Online Appendix for

"A Unified Approach to Measuring u^*"

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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:

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

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:

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

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.

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

[41] For 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.

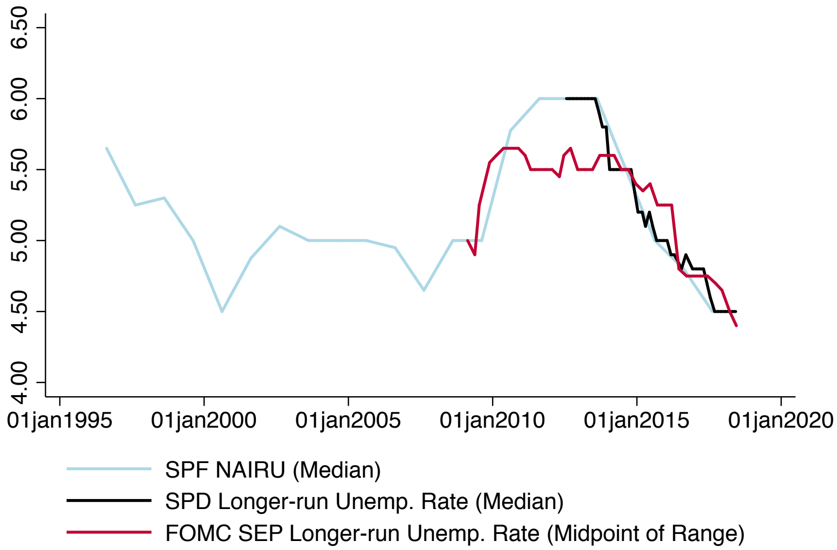

Figure C.2. Inflow and outflow rates for men (left panels) and for women (right panels) by age.

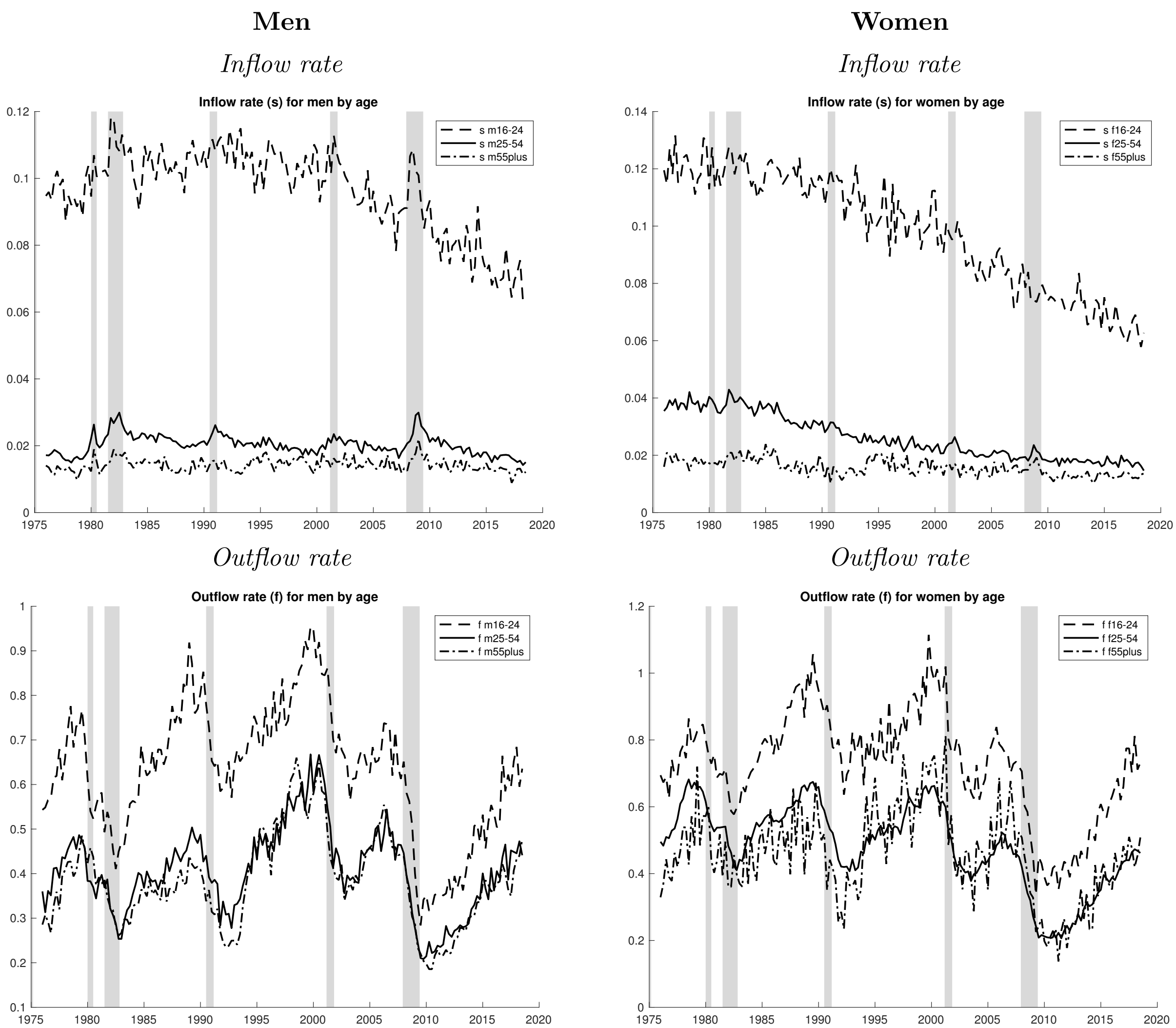

Figure C.3. 2011 Estimates of the NAIRU from the Federal Reserve System This figure reproduces Exhibit 12 from the presentation materials at the January 25-26, 2011 FOMC meeting. The left panel shows the distribution of estimates of NAIRU for three periods: pre-crisis, current, and in 2015; the right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

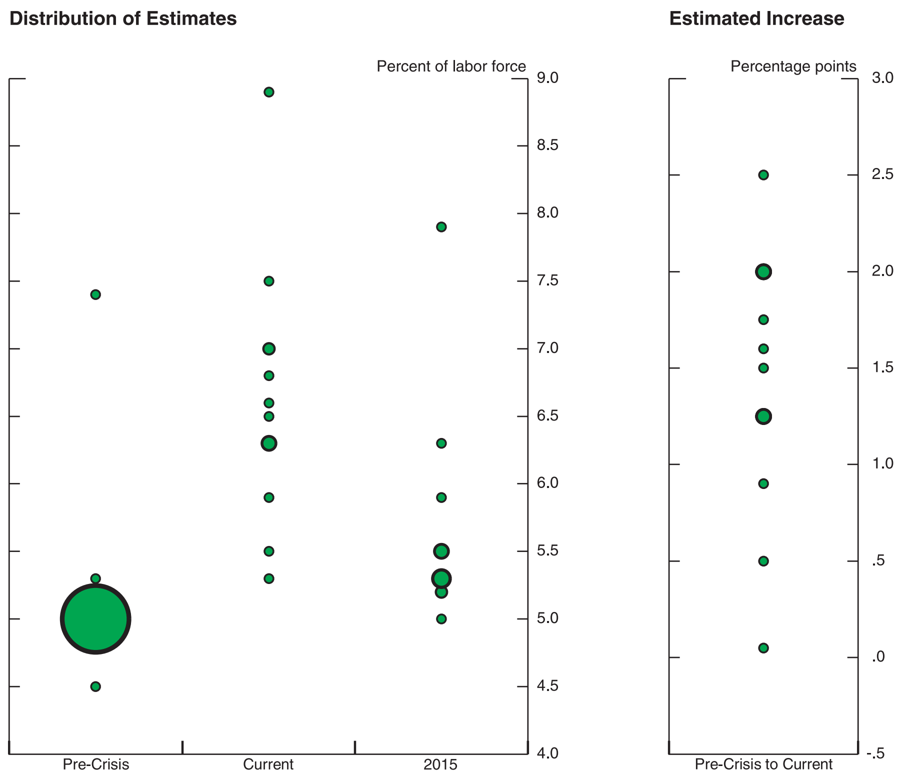

Table C.1. Inflow rate changes for 1977 to 1996, 1996 to 2018 and for full sample (1976 to 2018) and the contribution of each demographic group to the changes in the aggregate inflow rate.

	Aggregate	Women			Men		
	Change	16-24	25-54	55+	16-24	25-54	55+
				A. Inflow Rate			
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
				B. Outflow Rate			
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

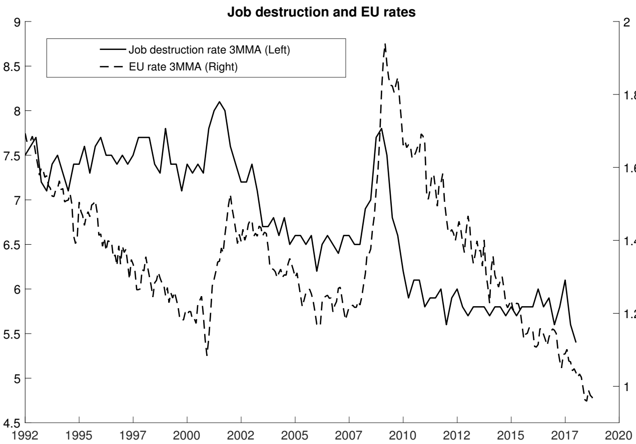

Figure C.5. Job reallocation and unemployment inflow rate (left) and job destruction and unemployment-to-unemployment flow rates.

Unemployment to employment flow

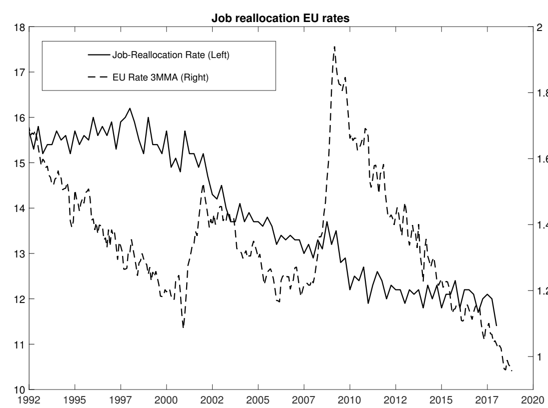

Table C.2. Unemployment inflow rate and employment-to-unemployment transition rate regressed on job destruction and job reallocation rates, averaged for three year non-overlapping periods.

	Inflow rate		E to U flow rate	
Regressors	(1)	(2)	(1)	(2)
Job destruction rate	0.582***		0.452***	
	(0.0687)		((0.0624)	
Job reallocation rate		0.277***		0.198***
		(0.0511)		(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:

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

where $\Delta^2 jd_{i,2012\text{-}2014} = (jd_{i,2012\text{-}2014} - jd_{i,1998\text{-}2000}) - (jd_{i,1998\text{-}2000} - jd_{i,1987\text{-}1989})$ and $\Delta^2\left(\frac{emp\,11+}{emp}\right)_{i,2014} = \left[\left(\frac{emp\,11+}{emp}\right)_{i,2014} - \left(\frac{emp\,11+}{emp}\right)_{i,1998}\right] - \left[\left(\frac{emp\,11+}{emp}\right)_{i,1998} - \left(\frac{emp11+}{emp}\right)_{i,1987}\right]$. 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
p-val.	(0.019)	(0.164)	(0.599)	(0.128)	(0.001)
IV	-0.948	-0.827	-1.111	-0.465	-0.905
90% conf. int.	[-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.