Online Appendix
"Declining Desire to Work and Downward Trends in Unemployment and Participation"

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1 Data

In the paper, we make use of two sets of transition rates: the first over 1976-2010 between the three labor market states E, U, N, and the second over 1994-2010 between the four labor market states E, U, N^w and N^n.

To measure individuals' transition probabilities p^{AB} from labor force status $A \in \{E, U, N\}$ to labor force status $B \in \{E, U, N\}$ over 1976-2010, we use matched CPS micro data from January 1976 through December 2010 and compute the number of workers moving from A to B each month. We then correct the measured transitions for the 1994 CPS redesign as described below. To measure individuals' transition probabilities p^{AB} from labor force status $A \in \{E, U, N^n, N^w\}$ to labor force status $B \in \{E, N^n, N^w\}$ over 1994-2010, we use matched CPS micro data from January 1994 through December 2010 and compute the number of workers moving from A to B each month.

In both cases, we then correct the measured transitions for time-aggregation bias.[1]

1.1 Correction for the 1994 CPS redesign

When measuring transition probabilities over 1976-2010, the 1994 redesign of the CPS (see e.g., Polivka and Miller, 1998) caused a discontinuity in some of the transition probabilities in the first month of 1994 (Abraham and Shimer, 2002).

To adjust the series for the redesign, we proceed as follows. We start from the monthly transition probabilities obtained from matched data for each demographic group. We take the post-redesign transition probabilities as the correct ones, and we correct the pre-94 value for the redesign. To do so, we estimate a VAR with the six hazard transition probabilities in logs estimated over 1994m1-2010m12 and as used in Barnichon and Nekarda (2012), and we

[1] We also implemented a correction for margin error that restricts the estimates of worker flows to be consistent with the evolution of the corresponding labor market stocks, as in Poterba and Summers (1986). We did not correct the data for classification error and spurious transitions (Abowd and Zellner (1985), Poterba and Summers (1986)), because it is not clear how one should correct for such classification error in the CPS survey (Elsby, Hobijn and Sahin, 2013). Elsby et al. report alternative correction methods, and the secular trends appear broadly unchanged.

use the model backcast the 93m12 transition probabilities[2] With these 93m12 values in hand, we obtain corrected transition probabilities over 1976m2-1993m12 by adding to the original probability series the difference between the original value in 93m12 and the inferred 93m12 value.

By eliminating the jumps in the transition probabilities in 1993m12, we are assuming that these discontinuities were solely caused by the CPS redesign. Thus, the validity of our approach rests on the fact that 1994m1 was not a month with large "true" shocks to the transition probabilities. We think that this is unlikely because there is no large movements in the aggregate job finding rate and aggregate job separation rate obtained from duration data (Shimer, 2012 and Elsby, Michaels and Solon, 2009) that do not suffer from these discontinuities. Indeed, these authors treat the 1994 discontinuity by using data from the first and fifth rotation group, for which the unemployment duration measure (and thus their transition probability measures) was unaffected by the redesign. Moreover, Abraham and Shimer (2002) used independent data from the Census Employment Survey to evaluate the effect of the CPS redesign on the average transition probabilities from matched data. They found that only λ^{UN} and λ^{NU} were significantly affected, and that, after correction of these discontinuities (using the CES employment-population ratio), none of the transition probabilities displayed large movements in 1994.

1.2 Correction for time-aggregation bias

The estimated transition probabilities suffer from time-aggregation bias because one can only observe transitions at discrete (in this case, monthly) intervals (Shimer, 2012).[3] We thus need to correct for time-aggregation bias for each demographic group. To do so, we use Shimer (2012) and Elsby et al. (2013)'s method that we generalize to a labor market with 4 states with $\{E, U, N^w, N^n\}$ (employed, unemployed, "want a job" nonparticipant, "not want a job" nonparticipant).

We consider a continuous time environment in which data are available only at discrete dates. For $t \in \{0, 1, 2...\}$, we refer to the interval $[t, t+1[$ as 'period t'. We assume that the transition of workers across labor market states can be described by a (four-state) Markov chain of order 1 with the transition matrix being constant during period t. The number of employed E, unemployed U, "want a job" nonparticipant N^w and "not want a job" nonparticipant N^n

[2] The number of lags were chosen to maximize out-of-sample forecasting performances. A similar VAR is used in Barnichon and Nekarda (2012) to forecast the six flow rates.

[3] Another issue is classification error (Abowd and Zellner, 1985 and Poterba and Summers, 1986). Although it is not clear whether one should apply these correction methods on the current CPS survey, Elsby, Hobijn and Sahin (2013) try different correction methods, and the secular trends are broadly unchanged.

then satisfies the system

$$Y_t = \tilde{P}_t Y_{t-1} \tag{1}$$

with

$$\tilde{P}_t = \begin{pmatrix} 1-p^{EU}-p^{EN^w}-p^{EN^n} & p^{UE} & p^{N^wE} & p^{N^nE} \\ p^{EU} & 1-p^{UE}-p^{UN^w}-p^{UN^n} & p^{N^wU} & p^{N^nU} \\ p^{EN^w} & p^{UN^w} & 1-p^{N^wU}-p^{N^wE}-p^{N^wN^n} & p^{N^nN^w} \\ p^{EN^n} & p^{UN^n} & p^{N^wN^n} & 1-p^{N^nU}-p^{N^nE}-p^{N^nN^w} \end{pmatrix}_t \tag{2}$$

where we omit the demographic group subscript i for clarity of presentation.

To recover the hazard rates from the measured transition probabilities (i.e., correct the transition probabilities for time-aggregation bias), we need to recover the instantaneous transition matrix P_t in the continuous time system

$$Y_t = P_t Y_{t-1} \tag{3}$$

The first-order differential equation (3) has solution $Y_t = V_t \Lambda_t V_t^{-1} Y_{t-1}$ with V_t the matrix of eigenvectors of P_t and Λ_t a diagonal matrix with the exponential of the eigenvalues of P_t on the diagonal. Contrasting with (1), it follows that $\tilde{P}_t$ has the same eigenvectors as P_t, so that one can construct P_t from $P_t = V_t \Lambda_t V_t^{-1}$ with V_t the matrix of eigenvectors of $\tilde{P}_t$ and Λ_t a diagonal matrix with the log of the eigenvalues of $\tilde{P}_t$ on the diagonal.

2 Decompositions of u_t, l_t and m_t

This section describes the decomposition of (i) the unemployment rate u_t, (ii) the participation rate l_t, and (iii) the share of "want a job" nonparticipants m_t.

2.1 Decomposition of u_t and l_t

We now describe the decomposition of u_t and l_t underlying Figures 6-9 in the main text.

Denoting $\omega_{it} = \frac{LF_{it}}{LF_t}$ the share of group $i \in \{1,..,K\}$ in the labor force and $\Omega_{it} = \frac{Pop_{it}}{Pop_t}$ the population share of group i, the aggregate unemployment and participation rates are given by

$$\begin{cases} u_t = \sum_{i=1}^{K} \Omega_{it} \frac{l_{it}}{l_t} u_{it} \\ l_t = \sum_{i=1}^{K} \Omega_{it} l_{it} \end{cases} \tag{4}$$

The steady-state unemployment rate of group i, $u_{it} = \frac{U_{it}}{LF_{it}}$, satisfies

$$\begin{aligned} u_{it} &= u(\{\lambda_{it}^{AB}\}), \quad A, B \in \{E, U, N\} \\ &= \frac{s_{it}}{s_{it} + f_{it}} \end{aligned}$$

where s_{it} and f_{it} are

$$\begin{cases} f_{it} = \lambda_{it}^{UE} + \lambda_{it}^{UN} \frac{\lambda_{it}^{NE}}{\lambda_{it}^{NE} + \lambda_{it}^{NU}} \\ s_{it} = \lambda_{it}^{EU} + \lambda_{it}^{EN} \frac{\lambda_{it}^{NU}}{\lambda_{it}^{NE} + \lambda_{it}^{NU}} \end{cases}. \tag{5}$$

Similarly, the steady-state labor force participation rate of group i, $l_{it} = \frac{LF_{it}}{Pop_{it}}$ satisfies

$$\begin{aligned} l_{it} &= l\left(\{\lambda_{it}^{AB}\}\right), \quad A, B \in \{E, U, N\} \\ &= \frac{s_{it} + f_{it}}{s_{it} + f_{it} + \frac{\lambda_{it}^{EU}\lambda_{it}^{UN} + \lambda_{it}^{UE}\lambda_{it}^{EN} + \lambda_{it}^{UN}\lambda_{it}^{EN}}{\lambda_{it}^{NE} + \lambda_{it}^{NU}}}. \end{aligned} \tag{6}$$

The identities in (4) are functions of the six hazard rates of each demographic group (the λ_{it}^{AB}s, $A, B \in \{E, U, N\}$, $i \in \{1, .., K\}$) and functions of the population shares (Ω_{it}, $i \in \{1, .., K\}$) of each group.

By taking a Taylor expansion of the identities in (4) around the mean of the hazard rates of each demographic group i ($\lambda_{it}^{AB} \simeq E\lambda_{it}^{AB}$) and around the mean of the population share ($\Omega_{it} \simeq \Omega_i \equiv E\Omega_{it}$) of each group, we can decompose the aggregate unemployment rate u_t and labor force participation rate l_t into the contribution of changes in demographics and the contributions of movements in each transition rate (stripped of demographic effects):[4]

$$\begin{cases} du_t = du_t^{\Omega} + du_t^{UE} + du_t^{UN} + du_t^{EU} + du_t^{EN} + du_t^{NU} + du_t^{NE} + \varepsilon_t^u \\ dl_t = dl_t^{\Omega} + dl_t^{UE} + dl_t^{UN} + dl_t^{EU} + dl_t^{EN} + dl_t^{NU} + dl_t^{NE} + \varepsilon_t^l \end{cases} \tag{7}$$

with $du_t^{\Omega} = \sum_{i=1}^{K} \beta_i^{\Omega} (\Omega_{it} - \Omega_i)$ capturing the contribution of demographics

and $du_t^{AB} = \sum_{i=1}^{K} \beta_i^{AB} \left(\lambda_{it}^{AB} - \lambda_i^{AB}\right)$, $A, B \in \{E, U, N\}$, β_i^{AB} the coefficients of the Taylor expansion, capturing the contribution of λ^{AB}, the transition rate from A to B to the unemployment

[4] By taking a Taylor expansion around the mean, instead of around an HP-filter trend or around last period's value as in Elsby et al. (2009) or Fujita and Ramey (2009), our decomposition has the advantage of covering all frequencies and hence allows us to analyze low-frequency movements (as well as cyclical movements). The coefficients of the Taylor expansion are available upon request. To guarantee that the approximation remains good however, we take a second-order approximation, which performs extremely well, as we show in the next section.

rate (holding the demographic structure of the population constant). ε_t^u is the Taylor approximation error. Similar notations apply to the decomposition of the labor force participation rate, but substituting β_i^{AB} with δ_i^{AB}, the coefficients of the Taylor expansion of l_{it}.

Finally, by using equation (3) in the main, we obtain the effect of changes in the share of "want a job" nonparticipants on unemployment, du_t^m

$$du_t^m = \sum_{i=1}^{K} \beta_i^{NU} \left[\left(\lambda_i^{N^w U} - \lambda_i^{N^n U} \right) - \frac{\lambda_i^{NU}}{\lambda_i^{NE}} \left(\lambda_i^{N^w E} - \lambda_i^{N^n E} \right) \right] (m_{it} - m_i) \tag{8}$$

and a similar expression holds for dl_t^m with

$$dl_t^m = \sum_{i=1}^{K} \left[\delta_i^{NU} \left(\lambda_i^{N^w U} - \lambda_i^{N^n U} \right) + \delta_i^{NE} \left(\lambda_i^{N^w E} - \lambda_i^{N^n E} \right) \right] (m_{it} - m_i) \, . \tag{9}$$

The upper panel of Figure 6 in the main text shows du_t^{Ω}, and the middle panel shows du_t^m. The top panel of Figure 7 in the main text shows du_t^{Ω}, the second panel shows $du_t^{NU} + du_t^{NE}$, the third panel shows $du_t^{EU} + du_t^{EN}$, and the fourth panel shows $du_t^{UE} + du_t^{UN}$. In the second panel, the dashed line reports du_t^m. Figures 8 and 9 in the main text are organized in a similar fashion for the aggregate participation rate.

Finally, we verify that the second-order Taylor expansions behind the stock-flow decompositions of unemployment and participation, equation (7) do indeed capture, to a good approximation, the movements in unemployment and participation. Figure 1 plots, in plain black, the steady-state unemployment rate along with, in dashed red, the unemployment rate implied by (7). We can see that our decomposition does an excellent job at capturing unemployment movements. Similarly, Figure 2 plots in plain black, the steady-state labor force participation rate along with, in dashed red, the labor force participation rate implied by (7). Again, our decomposition does an excellent job at capturing participation movements.

2.2 Decomposition of m_t

The accounting identity behind the stock-flow decomposition of m_t is given by the steady-state of the system (1). Specifically, letting λ_t^{AB} denote the hazard rate of transiting from state $A \in \{E, U, N^w, N^n\}$ to state $B \in \{E, U, N^w, N^n\}$, in continuous time, we have

$$\underbrace{\begin{pmatrix} \overset{\bullet}{U} \\ N^w \\ N^n \end{pmatrix}_t}_{\dot{s}_t} = L_t \underbrace{\begin{pmatrix} U \\ N^w \\ N^n \end{pmatrix}_t}_{s_t} + \underbrace{\begin{pmatrix} \lambda^{EU} \\ \lambda^{EN^w} \\ \lambda^{EN^n} \end{pmatrix}_t}_{g_t} Pop_t$$

with

$$L_t = \begin{pmatrix} -\lambda^{UE} - \lambda^{UN^w} - \lambda^{UN^n} - \lambda^{EU} & \lambda^{N^wU} - \lambda^{EU} & \lambda^{N^nU} - \lambda^{EU} \\ \lambda^{UN^w} - \lambda^{EN^w} & -\lambda^{N^wU} - \lambda^{N^wE} - \lambda^{N^wN^n} - \lambda^{EN^w} & \lambda^{N^nN^w} - \lambda^{EN^w} \\ \lambda^{UN^n} - \lambda^{EN^n} & \lambda^{N^wN^n} - \lambda^{EN^n} & -\lambda^{N^nU} - \lambda^{N^nE} - \lambda^{N^nN^w} - \lambda^{EN^n} \end{pmatrix}_t .$$

The steady-state of the system, s_t^*, is then given by

$$s_t^* = -L_t^{-1} g_t. \tag{10}$$

From the expression for s_t^*, (10), we can then define the steady-state variable of interest; in our case, the share of "want a job" nonparticipants $m_t = \frac{N_t^w}{N_t^w + N_t^n}$. We can then decompose the stock m_t into the contribution of the flows using a Taylor expansion of (10) around the mean of each hazard rate ($\lambda_t^{AB} \simeq \lambda^{AB} \equiv E\lambda_t^{AB}$)

$$m_t - m = \sum_{A \neq B} \gamma^{AB} \left(\lambda_t^{AB} - \lambda^{AB}\right) + \eta_t \tag{11}$$

with $A, B \in \{E, U, N^w, N^n\}$ and $\left\{\gamma^{AB}\right\}$ the coefficients of the Taylor expansion. Using (11) and data on transition rates between E, U, N^w and N^n over 1994-2010,[5] we can assess the separate contributions of each hazard rate to movements of m_t.

3 Some more facts

This section presents a number of additional facts mentioned in the main text of the paper.

3.1 The behavioral differences between N^w and N^n over time

To verify that the information conveyed by the answer to the question "Want a job" did not change too much over time, Figure 3 plots the evolution of the relative propensities to join Unemployment (U) and Employment (E) for "Want a job" (N^w) and "Not want a job" (N^n) nonparticipants: The solid line depicts p^{N^wU}/p^{N^nU} and the dashed line depicts p^{N^wE}/p^{N^nE}. We can see that the two ratios are remarkably stable over time.

3.2 Strong wage growth over 1995-2000

The second half of the 90s coincides with strong positive growth in real wages for all deciles of the income distribution. Figure 4 shows the cumulative changes in real wages since 1994

[5] Recall that transitions in and out of N^w or N^n are only available starting in 1994.

for different percentiles of the wage distribution.[6] Since higher wage leads to higher search intensity of primary workers, strong wage growth is unlikely to explain the decline in desire to work through its effect on primary earners. However, large gains in wage income imply large gains in real family income, which can, through the added-worker effect, lead to lower desire to work among secondary workers. Figure 5 shows a striking correlation between real median family income and the fraction of nonparticipants who do not want a job.

4 A more general accounting framework: Allowing for separate transition rates for N^w and N^n labor force entrants

The accounting framework underlying our results on the impact of a change in the share of "want a job" nonparticipants on unemployment and participation were calculated under the assumption that the transition of workers across labor market states could be described by a (four-state) Markov chain of order 1, in that only the current labor market state is relevant to determine an individual transition rate to another state.

This assumption is standard in the "Ins and Outs" literature that uses a two-state (unemployment and employment) or a three-state (unemployment, employment, nonparticipation) stock-flow accounting model to decompose unemployment fluctuations into the contributions of its flows.[7] This assumption amounts to summarizing worker heterogeneity with one variable: the current labor market status. Naturally, this assumption is a simplification of reality as it is well known that labor force entrants have different unemployment outflow rates than job losers (e.g., Elsby et al., 2009) or that long-term unemployed have lower exit rates than short-term unemployed.

In our paper, we made the same simplifying assumption in a four-state model of the labor market, and we posited that once a non-participant joins the labor force, he behaves like any other unemployed or unemployed worker so that his future transitions do not depend on whether that individual was formally a "want a job" or a "not want a job" non-participant.

In this section, we test the sensitivity of our results to that approximation by considering a richer framework in which we relax the assumption that a labor force entrant ("want a job" or not) behaves like the "average" labor force participant once he entered the labor force. Specifically, we posit that labor force participants can be of two types: (i) "New" labor force entrants and (ii) "Old" labor force entrants. Each type is characterized by its own transition rates, and "New" entrants become "Old" at some constant Poisson rate υ.[8]

[6] A very similar picture holds for all the other deciles of the income distribution. Wage measures were constructed from the CPS Outgoing Rotation Group microdata.

[7] Fujta and Ramey (2009), Elsby et al. (2009), Shimer (2012), Elsby et al. (2013).

[8] In fact, since a nonparticipant can be of two types ("Want a job" or "Not want a job"), we allow labor

4.1 Model

Specifically, we consider a labor market with 8 states: $(E, U, N^w, N^n, U^{N^w}, E^{N^w}, U^{N^n}, E^{N^n})$. An *Old* labor force entrant can be employed (E) or unemployed (U) and transit between these states or leave the labor force to become a "want a job" nonparticipant (N^w) or a "not want a job" nonparticipant (N^n). A "want a job" nonparticipant (N^w) who joins the labor force is a *New* labor force entrant, and he can be unemployed (U^{N^w}) or employed (E^{N^w}) and can then transit between these states or leave the labor force. Similar notations apply for a former "not want a job" nonparticipant (U^{N^n}, E^{N^n}). As stated previously, a New labor force entrant becomes Old at a rate υ.

Denoting $Y_t = \left(E, E^{N^w}, E^{N^n}, U, U^{N^w}, U^{N^n}, N^w, N^n\right)'_t$ the vector of the number of workers in each state at date t, we have

$$Y_t = P_t Y_{t-1} \tag{12}$$

with P_t a matrix capturing transition probabilities across states during period t.

For instance, for E_t, we have

$$E_t = (1 - p_t^{EU} - p_t^{EN^w} - p_t^{EN^n})E_{t-1} + U_{t-1}p_t^{UE} + E_{t-1}^{N^w}(1 - e^{-\upsilon}) + E_{t-1}^{N^n}(1 - e^{-\upsilon}) \tag{13}$$

with $(1 - e^{-\upsilon})$ capturing the probability that a "New" labor force entrant becomes "Old" within one period.

Similarly, for $E_t^{N^w}$, we have

$$E_t^{N^w} = (1 - p_t^{E^{N^w}U} - p_t^{E^{N^w}N^w} - p_t^{E^{N^w}N^n} - (1 - e^{-\upsilon}))E_{t-1}^{N^w} + N_{t-1}^w p_t^{N^w E^{N^w}} \tag{14}$$

and similarly for E^{N^n}, U, U^{N^w} and U^{N^n}.

Equations (13) and (14) show how a labor force entrant who is employed (E^{N^w}) is allowed to have different transition rates from an average employed worker (E).

4.2 Data

To measure the transition rates in and out of E^{N^w}, U^{N^w}, E^{N^n}, U^{N^n} as well as measure υ, we match the CPS micro data over *four* consecutive monthly surveys, that is we follow the labor force status over four consecutive months.[9]

force participants to be of three types: (i) "new" labor force entrants from "Want a job", (ii) "new" labor force entrants from "Not want a job" and (iii) "old" labor force entrants.

[9] The CPS is a rotating panel where individuals are surveyed for four consecutive months, left out for eight months, and then surveyed again for four consecutive months. It is thus possible to follow an individual for four consecutive months.

To measure the transition rates in and out of E^{N^w}, U^{N^w}, E^{N^n}, U^{N^n}, we proceed as in the 3- or 4-state case. For instance, we compute the probability $p_t^{U^{N^w}E}$ by calculating the probability that an individual who is an unemployed at t and was a "want a job" nonparticipant at $t-1$ finds a job at time $t+1$. We proceed similarly for the transition rates in and out of E^{N^n} and U^{N^n}.

To measure υ, the rate at which a New labor force entrant becomes Old, we compare the average transition probabilities of a labor force participant who entered the labor force 2 months ago with the transition probabilities of a labor force participant who entered the labor force one month ago.

Specifically, denote p_τ^{AB} the measured transition probability (between state A and B) of labor force entrants who entered the labor force τ times ago. p_0^{AB} is then the transition probability of a labor force entrant who just entered the labor force. Denote p^{AB} the transition probability of Old labor force entrants.

Denote N_τ the number of New labor force entrant who entered the labor force exactly τ times ago. We have that N_τ evolves according to

$$\frac{dN_\tau}{d\tau} = -\upsilon N_\tau$$

since New labor force entrants become Old at rate υ, which gives that

$$\frac{N_\tau}{N_0} = e^{-\upsilon\tau}.$$

We then have that the measured transition probability of labor force entrants who entered τ periods ago is given by

$$p_\tau^{AB} = e^{-\upsilon\tau} p_0^{AB} + (1 - e^{-\upsilon\tau}) p^{AB}, \tag{15}$$

i.e., a weighted average between the transition probability of a New labor force entrant and that of an Old labor force entrant, with the weight given by $\frac{N_\tau}{N_0}$, the fraction of labor force entrants who are still New after τ periods.

Rewriting (15) at $\tau = 1$ and $\tau = 2$ and re-arranging, we get

$$\upsilon = -\ln\left(\frac{p_2^{AB} - p^{AB}}{p_1^{AB} - p^{AB}}\right). \tag{16}$$

With measures of p_2^{AB}, p_1^{AB} and p^{AB} we can then recover υ through (16).

To measure p_2^{AB} and p_1^{AB}, we use the fact that we can match CPS micro data over four consecutive monthly surveys. First, to measure p_1^{AB}, the transition probability of a labor force participant who entered the labor force one month ago, we consider individuals who were nonparticipants in month 2, in the labor force in month 3, and we calculate the transition probabilities between month 3 and 4. Second, to measure p_2^{AB}, the transition probability of a labor force participant who entered the labor force 2 months ago, we consider individuals who were nonparticipants in month 1, in the labor force in month 2 and 3, and we calculate their transition probability between month 3 and 4.

Measuring p^{AB} is more difficult, since we cannot follow a worker for more than 3 periods. Instead, we will approximate p^{AB} with $p_{\geq 3}^{AB}$, the transition rate of individuals who entered the labor force more than 3 periods ago. To measure $p_{\geq 3}^{AB}$, we consider individuals who were in the labor force in months 1 and 2, and we calculate their transition probability between month 3 and 4.

Since υ can be calculated from different AB transitions, we use the average value implied by (16) and obtained for all possible AB transitions with $A = \{U, E\}$ and $B = \{U, E, N^w, N^n\}$. We obtain $\upsilon \simeq 0.2$, which implies that after one quarter, 50 percent of a cohort of New labor force entrants have become Old.

4.3 Decomposition of u_t and l_t

After correcting for time-aggregation bias as in the four-state case, we can use the stock-flow model (12) to quantify the contributions of the trend in the N^w-N^n and N^n-N^w transition rates on the aggregate unemployment rate. As shown in the main text, these two transition rates account for most of the fluctuations in the share of "want a job" nonparticipants, and a variance decomposition exercise using the generalized model (12) gives similar results with a total contribution of about 75 percent.

From the steady-state of (12), we can proceed as in the four-state case and use a Taylor expansion around the mean of each hazard rate to decompose the variations in unemployment du_t due to the movements in the flows $\lambda_t^{N^wN^n}$ and $\lambda_t^{N^nN^w}$:

$$du_t = \phi^{N^wN^n}\left(\lambda_t^{N^wN^n} - \lambda^{N^wN^n}\right) + \phi^{N^nN^w}\left(\lambda_t^{N^nN^w} - \lambda^{N^nN^w}\right). \tag{17}$$

We find that the decline in m_t coming from movements in $\lambda_t^{N^wN^n}$ and $\lambda_t^{N^nN^w}$ alone lowered unemployment by about .5 ppt and labor force participation by about 1.9 ppt. Thus, the results are similar (and confirm) the results reported in the paper using the simpler framework. Note that the results are actually stronger than in the main text, because decomposition (17) only captures movements in $\lambda_t^{N^wN^n}$ and $\lambda_t^{N^nN^w}$ which account for "only" 75 percent of the decline in m_t.

5 A model of family labor supply

We now present a labor supply model with intrafamilial choice. The model is deliberately stylized and will focus only on individuals' decision to enter the labor force.

We consider a sequential multiple-earner model in which the primary earner makes his/her work decision independently of the secondary earners. The first secondary earner, say the spouse, then makes his/her labor supply decision by maximizing utility, taking account of the primary earner's income. The next secondary earner, say a teenager living in the household, then makes his/her labor supply decision in a similar fashion. And so on, for the other family members.

We posit that there exist search frictions, so that each worker must search in order to get a job, and a worker can increase his/her job finding probability by increasing the intensity of search.

In the model, we interpret the nonemployment states –Nonparticipant who does not want a job (N^n), Nonparticipant who wants a job (N^w) and Unemployed (U)– as arbitrary distinctions introduced by the household survey and its imperfect measurement of search intensity. Specifically, while search intensity s is a continuous variable, a survey cannot precisely measure s. Instead, a household survey like the CPS can classify workers into different labor market states –Nonparticipant who does not want a job (N^n), Nonparticipant who wants a job (N^w) and Unemployed (U)– that correspond to different intensities of search. Specifically, with $\underline{s}$ and $\overline{s}$ threshold variables such that $0 <\underline{s}< \overline{s}$, an individual i is considered N^n for $s \in [0,\underline{s}[$, N^w $s \in [\underline{s}, \overline{s}[$ and U for $s \in [\overline{s}, +\infty[$.

We assume perfect consumption pooling, so that each household member has the same consumption level and each family member aims to maximize aggregate consumption net of his/her disutility of searching for work. Finally, the family derives unearned income d that is independent of labor market status, for instance asset income.

The timing of the model is a follows: in the first stage, the primary worker chooses search intensity s, suffers a search disutility cost $v(s)$ and finds a job with probability $p(s)$. If unmatched, the worker gets home production income h. If matched, the job pays a salary $w > h$. In the second stage, the first secondary worker solves a similar problem taking the income of the primary worker as given. As so on for the other family members. Once each family member has made his/her labor supply decision, all workers get paid, and the family consumes.

In a family of size n, the problem of worker $i \in \{1, n\}$ is then

$$\begin{cases} \max\limits_{\{c,s_i\}} nu(c) - v(s_i) \\ s.t. \quad nc = p(s_i)(w_i - h_i) + d + h_i + \Omega_{i-1} \end{cases}$$

where c is consumption per capita, s_i is search intensity, and $\Omega_{i-1} = \sum_{k=1}^{i-1} \omega_k$ is the total income generated by the "higher-order" workers with $\omega_k = \{w_k, h_k\}$ the income generated by the k-th member. Ω_{i-1} is taken as given by the ith worker.

For simplicity, we specify standard functional forms for the functions $u(.)$, $v(.)$ and $p(.)$, and posit $u(c) = \ln(c)$, $v(s) = \frac{\chi}{1+\sigma_s} s^{1+\sigma_s}$ and $p(s) = p_0 s^{\eta}$, $\eta < 1$.

It is easy to show that s_1, the search intensity of the primary worker, is determined by the first-order condition

$$\chi_1 s_1^{\sigma_s} = \frac{np'(s_1)(w_1 - h_1)}{p(s_1)(w_1 - h_1) + h_1 + d}. \tag{18}$$

Proceeding similarly for the ith member of the family, s_i is determined by

$$\chi_i s_i^{\sigma_s} = \frac{np'(s_i)(w - h)}{p(s_i)(w_1 - h_1) + h + d + \Omega_{i-1}} \tag{19}$$

where the only difference is that for secondary workers, the total income generated by the "higher-order" workers, Ω_{i-1}, influences the search intensity decision.

From (18) and (19), one can isolate a number of model parameters that influence search intensity, and thus the fraction of nonparticipants who report wanting a job:

1. Heterogeneous or time-varying preferences: Higher disutility of search lowers desire to work: $\frac{\partial s_i}{\partial \chi_i} < 0$.
   If the disutility of search varies with demographic characteristics such as age, gender or education, search intensity will vary with demographic characteristics, and a change in the composition of the population will affect the observed average desire to work. In addition, a change in individual preferences could lead to a decline in desire to work. For instance, a larger decline in χ for children of working age would lead to a stronger decline in desire to work among this group.

2. Asset income: Higher asset income lowers search intensity $\frac{\partial s_i}{\partial d} < 0$.
   A prominent example of a change in asset income is the large increase in networth during the high-tech bubble of the late 90s.

3. Returns to employment:

   (a) Higher wage increases desire to work among primary workers: $\frac{\partial s_1}{\partial w} > 0$.
   While higher wage increases the incentive to find a job (the substitution effect), it also raises expected income which lowers the incentive to find a job (the income

effect). Overall, the net effect is positive.[10] Changes in the returns to working can come from changes in market wages or from changes in the tax code.

(b) Higher wage has an ambiguous effect on desire to work among secondary workers:

$$\frac{ds_i}{dw} = \underbrace{\frac{\partial s_i}{\partial w}}_{>0} + \underbrace{\frac{\partial s_i}{\partial \Omega_{i-1}}}_{<0}\underbrace{\frac{d\Omega_{i-1}}{dw}}_{>0} \lesseqgtr 0, \quad i > 1.$$

In addition to the direct effect of higher returns to employment which increases search intensity, higher employment income lowers secondary workers' search intensity through the added-worker effect: As the family income generated by "higher-order" workers increases through higher wages, desire to work amongst secondary workers decline ($\frac{\partial s_i}{\partial \Omega_{i-1}} < 0$).

4. Returns to nonparticipation:

(a) Higher income from home production lowers desire to work among primary workers: $\frac{\partial s_1}{\partial h} < 0$.

(b) Higher income from home production has an ambiguous effect on desire to work among secondary workers:

$$\frac{ds_i}{dw} = \underbrace{\frac{\partial s_i}{\partial h}}_{>0} + \underbrace{\frac{\partial s_i}{\partial \Omega_{i-1}}}_{<0}\underbrace{\frac{d\Omega_{i-1}}{dh}}_{\lesseqgtr 0} \lesseqgtr 0, \quad i > 1.$$

The ambiguity occurs through the added-worker effect, as with higher returns to nonparticipation, but the mechanism is different. Higher returns to nonparticipation has an ambiguous effect on family income ($\frac{d\Omega_{i-1}}{dh} \lesseqgtr 0$), because while higher h raises Ω_{i-1} ceteris paribus, it also lowers the search intensity oh higher-order workers, which lowers their employment rate and thus Ω_{i-1}.

[10] Naturally, this prediction stems from our choice of functional forms for the utility function. We think our model specification is reasonable, because its prediction is (i) in line with standard labor supply models, in which higher wages raise participation, and (ii) consistent with empirical evidence that higher returns to working increases participation of unmarried individuals (e.g., Eissa and Leibman, 1996).

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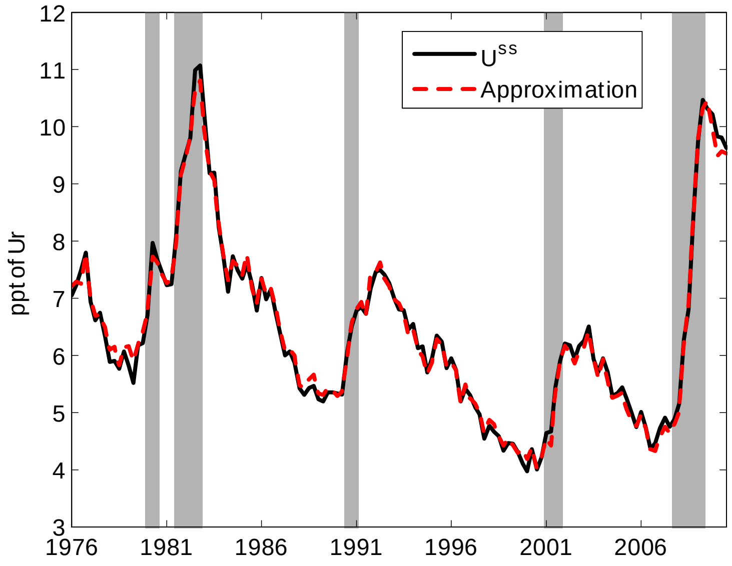

Figure 1: Steady-state unemployment rate ("U^{ss}") and unemployment predicted by our accounting decomposition ("Approximation"), 1976-2010.

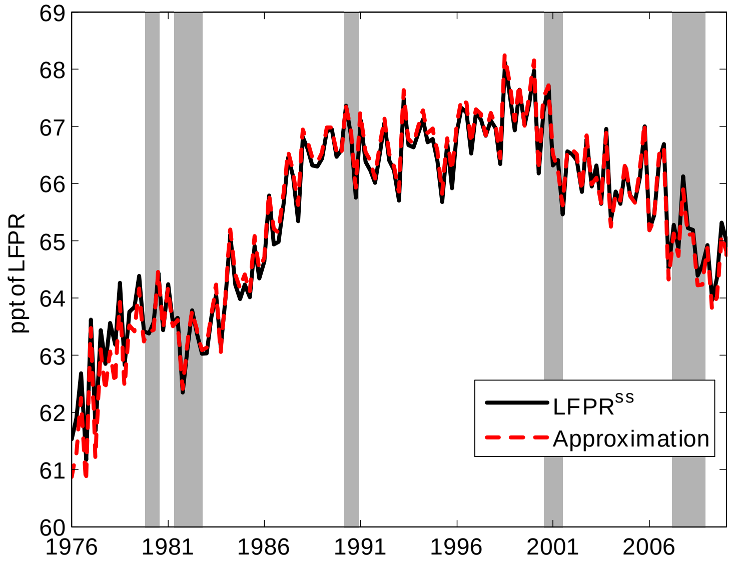

Figure 2: Steady-state labor force participation rate ("LFPR^{ss}") and participation rate predicted by our accounting decomposition ("Approximation"), 1976-2010.

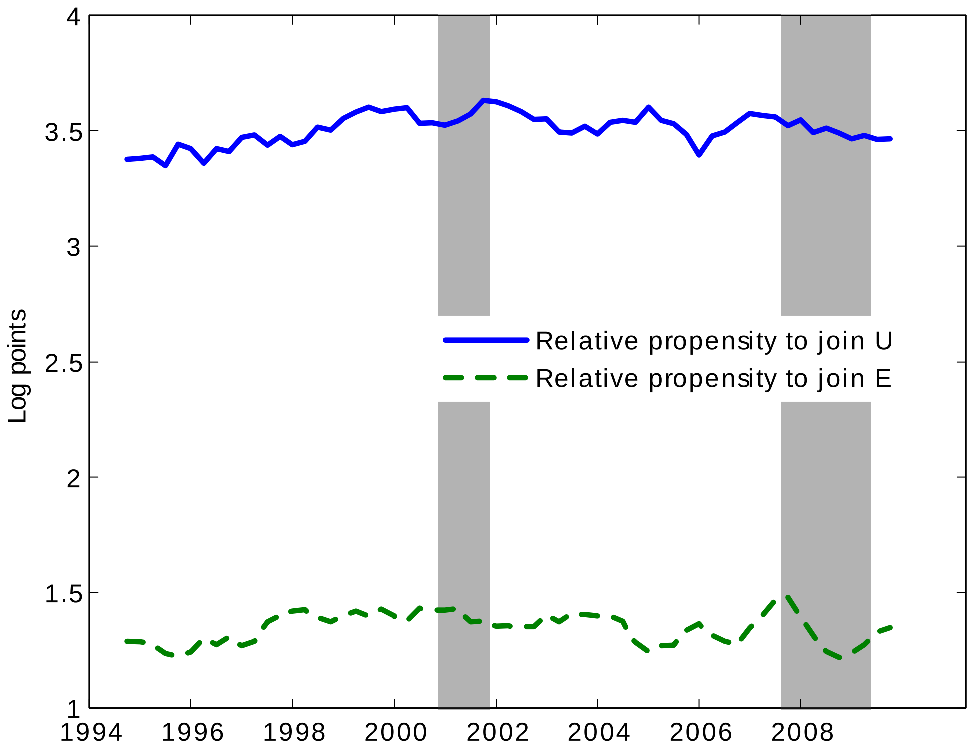

Figure 3: Relative propensities to join Unemployment (U) and Employment (E) for "Want a job" (N^w) and "Not want a job" (N^n) nonparticipants. The solid line depicts p^{N^wU}/p^{N^nU} and the dashed line depicts p^{N^wE}/p^{N^nE}. 4-quarter moving averages, 1994-2010.

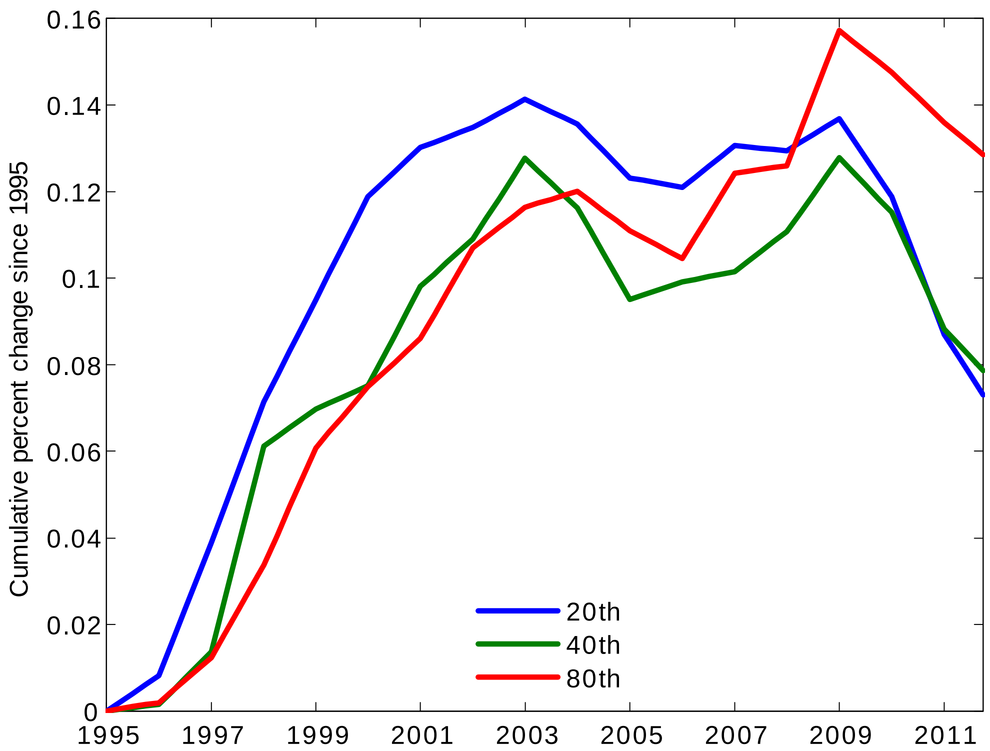

Figure 4: Cumulative change in real hourly wages of all workers, by wage percentile, 1995-2011.

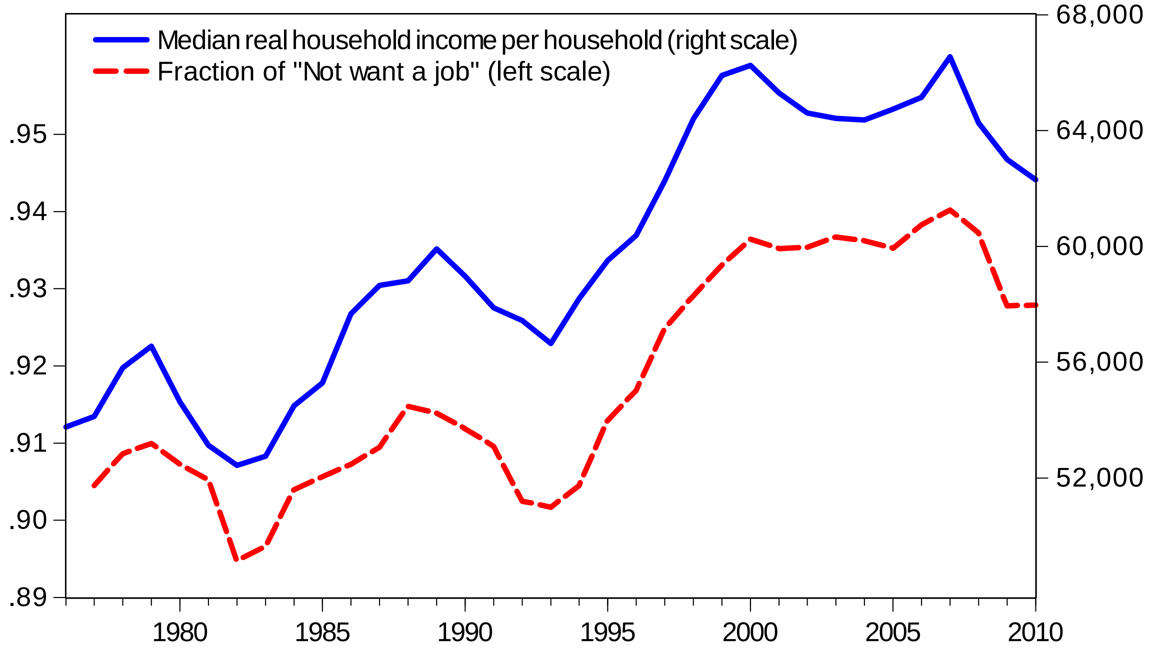

Figure 5: Median real income per household (in thousands of 2010 US$, right scale) and fraction of nonparticipants who report "Not wanting a job" (left scale), 1976-2010.

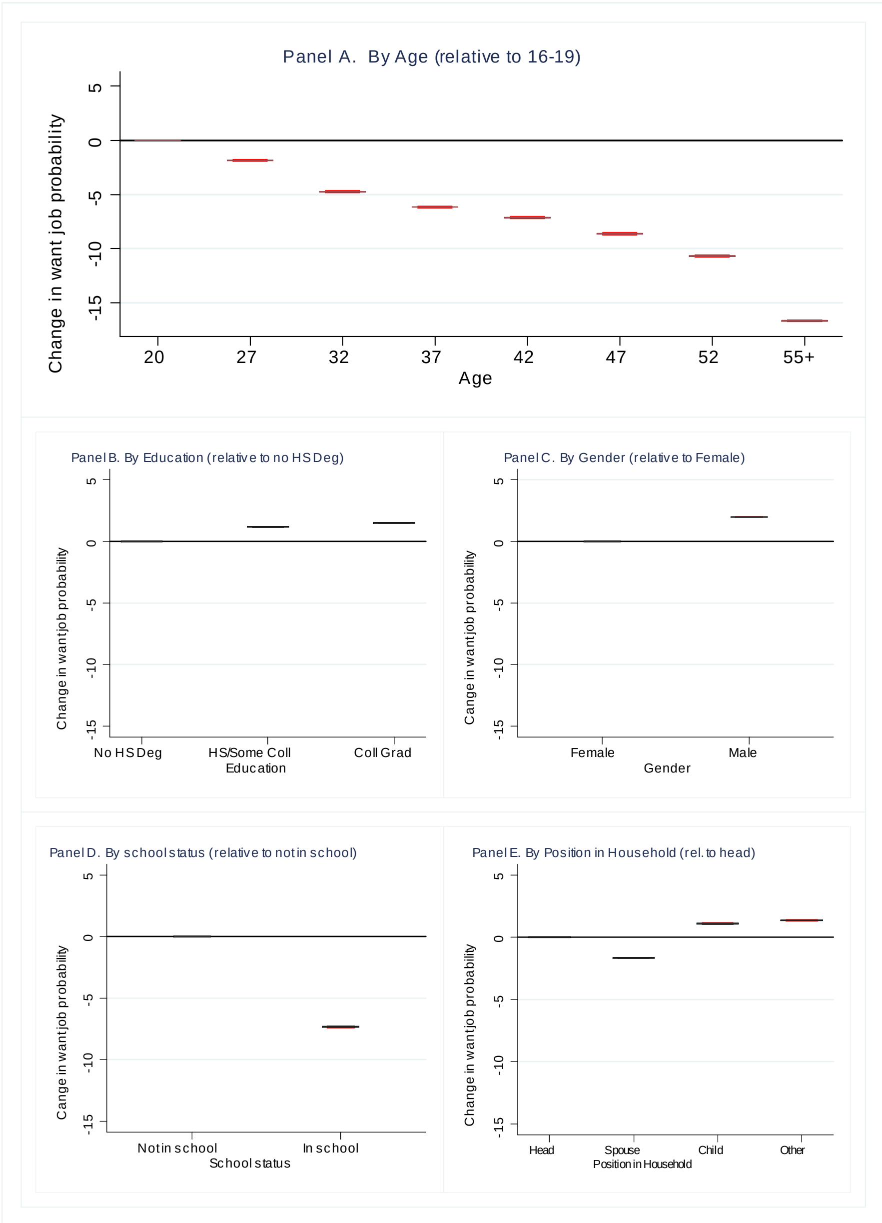

Figure 6: Demographic determinants of desire for work. Coefficient estimates of regression of "desire for work" on individual characteristics, 1988-2010. The black bars denote the point estimates and the red bars denote ± 2 standard-errors.

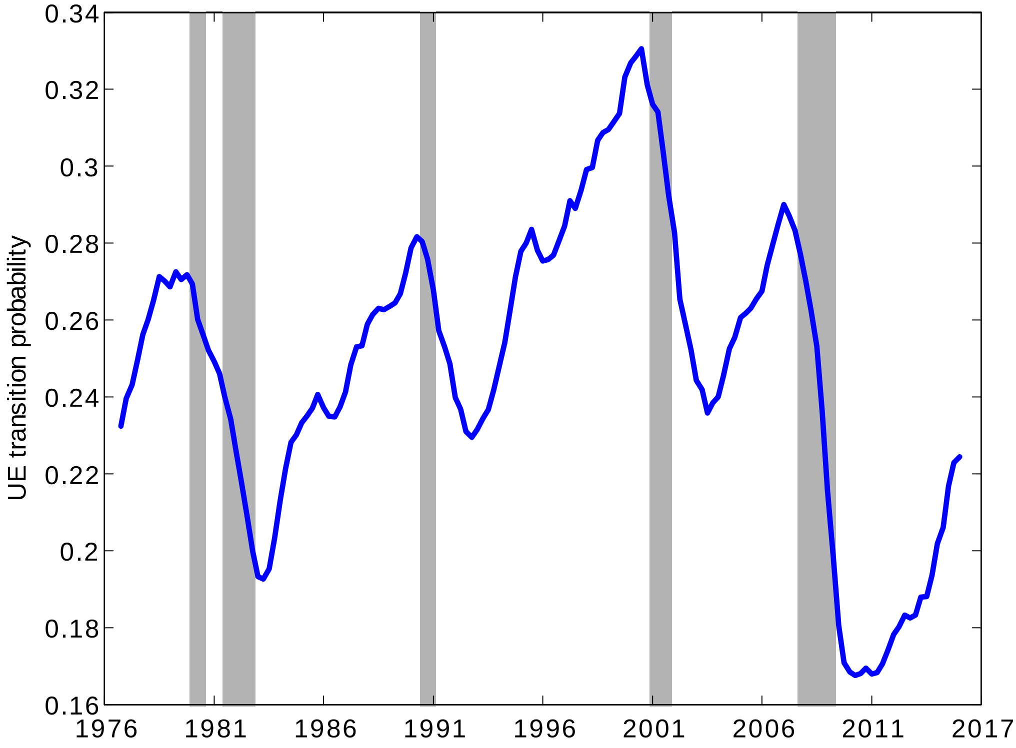

Figure 7: Monthly transition probability from Unemployment to Employment, 1976-2014. 4-quarter moving average.

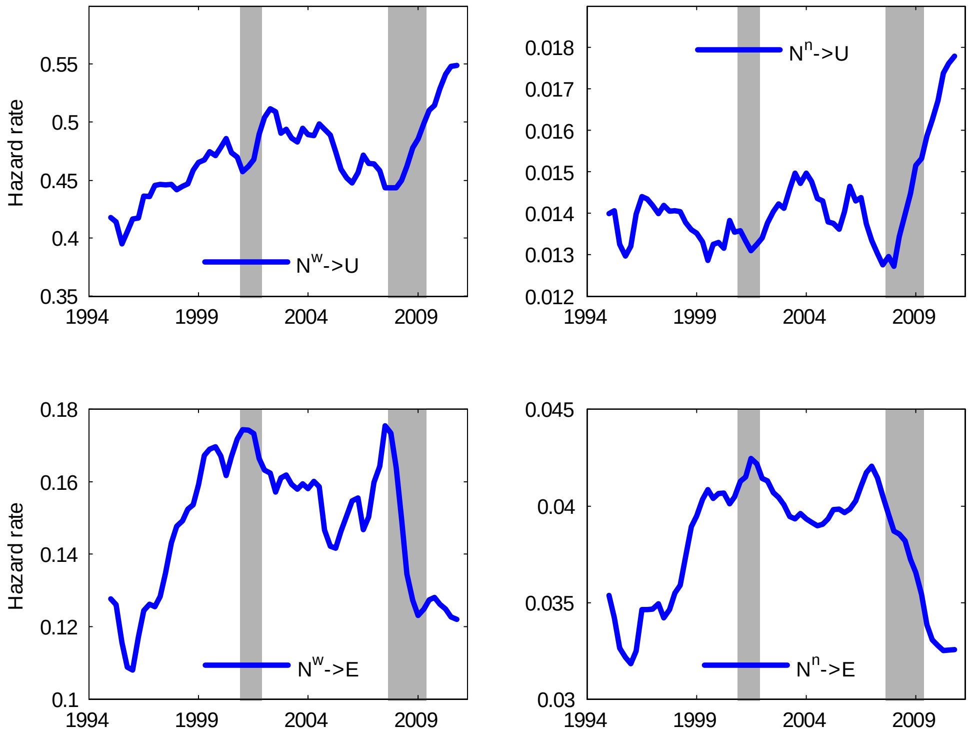

Figure 8: Monthly transition rate from "Want a job" (N^w) to Unemployment (U) (top-left panel), from "Not want a job" N^n to U (top-right panel), from N^w to Employment (E) (bottom-left panel), and from N^n to E (bottom–right panel). 4-quarter moving average, 1976-2010.

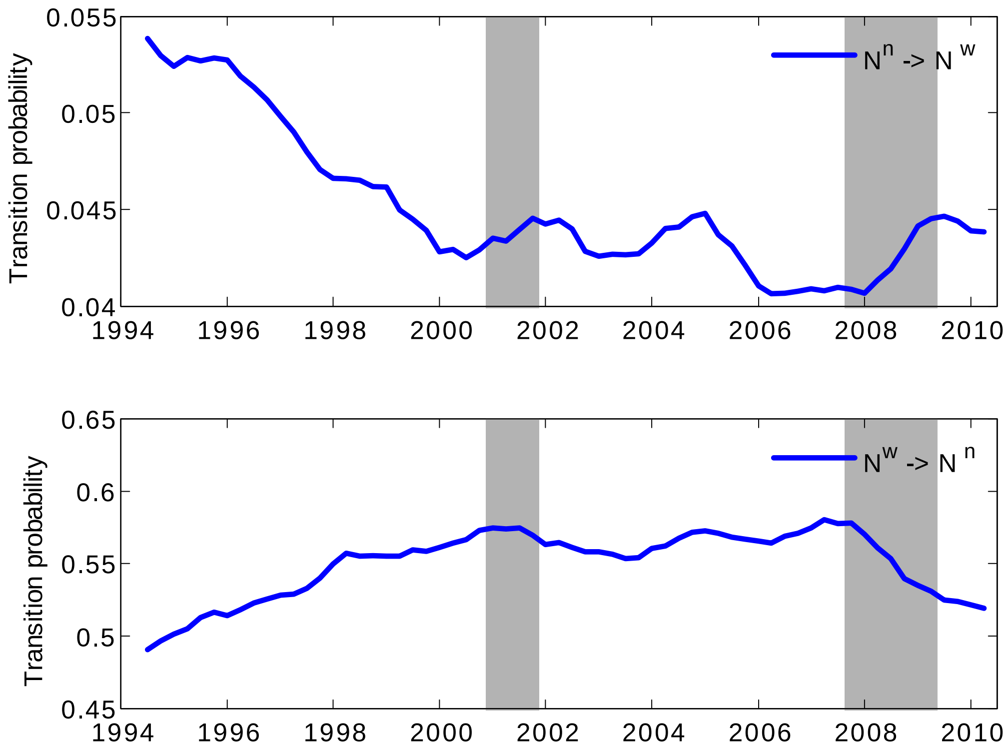

Figure 9: Monthly transition probability from "Not want a job" (N^n) to "Want a job" (N^w) (top panel) and from "Want a job" (N^w) to "Not want a job" (N^n) (bottom panel). 4-quarter moving average, 1976-2010.