and θ^f in equations (4) and (5) are defined as independent normal densities with mean 1 and standard deviation of 0.5. Finally, we should note that in order to assess the role of the choice of priors, we have re-estimated the model with uninformative priors and found broadly similar results.

Figure 4 shows the six inflow rates and their estimated secular trend with associated coverage intervals, for the part of the sample where such flows are observable.¹¹ These trends differ substantially by gender and age group. Females aged 16–24 and 25–54 show a pronounced downward trend starting in the 1980s, halving their level from early in the sample. The trend for males aged 16–24, displays a clear hump-shaped pattern peaking in the first half of the 1990s and then falling by about 30% by the end of the sample. The remaining three groups, prime age males and those older than 55, demonstrate a milder secular trend. However, prime-age males experience a notable decline in the inflow rate over the last decade or so. In contrast to the inflow rates, Figure 5 shows that outflow rates have fairly stable trends with the exception of females aged 25–54. For this latter group, the outflow rate has fallen since the early 1990s. All other groups show little evidence of a secular trend over our sample.

¹⁰The gamma parameters correspond to a shape factor of 1.5 and a scale factor of 0.01 for the outflow rate and of $(0.01)^2$ for the inflow rate.

¹¹Individual flow rates going back to 1960 are estimated with a considerable degree of uncertainty. For this reason, we report below only the aggregate trend for the whole sample.

Figure 4. Inflow rates by gender and age subgroups

This figure shows observed inflow rates (dashed line) along with median estimates of the secular trend ($\tau_t^{s,i}$, solid line) for the inflow rate for each age and gender subgroup. Shading denotes 68% and 95% coverage intervals.

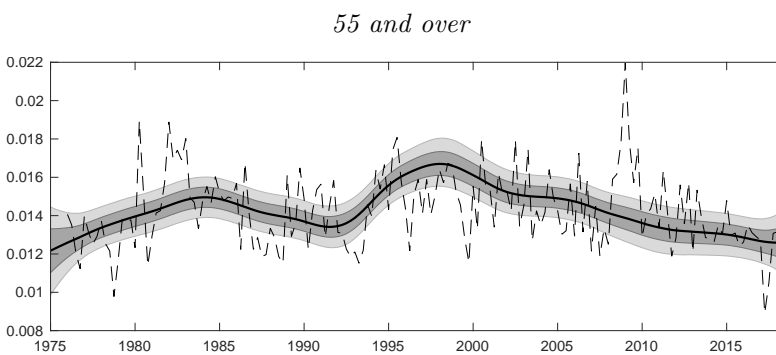
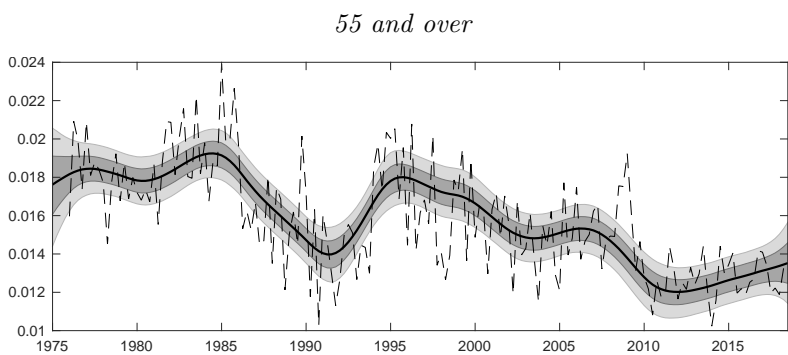
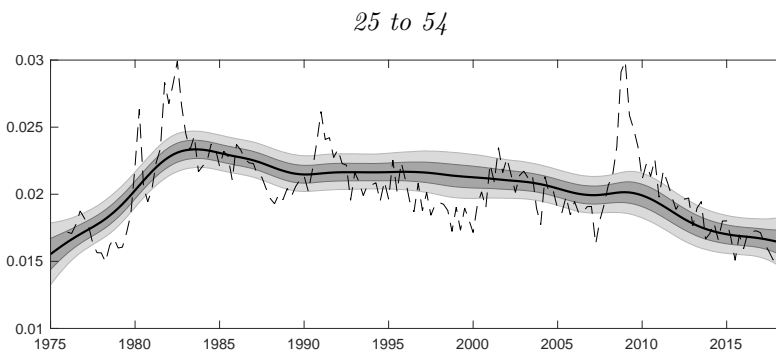
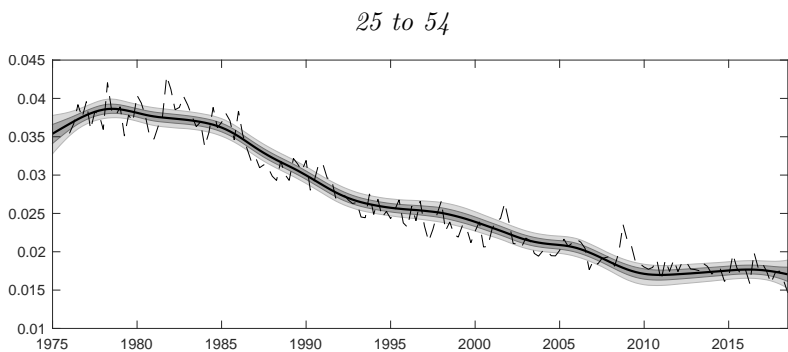
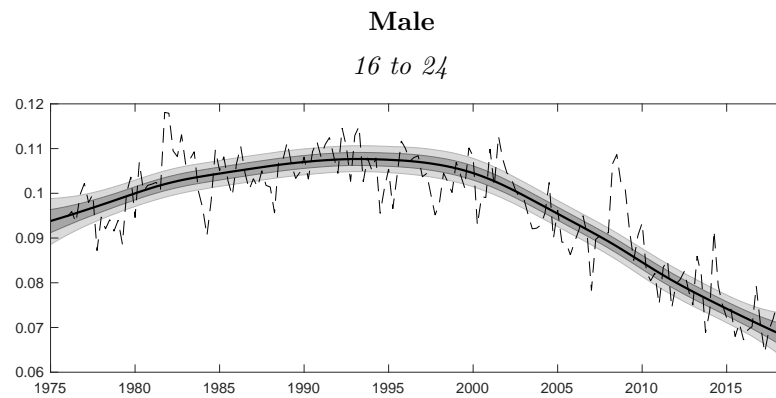
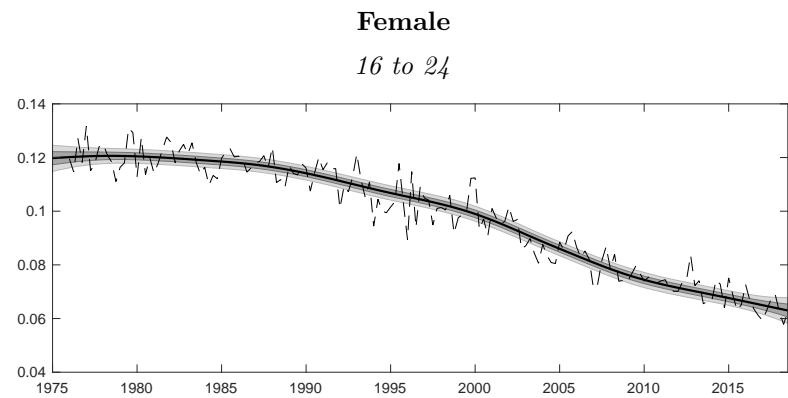
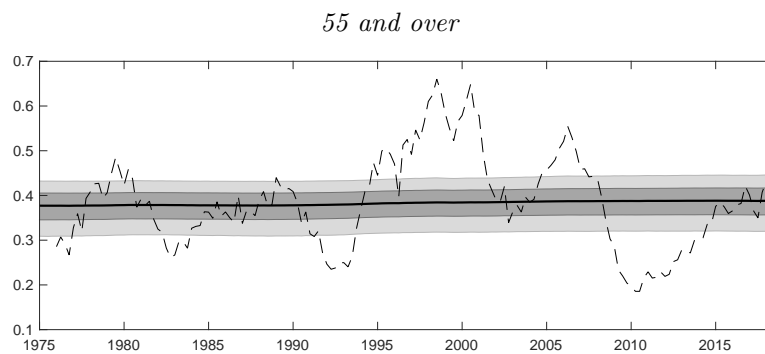
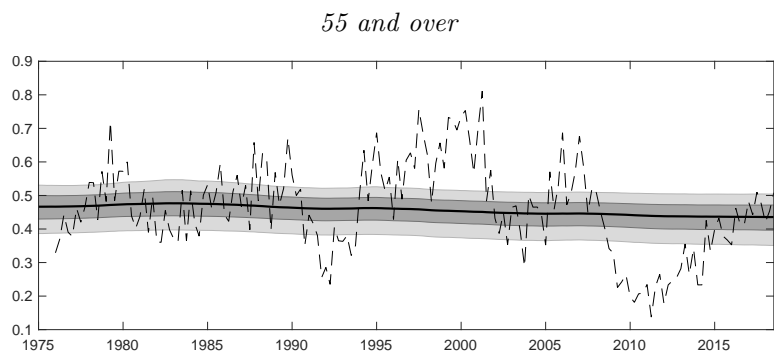
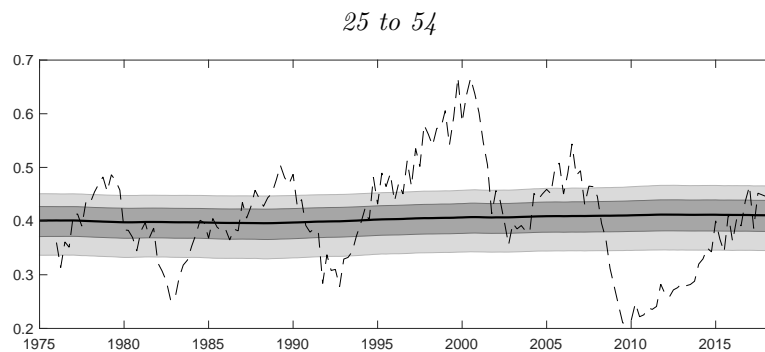
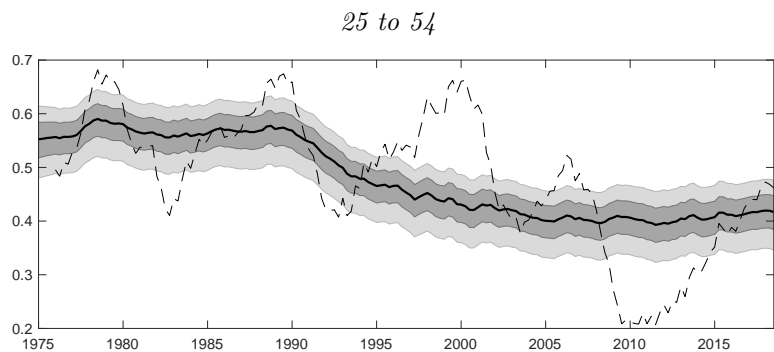
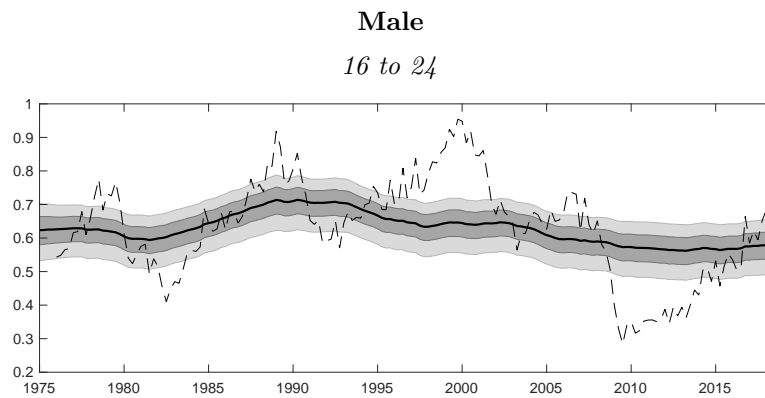
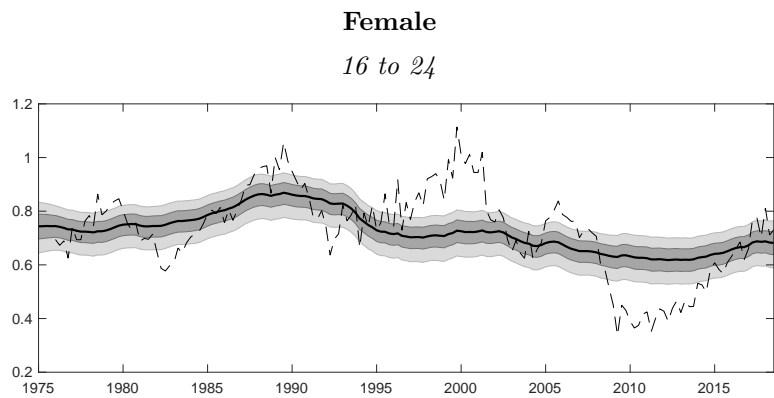


Figure 5. Outflow rates by gender and age subgroups

This figure shows observed outflow rates (dashed line) along with median estimates of the secular trend ($\tau_t^{f,i}$, solid line) for the outflow rate for each age and gender subgroup. Shading denotes 68% and 95% coverage intervals.



3.5 Secular Trend in the Unemployment Rate

We map the individual secular trends for each subgroup using appropriate weights to obtain \bar{s}_t and \bar{f}_t as:

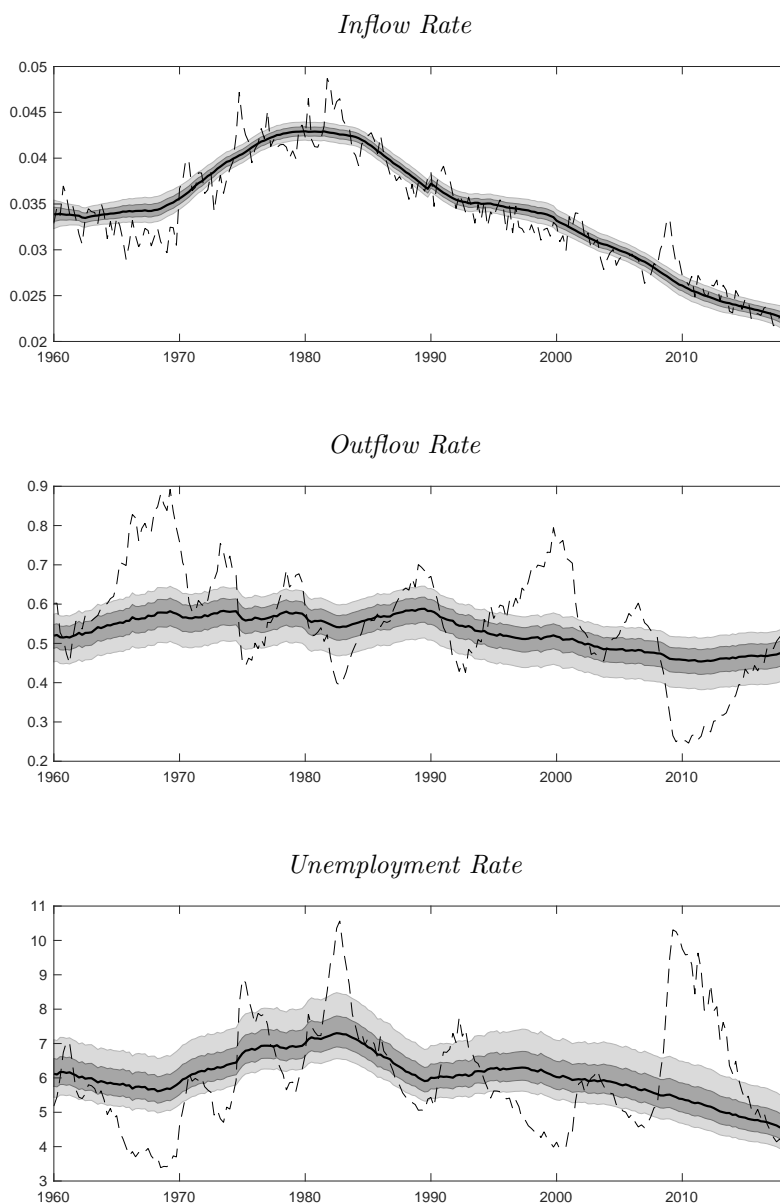
$$\bar{s}_t = \sum_{i=1}^6 \omega_{it}^s \hat{\tau}_t^{s,i}, \quad \bar{f}_t = \sum_{i=1}^6 \omega_{it}^f \hat{\tau}_t^{f,i}. \quad (14)$$

Figure 6 shows the aggregate inflow rate, outflow rate and unemployment rate along with their corresponding estimated secular trends, \bar{s}_t , \bar{f}_t and \bar{u}_t for the whole sample 1960-2018. The secular trend of the inflow rate shows a decline of about 50% since the 1980s. In contrast, the secular trend in the outflow rate is generally stable, but has fallen since the 1990s consistent with the evidence presented in [Davis, Faberman, Haltiwanger, Jarmin, and Miranda \(2010\)](#). Finally, the secular trend in the unemployment rate, \bar{u}_t , can be constructed using \bar{s}_t and \bar{f}_t and the steady-state approximation to the unemployment rate, via

$$\bar{u}_t = \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t}, \quad (15)$$

and is shown in the bottom panel of Figure 6. The trend unemployment rate was about 6% in 1960 and increases to over 7% in 1983. Since then it has displayed a clear downward trend, reaching about 4.5% by the end of the sample. Since the outflow rate shows little trending behavior we observe from equation (15) that the overall downward trend is driven by the numerator, \bar{s}_t . The secular trend in the unemployment rate is estimated with a reasonably high degree of precision; for example, the 68% confidence interval at the end of the sample is comfortably less than one percentage point.

Figure 6. Inflow rate, outflow rate and unemployment rate along with estimated secular trend
 Actual rates denoted by dashed lines, median estimates of secular trend (\bar{s}_t , \bar{f}_t , and \bar{u}_t) denoted by solid black lines. Shading denotes 68% and 95% coverage intervals.



To illuminate interesting features of the trends in labor market flows over the last 60 years we perform a number of counterfactual exercises using the model introduced above. While this analysis is mostly descriptive, in Section 6 we complement this analysis using more detailed micro-data to analyze the economic drivers of these changes.

1. Role of the decline in the outflow rate. As we observed in the previous section, \bar{f}_t shows only a very modest decline in our sample. However, this decline has a non-negligible role in the

behavior of the trend in the unemployment rate. In the top panel of Figure 7 we display two counterfactuals for \bar{u}_t :

- (i) \bar{u}_t when \bar{f}_t is set constant to its sample mean (blue line). We observe that, starting in 1990, we would have observed approximately half a percentage point lower value of \bar{u}_t . This exercise implies that the entirety of the downward trend in \bar{u}_t is driven by the inflow rate decline since it more than offsets the decline in the overall outflow rate.
- (ii) \bar{u}_t when \bar{f}_t^i for $i = 1 \dots, 6$ (red line) are re-estimated under the assumption that they are time invariant. We observe that this alternative tracks our baseline \bar{u}_t closely, suggesting that \bar{f}_t varies primarily through changes in the composition of the unemployed pool.

2. Role of age and gender composition. Section 3 summarized the sweeping demographic changes over the last 60 years that caused substantial shifts in age and gender composition. In this exercise we capture the direct effect of changing composition.

- (i) \bar{u}_t when the weights ω_{it}^s and ω_{it}^f are fixed at their 1976 level (red line). Between 1976 and late 1990s, the change in the shares account for some of the decline. After 2000, the counterfactual series are very close to our baseline \bar{u}_t estimate implying that the majority of the secular decline after 2000 reflects the trends in the group-specific flows rather than changes in the composition.

3. Role of young workers and women. The bulk of the decline in the secular trend of the unemployment rate is accounted for by the group-specific trends of young workers (aged 16-24) and prime age women until 2000. After the late 2000s, the decline is more broad based and goes beyond young workers and women.

- (i) \bar{u}_t when the inflow rate of young and prime age women is held constant at its 1985 level (red line). The secular trend in the unemployment rate would have experienced only a modest decline by 2000, highlighting the importance of women's role in the secular trend. After the late 2000s, the counterfactual series exhibits substantial decline pointing to a more broad base decline.
- (ii) \bar{u}_t when in addition to (i), young male workers also experienced constant inflow rates at their 1985 level (blue line). The secular trend in the unemployment rate would have been approximately constant up until 2010, before declining to slightly above 6.5%.

4. Impact of the Great Recession. Prime-age men and women aged 55 and older are the only two demographic groups who experienced a differential trend in their inflow rate after 2007. We interpret this change as the effect of the Great Recession and carry out a counterfactual exercise to capture its effect.

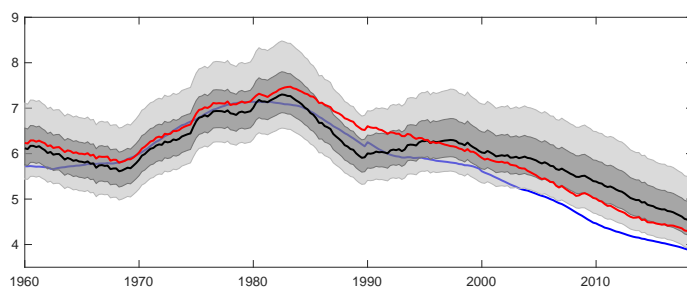
(i) \bar{u}_t when we fix the inflow rate for prime age males and women over 55 at their 2006 level, right before the onset of the Great Recession (red line, graph begins in 2005). The decline in the inflow rate for these subgroups have only a modest effect on the secular trend, accounting for less than 50 basis points at maximal impact. This suggests that the declining trend of the inflow rate is primarily driven by forces in place well before the beginning of the last recession.

This set of counterfactuals illustrates clearly that most of the steady decline in the secular trend of inflow rates is associated with strong declines in the group-specific, trend inflow rate of young workers and prime age women observed since the early 1980s up to the late 2000s. The secular decline in the last two decades or so is more broad based and cuts across demographic groups.

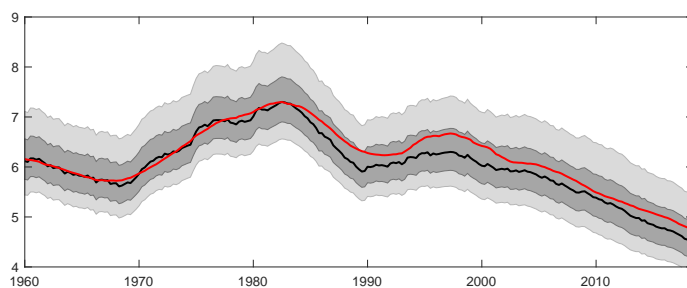
Figure 7. Counterfactual exercises

These figures show the baseline estimate of \bar{u}_t along with different counterfactual series (red or blue lines) based on the described scenarios. Shading denotes 68% and 95% coverage intervals.

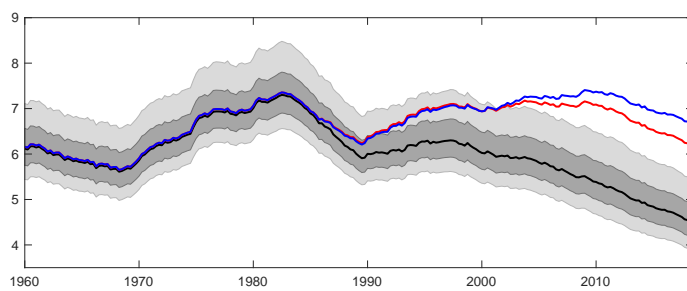
Counterfactual #1



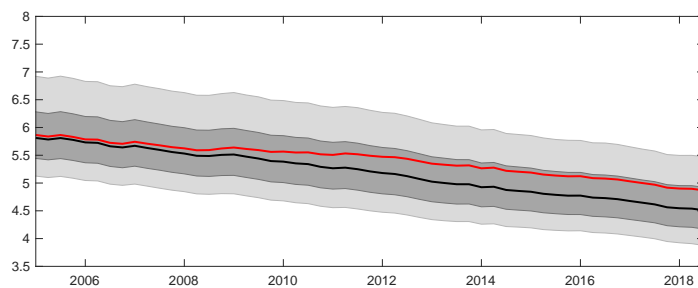
Counterfactual #2



Counterfactual #3



Counterfactual #4



4 A Simple Forward-Looking Phillips Curve

Thus far we have focused on the secular trend in the unemployment rate implied by trends in labor market flows. This is, however, conceptually distinct from the “natural rate of unemployment,” u_t^* , which is defined as the unemployment rate such that, controlling for supply shocks, inflation remains stable. While the New Keynesian model — which has become a popular framework for monetary policy analysis and the core structure in many monetary DSGE models — features a forward-looking Phillips curve, it is silent on u_t^* . Instead of relating inflation to the unemployment gap, it typically relates inflation to the output gap or real marginal costs (Woodford (2003), Galí (2015)). However, Galí (2011) re-introduces the unemployment rate into a New Keynesian model by rewriting the wage inflation equation, albeit with the assumption of a constant natural rate of unemployment. As described next, this motivates our formulation of the New Keynesian Phillips curve that connects inflation, π_t , to the unemployment gap, $u_t - u_t^*$, and retains forward-looking inflation expectations.

4.1 A Stylized New Keynesian Phillips Curve with Unemployment

We motivate our empirical specification of the New Keynesian Phillips curve with a stylized model based on Galí (2011). In this framework unemployment arises as a result of the market power of workers which is reflected in positive wage markups. In particular, we assume a large representative household with a continuum of members specializing in different types of labor services and who experience different levels of disutility from working. Prices are fully flexible but nominal wages are sticky: in each period, workers of a given type get to reset their wages with probability $1 - \theta_w$, similarly to Erceg, Henderson, and Levin (2000) and Calvo (1983).

Monopolistically competitive firms have access to a linear production function and produce using labor as the only input. Optimizing firms equate their marginal revenue and marginal costs:

$$a_t = w_t - p_t \tag{16}$$

where the exogenous process a_t is the combination of (log) productivity and mark-up shocks to firms, w_t denotes the log nominal wage, and p_t is the log of the good’s price. Given the wage, firms choose the quantity of workers employed, and the household assigns the workers with the lowest disutility of working. Since labor supply is elastic along the extensive margin, higher wage markups result in higher participation and therefore higher unemployment in the economy.

When they get to reset their wages, workers choose new wages that are a markup $\mu_{w,t}$ over a weighted average of current and expected future price-adjusted marginal rates of substitution. This results in a log-linearized wage Phillips curve of the form

$$\pi_t^w = -\kappa_w (\mu_{w,t} - \mu_{w,t}^*) + \beta E_t \pi_{t+1}^w \quad (17)$$

where $\kappa_w = (1 - \theta_w)(1 - \beta\theta_w) / (\theta_w((1 + \varphi\epsilon_w))) > 0$, φ is the steady-state labor supply elasticity, $-\epsilon_w$ is the steady-state elasticity of demand for labor of different types, $\pi_t^w = w_t - w_{t-1}$ denotes nominal wage inflation, $\mu_{w,t}$ is the cross-sectional average wage markup over the economy's average marginal rate of substitution, and $\mu_{w,t}^*$ is an exogenous process capturing both the time variation in the markup in the labor market, which in turn depends on the firms' elasticity of demand for labor of different types, as well as that of the labor supply elasticity. Iterating equation (17) forward, we obtain

$$\pi_t^w = -\kappa_w (\mu_{w,t} - \mu_{w,t}^*) - \kappa_w E_t \sum_{T=t}^{\infty} \beta^{T-t} (\mu_{w,T+1} - \mu_{w,T+1}^*) \quad (18)$$

When average wage markups are below their desired level, workers who reset their wage will adjust it upward, resulting in positive wage inflation. Equation (18) reveals the central feature of the New-Keynesian Phillips curve. The current gap is only one driver of inflation, and it might be a small contributor in the empirically relevant case if the slope of the curve, κ_w , is relatively flat. However, the discounted expected future path of the gap is a determinant of inflation as well. For a given level of the current gap, shifts in expectations have important implications for wage inflation—an insight lacking in the traditional backward-looking Phillips curve. The implication is then that it is important to take into account expectations when analyzing the relation between wage inflation and the markup gap.

Workers participate in the labor market only if their real wage is above their disutility from working, Galí (2011) shows that this implies that the unemployment gap is proportional to the markup gap so that wage inflation can be expressed as

$$\pi_t^w = -\kappa x_t + \beta E_t \pi_{t+1}^w \quad (19)$$

where $\kappa = \kappa_w \varphi > 0$, and x_t denotes the unemployment gap; here, the natural rate of unemployment (in deviation from its trend), defined as $z_t = u_t^* - \bar{u}_t = \varphi^{-1} \mu_{w,t}^*$, captures, in turn, time variation in

the firms elasticity of demand for different types of labor, as well as in the labor supply elasticity. Finally, using the identity relationship between price and wage inflation, we have

$$\pi_t^w = \pi_t + (w_t - p_t) - (w_{t-1} - p_{t-1}) = \pi_t + \Delta a_t \quad (20)$$

where for the last equality, we use the firms' profit maximizing condition (16). Using that expression to replace wage inflation in the wage Phillips curve, we obtain the price inflation New Keynesian Phillips curve expressed in terms of the unemployment gap:

$$\pi_t = -\kappa x_t + \beta E_t \pi_{t+1} + \beta E_t (\Delta a_{t+1} - \Delta a_t) \quad (21)$$

where $\kappa > 0$, the last component is an exogenous term measuring expected wage growth, which depends on productivity and price markup shocks.

4.2 Empirical Model

The model just described can be generalized in a variety of ways. In particular, we allow wages that are not optimally reset to be indexed to a combination of lagged inflation and the inflation target to better capture features of the data. Assuming rational expectations, the Phillips curve we consider in our empirical model thus takes the form,

$$\pi_t - \pi_t^* = \gamma(\pi_{t-1} - \pi_{t-1}^*) - \gamma\sigma_{\pi^*}\epsilon_t^{\pi^*} - \kappa E_t \sum_{T=t}^{\infty} \beta^{T-t} x_T - \beta \frac{1 - \rho_a}{1 - \beta\rho_a} \Delta a_t. \quad (22)$$

Here, π_t is determined by five core components: (i) π_t^* represents the drift in long-term inflation expectations and therefore the degree of anchoring and is assumed to evolve as

$$\pi_t^* = \pi_{t-1}^* + \sigma_{\pi^*}\epsilon_t^{\pi^*}; \quad (23)$$

(ii) π_{t-1} captures inertia in the inflation process; (iii) $x_t = u_t - u_t^*$ denotes the current unemployment gap which evolves as

$$x_t = a_{x,1}x_{t-1} + a_{x,2}x_{t-2} + \sigma_x\epsilon_t^x; \quad (24)$$

Here we adopt the common assumption of an exogenous data generating process for the unemployment gap (i.e., Laubach (2001), Galí (2011)). (iv) the discounted expectation of future unemployment

gaps discounted at the rate β ; (v) the shock Δa_t , which we assume evolves as:

$$\Delta a_t = \rho_a \Delta a_{t-1} + \sigma_a \epsilon_t^a. \quad (25)$$

In terms of the structural model described above, this shock corresponds to real wage growth. Given the evolution of the unemployment gap we can then rewrite equation (22) as,

$$\pi_t - \pi_t^* = \gamma(\pi_{t-1} - \pi_{t-1}^*) - \gamma\sigma_{\pi^*}\epsilon_t^{\pi^*} - \kappa w_{\pi,1}x_t - \kappa w_{\pi,2}x_{t-1} + \varsigma_t, \quad (26)$$

where $\varsigma_t = -\beta \frac{1-\rho_a}{1-\beta\rho_a} \Delta a_t$; $w_{\pi,1} = (1 - \beta(a_{x,1} + \beta a_{x,2}))^{-1}$ and $w_{\pi,2} = \beta a_{x,2} \cdot w_{\pi,1}$. As a result, observed inflation is measured as

$$\Pi_t = (\pi_t - \pi_t^*) + \pi_t^*, \quad (27)$$

and inflation expectations at different horizons j can be written as,

$$\mathbb{E}_t \Pi_{t+j} = \pi_t^* + \ell'_\pi F^j X_t \quad (28)$$

where $X_t = (\pi_t - \pi_t^*, x_t, x_{t-1}, \varsigma_t)'$, $\ell_\pi = (1, 0, 0, 0)'$ and $F = F(a_{x,1}, a_{x,2}, \gamma, \rho_\varsigma)$ is determined by equations (24)–(26).

The unemployment rate, u_t , may be expressed in terms of

$$u_t = x_t + z_t + \bar{u}_t \quad (29)$$

with $z_t = u_t^* - \bar{u}_t$, the deviation of the natural rate of unemployment from its secular trend, which follows:

$$z_t = \rho_z z_{t-1} + \sigma_{z,\varsigma} \sigma_\varsigma \epsilon_t^z \quad (30)$$

This specification allows for persistent deviations of u_t^* from the secular trend, but imposes that over the longer run, these deviations shrink toward zero.

The model can be cast in state-space form. Equations (23)–(26) together with equation (30) represent the transition equations in the state-space model, and equations (27)–(29) are the observation equations. We estimate the model over the sample 1960:Q1–2018:Q3 using quarterly data. Our observed measure of u_t is the civilian unemployment rate from the Bureau of Labor Statistics (BLS). Inflation is measured as core CPI inflation in quarterly annualized percent changes also available from

the BLS. We obtain a range of inflation expectations from different surveys of professional forecasters. For short-term inflation expectations we combine six-month ahead expectations, averaged across forecasters, from the Livingston survey (available at semi-annual frequency through our sample) and the Survey of Professional Forecasters (SPF, available since 1981Q3). For long-term inflation expectations we combine five-to-ten year ahead forecasts from Blue Chip Economic Indicators, Blue Chip Financial Forecasts and the SPF. For the years 1975–1977 we also use five-to-ten year ahead inflation expectations from the University of Michigan Consumer Sentiment survey (see Supplemental Appendix B for additional details about each series). Using equation (28), model-consistent six-month ahead inflation expectations are given by

$$\pi_t^* + (1/2)\ell'_\pi \sum_{j=1}^2 F^j X_t, \quad (31)$$

while five-to-ten year ahead expectations can be expressed as

$$\pi_t^* + (1/20)\ell'_\pi (1 - F)^{-1} (1 - F^{20}) F^{20} X_t. \quad (32)$$

We include independent measurement error for both short-term and long-term forecasts with standard deviation parameters σ_{12Q} and σ_{510Y} . All parameters are estimated using Bayesian methods with the exception of the discount rate β . This parameter is set to $\beta = 0.99$, a value commonly used in the literature. We split the parameters in two vectors; $\Theta^1 = (\gamma, \kappa, a_{x,1}, a_{x,2}, \rho_\zeta, \rho_z, \sigma_{z,\zeta})'$ and $\Theta^2 = (\sigma_x^2, \sigma_\zeta^2, \sigma_{\pi^*}^2, \sigma_{12Q}^2, \sigma_{510Y}^2)'$. Conditional on observing \bar{u}_t , this linear model can be estimated using the Gibbs sampler. In the first step the Metropolis Hastings algorithm is used to draw parameters from Θ^1 for which we do not know the posterior distribution (this is due to the fact that the matrices F^j are a nonlinear functions of the underlying model parameters). In the second step, the Kalman smoother is used to draw the unobserved states, including initial conditions. In the third step, conditional on the drawn unobserved states, parameters from Θ^2 are drawn using known posterior distributions.¹² Because we observe a full distribution of paths of \bar{u}_t , we have to add an additional step in the estimation to account for this uncertainty. We first draw a path for $\bar{u}_{1:T}$, obtained from the estimation in Section 3, and conditional on this draw we then proceed with the Gibbs sampler as described. We repeat this estimation procedure for a number of \bar{u}_t paths selected at random.¹³

¹²The estimation method follows quite closely [Del Negro, Giannone, Giannoni, and Tambalotti \(2018\)](#) which provides full details.

¹³In more detail, we draw 250 paths from the distribution of \bar{u}_t . For each of these draws, we run a chain of 10,000

This approach is motivated by the assumption, discussed in Section 3, that the unemployment trend \bar{u}_t is exogenous to the variables in the Phillips curve model.

4.3 Adding Information from Wages

Although Section 4.1, characterizes a simple wage Phillips curve, the discussion so far has not characterized the information available from observed wages. The importance of wages for assessing the unemployment gap has been emphasized by, for example, Solow (1964), Blanchard and Diamond (1989), or Galí (2011). Here we consider a second specification including *both* price and wage inflation. The goal here is to evaluate the impact of this additional information on our estimates of the natural rate of unemployment. Given that wages are measured with a considerable degree of noise we extract information from five alternative data sources.¹⁴ From the Employment Cost Index (ECI) release, we use growth in wages and salaries for private industry workers along with growth in total compensation for all civilian workers (both starting in 2001Q1). From the Establishment Survey, as part of the Employment Situation release, we use growth in average hourly earnings of all private sector employees and growth in average hourly earnings of production and nonsupervisory employees (starting in 2006Q1 and 1964Q1, respectively). From the Productivity & Costs release, we use growth in compensation per hour of the nonfarm business sector (starting in 1947Q1). All data are available from the BLS and growth rates are expressed at a quarterly, annualized rate.

The relation between wage and price inflation implied by the model in equation (20) implies

$$\pi_t^w = g_w + \pi_t^* + \gamma(\pi_{t-1} - \pi_{t-1}^*) - \gamma\sigma_{\pi^*}\epsilon_t^{\pi^*} - \kappa w_{\pi,1}x_t - \kappa w_{\pi,2}x_{t-1} - \frac{\beta^{-1} - 1}{1 - \rho_a}\varsigma_t, \quad (33)$$

where π_t^w denotes nominal wage growth and g_w is the (constant) mean growth rate of real wages. This can be used to obtain the following additional measurement equations to the model,

$$\Pi_t^{w,(j)} = \Theta^{(j)}\pi_t^w + \xi_t^{(j)},$$

where $j = 1, \dots, 5$ denote the individual nominal wage growth measures introduced above and where $\xi_t^{(j)}$ are first-order autoregressive measurement errors with autocorrelation coefficient $\rho_{\xi,(j)}$ and innovation standard deviation $\sigma_{\pi_w,(j)}$. We normalize the first loading coefficient $\Theta^{(1)} = 1$ and then

draws of the model parameters and states with the Gibbs sampler. Importantly, each parameters' chain is initialized by looking for a set of parameters close to the mode. We then randomly select 250,000 draws that we use to compute the joint distribution of parameters and states.

¹⁴We thank our discussant, Steve Davis, for this suggestion.

estimate the remaining loadings $(\Theta^{(2)}, \dots, \Theta^{(5)})$ along with $(g_w, \rho_{\xi,(1)}, \dots, \rho_{\xi,(5)}, \sigma_{\pi_w,(1)}, \dots, \sigma_{\pi_w,(5)})$. We view this as a particularly compelling exercise, given the relative stability of the wage Phillips curve over the sample, as shown in Galí (2011). In fact, the equation above is of a similar form as the one estimated in Galí (2011) with a few key differences. Our specification includes an inflation trend, π_t^* , and, importantly, the original specification assumes a constant level of the natural rate of unemployment which we eschew. We estimate this equation jointly with the rest of the model described in Section 4.2.

Table 1 shows the assumptions on the priors along with the properties of the posterior distribution for both model specifications. Notice first that the priors for the innovations' variance report only the mean, as the standard deviation is not defined; for these priors we use an Inverse-Gamma distribution with shape parameter of 1.5, enough to have a well defined mean. Second, the posterior distribution of the parameters for the two model specifications are broadly similar, with a few small differences discussed below. The process for the unemployment gap shows a high degree of persistence, consistent with medium-frequency business cycle movements in the unemployment rate. Regarding the Phillips curve, the slope is precisely estimated and in the range 0.02-0.04 across specifications, and it implies a fairly flat curve, as often found in the literature (e.g., Del Negro, Giannoni, and Schorfheide (2015)). The addition of wages as an observable delivers a slightly steeper slope, but it does not alter fundamentally the estimated link between the current gap and inflation. The Phillips curve does not display significant inflation inertia, given the estimate of γ in the range 0-0.2. The process for z_t is estimated to be highly persistent consistent with prolonged deviations of u_t^* from the secular trend of unemployment. The signal-to-noise ratio, $\sigma^{z,s}$ is tightly estimated in the a range of 0.12-0.15. Also in this case, the introduction of wage inflation implies a somewhat more volatile natural rate of unemployment, as we discuss in the next section. Finally, the measurement errors on the survey-based measures of expectations are estimated to have small variances allowing a tight mapping from observed expectations to the unobserved unemployment gap.

Priors for the five first-order autoregressive measurement errors (not shown in the table) in the wage equation are as follows. The prior on the innovations corresponds to an inverse-gamma with shape and scale parameters implying a diffuse prior consistent with a well defined mean of 1. The prior on the autocorrelation coefficient is normally distributed with zero mean and variance determined using the same parametrization with $\lambda = 0.1$ as in the VAR Minnesota prior. The priors are fairly diffuse. Finally, the priors on the loadings $\Theta^{(2)} \dots \Theta^{(5)}$ (also not shown in the table) are defined as

independent normal densities with mean 1 and standard deviation of 0.5.

Table 1. Parameter estimates

	Prior			Posterior (Inflation only)			Posterior (Infl. & Wage Infl.)		
	Dist.	Mean	Std	Mean	5%	95%	Mean	5%	95%
$a_{x,1}$	Gamma	1.25	0.200	1.59	1.50	1.68	1.53	1.45	1.61
$a_{x,2}$	Normal	0.000	1.00	-0.618	-0.703	-0.529	-0.568	-0.639	-0.491
θ_w	Beta	0.750	0.100	0.879	0.847	0.906	0.852	0.820	0.878
κ	–	0.113	0.114	0.019	0.011	0.031	0.028	0.018	0.041
γ	Beta	0.500	0.265	0.049	0.004	0.196	0.025	0.003	0.060
ρ_{u^*}	Beta	0.950	0.035	0.982	0.961	0.994	0.980	0.962	0.992
ρ_α	Beta	0.500	0.200	0.366	0.204	0.449	0.350	0.279	0.411
σ_x^2	InvGamma	0.12	–	0.043	0.032	0.054	0.043	0.032	0.055
σ_ζ^2	InvGamma	1.00	–	1.44	1.23	1.68	1.34	1.13	1.56
$\sigma_{\pi^*}^2$	InvGamma	0.12	–	0.067	0.053	0.083	0.069	0.054	0.087
$\sigma_{z,\zeta}$	InvGamma	0.150	0.050	0.103	0.077	0.132	0.120	0.090	0.152
$\sigma_{o,\pi^{510Y}}^2$	InvGamma	0.005	–	0.003	0.001	0.007	0.004	0.001	0.010
$\sigma_{o,\pi^{12Q}}^2$	InvGamma	0.500	–	0.153	0.122	0.188	0.165	0.128	0.208
g_w	Normal	0.4	0.05	–	–	–	0.439	0.363	0.521

Note: κ is calculated assuming $\kappa = (1 - \theta_w)(1 - \beta\theta_w)/\theta_w$.

Before moving on to the main empirical results, it is useful to consider a simplified version of the model to make concrete the appropriate interpretation of κ , the slope of the Phillips curve, in this forward-looking model. As mentioned above, the estimated slope is fairly small; however, this does not necessarily imply a weak link between the unemployment gap and inflation. For example, consider a simpler model where the unemployment gap, x_t , is an AR(1) process (i.e., $a_{x,2} = 0$) and set $\gamma = 0$. Then, solving forward for expectations, delivers the following relation between inflation and the contemporaneous unemployment gap,

$$\pi_t - \pi_t^* = -\frac{\kappa}{1 - a_{x,1}\beta}x_t + \zeta_t.$$

Given that $\beta = 0.99$ and we would expect a reasonably high degree of persistence in the unemployment gap so that $a_{x,1}$ is near one, then the coefficient relating actual inflation (in deviation from trend) and the unemployment gap would be much larger than κ . The same intuition applies to the more general model introduced in this section.

5 Measuring u_t^*

We estimate u_t^* since 1960 and show its evolution in the two panels of Figure 8. The top panel refers to the model using price inflation only, and the bottom panel shows the results where both prices and wages are used. Both model specifications yield comparable predictions in general with some differences highlighted below. Overall, the natural rate of unemployment is estimated quite precisely with a 95% coverage interval of about 2 percentage points in the model using price inflation only, and even narrower bands when wage information is added. When discussing ranges of the possible values of u_t^* at any particular point in time we will be referring to the 68% interval. In the first decade of the sample the natural rate hovers slightly below 6% and starts rising in the early 1970s and reaching comfortably above 7% by the late 1970s before falling to about 7% in 1983. The increase in the natural rate was the subject of a heated debate during the 1970s. Going back to earlier papers such as [Hall \(1970b,a\)](#), [Gordon \(1972, 1982\)](#), [Perry \(1978\)](#), or [Tobin \(1974\)](#), there appears to have been a consensus that the natural rate of unemployment increased to somewhere between 5.0% to as high as 7.0%. Interestingly these insightful analyses did not get much traction in policy circles and the Humphrey-Hawkins Full Employment and Balanced Growth Act of 1978 set an unemployment target of 4 percent for 1983. Subsequent research devoted substantial effort in trying to understand this period. For example, [Summers \(1986\)](#) states that *where Kennedy-Johnson economists set 4 percent as an interim full-employment target, contemporary policymakers would regard even the temporary achievement of 6 percent unemployment as a great success*. The natural rate then declines throughout the 1980s, consistently below the (median) secular trend of the unemployment rate (red solid line). More recent analysis of [Ball and Mankiw \(2002\)](#), estimated the natural rate to be around 5.4% in 1960 and rising to 6.8% in 1979 and to 4.9% in 2000. [Staiger, Stock, and Watson \(1997\)](#) also have similar estimates.

One of the key differences between the top and bottom panels concerns the behavior of the natural unemployment rates during the 1970s. While the model with prices only estimates the natural rate to increase along with the secular trend of unemployment, the richer specification including wages estimates a further increase in the natural rate. One possible explanation for this discrepancy is the wage-price controls implemented in the early 1970s and their relative effects on wage growth and price inflation. As shown in the top-panel of Figure 10, while inflation dips in the early 1970s, wage inflation remains robust, signaling a strongly negative unemployment gap. The Nixon administration imposed wage and price controls in August 1971 that lasted until April 1974. The program went

through four phases. The first two phases were more strict and accomplished only a slight reduction in wage growth but a marked decline in the rise in prices between 1971:3 and 1972:2.¹⁵ Phase II (which lasted until January 11, 1973) was followed by phases III and IV, but controls were generally relaxed in the last phases. Inflation started picking up in late 1972 while wage growth moderated. By the time wage-price controls were dismantled in April 1974, U.S inflation had reached double digits. In fact, both panels in Figure 9 show that, regardless of model specification, a substantial negative unemployment gap remains until the early 1980s.

The time period spanning the 1990s to the Great Recession is characterized by a fairly stable natural rate of unemployment, which remains rangebound between 4.5% and 5.5%. During this period, the median u_t^* remains consistently below its secular trend. To speculate, some of this decline might be due to the rapid growth of technological progress during that period.¹⁶ As shown in Figure 9, the unemployment gap had been consistently positive through the 1980s, around the deep monetary contractions of the Volcker disinflation period. It turned negative briefly in the late 1990s, but this dip is preceded and followed by the 1990-1991 and 2001 recessions.

Finally, during the pre-recession years 2005-2006 the natural rate of unemployment begins increasing towards its long-run trend. This period presents the second important difference between the two model specifications. Including both prices and wages in the estimation leads to a higher estimate of u_t^* which ends up overshooting its long-run trend, with its median estimate peaking in 2009-10 just under 6.0%. Conversely, the model specification employing only price inflation predicts a milder increase (with a median which peaks at 5.3%).¹⁷ The different estimates reflects a pick-up in wage growth in the period 2005-6, which we do not see in the measure of price inflation. Section 5.2 discusses the possible driving forces behind this increase. In the aftermath of the Great Recession the natural rate of unemployment gradually declines roughly in line with its secular trend. This finding implies that the fear of hysteresis following the Great Recession did not materialize as we discuss in the next section. Both model specifications deliver estimates of the natural rate toward the end of 2018 in the range of 3.4% to 4.5%, consistent with the current unemployment gap around zero.

¹⁵Gordon (1972, 1973).

¹⁶As then Chairman of the Federal Reserve Alan Greenspan said in a speech in 1998 on the New Economy: “Coupled with the quickened pace of productivity growth, wage and benefit moderation has kept growth in unit labor costs subdued in the current expansion. This has both damped inflation and allowed profit margins to reach high levels.” (Greenspan (1998))

¹⁷This is in line with the estimates of Daly, Hobijn, Şahin, and Valletta (2012) who estimated the natural rate to be between 5.5% and 6.6% with a preferred estimate at 6% at the end of 2011.

Importantly, as shown in Figures 9 and 10, the estimated Phillips curve is consistent with periods of large slack in the labor market and relatively stable inflation. This is perfectly illustrated by the Great Recession, which displays the largest unemployment gap in the sample, at around 4 percentage points, while price inflation declined only modestly. Indeed, while core CPI inflation was averaging 2.3% from 2005 to 2007, it declined to 1.4% on average in from 2009 to 2011. Most important for the stability of inflation is the fact that inflation expectations declined only modestly during and after the Great Recession, as shown in Figure 10. As indicated in our Phillips curve, equation (22), inflation expectations reflect the expected path of future unemployment gaps, and so the near-stability of inflation expectations in the aftermath of the Great Recession suggests that the unemployment gap was expected to close. This is consistent with the attenuated response of inflation to the large unemployment gap.

Our analysis of the Great Recession, through the lens of our estimation results, does not, however, imply that inflation is necessarily insensitive to the unemployment gap. In fact, we see that a somewhat smaller rise in the unemployment gap in the early 1980s caused a much more significant drop in inflation, with average core CPI inflation falling from 10.9% in the 1979-81 period to 4.4% in 1983-84. The key determinant is the behavior of inflation expectations, which dropped much more sharply in the early 1980s than was the case following the Great Recession. Comparison of the early 1980s with the Great Recession period stresses the importance of accounting for inflation expectations in explaining the behavior of inflation and the unemployment gap, and hence to estimate u_t^* .

The middle panel of Figure 10 shows the model-implied predictive distributions (grey shaded area) for the one-year ahead inflation forecast together with measured expectations from professional forecasters (red dots). It is worth pointing out that as inflation and inflation expectations have been reverting to their long-term trend (see bottom panel), the unemployment gap has been steadily closing. The middle panel also shows that alternative measures of one-year ahead expectations display a roughly similar pattern as those of professional forecasters. For example, measures of inflation expectations extracted from asset prices (cyan and green lines) are broadly in-line. The median of households' expectations from the Michigan survey (blue dots) behave differently since the early 2000s, predicting considerably higher inflation. Coibion and Gorodnichenko (2015) show how the difference between household and professional forecasters over this period can be explained by oil prices. This difference, however, shrinks significantly when one looks at the long-term inflation

expectations, shown in the bottom panel. These measures are of particular importance as they show the degree of anchoring of inflation expectations. As can be gleaned from the figure, all measures display a stable pattern after 1998 albeit at different levels, providing additional evidence to why the large unemployment gaps over these years were not associated with deflation.

Figure 8. The natural rate of unemployment, u_t^*

This plot shows the estimate of u_t^* for the inflation-only specification (top panel) and the inflation & wage inflation specification (bottom panel). The red dashed line denotes the median \bar{u}_t . Shading denotes 68% and 95% coverage intervals.

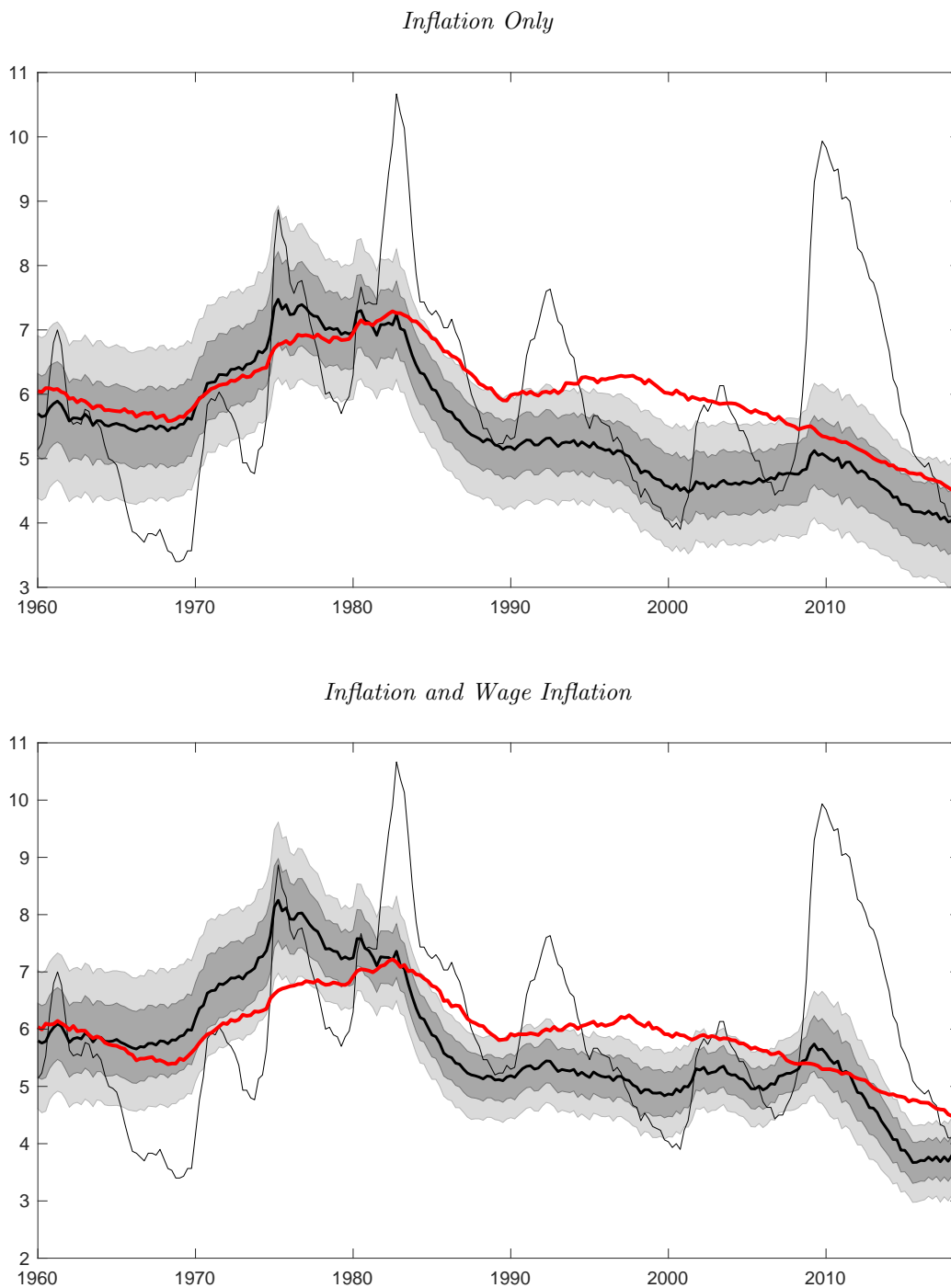


Figure 9. Unemployment gap

This plot shows the estimated unemployment gap, $u_t - u_t^*$, for the inflation-only specification (top panel) and the inflation & wage inflation specification (bottom panel). Shading denotes 68% and 95% coverage intervals.

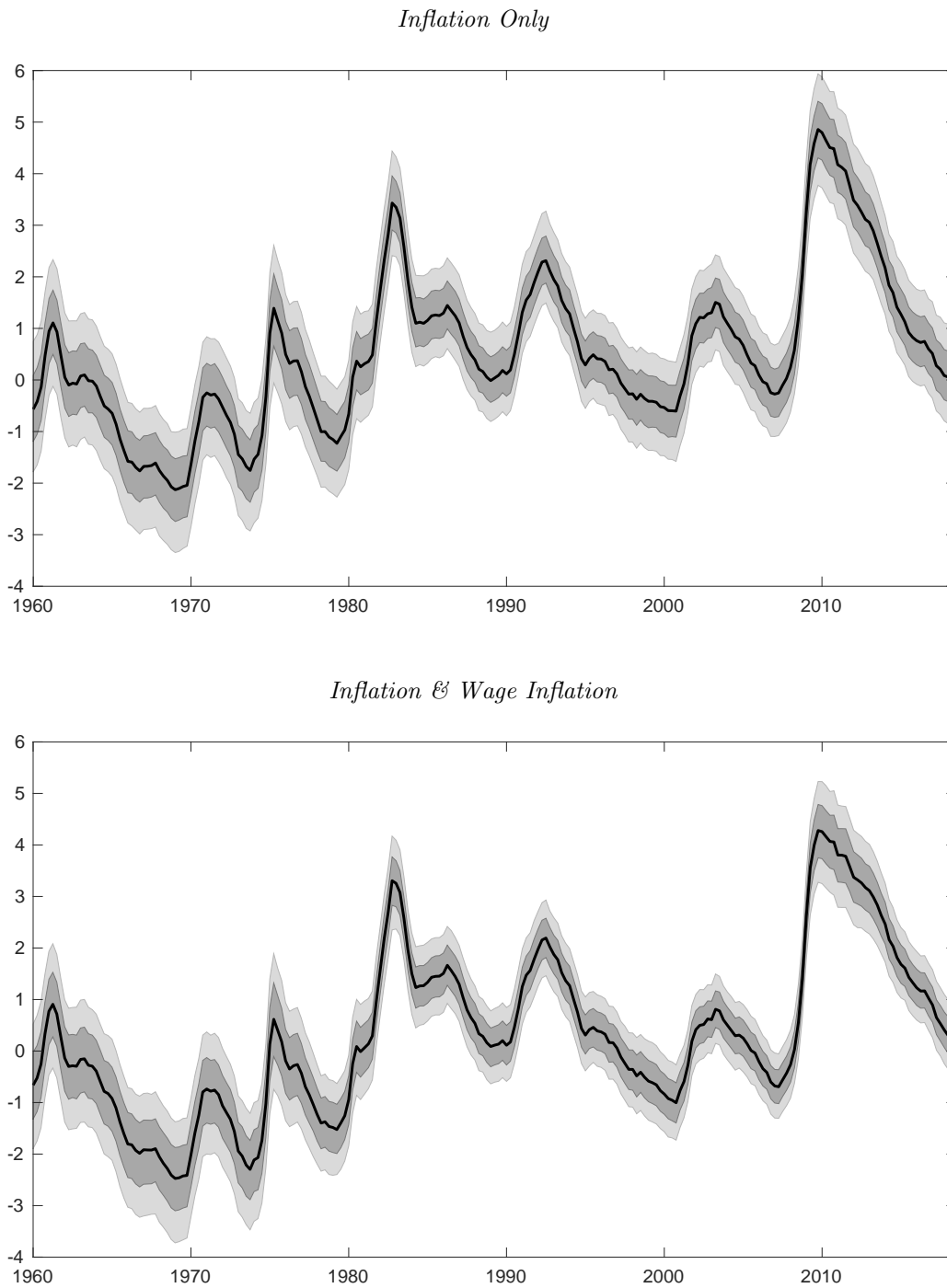
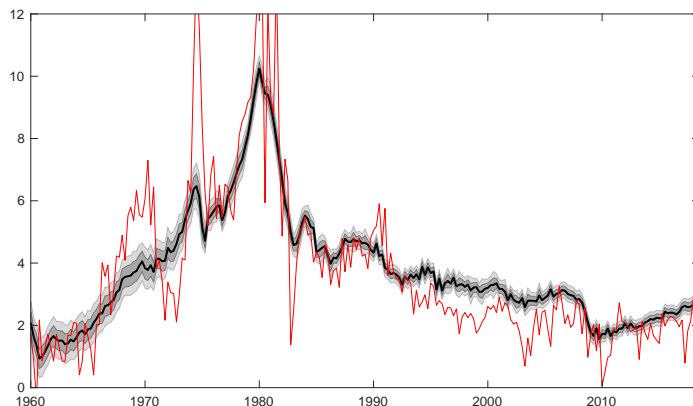


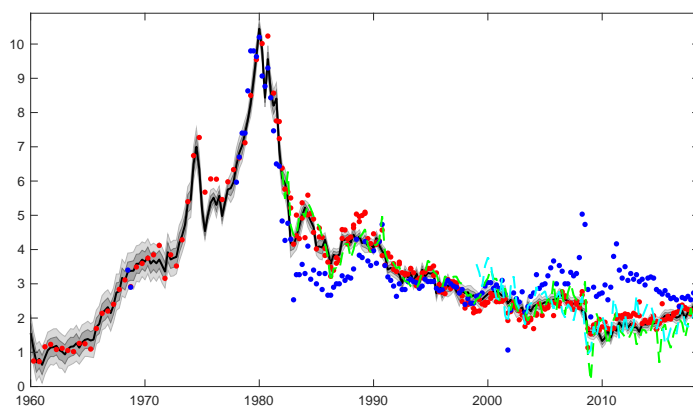
Figure 10. Inflation, inflation expectations, and wages

The top panel shows realized quarterly annualized inflation (solid red line) and the model predicted quarterly nominal wage inflation distribution (black line and grey shading). The middle panel shows survey-based one-year inflation expectations of professional forecasters (red dots), and households (blue dots), and model-implied expectations (black line and grey shading). The cyan and green lines show inflation expectations extracted from market prices from [Abrahams, Adrian, Crump, Moench, and Yu \(2016\)](#) (2-year) and [Haubrich, Pennacchi, and Ritchken \(2012\)](#) (one year), respectively. The bottom panel shows the same series from the middle panel but for the 5-year horizon beginning in 5 years. Shading denotes 68% and 95% coverage intervals.

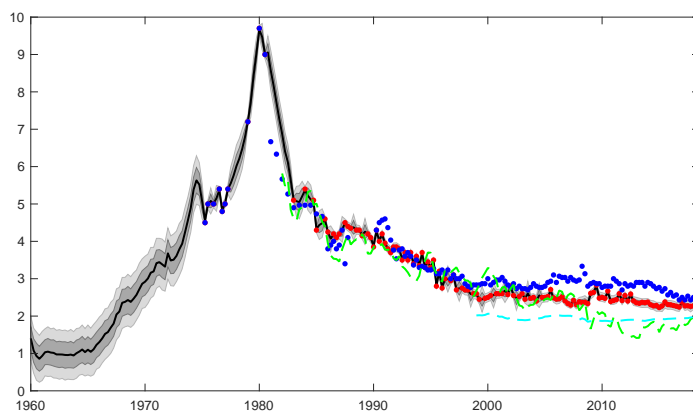
Price and Wage Inflation



One-Year Inflation Expectations



Long-Term Inflation Expectations



5.1 The Information Content of Inflation Expectations and the Secular Trend of the Unemployment Rate

In this section we assess the role of observed inflation expectations and the secular trend of the unemployment rate in our estimated u_t^* . Figure 11 shows the results from two different estimation exercises. The top panel shows the estimate of u_t^* (for the price inflation only specification) when only information about \bar{u}_t is provided along with the realized unemployment rate and inflation rate. In this case, the estimated u_t^* is essentially identical to \bar{u}_t (red dotted line) emphasizing the key role that inflation expectations play in identifying movements in the unemployment gap across the state of the business cycle (the same result is obtained including both price and wage inflation in the estimation). In the bottom panel we show the resulting u_t^* estimates when we further remove the secular trend from the observables. For this specification, we supply a stochastic process for the evolution of the trend, following the well-known model in Laubach (2001). The natural rate of unemployment follows the process

$$\bar{u}_t = \bar{u}_{t-1} + g_t, \quad (34)$$

and

$$g_t = g_{t-1} + \sigma_g \epsilon_t^g. \quad (35)$$

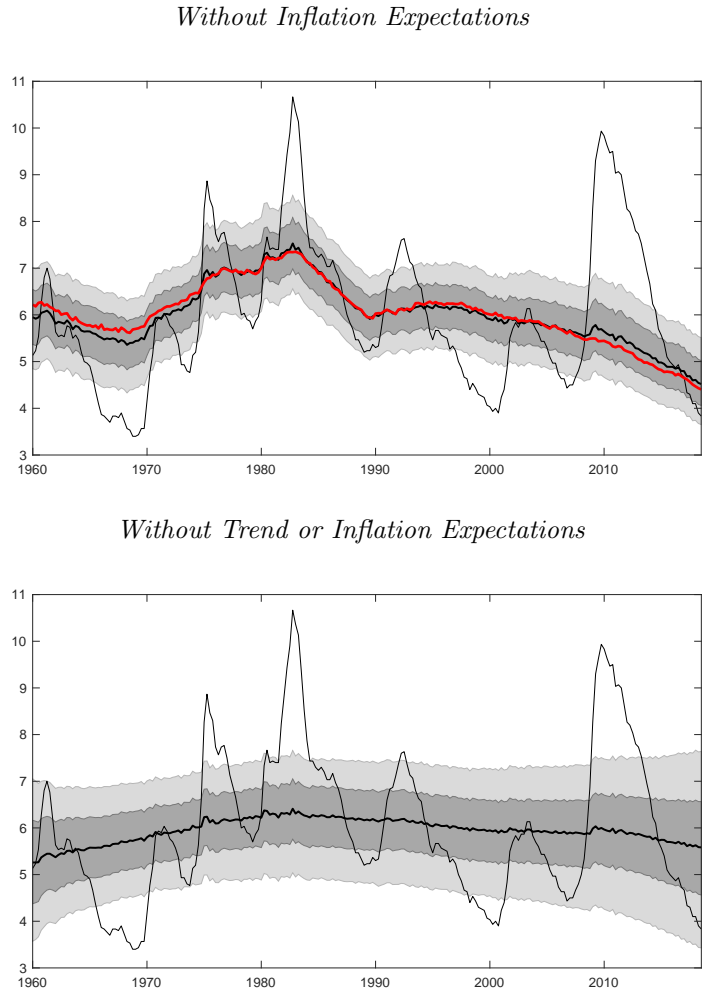
The model features no forward-looking behavior. Setting $\beta = 0$ delivers the Phillips curve

$$\pi_t - (1 - \gamma)\pi_t^* - \gamma\pi_{t-1} = -\kappa x_t + \varsigma_t, \quad (36)$$

where ς_t is assumed to be i.i.d. under this specification. We also fix the standard deviation σ_g to deliver a smooth estimate of the trend, similar to our earlier analysis. In doing so we reduce considerably the estimation uncertainty. In particular we set $\sigma_g = 0.02 \times \sigma_{u^*}$. As is clear from the bottom panel of Figure 11, the exercise shows there is very little information about the natural rate of unemployment once we focus only on the joint behavior of inflation and unemployment. We conclude that inflation expectations and the secular trend in unemployment are therefore critical for assessing u_t^* .

Figure 11. Phillips curve model without key inputs

This figure shows results from the inflation-only Phillips curve model without key inputs. The top panel shows the estimated u_t^* (black line) without inflation expectations as inputs. The red line represents the median estimate of \bar{u}_t . The bottom panel shows the estimated u_t^* (black line) without information from inflation expectations or the secular trend in the unemployment rate. Shaded areas denote 68% and 95% coverage intervals.



5.2 The Great Recession and Factors Affecting the Matching Efficiency

It is of special interest to focus on the behavior of the natural rate of unemployment during the Great Recession and its aftermath. The Great Recession was not only the deepest postwar downturn in the labor market, it was also followed by an unprecedented period of high unemployment rates. The unemployment rate remained stubbornly high, printing at 9% in January 2011 while many measures of economic activity had recovered by then. This disconnect triggered increased disagreement about the nature of the rise in the unemployment rate and whether the recession affected the workings of the labor market permanently. For example, Figure C.3 (in the Supplemental Appendix) summarizes the Federal Reserve Board and Federal Reserve Bank estimates of the NAIRU for three different

time periods: before the financial crisis in 2007, the current period (at the time), and 2015, as well as the increase between the first two time periods as of January 25-26, 2011.¹⁸ The figure shows that in 2011 there was increased disagreement not only about the current level of the natural rate but also its level going forward in 2015 suggesting that some participants viewed the natural rate of unemployment higher even in the medium-run due to hysteresis as in [Blanchard and Summers \(1986\)](#).

Careful examination of worker flows into and out of unemployment has shown that, while the inflow rate quickly returned to its pre-recession level and gradually trended down, the persistently low outflow rate accounted for the high unemployment. Therefore various explanations were suggested in the applied macro literature that operated through a long-lasting decline in the outflow rate such as rising mismatch, declining recruiting intensity and declining search effort of unemployed workers. This literature relied on rich micro data from various surveys, administrative data sources and online data sources to quantify the extent of fluctuations along the intensive margins of search and mismatch. We next provide a simple framework derived from the search and matching literature to summarize these measures and then compare and contrast them with our measure of the natural rate of unemployment.

The point of departure is the matching function that characterizes the technology that firms and workers match with each other building on Diamond-Mortensen-Pissarides and building on [Blanchard and Diamond \(1989\)](#) who argue that changes in matching efficiency that shift the Beveridge curve may shed light on the Phillips curve. In its basic form, the inputs to the matching function at time t are the v_t vacancies posted by firms looking to hire and u_t unemployed workers looking for jobs. To accommodate the intensity of recruiting and search effort we denote the *recruiting intensity* of the firms as q_t and the *search intensity* of workers as ι_t . A generalized Cobb-Douglas matching function that allows for shifts along the intensive margins of firm and worker search effort can then be written as

$$h_t = \Phi_t(q_t v_t)^\alpha (\iota_t u_t)^{1-\alpha} \quad (37)$$

where h_t is the total hires and $\alpha \in (0, 1)$ is the vacancy share. Φ_t is the aggregate matching efficiency parameter. As the specification shows, changes in q_t and ι_t would show up as a decline in the measured match efficiency. In addition mismatch between vacant jobs and unemployed workers: idle workers seeking employment in sectors, occupations, or industries different from those where

¹⁸<https://www.federalreserve.gov/monetarypolicy/files/FOMC20110126material.pdf>

the available jobs are, would manifest itself as a decline in Φ_t . Such misalignment between the distribution of vacancies and unemployment as well as a decline in the recruiting intensity/search effort would lower the aggregate outflow rate which is defined as $f_t = h_t/u_t$.

5.2.1 Mismatch

[Şahin, Song, Topa, and Violante \(2014\)](#) formalize the notion of mismatch by defining the economy as a large number of distinct labor markets segmented by industry, occupation, and geography.¹⁹ Each labor market i is frictional, i.e., the hiring process within a labor market is governed by a matching function. To assess the existence of mismatch, they examine whether, given the distribution of vacancies observed in the economy, it would be feasible to reallocate unemployed workers across markets in a way that reduces the aggregate unemployment rate. This involves comparing the actual allocation of unemployed workers across labor markets with an optimal allocation that assumes costless worker mobility across these markets. Since the only frictions in such an environment are the ones embodied within each market specific matching function, unemployment arising in this environment is purely frictional. The difference in unemployment between the observed allocation and the allocation implied by the optimal environment provides an estimate of the effect of mismatch.

[Şahin, Song, Topa, and Violante \(2014\)](#) calculate mismatch unemployment at the industry level using vacancy data from the JOLTS, which provides survey-based measures of job openings and hires at a monthly frequency, starting from December 2000, and at the occupation level using vacancy data from the HWOL dataset provided by The Conference Board (TCB). We plot an update of their occupation and industry mismatch unemployment measures in [Figure 12](#).

5.2.2 Recruiting Intensity

Recent research by [Davis, Faberman, and Haltiwanger \(2013\)](#) has stressed the importance of channels other than a vacancy posting in the search and matching process. They argue that channels that affect how quickly firms fill those vacancies should be taken into account as determinants of the hiring process. A variety of factors, such as variations in hiring standards, wages offered that differ from those of competitors, variations in the amount of screening effort, and the propensity to use informal hiring methods all contribute to what these authors refer to as *recruiting intensity*. They generate an aggregate time series of their measure of recruiting intensity using a generalized version of a

¹⁹In Supplemental Appendix [A](#), we present a simplified version of the derivation in [Şahin, Song, Topa, and Violante \(2014\)](#).

standard matching function and their derivation of the monthly evolution of hiring and vacancies in the JOLTS data. [Davis, Faberman, and Haltiwanger \(2013\)](#)'s recruiting intensity index provides us a normalized measure of q_t in the generalized Cobb-Douglas matching function.²⁰ We plot in [Figure 12](#) the counterfactual unemployment rate that is computed as the the difference between the actual unemployment rate and a counterfactual unemployment rate that holds recruiting intensity constant at its mean value over the sample period replicated from the Reserve Bank Report on Structural Unemployment in [Faberman and Şahin \(2011\)](#).²¹ This difference reflects the effect of changes in recruiting intensity on the unemployment rate.

5.2.3 Worker Search Effort and Extension of Unemployment Insurance Benefits

Another margin that is likely to be affected by aggregate conditions is unemployed workers' search effort. One often discussed policy that is linked to worker search effort is the extension of unemployment insurance (UI) benefits. In theory, receiving UI benefits for a longer period reduces the incentive of the unemployed to look for work. Similarly, it also increases unemployed workers' reservation wage, so that they may reject job offers that they would otherwise have accepted in the absence of these extended benefits. During the Great Recession, unemployment insurance benefits were extended to record lengths with individuals in most states being eligible for up to 99 weeks of UI (and, at a minimum, 60 weeks) in 2011. The Federal Reserve Board's Tealbook estimated that the extension of benefits raised the the natural rate of unemployment, which we plot in [Figure 12](#).²²

However, extension of UI is not the only channel that affected the worker search effort. [Mukoyama, Patterson, and Şahin \(2018\)](#) showed that during the Great Recession, the unemployment pool shifted towards workers who are more attached to the labor force who typically search harder for jobs. They showed that, as a consequence of this shift in the composition of the unemployed as well as the increased search effort in response to the declining household wealth, aggregate search effort in the economy increased during the Great Recession. They find that the increase in search intensity during and following the Great Recession moderated the increase in the unemployment rate. Absent this increase, the unemployment rate would have peaked at around 11 percent and would have been consistently higher by about 0.5 to 1 percentage point during the recovery. [Figure 12](#) shows the effect of the rise in workers' search effort on the unemployment rate.

²⁰We thank Steve Davis for providing updated data of the recruiting intensity index and Jason Faberman for sharing his replication code.

²¹<https://www.federalreserve.gov/monetarypolicy/files/FOMC20110101memo01.pdf>

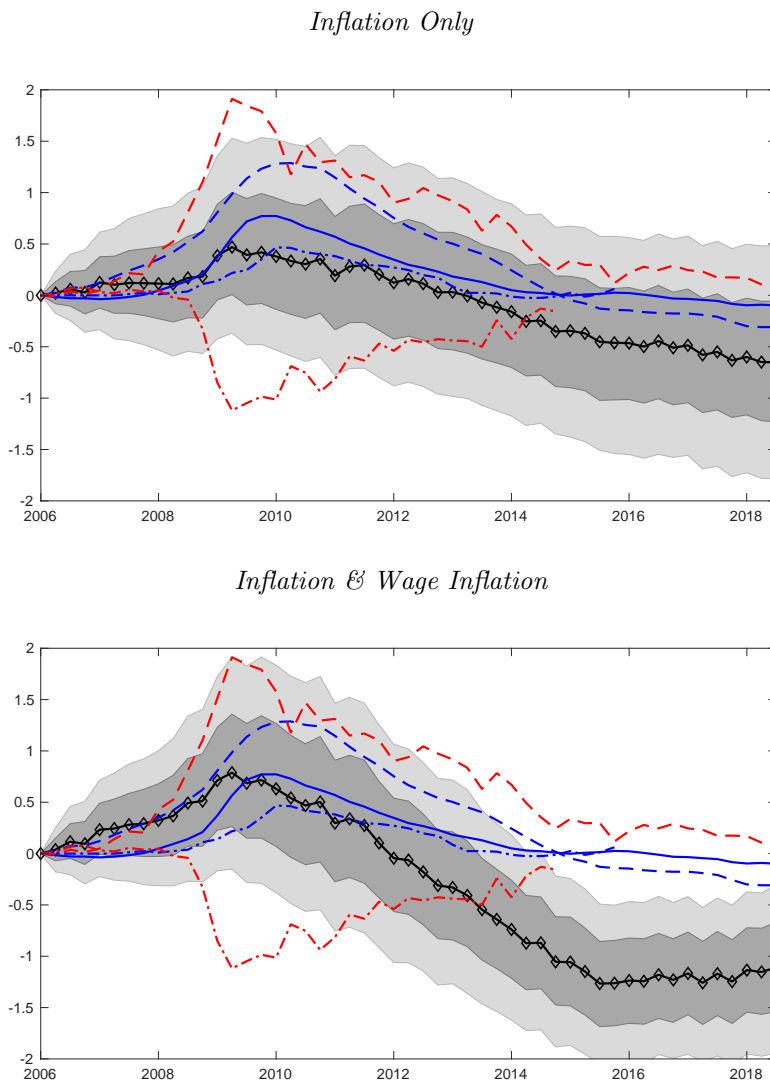
²²<https://www.federalreserve.gov/monetarypolicy/files/FOMC20121212tealbooka20121205.pdf>

5.3 Evolution of u^* and Factors Affecting the Matching Efficiency

In Figure 12 we show the evolution of our estimated u_t^* along with empirical estimates of the effects on unemployment of the persistent factors discussed in this section. All series are plotted in deviation from their level in 2006:Q1. There are two important features of these factors: (1) these persistent factors can only be measured as counterfactual gaps relative to an unemployment rate without additional assumptions; (2) these measures are not additive as they cannot be considered as independent from each other. That said, looking at the predictive distributions, we first observe that our measure of u_t^* aligns surprisingly well in terms of timing and magnitude with the evolution of these factors. The natural rate estimated using prices only is more aligned with industry mismatch unemployment and the effects of the extension of unemployment benefits (blue lines). Conversely, u_t^* measured including both prices and wages in the estimation initially is more aligned to the rise in occupational mismatch. While it displays a stronger increase relative to the inflation-only estimate, it still falls short of the observed spike in occupational mismatch and in the decline of recruiting intensity. Finally job search intensity moved sharply but in the opposite direction moderating some of the effects of other factors. Finally, notice that these factors return to their 2006 levels around 2014, while u_t^* continues to decline in-line with the falling secular trend \bar{u}_t . Put differently, while the effect of the Great Recession on the unemployment rate persisted for almost a decade, these factors did normalize eventually. As such, we focus on driving forces that pre-date the Great Recession when studying the secular trend in the unemployment rate in the next section.²³

²³This finding does not preclude persistent effects of the Great Recession on worker career paths (Davis and von Wachter (2011)).

Figure 12. Comparison of u_t^* to micro-based estimates. Estimated u_t^* , occupation and industry mismatch unemployment rates (dashed and solid blue line; source: The Conference Board Help Wanted OnLine Data Series), recruiting-intensity-adjusted unemployment rate (red dashed line), search-effort adjusted unemployment rate (red dash-dotted line) and UI extension adjusted unemployment rate (blue dash-dotted line). All series show changes relative to their level in 2006:Q1. Shading denotes 68% and 95% coverage intervals.



6 Changes in the U.S. Labor Market and Flow Dynamics

We have shown that the behavior of unemployment flows, especially the ongoing downward trend in the inflow rate, is the driver of the low levels of the natural rate of unemployment that the U.S. economy has been experiencing. In this section, we identify three important changes in the structure of the U.S. economy: increase in labor force attachment of women, decline in job destruction and job reallocation, and dual aging of workers and firms as the main drivers of the downward trend in the inflow rate.

As a prelude to our analysis in investigating the economic changes that affected the evolution of the inflow rate, we report the changes in the inflow rate for the 1976-1996 and 1996-2018 periods and decompose the total changes into changes accounted for by each gender and age group. For the inflow rate

$$s_t \approx \sum_i \omega_{it}^s s_{it} \quad (38)$$

where group i is defined as the interaction of gender and age. We consider three age groups, workers between 16 and 24, workers between 25 to 54 and workers older than 55 years old for each gender. Table 2 decomposes the change in the inflow rate into changes accounted for by each demographic group using a simple approximation

$$\Delta s(t, t') \approx \sum_i (\omega_{it'}^s s_{it'} - \omega_{it}^s s_{it}). \quad (39)$$

The table shows that women account for the majority of the decline in the inflow rate in the 1976-1996 period which coincides with the dramatic rise in the female labor force participation rate. In addition, during this period the baby boom cohort proceeded from younger ages to prime ages reducing the aggregate inflow rate. Interestingly, the decline in the 1996-2018 period is very similar among men and women suggesting a common factor after 1996.²⁴

We also calculate the counterfactual contribution of each group fixing their weights at their 1976 levels, a calculation that is often referred to as a shift-share analysis:

$$\Delta^C s(t, t') \approx \sum_i (\omega_{i1976}^s s_{it'} - \omega_{i1976}^s s_{it}). \quad (40)$$

This counterfactual calculation shows that around half of the decline in the 1976-1996 period can be accounted for by the changing weights. In other words, if the shares of each age and gender group remained at their 1976 level, the inflow rate would have only declined by 0.36 percentage point, about 50% of the actual decline. The message is very different for the 1996-2018 period. Changes in the age and gender composition played no role in accounting for the decline in the inflow rate in this period.²⁵ Shift-share analyses—while informative—do not necessarily capture the full effects of demographic change. However, we find it useful since it helps us guide our examination of drivers of

²⁴The changes in the outflow rate are harder to interpret since the outflow rate is persistent and strongly procyclical. We report the corresponding changes in f in the Supplemental Appendix.

²⁵This observation is consistent with the findings of [Davis and Haltiwanger \(2014\)](#) who show using various data sources that similar patterns apply to broader measures of worker allocation such as hires and separations.

the decline in the inflow rate.

Table 2. Shift share with fixed demographic composition. Inflow rate changes for 1976 to 1996, 1996 to 2018 and for full sample (1976 to 2018) and the actual and counterfactual contribution of each demographic group to the changes in the aggregate inflow rate.

	Aggregate	Women			Men		
	Change	16-24	25-54	55+	16-24	25-54	55+
<i>A. Actual contribution</i>							
1976 to 1996	-0.80	-0.55	-0.24	-0.04	-0.17	0.13	0.01
1996 to 2018	-1.24	-0.34	-0.33	0.00	-0.34	-0.20	0.03
1976 to 2018	-2.04	-0.90	-0.57	-0.03	-0.51	-0.06	0.05
<i>B. Counterfactual contribution with weights fixed in 1976</i>							
1976 to 1996	-0.36	-0.20	-0.32	-0.03	0.12	0.05	0.02
1996 to 2018	-1.29	-0.45	-0.23	-0.05	-0.42	-0.12	-0.02
1976 to 2018	-1.63	-0.65	-0.55	-0.08	-0.29	-0.06	0

Note: The counterfactual contributions are calculated using weights fixed at 1976 averages.

In light of our accounting exercise and building on the earlier literature on female labor supply and firm dynamics, we now turn to the analysis of three channels that we show are important drivers of the downward trend in the inflow rate.²⁶

6.1 Increased Labor Force Attachment of Women

The U.S experienced *Grand Gender Convergence* in the 20th century with female labor participation increasing from around 47% in 1976 to approximately 60% in 2000 (Goldin (2006)).²⁷ The main driver of the rise in female labor force participation rate was the increase in participation of married women with children. Women started to work longer into their pregnancy and started working after childbirth sooner than their counterparts in the 1960s likely due to changes in social norms, more widespread availability of maternity leave, and advances in maternal health and childcare. As labor market interruptions related to child bearing declined, women’s labor force attachment gradually increased.²⁸ The left panel of Figure 13 shows that employed women left the labor force at a much

²⁶It is possible that secular changes in factors affecting matching efficiency could have also played a role; however, these factors primarily affect the outflow rate which exhibits only a mild secular trend.

²⁷As discussed extensively in Goldin (2006) and references therein, a large literature examines the drivers of the dramatic rise in female labor force participation. Various drivers of this change have been identified such as technological change, contraceptive innovation (e.g., the birth control pill), a shift to a unilateral divorce regime, changes in social attitudes and norms toward married women working, advances in home production technology, a decline in maternal mortality, and the introduction of infant formula.

²⁸See the Census Bureau’s report: “2008 Current Population Report on Maternity Leave and Employment Patterns of First-time Mothers: 1961-2008” for detailed statistics characterizing the changing patterns.

lower rate in the 1990s than in the late 1970s. While we do not have labor market flows before 1976, tabulations in [Marston \(1976\)](#) showed that the employment-to-nonparticipation flow rate for white females aged 25 to 59 was 4.76% while it was only 0.37% for white males in the same age category for the period 1967-73. [Marston \(1976\)](#) argues that the high rate at which employed women leave the labor force was the main factor in the higher unemployment rates they experienced. Marston referred to this as possibly a consequence of *participation instability* almost antonymous to *increased labor force attachment*.

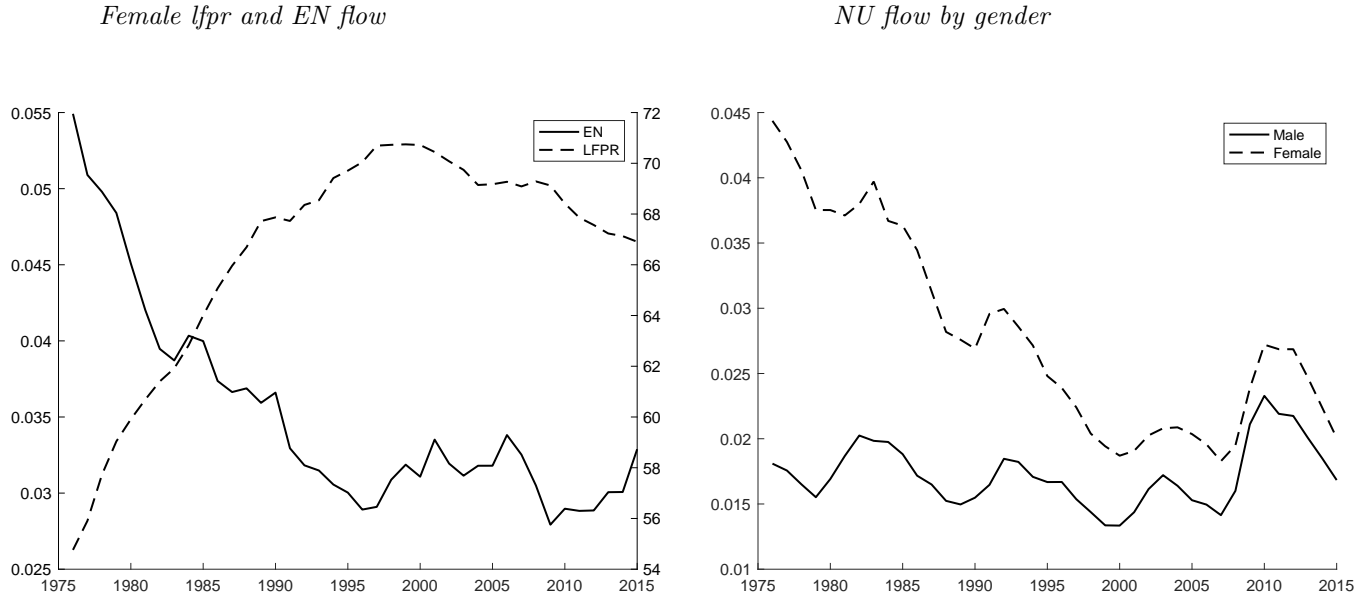
This decline in labor force exits has important implications for unemployment. Having uninterrupted employment spells allows workers to build more stable employment relationships which is likely to reduce frictional unemployment through a decline in the incidence of job loss and incidence of unemployment during re-entry into the labor force. Examination of gross-flows data from the CPS based on longitudinally matched monthly CPS micro data confirms this intuition. As the right panel of [Figure 13](#) shows, as labor force departures became less common for women, entry from out of the labor force into unemployment also became increasingly rare. In the late 1970s unemployment inflows from nonparticipation was around 4.5% of the labor force and has declined by more than half to around 2% by the late 1990s.²⁹

Women also became less likely to leave unemployment for nonparticipation, increasing their duration of unemployment. Consequently, both the inflow and outflow gaps disappeared. On net the decline in unemployment inflows dominated the rise in duration of unemployment causing a full convergence of the unemployment rate of women to levels similar to men.³⁰ To summarize, even though declining exits from employment to nonparticipation will not have an immediate effect on the unemployment rate, they affected women's unemployment rate by lowering frictional unemployment as shown by [Abraham and Shimer \(2002\)](#) using a flow decomposition and by [Albanesi and Şahin \(2018\)](#) using a three-state search and matching model.

²⁹[Abraham and Shimer \(2002\)](#) and [Albanesi and Şahin \(2018\)](#) show nonparticipation to unemployment flows as a fraction of the stock of nonparticipation. We normalize these flows by the labor force since the unemployment rate is measured as a share of the labor force. An alternative is to compute the unemployment inflows by reason of unemployment following [Elsby, Michaels, and Solon \(2009\)](#) who found that inflow rate for labor force entrants has declined starting in the early 1980s.

³⁰[Albanesi and Şahin \(2018\)](#) show while the gender unemployment gap has disappeared the relative cyclicity of unemployment by gender has not changed.

Figure 13. Labor force participation and flows. Female labor force participation rate and employment-to-nonparticipation flow rate (left) and nonparticipation-to-unemployment flows normalized by the labor force by gender (right) for ages 16 to 65 years old. Source: [Barnichon and Mesters \(2018\)](#)



6.1.1 Grand Gender Convergence in the Cross-State Data

Evidence from U.S. states also confirms the relationship in the aggregate data: the rise in the female labor force participation rate was accompanied by an increase in labor force attachment which, in turn, reduced frictional unemployment for women generating a full convergence of unemployment rates by gender. We examine the evolution of the gender gaps in unemployment inflow and outflows at the state level. We first define the gender participation rate gap in state i at time t as

$$\frac{lfpr_{tm}^i - lfpr_{tw}^i}{lfpr_{tw}^i}$$

and the unemployment inflow and outflow gaps as

$$\frac{s_{tw}^i - s_{tm}^i}{s_{tm}^i} \quad \text{and} \quad \frac{f_{tw}^i - f_{tm}^i}{f_{tm}^i}$$

with m denoting male outcomes and f female workers' outcomes.

Figure 14. Convergence of inflow and outflow gap. Participation and unemployment inflow/outflow gaps for the 1978-1980 and 2016-2018 periods.

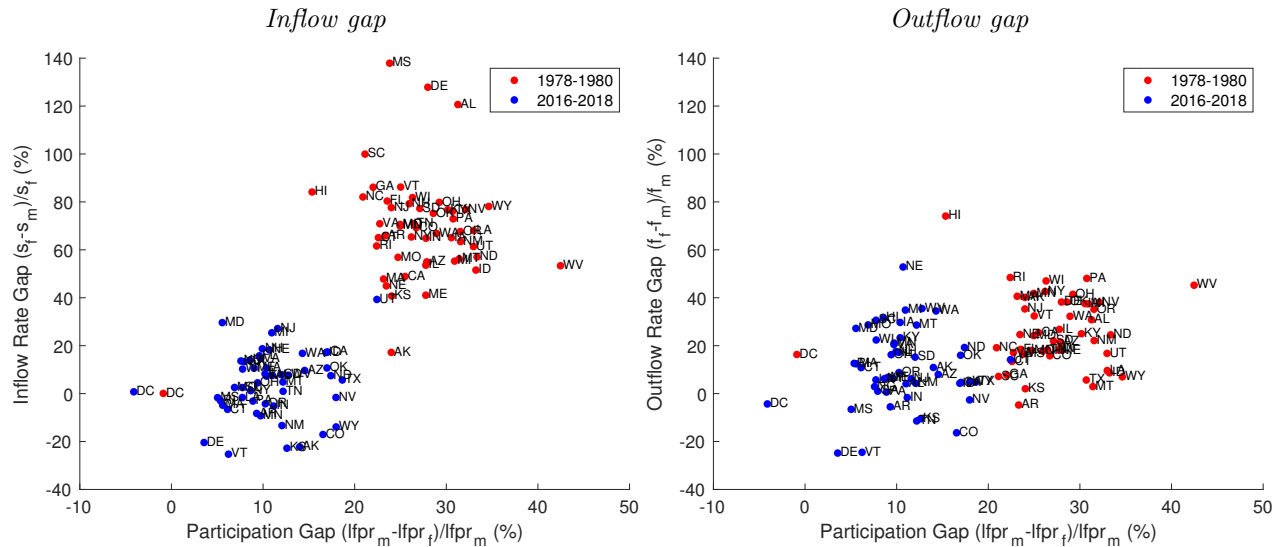


Figure 14 shows the state-level participation gaps and unemployment inflow and outflow gaps for the 1978-1980 and 2016-2018 periods. The convergence in labor market outcomes are clear. Moreover, unemployment inflows exhibit a starker convergence over time consistent with the patterns in the aggregate data.

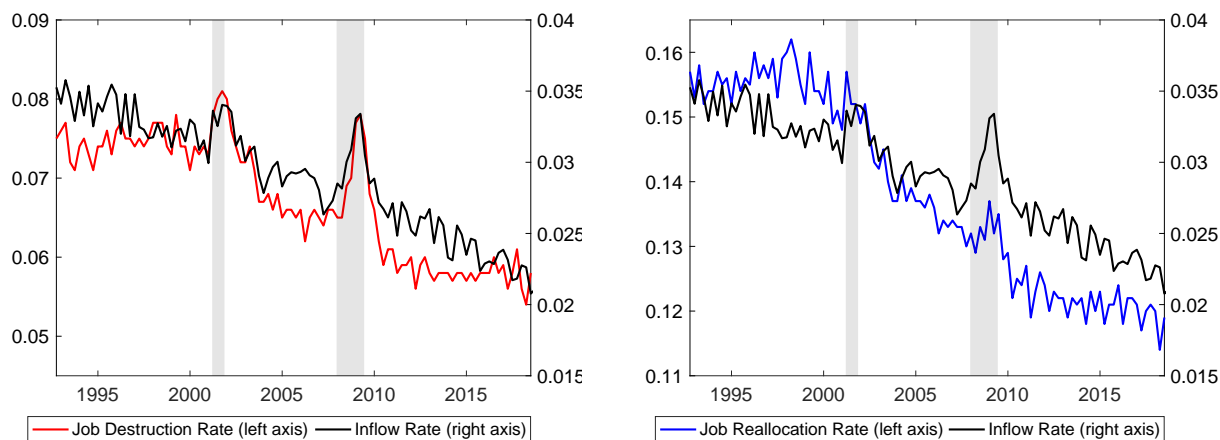
6.2 Decline in Job Destruction and Reallocation

While women play an important role in the evolution of unemployment flows, almost all demographic groups' inflows declined over time. Especially after 1996, declines in group-specific inflow rates were the sole driver of the decline in the inflow rate suggesting a common factor. Moreover, the rate employed workers transitioned into unemployment declined for both men and women despite the dramatic job destruction at the onset of the Great Recession. This pattern suggests that changes in labor demand factors likely played a role.

The decline in unemployment inflows coincided with the decline in the volatility of firm-level growth rates and job destruction as shown in Davis, Haltiwanger, Jarmin, and Miranda (2006) (see Figure 15). Search and matching models provide a natural link between the intensity of shocks that firms face and the incidence of unemployment. In this class of models with an endogenous job destruction margin, a decline in the intensity of firm-level shocks would lower job destruction and incidence of unemployment (Mortensen and Pissarides (1994)). Davis, Faberman, Haltiwanger, Jarmin, and Miranda (2010) formally examined this hypothesis showing that industry-level move-

ments in unemployment inflows are closely related to industry-level movements in several indicators for the intensity of idiosyncratic shocks for the 1990-2004 period. In this subsection, we extend [Davis, Faberman, Haltiwanger, Jarmin, and Miranda \(2010\)](#)'s analysis to the 1991-2017 period and evaluate the role of declining volatility on the trend decline in unemployment inflows and the employment-to-unemployment transition rate.

Figure 15. Job Destruction/Reallocation and Flows. Job destruction and inflow rates (left) and job reallocation and inflow rates (right).



We use the Business Employment Dynamics (BED) data which provide quarterly measures of job destruction at the industry level. We follow [Davis, Faberman, Haltiwanger, Jarmin, and Miranda \(2010\)](#) and aggregate the data to the following broad industry groups: construction, manufacturing, transportation and utilities, retail and wholesale trade, FIRE (finance, insurance and real estate), and services and exploit within-industry time variation, the preferred specification of [Davis, Faberman, Haltiwanger, Jarmin, and Miranda \(2010\)](#). The job destruction rate from quarter $t-1$ to t is computed as the sum of job losses that are the result of contractions in employment at existing establishments and the loss of jobs at closing establishments and is expressed as a rate by dividing through by total employment.

We find economically and statistically significant effects of job destruction and job reallocation on the inflow rate and the employment-to-unemployment transition rate. The decline in job destruction and reallocation could be interpreted as declining firm level volatility and could arise from a changing nature of shocks or the declining responsiveness to shocks by firms as in [Faberman \(2017\)](#) and [Decker, Haltiwanger, Jarmin, and Miranda \(2017\)](#).

Table 3. Unemployment inflow rate and employment-to-unemployment transition rate regressed on job destruction and job reallocation rates, quarterly data.

<i>Regressors</i>	Inflow rate		E to U flow rate	
	(1)	(2)	(1)	(2)
Job destruction rate	0.448*** (0.0266)		0.382*** (0.0202)	
Job reallocation rate		0.240*** (0.0198)		0.197*** (0.0128)
Observations	618	618	618	618
R-squared	0.935	0.927	0.950	0.933

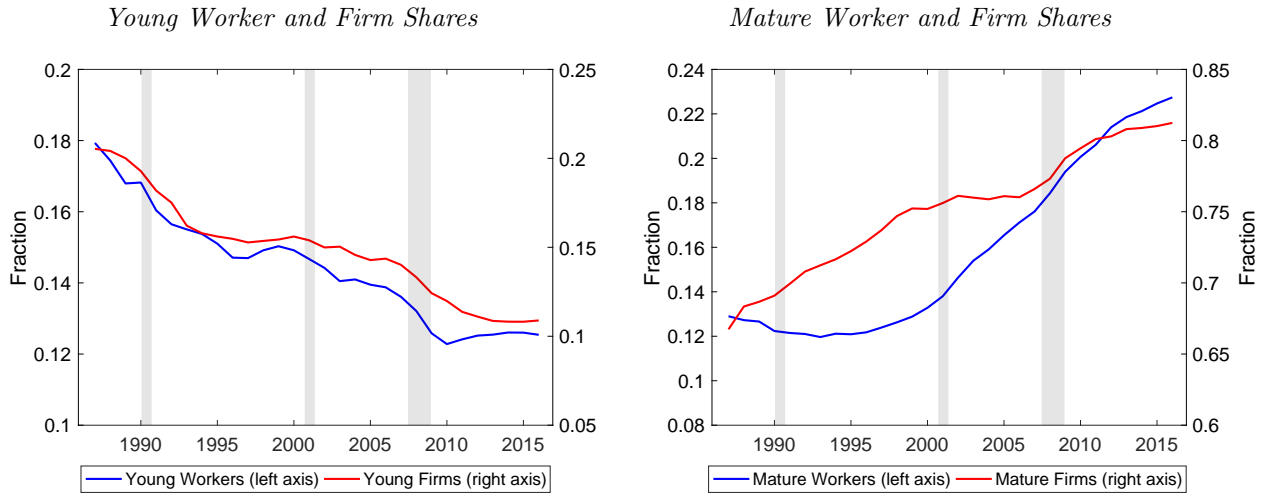
Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0$. Quarterly data from 1992:Q3-2018:Q1. Includes time and sector fixed effects, with seven industry sectors. Source: CPS

6.3 Dual Aging

The U.S. economy has been experiencing a striking shift towards older workers and older firms since the mid 1990s as we have discussed in Section 3. Around 18% of the labor force was comprised of workers between 16 to 24 years old (*young workers*) in 1987. By 2017, this fraction declined to around 10%.³¹ *Young firms*' (firms younger than 5 years old) employment share also followed a similar pattern with their employment share declining from around 20% to 10%. On the flip side, in 1987, firms 11 or more years old—which we call *mature firms* following Pugsley and Şahin (2019)—used to employ around two thirds of the workers in the economy. By 2017, that fraction increased to 80% as seen in Figure 16.

³¹In addition to the aging of the labor force, the ongoing decline in young workers' participation rate contributed to this notable decline. As Krueger (2017) argues the decline in participation of young workers was mostly offset by an increase in their college enrollment.

Figure 16. Dual aging of workers and firms. Employment share of 16-24 year old workers and employment share of 5 year old and younger firms and employment share of 55+ year old workers and employment share of firms 11 or more years old.



Both worker age and firm age are widely recognized as important observables in accounting for differences in economic outcomes of workers and firms.³² Table 4 shows the average unemployment inflow rates by worker age and job destruction rates by firm age. Younger workers are four times more likely to flow into unemployment than prime-age workers. Similarly, firms aged between one and five years old are twice as likely to destroy jobs than their older counterparts. These patterns suggest that a direct consequence of dual aging is a decline in unemployment inflows and job destruction.

Table 4. Inflow and Job Destruction Rates by Age. Average unemployment inflow rate by worker age in the CPS for 1976-2018 and the average job destruction rate by firm age in the BDS for 1987-2016.

Monthly inflow rates by worker age 1978-2018		Annual job destruction rates by firm age 1987-2016	
16-24	0.097	1-5	0.244
25-54	0.023	6-10	0.176
55+	0.015	11+	0.124

Note: The inflow rates are calculated using the CPS and the job destruction rates are calculated using the Business Dynamics Statistics (BDS)

We first conduct a simple worker-age-composition adjustment in the left panel of Figure 17. We set the age composition of workers to their 1976 shares. We use three age groups for workers: 16-24, 25-54 and 55 or older. The shift towards an older population by itself accounts for around a quarter

³²See Perry (1970) and Shimer (1998) for worker age and Haltiwanger, Jarmin, and Miranda (2013) and Fort, Haltiwanger, Jarmin, and Miranda (2013) for firm age.

of the decline in the inflow rate yet attributes a significant portion to the age-specific evolution of the inflow rate—a finding that resonates with our earlier analysis.

We repeat the same simple firm-age-composition adjustment in the right panel of Figure 17 setting the age composition of firms to their 1987 shares using the Business Dynamics Statistics (BDS) dataset. We use three age groups of firms: one to five years old, six to ten years old, and 11 or more years old. While it is hard to assess the exact fraction that this calculation accounts for due to the pronounced countercyclicality of the job destruction rate, the change in the firm age compositions seems to be about as important as worker aging. However, the bulk of the decline still remains unaccounted for similar to the inflow rate. This finding is consistent with Davis and Haltiwanger (2014) and Haltiwanger, Jarmin, and Miranda (2013) who also show that while the shifts in the worker and firm age compositions go in the right direction, they still remain short of explaining the majority of the decline in the unemployment inflow and job destruction rates.

Figure 17. Shift share analyses with fixed age composition. Unemployment inflow rate: aggregate and keeping the worker age composition unchanged at its 1976 shares (left) and job destruction rate: aggregate and keeping the firm age composition unchanged at its 1987 shares (right).



While the shift in worker and firm age composition falls short of accounting for the decline in the inflow rate, recent research has emphasized that aging could also affect the economy by affecting age-specific outcomes as in Shimer (2001), Karahan and Rhee (2017) and Engbom (2017). Shimer (2001) refers to the direct effect as the effect of aging arising solely from changes in the age composition and any additional effects as the indirect effect. These papers argue that the effect of aging goes beyond just shifting the composition of the economy in the context of unemployment, migration and various measures of dynamism.

We build on this insight and show that age composition of workers affect age-specific inflow rates and age composition of firms affects firm-age-specific job destruction rates suggesting that indirect effects also play a substantial role.

6.3.1 Dual Aging in the Cross-State Data

We now turn to geographic variation to examine the direct and indirect effects of dual aging on unemployment inflows and job destruction rates using cross-state data.

Worker demographics and unemployment inflows We should expect that states with larger changes in demographic makeup to be those who experienced the sharpest decline in inflow rates. Given the slow moving nature of demographic changes, it is natural to compare long-horizon changes in these variables. To do so we regress the change in the inflow rate for each state from its average value in 1978-1982 to its average value in 1997-2001 on the change in the share of those aged 15-24 relative to those aged 15-64 from 1978 to 1998. We choose to take five-year averages of the outflow rates, and these years in particular, to ensure that our long differences are not unduly affected by the state of the business cycle (the first year in our sample is 1978 and the subsequent recession began in January 1980). We focus on the period up until the late 1990s as that is the period over which the share of young people in the population moved dramatically; since then, the changes have been relatively modest. In Table 5 we show the results for this long-difference regression:

$$s_{i,1997-2001} - s_{i,1978-1982} = \beta_0 + \beta_1 \left[\left(\frac{\text{pop 15 to 24}}{\text{pop 15 to 64}} \right)_{i,1998} - \left(\frac{\text{pop 15 to 24}}{\text{pop 15 to 64}} \right)_{i,1978} \right] + \epsilon_i \quad (41)$$

The OLS estimate suggests that a decline of one percentage point in the share of young people in a state corresponds to a fall of about 0.15 percentage point in the inflow rate. A common choice of instrument in regressions with age shares is to use lagged age shares adjusted for the deterministic aging that would be expected to occur.³³ This strategy relies on the idea that lagged age shares are not informative about current business conditions—such as a labor demand shock—that could potentially move both the age composition and unemployment inflows contemporaneously. In this case, we need to forecast the share of young people in 1998 as of 1978. We use 1978 births along with the rest of the age distribution at the time to do so. In particular we forecast the long-horizon

³³In a recent example, [Davis and Haltiwanger \(2014\)](#), estimate the effect of reallocation measures on employment and unemployment outcomes by age, gender and education using instruments based on age shares at the state level.

change by replacing

$$\left(\frac{\text{pop 15 to 24}}{\text{pop 15 to 64}}\right)_{i,1998} - \left(\frac{\text{pop 15 to 24}}{\text{pop 15 to 64}}\right)_{i,1978}$$

with

$$\left(\frac{6 \cdot (1978 \text{ births}) + \text{pop 1 to 4}}{6 \cdot (1978 \text{ births}) + \text{pop 1 to 44}}\right)_{i,1978} - \left(\frac{\text{pop 15 to 24}}{\text{pop 15 to 64}}\right)_{i,1978}$$

In words, to estimate the population of 15 to 24 year olds in 1998 requires an estimate of the number of births in 1979-83 along with births and the population of 1-4 year olds in 1978. We estimate the number of births in 1979-83 by assuming births are constant at their 1978 level over that period. The IV estimate, also shown in Table 5, is slightly larger than the OLS estimate, and weak-IV robust confidence intervals comfortably reject the null of a slope of zero.³⁴ These preceding results are similar in spirit to that of the shift-share analysis we have already conducted in Table 2.

We next replace the long-horizon differences in inflow rates for all workers by the corresponding changes for workers below 25, aged 25 to 54 and those 55 and over. This allows us to assess whether the maturing population—the decline in young people—is correlated with declines in the inflow rate for prime and older workers. The results are suggestive that the change in the share of young people is associated with changes in separation rates across age groups (second column). If we dig deeper and run these regressions by each age group separately we observe that a higher share of young people is positively associated to the inflow rates of all groups with the effect declining by age (last three columns). The most striking finding perhaps is the observation that prime-age workers' unemployment inflow rate declines with the share of young workers in the economy. These results suggest that separation rates of prime age workers, in particular, were affected by the maturing population.

³⁴Although we employ weak-instrument robust confidence intervals, we note for reference that the first-stage F-statistic is approximately 90.

Table 5. Changes in Inflow Rates and Population Composition. This table reports regressions results for the specification of equation (41). The second row reports p-values associated with the OLS estimate with robust standard errors; the fourth row reports weak-instrument robust confidence intervals constructed by inverting the Anderson-Rubin test (Mikusheva and Poi (2006)). The “All Ages” specification includes age effects.

	Long Horizon Change in Inflow Rate for:				
	Overall	All Ages	16-24	25-55	55+
OLS	0.157	0.089	0.143	0.076	0.049
<i>p-val.</i>	(0.006)	(0.260)	(0.489)	(0.051)	(0.641)
IV	0.186	0.174	0.334	0.099	0.049
<i>90% conf. int.</i>	[0.05, 0.33]	[-0.00, 0.36]	[-0.17, 0.88]	[0.01, 0.20]	[-0.06, 0.24]
Obs.	50	148	50	50	48

Note: Results omit the District of Columbia.

Firm demographics and job destruction To investigate the role of firm aging we follow a similar empirical strategy as in the case of worker demographics. We should expect that states with more substantial shifts towards older firms to be those who experienced the biggest decline in job destruction. We again consider long changes in job destruction due to the slow moving firm demographics as shown in Figure 16. We compare the 3-year average of job destruction rates in 1987–1989 to 2012–2014 and examine how they are affected by the aging of firms using the change in employment share of firms 11 years and older as a proxy for aging. This choice of regressor is motivated by the work of Haltiwanger, Jarmin, and Miranda (2013) who show that most of the young-firm dynamics continue throughout the first ten years of firms.

In Table 5 we show the results for this long-difference regression using OLS:

$$jd_{i,2012-2014} - jd_{i,1987-1989} = \beta_0 + \beta_1 \left[\left(\frac{emp\ 11+}{emp} \right)_{i,2014} - \left(\frac{emp\ 11+}{emp} \right)_{i,1987} \right] + \epsilon_i \quad (42)$$

using job destruction data by state from the Business Dynamics Statistics (BDS). The OLS estimate implies that a one percentage point increase in the employment share of mature firms in a state corresponds to a fall of about 0.28 percentage point in the job destruction rate. This effect is both statistically and economically significant and more substantial quantitatively than the implication of the shift-share analysis. However it is subject to the usual critique that firm demographics and job destruction could be affected by common shocks. To address this concern we devise an IV strategy that parallels the IV approach that we have employed for worker demographics. To do so we use

the employment share of new firms (births) in 1979 as the instrument.³⁵ Sedláček and Sterk (2017) illustrate the strong persistence over time in employment shares of startups. Since surviving firms which originated in 1979 will not be aged 11 years until after 1987, then these lagged employment shares of startups should forecast the subsequent long-horizon change of employment shares in old firms.³⁶ The bottom rows of Table 6 show that the IV estimate is even stronger suggesting a more substantial effect of firm aging on job destruction. In fact, the OLS estimate is outside the 90% weak-instrument robust confidence interval.

We next assess the indirect effect of firm aging on job destruction by investigating the relation between firm demographics and job destruction rates by firm age. In the second column, we pool the job destruction rates for all three age groups and include age effects. In concert with the overall results, the IV estimates suggest a larger magnitude of effect. In the last three columns, we consider individual specifications for each age group. We see clear negative effects of firm aging on job destruction of all firm-age groups suggesting that the shift in the age composition of firms is not the only effect of aging on job destruction. An older firm age distribution implies a lower overall job destruction rate by lowering job destruction for firms of all ages. We should also note that, across five specifications, the p-value associated with the IV estimates are all smaller than 0.01. To ensure that our results are not driven by, for example the type of industries that prevail in each state, we also report results for a panel version of equation (42), splitting the long-horizon change into observations of changes over two sub-periods and taking the change (in the change) to account for unobserved heterogeneity (Table C.3 in the Supplemental Appendix). Although the confidence intervals widen considerably we continue to observe an estimated negative relationship and reject the null at at least the 10% level as judged by the weak-IV robust confidence intervals for all but the 6Y-10Y age category.

Our analysis showed that changes in worker and firm demographics, that we refer to as the *dual aging* of the U.S. economy, are important drivers of the decline in job destruction and unemployment inflows—two measures that we linked in the preceding subsection. While the change in worker demographics is directly attributable to the baby boom, the drastic increase in births following World War II, the emphasis on aging of firms is relatively new as data have only recently become available. However, Pugsley and Şahin (2019) using a firm dynamics framework showed that the intuition is

³⁵Although the BDS data begin in 1977 we use 1979 due to measurement concerns discussed in Pugsley and Şahin (2019).

³⁶Although we employ weak-instrument robust confidence intervals, we note for reference that the first-stage F-statistic is approximately 28.

very similar for firms: declining firm births almost fully account for the shift of employment towards older firms. Moreover, [Karahan, Pugsley, and Şahin \(2018\)](#) show that the origin of the decline in firm entry is the decline in the labor supply growth arising from the aging of the baby boom cohort and the flattening out of the female labor force participation rate. These downward trends in unemployment inflows and job destruction pertain to a broader set of worker and job reallocation measures as first documented by [Davis, Haltiwanger, Jarmin, and Miranda \(2006\)](#). Relatedly, recent research by [Davis and Haltiwanger \(2014\)](#) showed that, in addition to shifts to older businesses and an aging workforce, policy developments that suppress reallocation such as occupational labor supply restrictions, exceptions to the employment-at-will doctrine, the establishment of protected worker classes, and job lock associated with employer-provided health insurance are among the policy factors that suppress labor market fluidity. While the analysis of these factors are beyond the scope of our paper, we believe that the interaction of policy decisions with labor market reallocation is an important issue for better understanding many important aggregates such as unemployment, employment, productivity, and wages.

Table 6. Changes in Job Destruction Rates and Firm Age Composition. This table reports regressions results for the specification of equation (42). The second row reports p-values associated with the OLS estimate with robust standard errors; the fourth row reports weak-instrument robust confidence intervals constructed by inverting the Anderson-Rubin test ([Mikusheva and Poi \(2006\)](#)). The “All Ages” specification includes age effects.

	Long Horizon Change in Job Destruction Rate for:				
	Overall	All Ages	1Y-5Y	6Y-10Y	11Y+
OLS	-0.284	-0.254	-0.261	-0.303	-0.197
<i>p-val.</i>	(0.008)	(0.002)	(0.146)	(0.025)	(0.035)
IV	-0.492	-0.571	-0.805	-0.595	-0.312
<i>90% conf. int.</i>	[-0.73, -0.33]	[-0.76, -0.41]	[-1.35, -0.45]	[-0.95, -0.34]	[-0.50, -0.16]
Obs.	50	150	50	50	50

Note: Results omit the District of Columbia.

7 Conclusion

We estimate the natural rate of unemployment in the 1960-2018 period by unifying two distinct estimation approaches popular in the literature. We exploit a rich set of labor market and inflation expectations data to provide tight estimates of the natural rate and study the underlying determinants of its movements. As of the third quarter of 2018, we estimate that u_t^* was around 4%; in

particular, using only information from price inflation we estimate that u_t^* stood at 4.0% with a 68% confidence interval of 3.5% to 4.5%. When we add information from wage inflation the estimate shifts down slightly to 3.9% with associated confidence interval of 3.4% to 4.2%. Our natural rate estimate is around 60 basis points lower than that of the CBO's estimate and 50 basis points lower than the median longer-run unemployment rate projection from the FOMC's Summary of Economic projections.^{37,38} Importantly, our estimates imply that the unemployment gap was roughly closed toward the end of 2018.

During the Great Recession, we find that the unemployment gap peaked at around 4 percentage points, far more severe than in any other downturn since the 1960s. Moreover, the closing of the unemployment gap has occurred only slowly, falling below 2 percentage points in late 2014—about five years after the recession ended, and closing entirely only recently. We confront the micro-data based estimates of the rise in the natural rate during the Great Recession and find that our estimate of the rise is, remarkably, in agreement with the rise in mismatch unemployment, both in terms of timing and magnitude. We view this similitude an important success as these measures use almost completely separate sources of information.

Our analysis highlights a slow-moving secular trend that has been dragging down the unemployment rate since the early 1980s. This downward trend, until the late 1990s, was mostly driven by young workers and prime-age women while the secular trend in the last two decades is common across age and gender groups. We identify the rise in female labor force attachment, decline in job destruction and reallocation intensity, and dual aging of workers and firms in the economy as key drivers of this trend. Furthermore, we view these three developments as major changes which have had, and will continue to have, important and long-lasting effects on the economy.

The female labor force participation rate flattened in the late 1990s and the unemployment rate for women fully converged to that of men. The participation gap improved minimally since then mostly on account of the deterioration of male participation outcomes and a gap of about 14 percentage points still exists between prime-age men and women. Our analysis of labor force attachment suggests that declining male attachment is an upside risk for unemployment going forward even though its effects are, thus far, more than offset by the downward trend in job destruction. Another implication of our findings is that improvements in child-care availability and maternity leave policy for women would also lower the natural rate of unemployment by increasing women's labor force attachment.

³⁷<https://www.cbo.gov/system/files?file=2019-01/54918-Outlook-Chapter2.pdf>

³⁸<https://www.federalreserve.gov/monetarypolicy/files/fomcprojtab120180926.pdf>

The aging of the population was predictable as early as the 1960s and its consequences for innovation, productivity, government budgets, tax policy, social security, the labor market, and political economy have inspired an abundance of analyses and policy recommendations.³⁹ While the discussion on the effects of aging goes back decades, there is still room for further research on this topic as its effects on other parts of the economy—such as the decline in firm entry and aging of firms—have taken shape. Another important implication of aging is the decline in workers’ bargaining power as recently analyzed by [Glover and Short \(2018\)](#). Using cross-sectoral variation they find that older workers receive a smaller share of their marginal product than do younger workers and link the recent demographic trends in the U.S. to the declining bargaining power of workers. Since both worker and firm demographics are slow moving, and would likely take a long time to reverse, we expect these effects to persist.

Admittedly (and hopefully), our paper is not the last word on the natural rate of unemployment. However, we view our unified framework as a useful tool for future policy analyses as it provides a bridge between the Phillips curve literature and the macro-labor literature which focuses on measuring labor market efficiency by exploiting rich cross-sectional information. Moreover, the development of detailed micro data sources is a relatively recent development and we expect that further progress harmonizing these two approaches will be made in future work.

³⁹An insightful article by [Cutler, Poterba, Sheiner, and Summers \(1990\)](#) lays out various issues related to aging.

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Online Appendix for
“A Unified Approach to Measuring u^* ”

Richard K. Crump

(Federal Reserve Bank of New York)

Marc Giannoni

(Federal Reserve Bank of Dallas)

Stefano Eusepi

(University of Texas at Austin)

Ayşegül Şahin

(University of Texas at Austin)

A Derivation of Mismatch Unemployment

This derivation follows [Şahin, Song, Topa, and Violante \(2014\)](#). While they allow for matching efficiencies to vary by sector, we derive mismatch unemployment under homogenous matching efficiency.

There are I distinct frictional labor markets with Cobb-Douglas matching function: $h_{it} = \phi_t v_{it}^\alpha u_{it}^{1-\alpha}$. New production opportunities (vacancies) v_i arise exogenously and there are u_i unemployed workers in market i . The optimal allocation of unemployed workers across labor markets in their environment requires that weighted vacancy-unemployment ratios be equated across labor markets:

$$\frac{v_1}{u_1^c} = \frac{v_i}{u_i^c} \dots = \frac{v_I}{u_I^c} = \frac{v}{u}$$

In its simplest form, where all labor markets have the same productivity and market-specific matching function, this requires that the market-specific vacancy-unemployment ratios be all the same. Therefore, in the homogeneous case, any deviation of a specific markets tightness from the aggregate labor market's tightness is a sign of mismatch. The mismatch index—which provides a measure of the fraction of hires lost because of misallocation—is defined as

$$\mathcal{M}_t^h \equiv \frac{h_t^c - h_t}{h_t^c} = 1 - \sum_{i=1}^I \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \in [0, 1]$$

Mismatch causes a shift in the aggregate matching function:

$$h_t = \sum_{i=1}^I \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \cdot \phi_t v_t^\alpha u_t^{1-\alpha} = (1 - \mathcal{M}_t^h) \cdot \phi_t v_t^\alpha u_t^{1-\alpha}$$

Writing equation (2) in discrete time and dividing by L_t gives us the evolution of the observed unemployment dynamics

$$u_{t+1} = u_t + s_t(1 - u_t) - f_t u_t$$

Aggregate outflow rate without mismatch

$$f_t^c = \Phi_t \cdot \left(\frac{v_t}{u_t^c} \right)^\alpha = f_t \cdot \frac{1}{(1 - \mathcal{M}_t^h)} \left(\frac{u_t}{u_t^c} \right)^\alpha$$

Counterfactual unemployment dynamics in absence of mismatch can easily be computed using the law of motion for unemployment with the counterfactual outflow rate:

$$u_{t+1}^c = u_t^c + s_t(1 - u_t^c) - f_t^c u_t^c$$

Mismatch unemployment is then given by $u_t - u_t^c$.

B Data Sources

B.1 Labor Market Data

Current Population Survey (CPS) We calculate the number employed, the number unemployed, and the number unemployed less than five weeks for each month from the Current Population Survey (CPS) by age, gender, state and industry. As discussed by [Polivka and Miller \(1998\)](#) and [Abraham and Shimer \(2002\)](#), the 1994 redesign of the CPS changed the way the survey measures unemployment duration for all of the survey’s eight “rotation groups” except the first and fifth. The resulting reduction in the number counted as short-term unemployed induced a discontinuity in the series. We follow [Elsby, Hobijn and Şahin \(2010\)](#) for the correction.

The Current Population Survey (CPS) reports the labor market status of the respondents each month that allows the BLS to compute important labor market statistics like the unemployment rate. In particular, in any given month a civilian can be in one of three labor force states: employed (E), unemployed (U), and not in the labor force (N) making it possible to compute monthly transition rates between three labor market states. We exploit the replication files of [Barnichon and Mesters \(2018\)](#) who provided a carefully computed estimates of labor market flows by age and gender.

Business Employment Dynamics (BED) Business Employment Dynamics is a set of statistics generated from the Quarterly Census of Employment and Wages program. These quarterly data series consist of gross job gains and gross job losses statistics from 1992 forward. These data help to provide a picture of the dynamic state of the labor market. The change in the number of jobs over time is the net result of increases and decreases in employment that occur at all private businesses in the economy. Business Employment Dynamics (BED) statistics track these changes in employment at private-sector establishments from the third month of one quarter to the third month of the next. The difference between the number of gross job gains and the number of gross job losses is the net change in employment.

Business Dynamics Statistics (BDS) The Business Dynamics Statistics (BDS) provides annual measures of business dynamics for the economy and aggregated by establishment and firm characteristics. We use firm-age-specific job destruction rates by state from the publicly available BDS database for 1977-2014. The BDS is created from the Longitudinal Business Database (LBD), a confidential database available to qualified researchers through secure Federal Statistical Research Data Centers.

Job Openings and Labor Turnover Survey (JOLTS) and Help Wanted Online Data (HWOL) We use vacancy data from the Job Openings and Labor Turnover Survey (JOLTS), which provides survey-based measures of job openings and hires at a monthly frequency, starting from December 2000, for seventeen industries roughly corresponding to the 2-digit NAICS classification to calculate the mismatch index. At the occupation level, we use vacancy data from the Help Wanted OnLine (HWOL) dataset provided by The Conference Board (TCB) starting in May 2005. This is a novel data set containing the universe of online advertised vacancies posted on internet job boards or in newspaper online editions. It covers roughly 16,000 online job boards and provides detailed information about the characteristics of advertised vacancies for three to four million unique active ads each month.

B.1.1 Inflation Expectations Data

We utilize survey data from a variety of sources to capture inflation expectations in the U.S.

Blue Chip Economic Indicators The Blue Chip Economic Indicators (BCEI) is a survey of professional forecasters that has been running since 1976. The survey is typically released on the 10th of each month, and is based on 50-plus responses that have been collected during the first week of the same month. The survey focuses primarily on economic variables such as those in the NIPA tables, but also includes forecasts for CPI inflation. The participants of the survey range from large commercial banks, broker dealers, insurance companies, large manufacturers, economic consulting firms, GSEs and others. Beginning in March 1979, BCEI began querying respondents on their forecasts for a selection of variables over the following five years. Later that year, these special questions included longer horizons including 6-to-10 years ahead or 7-to-11 years ahead. We merge responses for either horizon to form a single series. These biannual questions have generally been conducted in the March and October surveys. Blue Chip Economic Indicators is owned by Wolters Kluwer.

Blue Chip Financial Forecasts The Blue Chip Financial Forecasts Survey (BCFF) is a monthly survey of about 50 professional forecasters that has been running since 1982. The survey is typically released on the first day of the month, and is based on participants’ responses that have been collected during the last

week of the previous month. The survey focuses primarily on financial variables such as interest rates (as compared to the BCEI) but also includes forecasts for major macroeconomic variables (such as output and inflation). The participants of the survey range from broker-dealers to economic consulting firms, and the identity of the participants is known for their shorter-term forecasts (out to as much as six-quarters ahead). For longer horizons the consensus (i.e., mean) forecast is provided for each variable. Beginning in 1983, BCFF began querying respondents on their forecasts for a selection of variables over the following five years (once in 1983 and twice in 1984 and 1985). Starting in 1986 these biannual special questions included longer horizons including 6-to-10 years or 7-to-11 years ahead. We merge responses for either horizon to form a single series. Between March 1986 and March 1996 longer-run forecasts are provided in the March and October surveys. From December 1996 onward, long-run forecasts are provided in the June and December releases. The only exception to this rule is that long-run forecasts were provided in the January 2003 survey instead of the December 2002 survey. Blue Chip Financial Forecasts is owned by Wolters Kluwer.

Livingston Survey The Livingston Survey was begun in June 1946 by Joseph Livingston, but was taken over in 1990 by the Federal Reserve Bank of Philadelphia.⁴⁰ The survey is conducted twice a year in June and December and was conducted when Livingston worked at the *Philadelphia Inquirer*. He sent his survey to professional economists. Note that the target CPI measure is the index value in the last month of the quarter. We use the 1-2 quarter ahead and 3-4 quarter ahead forecasts which are available beginning in 1946.

SPF The Survey of Professional Forecasters (SPF) is conducted on a quarterly basis by the Federal Reserve Bank of Philadelphia (FRBP). The survey began in the fourth quarter of 1968 and, at that time, was conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) before being taken over by the FRBP in the second quarter of 1990.⁴¹ The forecasts are anonymous but are given specific industry identifiers which were updated in 2007. We use the average of the next four quarters ahead CPI forecasts which are available since 1981:Q3.

University of Michigan Consumer Sentiment The UM Consumer Sentiment survey (UM) is a survey of households which began in 1946. The survey queries respondents on a variety of subjects related to current conditions and expectations for the future. The questions range specific to the household along with national conditions. We use data on long-term inflation expectations from the survey.

⁴⁰For more details on the survey see <https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/livingston-survey/livingston-documentation.pdf?la=en>.

⁴¹For more details on the survey see <https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf?la=en>.

C Additional Tables and Figures

Figure C.1. Long-run unemployment forecasts.

The figure shows the evolution of professional forecasters and the FOMC's long-run forecasts of the unemployment rate. The light blue line is the median NAIRU estimate of the survey of professional forecasters (SPF), the black line is the median of the longer-run unemployment rate in the survey of primary dealers (SPD), and the red line is the midpoint of the range of estimates of the longer-run unemployment rate in the FOMC's summary of economic projections.

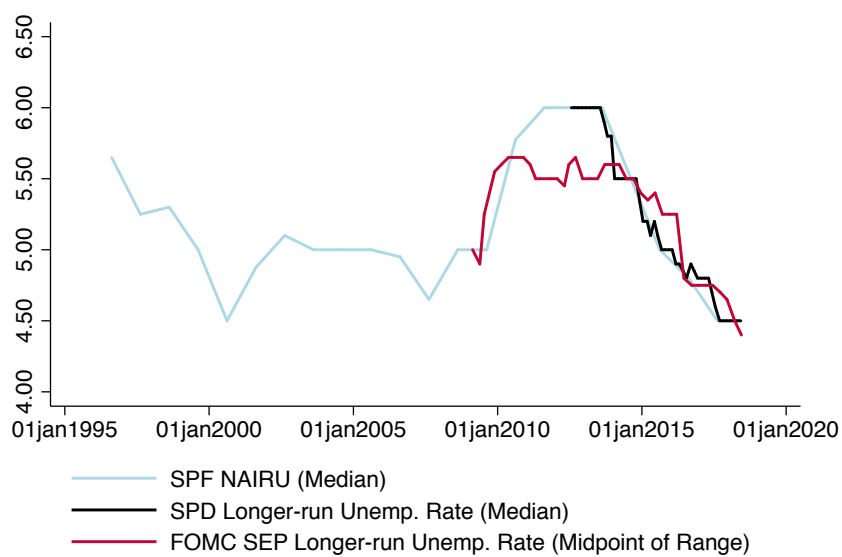


Figure C.2. Inflow and outflow rates for men (left panels) and for women (right panels) by age.

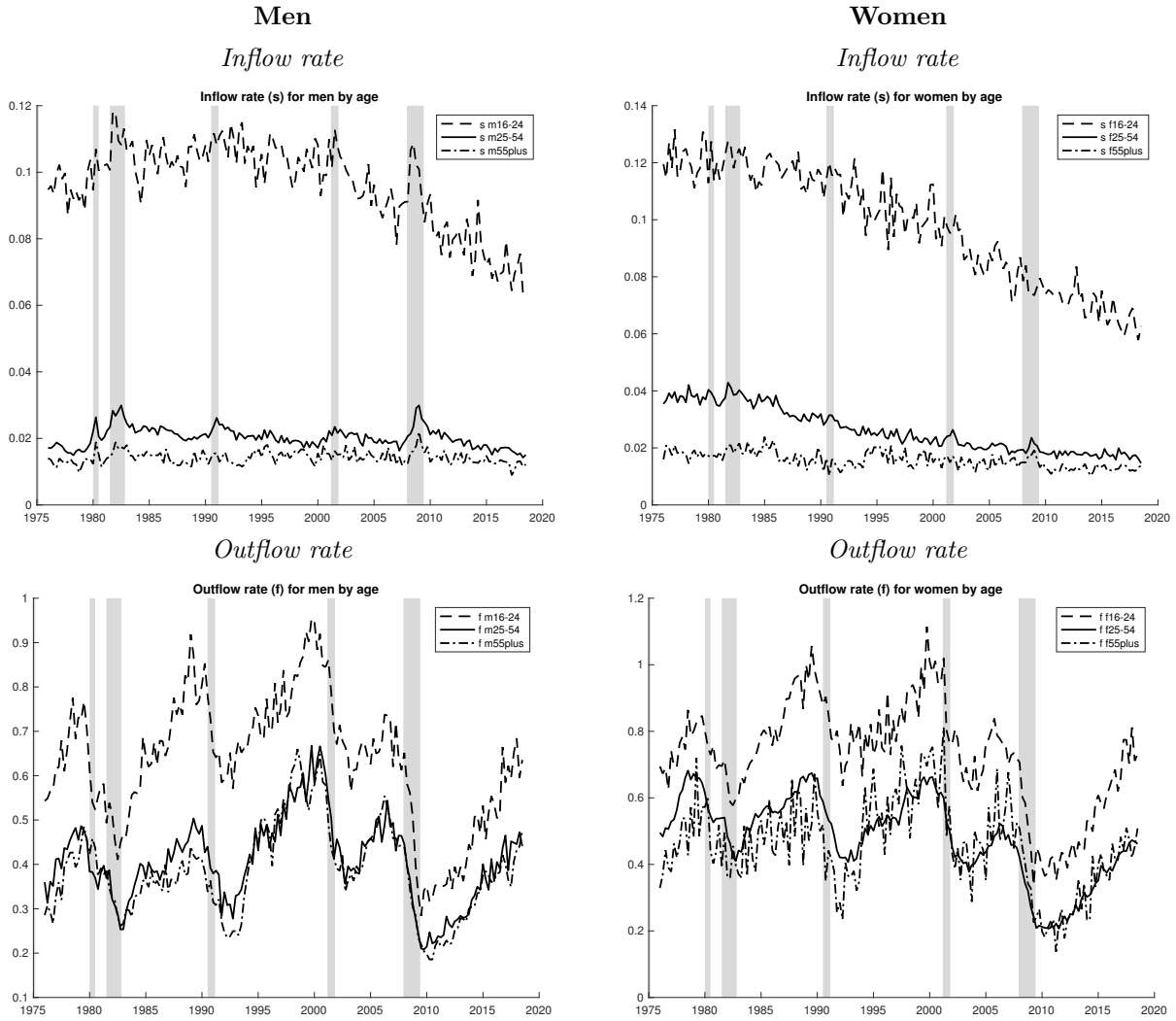


Figure C.3. 2011 Estimates of the NAIRU from the Federal Reserve System This figure reproduces Exhibit 12 from the presentation materials at the January 25-26, 2011 FOMC meeting. The left panel shows the distribution of estimates of NAIRU for three periods: pre-crisis, current, and in 2015; the right panel shows the distribution of the change in the estimate between the pre-crisis period and the current period.

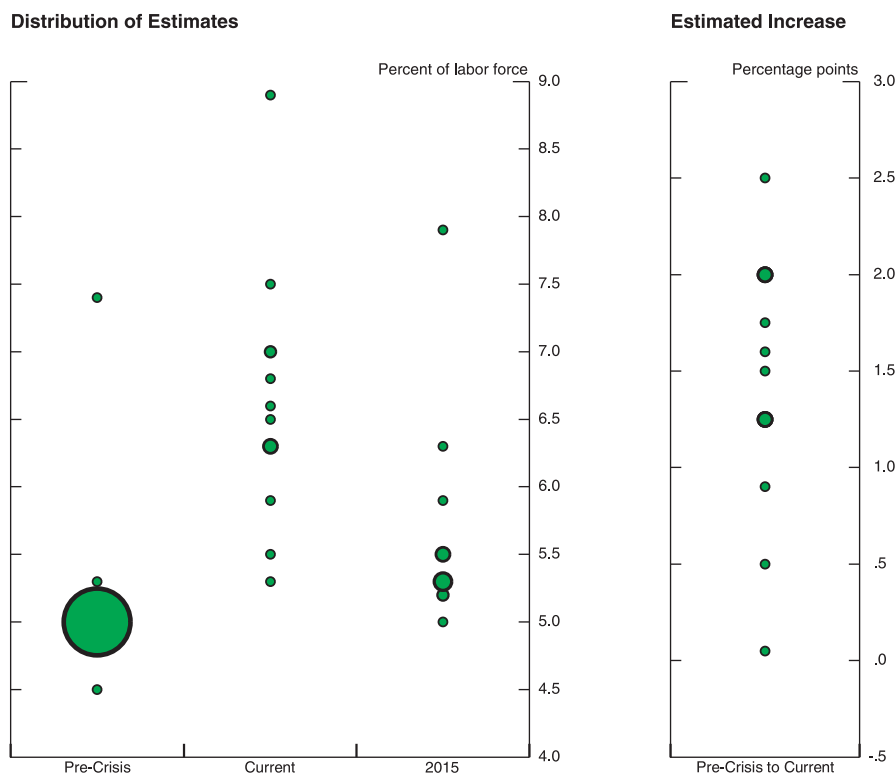


Table C.1. Inflow rate changes for 1977 to 1996, 1996 to 2018 and for full sample (1976 to 2018) and the contribution of each demographic group to the changes in the aggregate inflow rate.

	Aggregate	Women			Men		
	Change	16-24	25-54	55+	16-24	25-54	55+
<i>A. Inflow Rate</i>							
1976 to 1996	-0.80	-0.55	-0.24	-0.04	-0.17	0.13	0.01
1996 to 2018	-1.24	-0.34	-0.33	0.00	-0.34	-0.20	0.03
1976 to 2018	-2.04	-0.90	-0.57	-0.03	-0.51	-0.06	0.05
<i>B. Outflow Rate</i>							
1976 to 1996	9.45	-1.47	4.16	0.25	0.34	6.00	0.28
1996 to 2018	-6.50	-3.33	-2.47	1.76	-3.89	-1.15	2.15
1996 to 2018	2.95	-4.81	1.68	2.02	-3.54	4.84	2.43

Note: The counterfactual contributions are calculated using weights fixed at 1976 averages.

Figure C.4. Job destruction and employment-to-unemployment flow rates.

Employment to unemployment flow

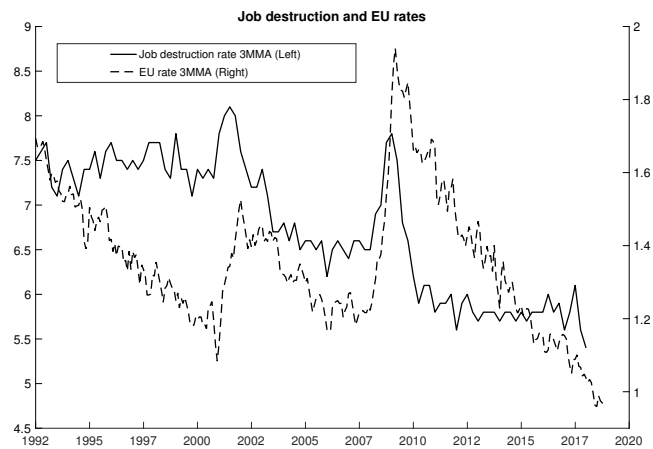


Figure C.5. Job reallocation and unemployment inflow rate (left) and job destruction and unemployment-to-unemployment flow rates.

Unemployment to employment flow

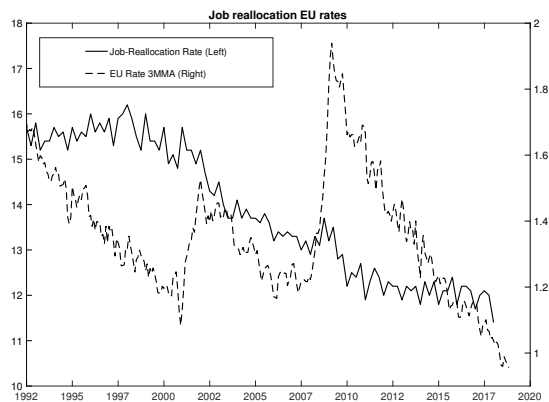


Table C.2. Unemployment inflow rate and employment-to-unemployment transition rate regressed on job destruction and job reallocation rates, averaged for three year non-overlapping periods.

<i>Regressors</i>	Inflow rate		E to U flow rate	
	(1)	(2)	(1)	(2)
Job destruction rate	0.582*** (0.0687)		0.452*** (0.0624)	
Job reallocation rate		0.277*** (0.0511)		0.198*** (0.0363)
Observations	48	48	48	48
R-squared	0.969	0.956	0.980	0.956

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0. Three-year averages for 1993-2018. Includes time and sector fixed effects, with seven industry sectors.

Table C.3. Changes (in Changes) in Job Destruction Rates and Firm Age Composition. This table reports regressions results for the regression equation:

$$\Delta^2 jd_{i,2012-2014} = \beta_0 + \beta_1 \cdot \Delta^2 \left(\frac{emp\ 11+}{emp} \right)_{i,2014} + \epsilon_i$$

where $\Delta^2 jd_{i,2012-2014} = (jd_{i,2012-2014} - jd_{i,1998-2000}) - (jd_{i,1998-2000} - jd_{i,1987-1989})$ and $\Delta^2 \left(\frac{emp\ 11+}{emp} \right)_{i,2014} = \left[\left(\frac{emp\ 11+}{emp} \right)_{i,2014} - \left(\frac{emp\ 11+}{emp} \right)_{i,1998} \right] - \left[\left(\frac{emp\ 11+}{emp} \right)_{i,1998} - \left(\frac{emp\ 11+}{emp} \right)_{i,1987} \right]$. The instrumental variable is the employment share of new firms in 1979. The second row reports p-values associated with the OLS estimate with robust standard errors; the fourth row reports weak-instrument robust confidence intervals constructed by inverting the Anderson-Rubin test (Mikusheva and Poi (2006)). The “All Ages” specification includes age effects.

	Long Horizon Change in Job Destruction Rate for:				
	Overall	All Ages	1Y-5Y	6Y-10Y	11Y+
OLS	-0.380	-0.195	0.173	-0.350	-0.407
<i>p-val.</i>	(0.019)	(0.164)	(0.599)	(0.128)	(0.001)
IV	-0.948	-0.827	-1.111	-0.465	-0.905
<i>90% conf. int.</i>	[-2.39, -0.53]	[-1.53, -0.37]	[-4.47, -0.05]	[-1.57, 0.44]	[-2.17, -0.54]
Obs.	50	150	50	50	50

Note: Results omit the District of Columbia.