

# The Micro and Macro of Disappearing Routine Jobs: A Flows Approach\*

Guido Matias Cortes

University of Manchester and RCEA

matias.cortes@manchester.ac.uk

Nir Jaimovich

Duke University and NBER

nj41@duke.edu

Christopher J. Nekarda

Federal Reserve Board

christopher.j.nekarda@frb.gov

Henry E. Siu

University of British Columbia and NBER

hankman@mail.ubc.ca

This Draft: July 8, 2014

## Abstract

The U.S. labor market has become increasingly polarized since the 1980s, with the share of employment in middle-wage occupations shrinking over time. This job polarization process has been associated with the disappearance of per capita employment in occupations focused on *routine tasks*. We use matched individual-level data from the CPS to study labor market flows into and out of routine occupations and determine how this disappearance has played out at the “micro” and “macro” levels. At the macro level, we determine which changes in transition rates account for the disappearance of routine employment since the 1980s. We find that changes in three transition rate categories are of primary importance: (i) that from unemployment to employment in routine occupations, (ii) that from labor force non-participation to routine employment, and (iii) that from routine employment to non-participation. At the micro level, we study how these transition rates have changed since job polarization, and the extent to which these changes are accounted for by changes in demographic composition or changes in the behavior of individuals with particular demographic characteristics. We find that the preponderance of changes is due to the propensity of individuals to make such transitions, and relatively little due to demographics. Moreover, we find that changes in the transition propensities of the young are of primary importance in accounting for the fall in routine employment.

---

\*We thank David Dorn, Giuseppe Moscarini, Anne Polivka, and seminar participants at Yale, Rochester, Aachen, IZA, the CIREQ Labor Workshop on Unemployment and the CEA, SOLE and TASKS Conferences for their helpful comments and suggestions. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. Siu thanks the Social Sciences and Humanities Research Council of Canada for support.

# 1 Introduction

During recent decades, labor markets in the United States and other developed countries have become increasingly polarized: the share of employment in middle-wage jobs has declined, while employment in both high- and low-wage jobs has increased. This “hollowing out” of the middle of the wage distribution has been linked to the declining share of employment in occupations with a high content of *routine tasks* – those activities that can be performed by following a well-defined set of procedures (see, for instance, Autor et al. (2006), Goos and Manning (2007), Goos et al. (2009) and Acemoglu and Autor (2011)). In fact, not only has the *share* of employment in routine jobs fallen over time, but so has the *level* of per capita employment in such occupations.<sup>1</sup>

In spite of the growing literature on polarization, relatively little is known regarding the process by which routine occupations have declined, both in terms of how this employment is disappearing, and who the disappearance is affecting at the microeconomic level. In this paper, we use matched individual-level data from the monthly Current Population Survey (CPS) to analyze transitions into and out of employment in routine occupations. At the aggregate or “macro” level, we determine which changes in transition rates, and at which points in time, account for the disappearance of routine employment since the 1980s. At the “micro” level, we study how these key transition rates have changed, and the extent to which these are accounted for by changes in demographic composition or in the behavior of individuals with particular demographic characteristics.

Characterizing the process by which routine employment is disappearing serves as an important guide in formalizing and evaluating theories of job polarization. It is equally important to the understanding of the changing labor market opportunities faced by different demographic groups, and in assessing policy implications. For example, the appropriate policy response would potentially be different if the decline of routine occupations is accounted for by changes in the occupational choices of labor market entrants than if it is due to increasing exit rates out of the labor force of prime-aged workers from routine employment.

In Section 2 we describe how we use data from the matched CPS to construct nationally representative flows into and out of routine employment at a monthly frequency from 1976 to 2012. Our approach involves classifying sampled individuals in each month according to their labor market status (employed, unemployed, or not in the labor force) and their current or most recent occupational group (non-routine cognitive, routine cognitive, routine manual or non-routine manual, discussed in detail below), and tracking their transitions over time.

We first investigate which changes in transition rates are key in accounting for the decline of per capita routine employment. We perform a series of counterfactual experiments in Section 3 to determine how much of the fall would have been prevented if particular transition rates had remained at the levels observed prior to the onset of polarization.<sup>2</sup>

These results indicate that the bulk of the disappearance of routine employment is accounted for

---

<sup>1</sup>Autor et al. (2003) and the subsequent literature discuss how technological progress has substituted for labor in routine tasks. See also Firpo et al. (2011), Goos et al. (2010), and the references therein regarding the role of outsourcing and offshoring in job polarization.

<sup>2</sup>Our counterfactual analysis is similar in spirit to the literature analyzing the role of job finding rates and job separation rates in accounting for unemployment volatility over the business cycle (e.g. Hall (2006), Shimer (2012) and Elsby et al. (2009)). The main difference is that we analyze long-run changes in employment levels, distinguishing between employment in different occupational groups.

by three changes. The first is a fall in transition rates from unemployment to employment in routine occupations. This includes falls in both “return” job finding rates—for the unemployed with most recent employment in a routine job—and “switching” job finding rates—for the unemployed with most recent employment in a non-routine job. The second important change is a fall in transition rates from labor force non-participation to routine employment. The third is a rise in transition rates from routine employment to non-participation. Changes in the finding rates into routine employment (the first and second factors) are important in accounting for the decline both leading into the Great Recession and, especially, thereafter. Changes in the separation rate from routine employment to non-participation are important prior to 2007. Together, changes in these three sets of transition rates account for nearly two-thirds of the long-run decline in routine employment.

Our second contribution involves a detailed, micro-level analysis of the key changes in transition rates across the pre- and post-job polarization eras. We ask whether the observed changes can be attributed to changes in the demographic composition of individuals in the relevant labor market states, or to changes in the transition propensities of individuals with given demographic characteristics. Our analysis in Section 4 involves the estimation of standard Oaxaca-Blinder decompositions in order to isolate these two effects.

The results indicate that the changes are primarily accounted for by changes in transition propensities, rather than changes in composition. Conditional on demographic characteristics, we observe falls in the propensity to transition into routine manual employment from both unemployment and non-participation. In addition, there has been a rise in the propensity to transition out of routine manual employment to non-participation. These propensity changes have been particularly acute for males, the young, and those with low levels of education.

For routine cognitive occupations, we observe similar changes in propensities: falls in the propensity to transition into employment from unemployment and non-participation, and rises in the propensity to transition out of employment to non-participation, conditional on demographic characteristics. The fall in the propensity to transition from unemployment to routine cognitive employment is particularly strong for whites, females, the prime-aged, and those with higher levels of education. The rise in the propensity to transition to non-participation from routine cognitive employment is strongest for men and the young.

Finally, we revisit our counterfactual exercises in greater detail in Section 5. The changes in key transition rates identified in Section 3 are driven by demographic change and changes in propensities. Our final contribution is to disentangle the relative importance of these channels in the aggregate. We find that change in the demographic composition of the U.S. population can account for at most 30% of the total long-run decline in per capita routine manual employment, and less than 10% of the decline in per capita routine cognitive employment. By contrast, we find that changes in the *propensity* to transition from unemployment and non-participation into routine employment and, to a lesser extent, from routine employment to non-participation are primarily responsible for the disappearance of routine jobs. In particular, changes in the transition propensities of the young are of greatest importance.

As stated above, very little attention has been paid to the labor market dynamics underlying the

phenomenon of job polarization.<sup>3</sup> Two recent papers are related to our analysis. Foote and Ryan (2014) analyze worker flows in the context of polarization, distinguishing between routine workers employed in different industries. The goal of their paper differs from ours in that they are interested in understanding the cyclical properties of these flows rather than their relationship with the long-term decline in routine employment per capita. Meanwhile, Smith (2013) describes the evolution over time of a number of transition rates into and out of routine employment and performs steady-state counterfactuals to analyze the importance of different transition rates in accounting for the decline of routine employment. Our analysis differs from his in a number of ways. First, our regression analysis and Oaxaca-Blinder decompositions allow us to determine not only the extent of transition rate change over time, but also how this change is decomposed into demographic change and propensity change, as well as which demographic groups have experienced the largest changes in transition rates. Second, we distinguish between routine manual and routine cognitive occupations which, as we discuss below, are very heterogeneous in terms of their demographic composition and their evolution over time. Third, while Smith (2013) focuses on transitions between unemployment and employment, we specifically analyze transitions into and out of the labor force, which we find to be key in accounting for the decline in routine employment. Fourth, by using data from the 1970s, we are able to analyze how transition rates have change relative to their levels prior to the onset of job polarization. Finally, our detailed counterfactuals allow us to disentangle the role of demographic change and propensity change in accounting for the decline of routine employment.

## 2 Data

We use matched monthly data from the Current Population Survey (CPS), the main source of labor market statistics in the United States. The data spans the period from January 1976 until December 2012. We restrict the sample to individuals aged 16 to 75. We make use of the fact that the CPS is a rotating sample: households included in the survey are sampled for four consecutive months, then leave the sample for eight months before returning for another four months. Given this sampling structure, up to 75% of households are potentially matched across consecutive months. In practice, the fraction of households matched is lower (around 70% on average), primarily due to the fact that the CPS is an address-based survey, and therefore households that move to a new address are not followed. Also, in certain months the CPS made changes to household identifiers, making it impossible to match individuals across these modifications.<sup>4</sup> Details regarding the algorithm used to match individuals across months can be found in Nekarda (2009).

The main advantage of the CPS is its large sample size, and that it is designed to be representative of the entire US population at each point in time. A second advantage is its high frequency, allowing for the observation of individual-level transitions across labor market states at a monthly frequency. A final, and important, advantage is its time coverage, spanning periods both prior to the onset of job polarization and afterward (as we discuss further below).<sup>5</sup>

---

<sup>3</sup>Evidence based on changes at the local labor market level, rather than on individual-level worker flows, is provided by Autor and Dorn (2009) and Autor et al. (2013). Cortes (2014) uses panel data to analyze the occupational mobility patterns of workers switching out of routine jobs.

<sup>4</sup>This occurs in January 1978, July 1985, October 1985, January 1994, June 1995 and September 1995.

<sup>5</sup>By contrast, while the Panel Study of Income Dynamics tracks individuals over a longer time period, its sample size

In using the CPS, the main challenge is the major survey redesign implemented in 1994, inducing certain data discontinuities. In addition to this, the occupation coding system used in the survey has changed approximately every ten years, which provides additional minor challenges. We discuss each of these issues in more detail below. The remainder of this section describes how we use the CPS data to classify individuals according to their labor force status and occupation, and how we construct transition rates across different labor market states. These data are then used to analyze the proximate causes for the disappearance of routine employment.

## 2.1 Labor Force and Occupation Categories

We use the information in the CPS to categorize all individuals in the sample according to their labor force status—employed, unemployed, or not in the labor force—and their current or most recent occupation. The CPS records employed workers’ description of their current occupation in their main job, and also unemployed workers’ description of their occupation in their most recent job (if they have ever worked before). The individual’s description is then assigned a 3-digit occupation code.<sup>6</sup> While the CPS records occupational data for employed and unemployed workers, this is not the case for those who are classified as being out of the labor force.<sup>7</sup> We are therefore constrained in our analysis to consider only one labor force non-participation category that does not distinguish based on previous occupation.

Following the recent literature (e.g., Acemoglu and Autor (2011), Autor and Dorn (2013), Cortes (2014), Jaimovich and Siu (2012)), we consider four broad occupational groups; we do this by delineating occupations along two dimensions of the characteristics of tasks performed on the job: “cognitive” versus “manual,” and “routine” versus “non-routine.” The distinction between cognitive and manual occupations is straightforward, characterized by differences in the extent of mental versus physical activity. The distinction between routine and non-routine jobs is based on the work of Autor et al. (2003). If the tasks involved can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures, the occupation is considered routine. If instead the job involves a variety of tasks, requiring flexibility, problem-solving, or human interaction skills, the occupation is non-routine. As such, the four occupational groupings are: non-routine cognitive, routine cognitive, routine manual and non-routine manual.

To illustrate the nature of these groupings, using the 2010 Standard Occupational Classification and Coding Structure’s “high-level aggregation,” *non-routine cognitive* occupations are Management, Business, Science, and Arts Occupations; *routine cognitive* are Sales and Office Occupations; *routine manual* are Construction and Maintenance Occupations, and Production, Transportation, and Material Moving Occupations; and *non-routine manual* are Service Occupations.<sup>8</sup> The occupation codes used

---

is much smaller (making it problematic for the analysis of transitions across detailed occupational/labor market states) and available only at the annual or bi-annual frequency. While the Survey of Income and Program Participation is at a monthly frequency and has, in certain waves, sample sizes comparable to the CPS, it begins after the onset of job polarization making it impossible to analyze changes in flows before and after job polarization.

<sup>6</sup>For matched individuals who are unemployed and have a missing occupation code, we impute their previous month’s occupation code, if it is available. We make the imputation for several consecutive months, if necessary. Throughout the paper, we exclude observations for employed workers within the occupations of Farming, Fishing, Forestry and Military.

<sup>7</sup>The exception is when they are in the ‘outgoing rotation group’ (i.e., in their fourth or eighth month in the sample) but this information is not useful as we cannot match these individuals to the following month.

<sup>8</sup>See <http://www.bls.gov/soc/#classification>.

by the CPS have changed over time, specifically in 1983, 1992, 2003 and 2011, transitioning between the 1970, 1980, 1990, 2000, and 2010 classification systems. In order to maintain consistency through the time coverage of our data, we map each 3-digit occupation code across the five classification systems used by the BLS since 1976 into the four occupation categories; details of the mapping are in Appendix Table A.1.<sup>9</sup>

Given this, we classify each individual in each month in the sample into one of ten mutually exclusive categories: employed in one of the four occupation groups, unemployed with previous job in one of the four occupation groups, unemployed with no previous occupation, or not in the labor force. For future reference we refer to these ten groups as follows. *NLF* denotes individuals who are not in the labor force. *ENRC*, *ERC*, *ERM*, and *ENRM* denote those currently employed in non-routine cognitive, routine cognitive, routine manual, and non-routine manual occupations, respectively. *UNRC*, *URC*, *URM*, and *UNRM* denote those currently unemployed whose last job was in each occupational group. Finally, *UX* denotes people currently unemployed for whom we do not observe their most recent occupation (for example because they have no previous work experience).

The average monthly fraction of the sample in each of the categories for the periods before and after 1990 is presented in Table 1.<sup>10</sup> Table 2 presents descriptive statistics for the full sample, each of the four employment groups, and for non-participants. As is evident, there is important heterogeneity across occupations in demographic composition. For instance, there is a clear relationship between the occupation groups and skills as measured by education: the level of education is highest in non-routine cognitive occupations, and lowest in non-routine manual ones. Routine occupations tend to employ middle-skilled workers (high school graduates and those with some college education). Similarly, there is clear heterogeneity in gender composition: while routine cognitive occupations are predominantly female, routine manual ones are predominantly male.

Figure 1 displays the time series of each of the four stocks of per capita employment in our monthly CPS sample. Despite our best effort to define consistent occupational groups, there is an obvious discontinuity in 1983 with the introduction of the 1980 occupation codes.<sup>11</sup> The discontinuity re-allocates employment from the non-routine cognitive group to routine cognitive. In spite of this, the figure illustrates the obvious rise in per capita non-routine employment.

The dynamics of routine manual and routine cognitive employment are quite different. Per capita employment in routine manual occupations begins to disappear in the early 1980s. The business cycle dimension discussed in Jaimovich and Siu (2012) is evident: employment in these occupations falls

<sup>9</sup>In the November 2013 version of this paper, we categorized occupations using the crosswalk of Autor and Dorn (2013), itself an adaptation of Meyer and Osborne (2005). This methodology converts all of the 3-digit occupation codes from the 1970, 1980, 1990, and 2000 systems to a common coding system. We developed our own crosswalk to convert the 2010 codes. The common codes are then aggregated into the four broad categories. The results from that methodology are largely unchanged relative to the current one; we refer the reader to the previous version of our paper for details. However, using the Autor and Dorn (2013) crosswalk generates noticeable discontinuities in the non-routine cognitive and routine cognitive groups between the 1990 and 2000 classification systems; these discontinuities are avoided by the current methodology.

<sup>10</sup>We choose 1990 as a natural split since it divides our 1976-2012 sample period in half. Moreover, as we discuss below, post-1990 is roughly the period when polarization forces are observed for both routine cognitive and routine manual occupations.

<sup>11</sup>Because of the major changes instituted between the 1970 and 1980 classification systems, this discontinuity is a feature of all categorization methodologies that assign 3-digit level codes to one of the occupation groups. See, for instance, the discussion of the Autor and Dorn (2013) methodology in the November 2013 version of this paper, and also Jaimovich and Siu (2012) for further discussion.

Table 1: Employment/Occupation categories and average monthly fraction of sample

Category	1976-1989	1990-2012
Employed: Non-Routine Cognitive	18.1%	22.7%
Employed: Routine Cognitive	16.6%	17.1%
Employed: Routine Manual	18.7%	15.8%
Employed: Non-Routine Manual	8.9%	10.3%
Unemployed: Non-Routine Cognitive	0.5%	0.7%
Unemployed: Routine Cognitive	0.9%	1.0%
Unemployed: Routine Manual	1.9%	1.4%
Unemployed: Non-Routine Manual	0.9%	0.8%
Unemployed: No Occupation Reported	0.6%	0.4%
Not in the labor force	32.9%	29.8%

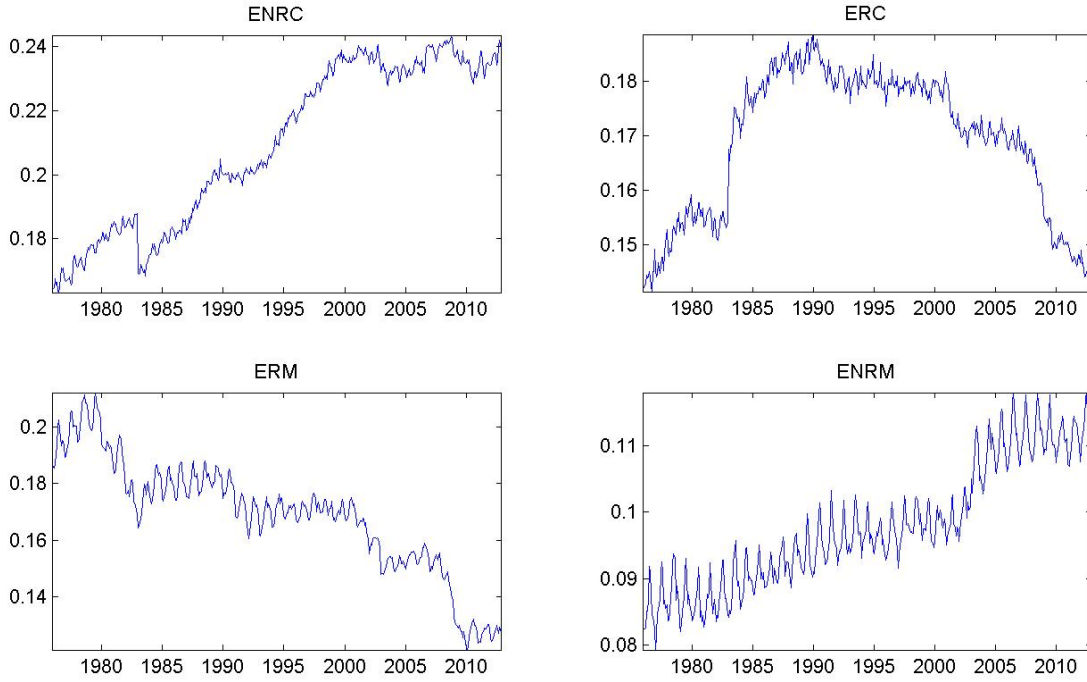
Note: Workers employed in Farming, Fishing, Forestry and Military occupations excluded from the sample.

Table 2: Descriptive Statistics

1976-1989						
	Full	<i>ENRC</i>	<i>ERC</i>	<i>ERM</i>	<i>ENRM</i>	<i>NLF</i>
Average age	40.04	39.71	36.54	36.63	35.44	46.74
<i>Fractions within the occupation group</i>						
HS dropouts	0.280	0.055	0.104	0.325	0.356	0.431
HS graduates	0.558	0.427	0.750	0.636	0.591	0.483
College graduates	0.162	0.518	0.146	0.039	0.053	0.086
Male	0.480	0.601	0.321	0.817	0.418	0.301
Non-White	0.135	0.086	0.102	0.133	0.200	0.146
Married	0.634	0.724	0.619	0.684	0.518	0.624
<i>Total number of observations (millions)</i>						
Unweighted	17.7	3.2	2.9	3.2	1.6	5.8
1990-2012						
	Full	<i>ENRC</i>	<i>ERC</i>	<i>ERM</i>	<i>ENRM</i>	<i>NLF</i>
Average age	41.58	42.05	38.98	39.14	36.80	46.81
<i>Fractions within the occupation group</i>						
HS dropouts	0.184	0.021	0.078	0.216	0.234	0.317
HS graduates	0.578	0.383	0.717	0.721	0.675	0.539
College graduates	0.237	0.596	0.204	0.063	0.091	0.144
Male	0.488	0.504	0.355	0.840	0.429	0.372
Non-White	0.174	0.138	0.155	0.157	0.219	0.194
Married	0.580	0.685	0.574	0.622	0.484	0.543
<i>Total number of observations (millions)</i>						
Unweighted	26.7	6.2	4.5	4.1	2.7	7.9

Note: *ENRC* stands for non-routine cognitive employment, *ERC* for routine cognitive employment, *ERM* for routine manual employment, *ENRM* for non-routine manual employment, and *NLF* for not in the labor force. The HS graduates group includes individuals with some college education.

Figure 1: Employment Stocks per Capita in Monthly CPS data



during recessions, and fails to recover during the subsequent expansion periods. This is true of all episodes in the sample period: the back-to-back recession of 1980/82, the recessions of 1991 and 2001, and the recent Great Recession. By contrast, per capita employment in routine cognitive occupations grows through the 1980s, before reversing in the early 1990s. Its decline and lack of recovery are evident following the 1991 and 2001 recessions. This pattern is repeated in a dramatic manner beginning in 2007: a sharp disappearance in the Great Recession with no recovery since. Our analysis focuses on the factors contributing to the fall in the two categories of routine employment, taking into account the differences in timing.

## 2.2 Construction of Transition Rates

We use information on the labor force status and occupation at the individual level to construct monthly transition rates across the ten labor market states. Specifically, we compute the date  $t$  transition rate between labor market state  $A$  and state  $B$  as the number of individuals switching from  $A$  at date  $t$  to  $B$  at date  $t + 1$ , divided by the number of individuals in state  $A$  that we are able to match between dates  $t$  and  $t + 1$ .<sup>12</sup> This generates a  $10 \times 10$  matrix of transition rates,  $\rho_t$ , for each month  $t$  in our sample. This matrix can be split into sub matrices as follows:

<sup>12</sup>That is, individuals who leave the sample between  $t$  and  $t + 1$  (outgoing rotation group, attritioners) are excluded from the computation of transition rates. Each matched individual is weighted in our computation using the CPS sample weights in month  $t$ .



$$\rho_t = \begin{bmatrix} \rho_t^{EE} & \rho_t^{EU} & \rho_t^{EN} \\ \rho_t^{UE} & \rho_t^{UU} & \rho_t^{UN} \\ \rho_t^{NE} & \rho_t^{NU} & \rho_t^{NN} \end{bmatrix}, \quad (1)$$

where:

- $\rho_t^{EE}$  ( $4 \times 4$ ): employment “stayer” rates and “job-to-job” transition rates across occupations for employed workers,
- $\rho_t^{EU}$  ( $4 \times 5$ ): job separation rates,<sup>13</sup>
- $\rho_t^{EN}$  ( $4 \times 1$ ): exit rates from employment to non-participation,
- $\rho_t^{UE}$  ( $5 \times 4$ ): job finding rates,
- $\rho_t^{UU}$  ( $5 \times 5$ ): unemployment stayer rates,
- $\rho_t^{UN}$  ( $5 \times 1$ ): exit rates from unemployment to non-participation,
- $\rho_t^{NE}$  ( $1 \times 4$ ): entry rates from non-participation to employment,
- $\rho_t^{NU}$  ( $1 \times 5$ ): entry rates from non-participation to unemployment,
- $\rho_t^{NN}$  ( $1 \times 1$ ): non-participation stayer rates.

The evolution of the stock of individuals in each of the ten labor market states is governed by the following law of motion:

$$\underbrace{Stocks_{t+1}}_{(10 \times 1)} = \underbrace{\rho_t}_{(10 \times 10)} * \underbrace{Stocks_t}_{(10 \times 1)} \quad (2)$$

where  $Stocks_t = [ENRC_t \ ERC_t \ ERM_t \ ENRM_t \ UNRC_t \ URC_t \ URM_t \ UNRM_t \ UX_t \ NLF_t]'$  is the vector of the fraction of working age population in each labor market state. To understand the dynamics implied by equation (2), consider the evolution of employment in routine-manual occupations. The change in this stock across two months depends on the “inflows” of individuals—from unemployment, out of the labor force, and employment in other occupations—relative to the “outflows” to unemployment, non-participation, and employment in other occupations. Equation (2) summarizes these inflows and outflows by the size of each of the stocks and the corresponding transition rates between them.

To understand the evolution of  $ERC$  and  $ERM$ , we focus on the changes in the matrix of transition rates,  $\rho_t$ . This allows us to determine which types of transitions are particularly important in accounting for the decline in routine employment observed in recent decades. We do this by performing a number of counterfactual experiments discussed in the next section.

Before proceeding to the counterfactual experiments, it is important to determine whether the law of motion provides a good approximation of the stocks, measured cross-sectionally. This may not be the

---

<sup>13</sup>The fifth column represents transitions into the unemployment category with unknown previous occupations. All entries in this column are equal to zero.

case as equation (2) relies only on an initial measure of stocks and iterates forward using the subsequent transition rates. Due to entry and exit from the sample (given the rotating nature of the sample, as well as attrition), the transition rates computed from matched individuals may not necessarily replicate the stocks. Figure 2 plots the fraction of the population employed in each occupation group, and those out of the labor force from 1976:1 to 2012:12. The stocks measured from all individuals are the blue, solid lines; the estimates based on equation (2) are the green, hatched line.<sup>14</sup>

As is evident from the figure, data derived from transition rates in the matched CPS sample tend to underestimate the fraction of employed workers, and overestimate the fraction out of the labor force.<sup>15</sup> By the end of our sample period, the labor force non-participation rate is overestimated by approximately two percentage points. Interestingly, we find that the gap in employment is due entirely to an underestimation of the fraction of people working in non-routine occupations; the employment rate in routine occupations is estimated quite accurately.<sup>16</sup> Overall, a comparison of the series depicted in Figure 2 indicates that the stocks based on the law of motion follow similar long-run paths to those based on the full data, especially for routine employment. This rationalizes our approach of focusing on transition rates derived from labor market flows in order to understand the long-run disappearance of routine jobs.

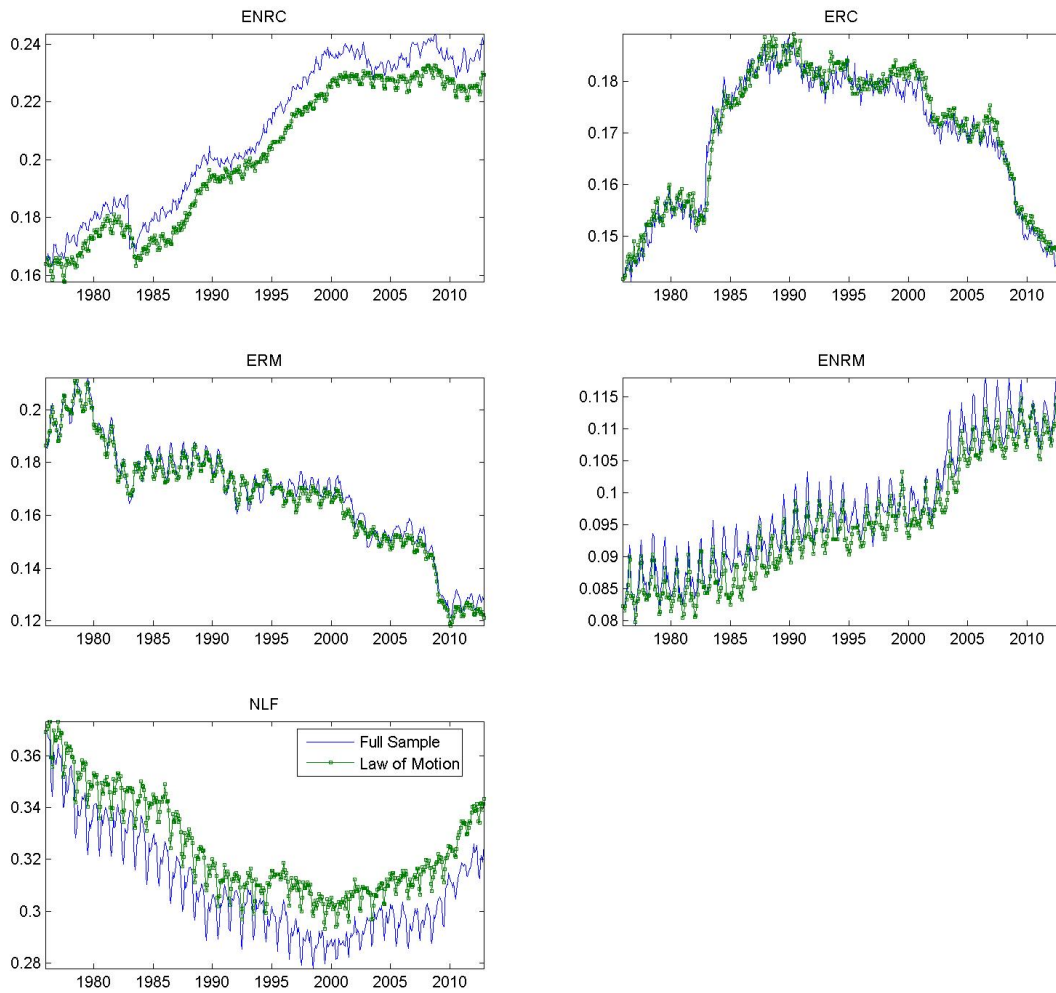
As previously discussed, the main data challenge that arises in analyzing the evolution of transition rates is the discontinuity induced by the CPS survey redesign. In 1994, the CPS switched to a method of dependent interviewing, whereby information collected in the previous month’s interview is imported into the current interview to ease respondent burden and improve data quality. For occupation data, interviewers asked whether the interviewee had the same job as in the previous month; if the answer was yes, the individual would automatically receive the same occupation code. Dependent coding substantially reduced the occurrence of spurious transitions across occupations at the monthly frequency (see Kambourov and Manovskii (2013) and Moscarini and Thomsson (2007)). As a result, this generates a discrete break in the transition rates across occupations for those reporting employment in consecutive months. This fall in the rate of “job-to-job” occupational mobility is evident, even at the very coarse, 4-group level of disaggregation that we study. In addition, the CPS redesign also induces a discontinuity in the measured monthly transition rates between non-participation and unemployment. In the analysis below, we are cautious when considering changes over time that involve transition rates featuring these discontinuities. Nonetheless, Figure 2 indicates that even with these discontinuities in 1994, the use of estimated transition rates in the law of motion generate stocks that replicate the dynamics of the true stocks remarkably well.

<sup>14</sup>For months where we have missing transition rate data because of the change in the CPS sample identifiers or because of changes in the occupational coding system, we keep the transition rates as missing, leaving stocks as constant.

<sup>15</sup>We note that “margin error,” as documented by Frazis et al. (2005) and others, generates a qualitatively similar discrepancy when stocks are constructed by adding and subtracting gross flows in matched CPS data. Discrepancies generated by margin error accumulate over time. By contrast, our procedure does not suffer from margin error as the discrepancy does not accumulate. We note that one important difference in our procedure (relative to the cumulative addition of gross inflows and outflows) is that we iterate on transition rates defined only for individuals who are matched across consecutive months. As such, our procedure essentially imputes to those who leave the sample the same transition probabilities as those who remain.

<sup>16</sup>Another interesting finding (not shown) is that there is no evidence of differential rates of attrition across labor force categories.

Figure 2: Stocks from Full Sample and based on Law of Motion



### 3 The key changes in aggregate transition rates

In this section, we investigate which changes in transition rates play the most important role in accounting for the decline in per capita routine employment in the past 30 years. We do this through a number of counterfactual experiments where we isolate the effect of certain transition rates on the evolution of routine employment.

It is worth emphasizing why we perform these counterfactual experiments rather than simply looking at the change in transition rates over time. What matters for the evolution of the stock of routine employment are the inflows and outflows to and from this labor market state. These inflows and outflows are themselves a product of the transition rates *and* the stocks of all the different labor market states. Thus, a relatively large change in a transition rate might have little quantitative effect on routine employment if the transition rate is small to begin with, or if the source stock is small (e.g., one of the unemployment categories). On the other hand, a transition rate change which, by itself, is small could have a substantial impact on routine employment if the source group is large (e.g., labor force non-participants). By performing counterfactual experiments we are able to determine the quantitative importance of particular transition rates in accounting for the disappearance of routine employment.

As a first step, given that transition rates such as job finding rates and separation rates vary significantly over the business cycle, we divide the time series into recessionary phases (based on NBER peak to trough dates) and non-recessionary phases (which include all other months in the sample). Table 3 lists the 11 individual phases in our sample, from 1976 to 2012. We denote the five recessions as R1 through R5, and the six expansion phases as E1 through E6.

Table 3: List of individual business cycle phases

Recessions:	Expansions:
	1976m1-1979m12 (E1)
1980m1-1980m7 (R1)	1980m8-1981m6 (E2)
1981m7-1982m11 (R2)	1982m12-1990m6 (E3)
1990m7-1991m3 (R3)	1991m4-2001m2 (E4)
2001m3-2001m11 (R4)	2001m12-2007m11 (E5)
2007m12-2009m6 (R5)	2009m7-2012m12 (E6)

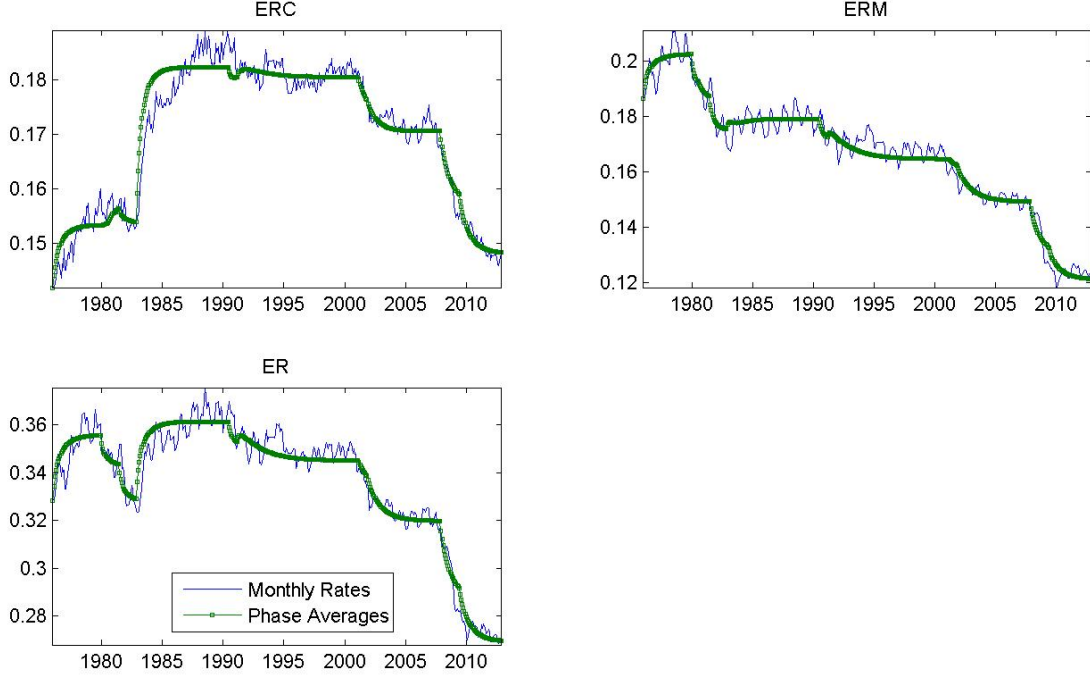
Notes: The phase numbers as referred to throughout the text are given in parentheses.

We then calculate the average of each transition rate during each phase. These average transition rates are used in our counterfactual analysis. Specifically, we replace the average value of particular transition rates during the post-polarization period with the average value from the appropriate pre-job polarization phases. The advantage of using average values for the counterfactuals is that they represent a better “summary statistic” for the transition rates within a phase, relative to choosing an arbitrary monthly value from the same phase.

Figure 3 plots the evolution of the stocks of routine employment (cognitive, manual, and total) when using the phase-by-phase averages of the transition rates (for each of the 11 phases) in the law of motion from equation (2), instead of their monthly values.<sup>17</sup> We call these the *stocks based on*

<sup>17</sup>Due to the January 1994 redesign of the CPS and the discontinuities that this induces in certain transition rates,

Figure 3: Stocks Based on Law of Motion using Monthly Rates and Phase Averages



*average rates*. The figure also plots the stocks based on the true monthly rates which were shown in Figure 2. The two data series differ to the extent that the average transition rates fail to capture changes in transition rates *within* a phase. Evidently, the stocks based on average rates provide a good approximation of the data; eliminating the high frequency movements in transition rates does not obscure the dynamics underlying the long run decline in routine employment.

For routine manual occupations, the forces of job polarization become evident beginning around 1980. Per capita routine manual employment declines from a pre-1980 peak of 20.24 percent of the population to 12.15 in 2012:12, representing a fall of 40%. As discussed in Section 2, job polarization does not become evident in routine cognitive occupations until around 1990. From the 1990s peak of 18.24 percent of the population, employment falls to 14.83 percent in 2012:12. As a result, per capita employment in all routine occupations falls from a peak value of 36.14 to 26.97 in 2012:12, a fall of 9.17 percentage points. This  $9.17/36.14 \approx 25\%$  decline is what we seek to explain.

In our counterfactual experiments, we allow all of the average transition rates to evolve phase-by-phase as observed in the data *except* for certain ones that are held constant at their pre-polarization averages. To ensure that the transition rates out of any given labor market state sum to one, the difference between the observed and the counterfactual transition rate is allocated to the corresponding diagonal element of the  $(10 \times 10)$  transition matrix  $\rho$ .<sup>18</sup> A switching rate is considered to be important

the averages for phase E4 used in this section are calculated over the period 1994:1 to 2001:2.

<sup>18</sup>As an example, suppose we consider an experiment where the  $NLF \rightarrow ERM$  rate is lowered by  $x$  relative to the data. Then the non-transition rate  $NLF \rightarrow NLF$  is raised by  $x$ , so that the sum of all rates out of  $NLF$  remains equal to one. Our results are robust to an alternative method, where instead of allocating the difference between the observed

in accounting for the fall in routine employment if, by holding it constant at pre-polarization levels, a substantial fraction of the fall is mitigated.<sup>19</sup> When analyzing the results we focus on the fall in per capita routine employment at two key points in time: (i) early 2007, just prior to the Great Recession, and (ii) the expansionary period up to the end of 2012. Implicit in these choices is the fact that transition rates during recessions are not of primary importance in accounting for the 30 year decline in routine employment. Because recessions are short events, it is the behavior of transition rates during expansions that dictate long-run dynamics.

In principle, there are 90 counterfactual experiments to consider, one for each of the off-diagonal transition rates in the matrix  $\rho$ . Unsurprisingly, not all of these have quantitatively relevant impacts on the evolution of routine employment. For instance, rates that do not directly govern flows in or out of routine employment (e.g.,  $NLF \rightarrow ENRC$ ,  $ENRM \rightarrow UNRM$ ) have only indirect effects, via the source pools of individuals that may eventually transition into routine employment; we find that—in isolation—these have negligible effects. As such, our findings focus on transition rates that correspond directly to inflows and outflows to and from routine employment. Moreover, for the sake of brevity, we do not report results for all of these direct transition rates, and discuss only those of quantitative importance.<sup>20</sup>

In choosing the time period we consider to be representative of the pre-polarization era, we account for the difference in timing of when routine cognitive and routine manual employment begin to decline. We consider the expansion of the late-1970s and the recession in 1980 as the pre-polarization phases for routine manual occupations. In the counterfactual experiments where we hold inflow (outflow) rates to (from)  $ERM$  fixed, we replace: (i) their average value during recessions R2 through R5 with the average for R1, and (ii) their average value during expansions E2 through E6 with the average for E1. For routine cognitive, we consider R2 and E3 to be the benchmark, pre-polarization phases, and run counterfactuals on phases R3 through R5 and E4 through E6.

### 3.1 The role of inflows to routine employment

#### Inflows from unemployment

In our first experiment we set the transition rates from all categories of unemployment into employment in a routine occupation at their pre-job polarization levels. This entails holding a total of 10 transition rates constant: from unemployment with previous job in each of the four occupational categories, and from unemployment with unknown or no previous occupation, into employment in either a routine manual or routine cognitive occupation. All other transition rates are allowed to evolve phase-by-phase as they do in the data.

To visualize the relationship between the benchmark and counterfactual transition rate series,

---

and the counterfactual transition rates to the diagonal of the transition matrix, we allocate this difference proportionally across the remaining 9 transition rates out of the source labor market state being considered. As an example, consider again the experiment where the  $NLF \rightarrow ERM$  rate is lowered by  $x$ . Then the transition rates out of  $NLF$  towards all other categories (including to itself) are adjusted so that overall they are raised by  $x$  but their relative magnitudes remain the same.

<sup>19</sup>Shimer (2012) performs a similar style of counterfactuals to determine the contribution of various transition rates to fluctuations in the unemployment rate.

<sup>20</sup>Because of the issues with measurement error before 1994 in the job-to-job transitions rates across occupations (discussed in Section 2.2), we do not consider these here. We revisit this in the counterfactuals of Section 5.

Figure 4: Benchmark and Counterfactual Transition Rates from Unemployment to Routine Manual Employment

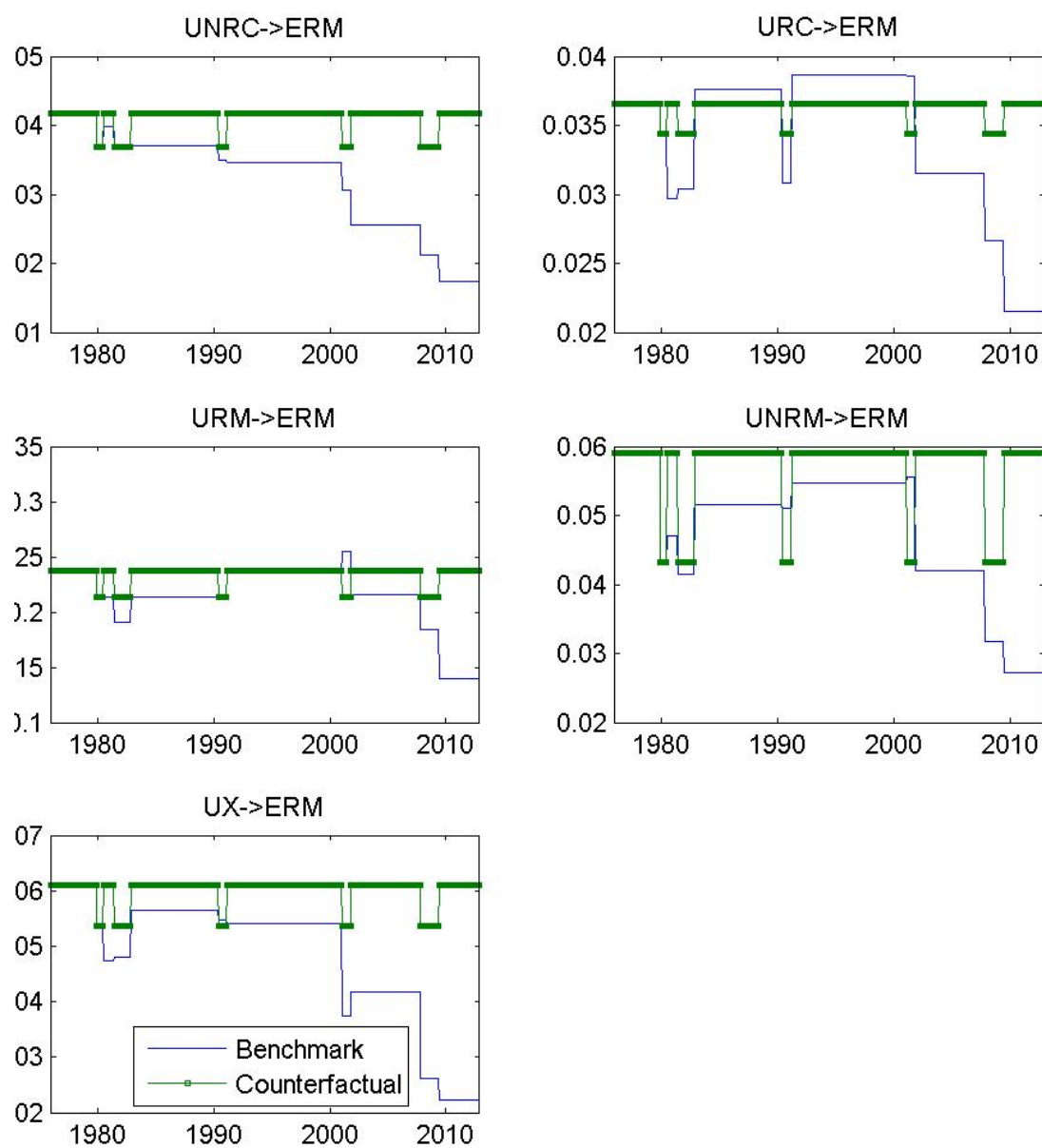


Figure 5: Benchmark and Counterfactual Transition Rates from Unemployment to Routine Cognitive Employment

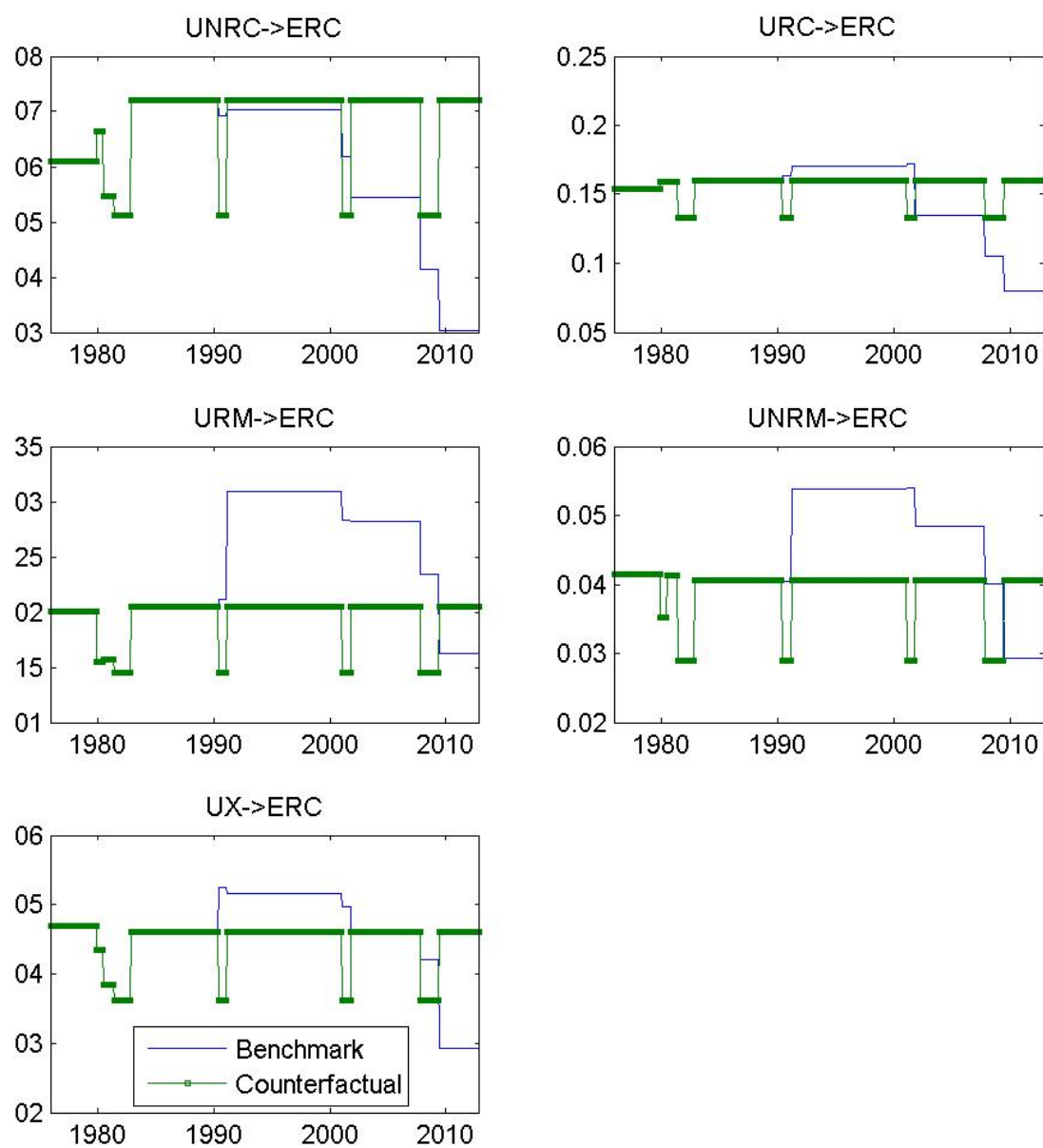
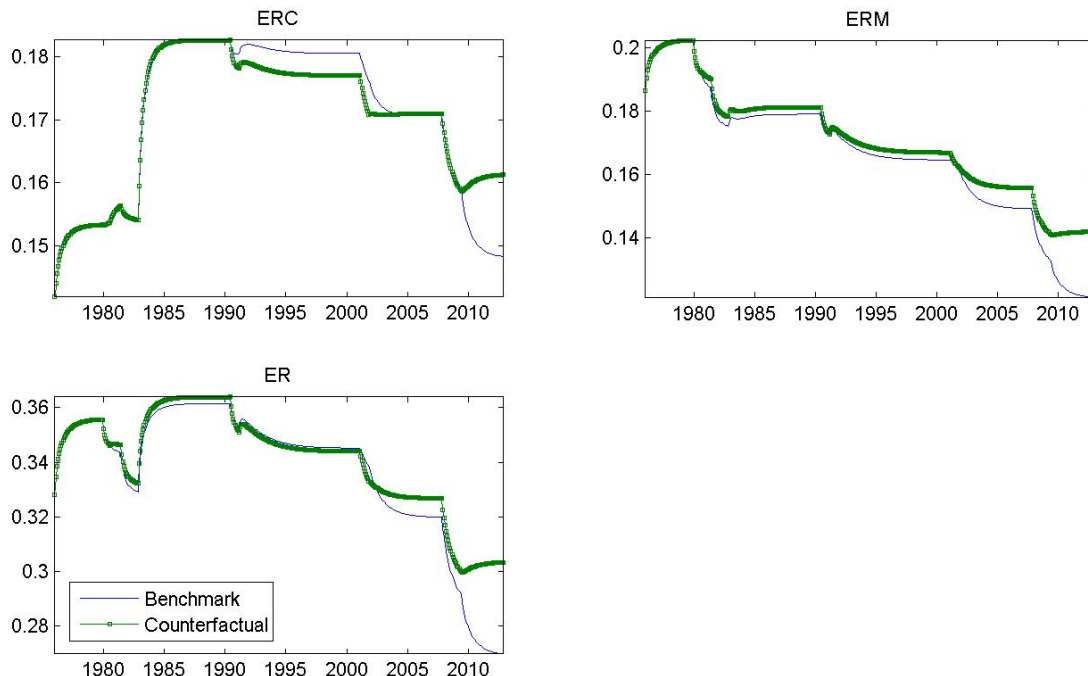




Figure 6: Counterfactual Routine Employment: Inflow rates from Unemployment to Routine Employment at their pre-polarization levels



Figures 4 and 5 plot these ten transition rates. The benchmark series, in solid blue lines, evolve according to the averages observed in the data. The counterfactual series, in hatched green lines, use the averages from the pre-polarization phases during all subsequent recessions and expansions.

Figure 4 clearly illustrates the declining transition rate from *UNRC*, *UNRM*, and *UX* into routine manual employment over time, relative to the pre-polarization period. The decline in the transition rate for the unemployed with previous routine job (*URC* and *URM*) is also evident from the 2002 expansion (E5) onward. In Figure 5, declines in the transition rate to *ERC* from all unemployment groups are evident from the end of the Great Recession, and from *UNRC* and *URC* from E5 onward. Figure 5 also reveals that during the 1990s transition rates from *URM*, *UNRM*, and *UX* into *ERC* were actually higher than they were in the 1980s; this is also true of the 2000s for *URM*  $\rightarrow$  *ERC* and *UNRM*  $\rightarrow$  *ERC*.

The resulting counterfactual series for routine employment are displayed in Figure 6. The counterfactual experiment mitigates the fall in routine manual employment from 1980 onward. Per capita routine manual employment falls to 15.58 percent of the population in 2007 (as opposed to 14.94 in the actual data), and 14.20 in 2012 (as opposed to 12.15). Hence, holding the various  $U \rightarrow ERM$  rates—the so called “job finding rates” into routine manual employment—at pre-polarization levels mitigates 12% and 26% of the fall in the two time periods, respectively.

In the case of routine cognitive occupations, the counterfactual actually predicts lower employment during the boom of the 1990s (E4) relative to the 1980s (E3). This, of course, is due to the fact that

the actual transition rates from  $URM$ ,  $UNRM$ , and  $UX$  into  $ERC$  during this period were higher. By 2007, the counterfactual series falls to 17.10, essentially the same level as the actual data; prior to the Great Recession,  $U \rightarrow ERC$  rates explain none of the overall decline. However, in the subsequent expansion period, counterfactual routine cognitive employment falls only to 16.12 (instead of 14.83 in the data). Hence, job finding rates into  $ERC$  account for a sizeable 38% of the total decline, due to the counterfactual’s ability to mitigate the continued fall since the end of the Great Recession.

As a result, had the transition rates from  $U \rightarrow ER$  (both manual and cognitive) not changed from their pre-polarization values, routine employment would have remained higher. This is especially true from 2002 onward. Overall, holding the inflow rates from unemployment at their pre-polarization levels mitigates 17% of the fall in routine employment up to 2007, and 37% of the fall up to the end of 2012.

Of the 10 transition rates considered in this experiment, two are of disproportionate importance in terms of the quantitative results. These are the rates at which unemployed workers who previously held routine jobs “return” to employment in a routine occupation: the  $URM \rightarrow ERM$  and  $URC \rightarrow ERC$  rates. Of the total mitigating effect generated by this counterfactual, approximately 50% is due to these two transition rates alone. The remaining effect is due to the other eight transition rates and their interaction with these “return job finding rates” to routine employment. As such, our analysis in latter parts of this paper pays particular attention to these transition rates.

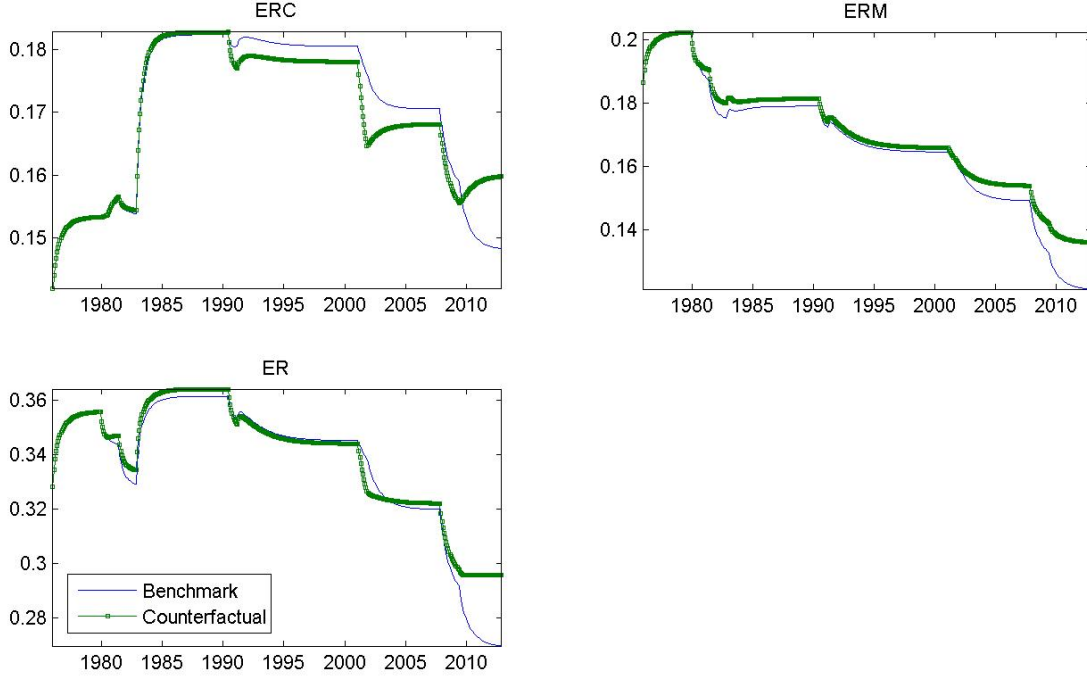
### **Inflows from non-participation**

Our next experiment sets the transition rates from labor force non-participation to routine employment at their pre-job polarization levels. All other transition rates (including the inflows from unemployment) are allowed to evolve phase-by-phase as they do in the data. Figure 7 displays the results. For routine manual occupations, this counterfactual mitigates the per capita employment decline throughout the post-polarization period. The effect is particularly evident from the expansion E5 onward. The counterfactual series for  $ERM$  falls to 15.41 in 2007, and 13.62 in 2012. Hence, this experiment mitigates 9% and 18% of the fall in routine manual employment in the two periods, respectively.

For routine cognitive occupations, the  $NLF \rightarrow ERC$  rate was actually higher during the 1990s and 2000s expansion, relative to the 1980s. As such, the counterfactual predicts lower per capita routine cognitive employment during this period. However, since the end of the Great Recession, the transition rate from non-participation to routine cognitive employment has been much lower compared to the pre-polarization period. As a result, counterfactual routine cognitive employment falls only to 15.98 by the end of 2012. Hence, changes in the  $NLF \rightarrow ERC$  rate account for 33% of the total per capita employment decline in routine cognitive occupations, concentrated exclusively in the period since 2009.

Overall, the counterfactual for total per capita routine employment falls to 32.22 by 2007, and 29.59 by the end of the sample period. Thus, had the non-participation to routine employment transition rates not changed from their pre-polarization values, the fall of routine employment from its pre-1980 peak would have been mitigated by 5% and 29%, in each of the time periods respectively.

Figure 7: Counterfactual Routine Employment: Inflow rates from Non-Participation to Routine Employment at their pre-polarization levels



### 3.2 The role of outflows from routine employment

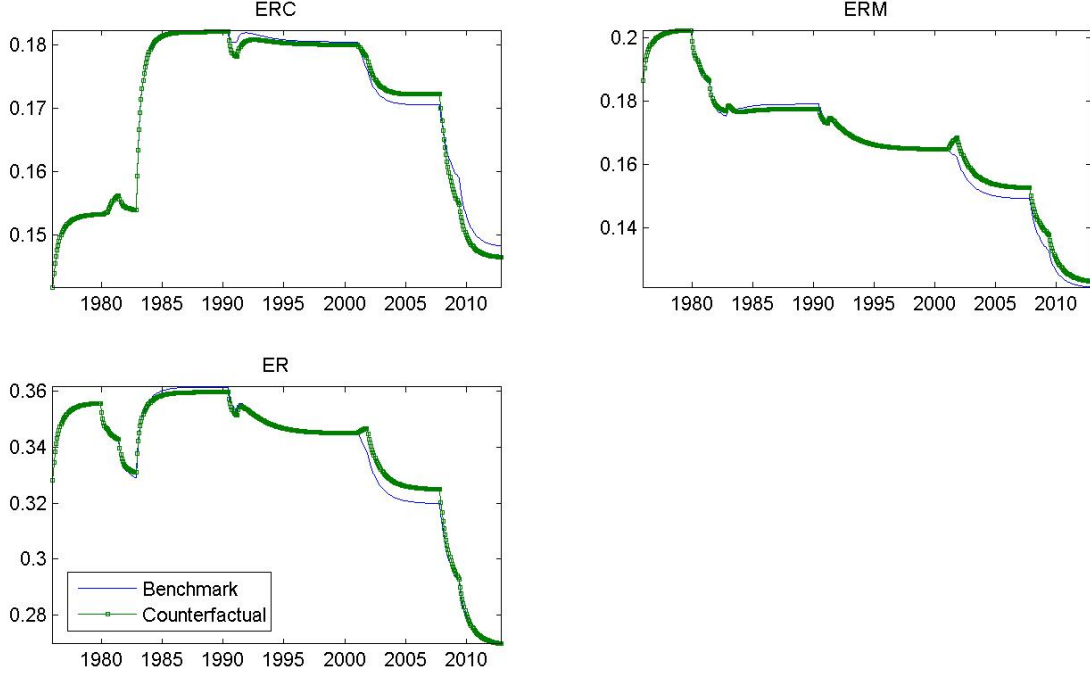
#### Outflows towards non-participation

We next consider the transition rates from routine employment to labor force non-participation. As Figure 8 indicates, this counterfactual has a modest effect on the decline in per capita routine employment. For routine manual occupations, the counterfactual series falls from a pre-1980 peak of 20.24 to 15.28 in 2007, then again to 12.33 by the end of 2012. Hence, holding the  $ERM \rightarrow NLF$  transition rate at pre-polarization values mitigates 7% and 2% of the fall, respectively.

For routine cognitive occupations, the counterfactual time series falls to 14.66 by the end of the time period, below the actual level of 14.83. This is because outflows to non-participation have actually been lower since 2007 than prior to polarization. Hence, the change in the  $ERC \rightarrow NLF$  explains none of the decline observed over the whole time period. However, the counterfactual falls only to 17.22 by 2007. Hence, prior to the Great Recession, the employment to non-participation rate accounts for 14% of the decline in  $ERC$ .

Overall, holding the outflow to non-participation rates constant at their pre-polarization values has essentially no effect on the decline in per capita routine employment after the Great Recession. However, this experiment does indicate that changes in these transition rates are relevant in accounting for the decline prior to the recession. From the pre-1980 peak to 2007, approximately 12% of the decline in routine employment is accounted for by such changes.

Figure 8: Counterfactual Routine Employment: Outflow rates to Non-Participation from Routine Employment at their pre-polarization levels



### 3.3 Summary

The results from the various counterfactual experiments are summarized in Table 4. In short, we find that, on their own, changes in the transition rates from: (i) unemployment to routine employment,  $U \rightarrow ER$  (in particular, the return job finding rates,  $URM \rightarrow ERM$  and  $URC \rightarrow ERC$ ), (ii) labor force non-participation to routine employment,  $NLF \rightarrow ER$ , and (iii) routine employment to non-participation,  $ER \rightarrow NLF$ , account for the bulk of the disappearance of routine employment. Changes in the “finding rates” into routine employment—factors (i) and (ii)—are important for the decline both leading into the Great Recession and, especially, thereafter. By contrast, changes in the “separation rate” from routine employment to non-participation matter prior to 2007.<sup>21</sup>

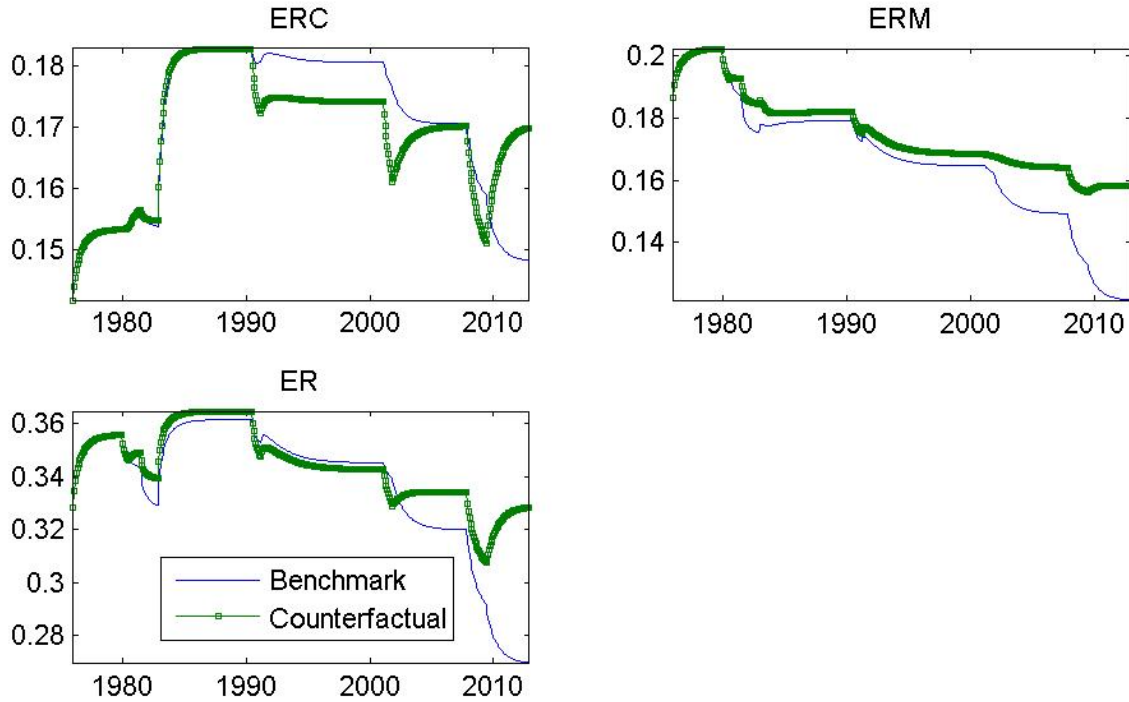
To further explore the quantitative role of these changes, we conduct a comprehensive counterfactual in Figure 9 in which we simultaneously hold all of these key transition rates to their pre-polarization values. From a pre-1980 peak of 36.14, the counterfactual series falls to 33.42 in 2007, and to 32.82 in 2012. Relative to the actual time series for per capita routine employment, holding these transition rates fixed mitigates 34% of the decline leading into the Great Recession, and 64% of the decline to the end of the sample.

<sup>21</sup>Moreover, changes in the separation rate from routine employment to unemployment were found to have essentially no quantitative impact on the dynamics of per capita routine employment. For brevity, those results have not been presented.

Table 4: Summary of Results from Counterfactual Experiments

	ER		ERM		ERC	
	Peak: 36.14		Peak: 20.24		Peak: 18.24	
	2007:1	2012:12	2007:1	2012:12	2007:1	2012:12
<b>Baseline</b>	32.00	26.97	14.94	12.15	17.06	14.83
<b>Counterfactual where transition rates are held at pre-polarization levels for:</b>						
Inflows from Unemployment	32.68	30.33	15.58	14.20	17.10	16.12
<i>Mitigated %</i>	16.5%	36.6%	12.2%	25.5%	3.4%	37.8%
Inflows from Non-Participation	32.22	29.59	15.41	13.62	16.81	15.98
<i>Mitigated %</i>	5.3%	28.5%	8.9%	18.2%	-21.2%	33.7%
Outflows to Non-Participation	32.51	26.98	15.28	12.33	17.22	14.66
<i>Mitigated %</i>	12.3%	0.1%	6.5%	2.3%	13.6%	-5.0%
All Three Above	33.42	32.82	16.42	15.84	17.01	16.99
<i>Mitigated %</i>	34.3%	63.8%	27.9%	45.6%	-4.6%	63.3%

Figure 9: Counterfactual Routine Employment: Three key sets of transition rates at their pre-polarization levels



## 4 Decomposition of transition rate changes

The previous section identifies changes in three sets of transition rates that account for a substantial fraction of the disappearance of per capita routine employment. Two of these rates reflect the probability that individuals transit into employment in routine occupations: one from the state of labor force non-participation, and the other from unemployment. The other reflects the probability that individuals transit from routine employment into non-participation.

It is well known that the probability of switching between particular labor market categories varies significantly across demographic groups. For example, young individuals are more likely to transit from unemployment to employment relative to those who are older. Changes in the demographic composition of the population could therefore be responsible, to some extent, for the changes over time in the transition rates into and out of routine employment.

In this section we determine the extent to which the observed changes in the key transition rates since the era of job polarization can be attributed to: (i) changes in the demographic composition of individuals in various labor market/occupation categories, and (ii) changes in the propensities to make certain transitions for individuals from particular demographic groups.

Disentangling these two forces allows us to argue whether the changes in the key transition rates are attributable to forces responsible for job polarization. For example, if transition rate changes were due principally to the aging of the U.S. population, one might argue that polarization is a natural consequence of demographic change.<sup>22</sup> By contrast, if the changes are due principally to changes in propensities and vary across routine and non-routine occupations, a stronger case can be made for the role of job polarization forces. Our analysis also allows us to determine which demographic groups have experienced the most pronounced changes in transition rates.

We proceed as follows. Let  $\rho_{it}^{AB}$  be a dummy variable defined at the individual level for all individuals who are in labor market state A in period  $t$ . This dummy is equal to 1 if individual  $i$  switches from state A to state B between month  $t$  and month  $t + 1$ , and equal to zero otherwise. Consider the following linear probability model for  $\rho_{it}^{AB}$ :

$$\rho_{it}^{AB} = X_{it}^A \beta + \epsilon_{it}. \quad (3)$$

Here,  $X_{it}^A$  comprises a set of standard demographic variables available in the CPS, as well as controls for seasonality. The demographic variables we include are age (dummy variables for 6 age bins: 16-24, 25-34, ..., 55-64, and 65+), education (dummies for less than high school, high school diploma or some post-secondary, and college graduate), gender, race (white versus other), and marital status (married versus other).

We estimate equation (3) for each of the transition rates in the matrix  $\rho$  from equation (1), focusing primarily on the set of transition rates identified in Section 3 as being quantitatively important in accounting for the decline of per capita routine employment. We perform the estimation separately for each of the 11 recession and expansion phases listed in Table 3. This means that the estimated

---

<sup>22</sup>Of course, such an argument is only valid for demographic composition changes that are orthogonal to changes in the labor market. Along other dimensions the argument is less clear cut; for instance, it could be argued that increasing educational attainment has been driven to some extent by the desire of individuals to attain non-routine cognitive jobs as opposed to routine ones. Such issues cannot be settled simply within this empirical framework.

vector of coefficients  $\beta$  is allowed to vary across different phases of the business cycle and over time. By analyzing the changes in the estimated coefficients, we determine which demographic groups have experienced the largest changes in transition propensities.

Next, we perform a standard Oaxaca-Blinder (OB) decomposition of the transition rates. Consider two different time periods denoted period 0 and period 1. For example, period 0 could be the expansionary period of the late 1970s, and period 1 the expansionary period of the 2000s. We use the estimated coefficients,  $\hat{\beta}$ , for each period, along with information on the evolution of the demographic variables in  $X^A$ , to decompose the change in the average transition rate across the two periods as:

$$\begin{aligned}\bar{\rho}_0^{AB} - \bar{\rho}_1^{AB} &= (\bar{X}_0^A \hat{\beta}_0) - (\bar{X}_1^A \hat{\beta}_1) \\ &= (\bar{X}_0^A - \bar{X}_1^A) \hat{\beta}_0 + (\bar{X}_1^A) (\hat{\beta}_0 - \hat{\beta}_1)\end{aligned}\tag{4}$$

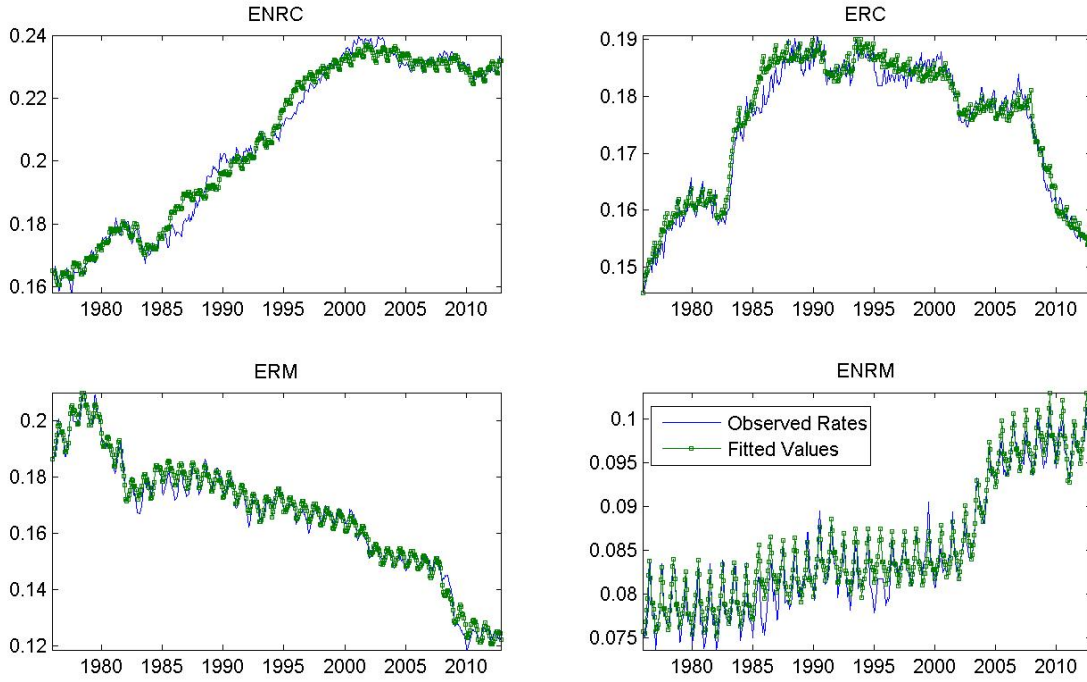
The change in the transition rate across periods 0 and 1 (on the left-hand side of the equation) can be decomposed into two parts. The first, given by the first term in equation (4), is the component that can be attributed to changes in the demographic composition of individuals in labor market state A across periods 0 and 1. The second part can be attributed to changes in the vector of coefficients  $\hat{\beta}$ . This reflects changes in the propensities to transition from state A to B for particular demographic groups. We thus decompose transition rate changes from the pre- to the post-polarization era into changes that are “explained” or “unexplained” by observables.

We perform the OB decomposition in equation (4) to analyze changes across comparable phases of the cycle, such as pre-polarization versus post-polarization recessions, or pre-polarization versus post-polarization expansions. In what follows, we do not discuss the results of the exercise for recessions: the transition rates that we focus on do not feature much in the way of systematic change across different recessions. Moreover, as discussed previously, because recessions are short events (lasting, on average, 11 months during our sample period), it is the behavior of transition rates during expansionary phases that dictate the long-run dynamics of the labor market stocks of interest.

As discussed in Section 3, we consider the relevant pre-polarization expansion period for routine manual employment to be represented by the late 1970s, specifically phase E1. For all of the transition rates into or out of routine manual employment, our OB decomposition analyzes the change in each subsequent expansion relative to E1. For routine cognitive employment, we consider the relevant pre-polarization expansion period to be given by the mid-to-late 1980s, phase E3. Therefore, in our OB decomposition for transition rates into or out of routine cognitive employment, we consider E3 to be our baseline period 0, as denoted in equation (4).

Before proceeding to the results, we illustrate the fit of our linear probability regression model. We use the results from the estimation of equation (3) to construct fitted values of the series of transition rates across each pair of labor market states. We use these fitted values in the law of motion in equation (2) to construct the implied stocks of each labor market state over time. These are presented in Figure 10 for the four employment groups, along with the stocks built with the observed monthly transition rates as shown in Figure 2. The fact that the two series track each other remarkably well indicates that our regression specification generates a good fit to the data.

Figure 10: Stocks based on law of motion using observed rates and regression estimates



## 4.1 Routine Manual Employment

### Inflows from Unemployment

As discussed in Section 3, one of the key transition rates accounting for the decline in routine occupations is the rate at which unemployed workers transition to routine employment ( $U \rightarrow ER$ ). Quantitatively, the most important of these is the rate at which unemployed individuals who previously held routine jobs transition back to a routine job ( $UR \rightarrow ER$ ), which we refer to as the “return job finding rate.” We begin by analyzing the change in this transition rate for routine manual workers since job polarization.

Table 5 presents results from the estimation of equation (3) for routine manual occupations, separately for each expansion period between 1976 and 2012. In all of our regression specifications, the excluded group is 45-54 year old, single, white females, with high school diplomas or some post-secondary education (but less than a college degree).<sup>23</sup> The first column presents results for the pre-polarization period of 1976m1-1979m12; the remaining four columns are for the subsequent post-polarization expansions.

Comparing the first and last column illustrates how the influence of various covariates on the return job finding rate has changed from the late 1970s to the period following the Great Recession. The estimated constant terms indicate that the monthly  $URM \rightarrow ERM$  transition probability has

<sup>23</sup>Our regressions also include a full set of monthly dummies to control for seasonality, which we do not report here. Hence, our excluded group are technically individuals with the demographic characteristics detailed above, observed in the month of January.



Table 5: Linear Probability Regression:  $URM \rightarrow ERM$ 

	1976m1- 1979m12	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
constant	0.1270** (0.0097)	0.1517** (0.0068)	0.1378** (0.0072)	0.1307*** (0.0089)	0.0514** (0.0077)
married	0.0438** (0.0045)	0.0308** (0.0031)	0.0423** (0.0035)	0.0396** (0.0045)	0.0314** (0.0038)
non-white	-0.0672** (0.0048)	-0.0685** (0.0032)	-0.0648** (0.0035)	-0.0682** (0.0047)	-0.0517** (0.0039)
male	0.0989** (0.0042)	0.0764** (0.0030)	0.0935** (0.0034)	0.1105** (0.0044)	0.0742** (0.0039)
16-24 yrs	0.0035 (0.0070)	0.0002 (0.0051)	-0.0120* (0.0054)	-0.0246** (0.0066)	-0.0079 (0.0058)
25-34 yrs	0.0024 (0.0071)	0.0024 (0.0048)	0.0068 (0.0051)	0.0108 (0.0064)	0.0186** (0.0053)
35-44 yrs	0.0019 (0.0080)	0.0007 (0.0051)	0.0047 (0.0052)	0.0032 (0.0063)	0.0260** (0.0053)
55-64 yrs	-0.0278** (0.0090)	-0.0372** (0.0061)	-0.0246** (0.0070)	-0.0228** (0.0079)	-0.0251** (0.0056)
65+ yrs	-0.1340** (0.0125)	-0.0656** (0.0130)	-0.0512** (0.0129)	-0.0656** (0.0138)	-0.0255* (0.0105)
low educ	-0.0148** (0.0041)	-0.0247** (0.0029)	-0.0258** (0.0033)	0.0036 (0.0046)	0.0228** (0.0043)
high educ	-0.0825** (0.0116)	-0.0638** (0.0078)	-0.0580** (0.0084)	-0.0401** (0.0098)	-0.0092 (0.0079)
$R^2$	0.0267	0.0181	0.0216	0.0240	0.0178
no of obs	48749	105487	90359	52330	47602

Notes: Table presents regression coefficients; excluded group is single, white, female, 45-54 years old, middle education level; see text for complete list of variables included in analysis. \* :  $p < 0.10$ ,

\*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table 6: Oaxaca Decomposition:  $URM \rightarrow ERM$ 

	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1976m1-1979m12): 23.12%				
Difference:	-2.29%** (0.258)	-0.972%*** (0.269)	-1.62%*** (0.305)	-9.25%*** (0.285)
<b>Composition</b>	+0.506%*** (0.100)	+0.276%** (0.135)	+0.197% (0.166)	+0.581%*** (0.206)
male	+0.378%*** (0.038)	+0.524%*** (0.042)	+0.661%*** (0.049)	+1.12%*** (0.063)
age	+0.224%*** (0.072)	+0.288%*** (0.088)	+0.113% (0.099)	-0.119% (0.133)
education	+0.105%*** (0.037)	+0.133%** (0.053)	+0.134%* (0.075)	+0.136% (0.097)
<b>Propensities</b>	-2.80%*** (0.270)	-1.25%*** (0.294)	-1.82%*** (0.338)	-9.83%*** (0.346)
male	-1.74%*** (0.416)	-0.428% (0.442)	+0.930%* (0.511)	-2.10%*** (0.508)
age	-0.456% (0.717)	-0.504% (0.709)	-0.648% (0.709)	+0.669% (0.626)
education	-0.332% (0.212)	-0.304% (0.202)	+0.711%*** (0.208)	+1.28%*** (0.179)
constant	+2.47%** (1.23)	+1.09% (1.25)	+0.371% (1.36)	-7.56%*** (1.28)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

decreased by 7.56 percentage points for the excluded demographic group. Inspecting the change for the remaining variables indicates that the fall in transition propensity was experienced broadly across essentially all demographic groups. The change has been especially strong for males (whose transition probability has fallen 2.47 percentage points more than their female counterparts) and 16-24 year olds (1.14 p.p. more than 45-54 year olds). Comparing the pre-polarization period with the remaining post-polarization expansions (of the 1980s, 1990s, and early 2000s), we see that the  $URM \rightarrow ERM$  transition probability actually rose for the excluded group. Hence, the fall in the return job finding rate experienced in the aggregate is not due to individuals of those demographic characteristics. Instead, the fall in transition propensity is found among men, high school dropouts, and especially the young (16-24 year olds).

Table 6 summarizes the results of the OB decomposition for the return job finding rate for routine manual occupations. As mentioned above, we take the expansion period of the 1970s as the baseline, pre-polarization period and compare subsequent expansions to it. We present the total difference in the average transition rate across periods, as well as the effect owing to “explained” factors (namely, changes in demographic composition) and “unexplained” factors (changes in propensities). For brevity, we do not present the detailed decomposition results for all explanatory variables, but instead, report

results for selected covariates.<sup>24</sup>

As is obvious from the rightmost column, there has been a precipitous fall in the  $URM \rightarrow ERM$  rate since the end of the Great Recession. Since July of 2009, the monthly return job finding rate has averaged 13.87%. This compares to an average rate of 23.12% in the expansion of the late-1970s. The sharp decline in the return job finding rate is one of the key contributors to the lack of recovery in routine manual employment since the end of the recession.

The fall is due entirely to unexplained factors; demographic change alone actually predicts a rise in the return job finding rate. Specifically, the explained effect implies that, if transition propensities (conditional on demographics) had remained at their 1970s levels, the return job finding rate would have *increased* by 0.58 percentage points, given the compositional change in the pool of unemployed routine manual workers. This is driven by increases in the fraction of the  $URM$  who are male and with the middle level of educational attainment (as shown in Table 5, both of these categories are more likely to transition to  $ERM$ , relative to females and those with either high or low education, respectively).

By contrast, the total unexplained effect implies that changes in transition propensities imply a fall in the return job finding rate of almost 10%. The effect of the constant is that attributable to the change in the conditional transition probability for the excluded group; as discussed above, this has fallen by more than 7 percentage points. The effect due to the male dummy variable implies that the change in transition probability for this group has contributed an additional 2% fall.<sup>25</sup>

The fall in the return job finding rate since 2009 is not unique to routine manual occupations, and is shared by all occupation groups. However, as we discuss below in Subsection 4.4, the fall is much larger for routine occupations relative to non-routine ones. That is, the Great Recession and its aftermath had a disproportionately large effect on routine employment, greatly accelerating the job polarization process.

Even prior to the Great Recession, Table 6 indicates that the average  $URM \rightarrow ERM$  transition rate has fallen in all expansion periods relative the late 1970s. These differences are large and statistically significant at the 1% level. Again, these falls occurred despite compositional changes (the increasing fraction of males and middle-educated workers among the unemployed routine manual) predicting a rise. Hence, the fall in return job finding rates is driven entirely by changes in propensity in all expansions since the onset of job polarization. As discussed in relation to Table 5, the fall in transition propensity is particularly acute for the youngest age group (16-24 year olds), and those with high school or some post-secondary education.

Next we consider the changes in transition rates from unemployment for those previously working in a non-routine occupation, into routine manual employment:  $UNRC \rightarrow ERM$  and  $UNRM \rightarrow ERM$ . We refer to these as “switching job finding rates.” For brevity, we do not present the results of these linear probability regressions and OB decompositions, and instead summarize as follows. As with the  $URM$  return job finding rates, the switching job finding rates into routine manual employment display large falls following the Great Recession. This again indicates the important impact the recession had

---

<sup>24</sup>The full detailed decomposition is available from the authors upon request.

<sup>25</sup>As discussed above, the fall in the estimated coefficient for 16-24 year olds would imply an additional negative effect in the OB decomposition. But taken together, all ages aside from the excluded group of 45-54 year olds generate a positive unexplained effect.

on the recent evolution of routine employment.

However, even prior to 2007, important changes occurred. As can be seen in Figure 4, both the  $UNRC \rightarrow ERM$  and  $UNRM \rightarrow ERM$  rates experienced significant declines throughout the polarization era. The changes in  $UNRC \rightarrow ERM$  are largely explained, owing to aging and rising educational attainment of unemployed non-routine cognitive workers (older and more educated individuals are less likely to switch into a routine manual jobs). By contrast, the fall in the  $UNRM \rightarrow ERM$  is almost entirely due to unexplained changes: the fall in propensity is concentrated among the young (16-24 years old), the middle-educated, and males.

Finally and importantly, this fall in switching job finding rates *into*  $ERM$  was not exhibited in transition rates for unemployed routine manual workers switching into employment in non-routine occupations. We discuss this in detail in Subsection 4.5.

### Inflows from Non-participation

Next, we consider the change in transition rates from labor force non-participation to routine manual employment ( $NLF \rightarrow ERM$ ) since the onset of job polarization. As discussed in Section 3, changes in these transition rates account for about 29% of the total decline in per capita routine employment.

For brevity, we present the estimation results for the linear probability model, equation (3), in the Appendix, and provide a summary here as follows. The fall in the  $NLF \rightarrow ERM$  rate in every post-polarization expansion relative to the late 1970s is not experienced by all demographic groups. This is evident from the change in the estimated constant term; for the excluded group, the transition probability has remained essentially the same over time. Hence, the fall is concentrated in specific demographic groups. The fall in the transition rate to routine manual employment is particularly strong for low-educated, young (16-24 year old), and male labor force non-participants.

Table 7 summarizes the results of the Oaxaca-Blinder decomposition for the  $NLF \rightarrow ERM$  transition rate. Again, we take the expansion period of the 1970s as the pre-polarization baseline period. As is obvious, there has been a precipitous fall in the  $NLF \rightarrow ERM$  rate since the end of the Great Recession. The steep decline in this employment “finding rate” (out of non-participation) is one of the key contributors to the lack of recovery in routine manual employment since the recession. However, even prior to the Great Recession, we see that the average  $NLF \rightarrow ERM$  transition rate is lower in all periods since the late-1970s.

We find that the unexplained effect consistently predicts a decline, across all expansion periods. That is, the propensity to make the  $NLF \rightarrow ERM$  transition is significantly lower. This effect is generated by propensity changes among males, the young, high school dropouts, and singles. These negative unexplained changes are offset by changes in the composition of labor force non-participants. Specifically, the rising proportion of males and, to a lesser extent, singles in non-participation predicts a rise in the  $NLF \rightarrow ERM$  rate (since these individuals, relative to females and marrieds, have a higher probability of transiting to routine manual employment).

### Outflows Towards Non-Participation

Finally, we investigate the change in transition rates from employment in routine manual occupations to labor force non-participation ( $ERM \rightarrow NLF$ ). For brevity, we present the estimation results

Table 7: Oaxaca Decomposition:  $NLF \rightarrow ERM$ 

	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1976m1-1979m12): 1.18%				
Difference:	-0.075%*** (0.015)	-0.041%*** (0.015)	-0.086%*** (0.016)	-0.379%*** (0.016)
<b>Composition</b>	+0.029%*** (0.005)	+0.118%*** (0.007)	+0.230%*** (0.008)	+0.284%*** (0.010)
male	+0.126%*** (0.003)	+0.225%*** (0.004)	+0.278%*** (0.005)	+0.332%*** (0.006)
married	+0.015%*** (0.001)	+0.035%*** (0.002)	+0.049%*** (0.003)	+0.066%*** (0.004)
education	-0.015%*** (0.002)	-0.037%*** (0.003)	-0.063%*** (0.004)	-0.075%*** (0.005)
<b>Propensities</b>	-0.104%*** (0.015)	-0.159%*** (0.016)	-0.316%*** (0.019)	-0.663%*** (0.020)
male	-0.146%*** (0.014)	-0.201%*** (0.016)	-0.244%*** (0.017)	-0.480%*** (0.019)
age	-0.110%*** (0.039)	-0.089%** (0.038)	-0.246%*** (0.041)	-0.231%*** (0.044)
education	-0.051%*** (0.015)	-0.082%** (0.014)	-0.088%*** (0.015)	-0.050%*** (0.015)
constant	+0.202%*** (0.063)	+0.225%*** (0.063)	+0.251%*** (0.068)	+0.092% (0.074)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table 8: Oaxaca Decomposition:  $ERM \rightarrow NLF$ 

	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1976m1-1979m12): 2.34%				
Difference:	-0.121%*** (0.027)	-0.039% (0.027)	+0.173%*** (0.031)	+0.113%*** (0.038)
<b>Composition</b>	-0.180%*** (0.010)	-0.275%*** (0.014)	-0.289%*** (0.017)	-0.223%*** (0.021)
male	+0.004% (0.002)	+0.008%*** (0.002)	-0.065%*** (0.003)	-0.087%*** (0.004)
age	-0.163%*** (0.006)	-0.262%*** (0.008)	-0.244%*** (0.010)	-0.187%*** (0.013)
education	-0.096%*** (0.005)	-0.147%*** (0.008)	-0.151%*** (0.009)	-0.172%*** (0.011)
<b>Propensities</b>	+0.059%** (0.026)	+0.236%*** (0.027)	+0.462%*** (0.032)	+0.336%*** (0.041)
male	+0.431%*** (0.071)	+0.615%*** (0.071)	+0.463%*** (0.087)	+0.746%*** (0.108)
married	+0.400%*** (0.047)	+0.460%*** (0.043)	+0.418%*** (0.047)	+0.446%*** (0.054)
education	+0.031% (0.020)	+0.066%*** (0.017)	+0.056%*** (0.020)	+0.031% (0.024)
constant	-0.747%*** (0.130)	-0.884%*** (0.129)	-0.457%*** (0.148)	-0.773%*** (0.186)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

for the linear probability regression in the Appendix, and simply provide a summary here. Not all demographic groups have seen a rise in the  $ERM \rightarrow NLF$  rate since the onset of job polarization. However, significant increases are observed for the young (16-24 year olds), the married, as well as among males and high school dropouts.

Table 8 summarizes the decomposition results for this transition rate. In contrast to the “finding rates” discussed above, there is no distinct break in the  $ERM \rightarrow NLF$  rate since the end of the Great Recession. Instead, we see an increase beginning after the 2001 recession, continuing through the end of the sample period.

This rise in the labor force exit rate for employed routine manual workers has occurred despite compositional changes that predict the opposite. Two explained factors are particularly pronounced in this case. The first is the rising education levels of routine manual workers, as increased schooling is associated with higher labor force attachment. Second, the shifting age composition of routine manual workers, away from the young (16-24 year olds) toward prime ages (35-54 year olds), similarly predicts a lower  $ERM \rightarrow NLF$  rate.

Hence, the observed rise in the exit rate towards non-participation is due entirely to unexplained factors. Indeed, increased exit propensities are observed in all four expansion periods since job polar-

ization. This propensity effect is particularly strong for males and those who are married.

## Summary

To summarize, we find important changes in the transition rates into and out of routine manual employment. Relative to their pre-job polarization benchmarks, the finding rates into employment – from both unemployment and non-participation – have fallen since the 1980s. These falls are especially pronounced in the years since the Great Recession. These changes in the  $URM \rightarrow ERM$  and  $NLF \rightarrow ERM$  rates have prevailed, despite demographic change that predicts both to have risen in the past 30 years. Hence, the fall in finding rates is entirely due to changes in propensities that have more than offset these explained factors.

The rise in the exit rate from routine manual employment to non-participation began in the 2000s, with no marked break following the Great Recession. This rise in the exit rate occurred despite demographic change predicting the opposite implying that, again, the observed change is due entirely to changes in propensities that have more than offset explained factors.

## 4.2 Routine Cognitive Employment

### Inflows from Unemployment

In this subsection, we analyze the change in the transition rates from unemployment to routine cognitive employment. We begin with the return job finding rate,  $URC \rightarrow ERC$ . Table 9 presents results from the estimation of equation (3) for routine cognitive occupations. As before, the excluded group is 45-54 year old, single, white females, with high school diplomas or some post-secondary education (but less than a college degree). The first column presents results for the pre-polarization period of 1982m12-1990m6; the remaining columns are for the subsequent post-polarization expansions.

Comparing the first and last column, there has been a precipitous fall in the return job finding rate into routine cognitive employment since the Great Recession. The estimated constant terms indicate a fall of 10.71 percentage points for the excluded group. From the change in the remaining variables, the fall in  $URC \rightarrow ERC$  rate was experienced broadly across all demographic groups, but has been especially strong for females (3.51 p.p. greater than their male counterparts), whites, those with higher levels of education, and to a lesser extent, the prime-aged (45-54 year olds). Comparing the pre-polarization period with the remaining post-polarization expansions (of the 1990s and early 2000s), we see similar changes as since the Great Recession, though less quantitatively pronounced.

Table 10 summarizes the results for the OB decomposition. In all three post-polarization expansions, the average return job finding rate for unemployed routine cognitive workers is lower than in the expansion of the 1980s; this change is especially pronounced and statistically significant beginning in the early-2000s.

The composition effect predicts a fall in all three periods. This is due primarily to a rise in the share of males and non-whites in the unemployment pool (both groups experience lower transition probabilities to routine cognitive employment compared to females and whites, respectively). From the expansionary period of the 2000s onward, the fall in the return job finding rate is driven by both explained and unexplained factors, with the latter being more important. The unexplained component

Table 9: Linear Probability Regression:  $URC \rightarrow ERC$ 

	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
constant	0.1856*** (0.0081)	0.1707*** (0.0073)	0.1526*** (0.0085)	0.0785*** (0.0068)
married	0.0007 (0.0037)	0.0057 (0.0036)	0.0086** (0.0043)	0.0070** (0.0034)
non-white	-0.0684*** (0.0039)	-0.0498*** (0.0037)	-0.0362*** (0.0043)	-0.0187*** (0.0035)
male	-0.0494*** (0.0038)	-0.0453*** (0.0035)	-0.0387*** (0.0039)	-0.0143*** (0.0032)
16-24 yrs	0.0336*** (0.0064)	0.0481*** (0.0058)	0.0414*** (0.0062)	0.0321*** (0.0052)
25-34 yrs	-0.0031 (0.0062)	0.0047 (0.0055)	0.0182*** (0.0062)	0.0070 (0.0048)
35-44 yrs	0.0018 (0.0067)	-0.0051 (0.0057)	0.0077 (0.0063)	0.0022 (0.005)
55-64 yrs	-0.0203** (0.0084)	-0.0187** (0.0073)	0.0059 (0.0077)	-0.0049 (0.0053)
65+ yrs	-0.0207 (0.015)	-0.0015 (0.0118)	0.0171 (0.0141)	0.0034 (0.0087)
low educ	-0.0573*** (0.0043)	-0.0540*** (0.0042)	-0.0466*** (0.0049)	-0.0189*** (0.0048)
high educ	0.0223*** (0.006)	0.0208*** (0.0052)	-0.0048 (0.0056)	0.0096** (0.0043)
$R^2$	0.0158	0.0130	0.0089	0.0041
no of obs	55119	62436	41453	37621

Notes: Table presents regression coefficients; excluded group is single, white, female, 45-54 years old, middle education level; see text for complete list of variables included in analysis. \* :  $p < 0.10$ ,

\*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$



Table 10: Oaxaca Decomposition:  $URC \rightarrow ERC$ 

	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1982m12-1990m6): 15.80%			
Difference:	-0.186% (0.246)	-2.34%*** (0.264)	-7.89%*** (0.241)
<b>Composition</b>	-0.336%*** (0.059)	-0.534%*** (0.085)	-0.619%*** (0.120)
male	-0.129%*** (0.022)	-0.336%*** (0.035)	-0.443%*** (0.043)
non-white	-0.206%*** (0.030)	-0.274%*** (0.036)	-0.274%*** (0.038)
education	-0.028% (0.024)	+0.095%*** (0.032)	+0.471%*** (0.049)
<b>Propensities</b>	+0.149% (0.245)	-1.81%*** (0.269)	-7.27%*** (0.261)
male	+0.127% (0.155)	+0.392%** (0.188)	+1.27%*** (0.184)
non-white	+0.477%*** (0.144)	+0.885%*** (0.161)	+1.36%*** (0.149)
education	+0.074% (0.161)	-0.144% (0.174)	+0.289%* (0.160)
constant	-1.78% (1.11)	-3.66%*** (1.20)	-10.9%*** (1.08)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table 11: Oaxaca Decomposition:  $NLF \rightarrow ERC$ 

	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1982m12-1990m6): 1.58%			
Difference:	+0.021% (0.015)	+0.046%*** (0.017)	-0.359%*** (0.018)
<b>Composition</b>	+0.047%*** (0.004)	+0.173%*** (0.005)	+0.213%*** (0.007)
education	+0.063%*** (0.002)	+0.115%*** (0.003)	+0.154%*** (0.004)
age	+0.023%*** (0.003)	+0.108%*** (0.003)	+0.129%*** (0.004)
<b>Propensities</b>	-0.026%* (0.015)	-0.128%*** (0.018)	-0.572%*** (0.019)
non-white	+0.038%*** (0.007)	+0.083%*** (0.009)	+0.086%*** (0.010)
age	+0.121%*** (0.044)	+0.118%** (0.046)	-0.015% (0.049)
constant	-0.085% (0.068)	-0.151%** (0.076)	-0.684%*** (0.081)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

predicts falls in the  $URC \rightarrow ERC$  propensity for essentially all demographic groups. This propensity effect is strongest for whites, females, the highly educated, and prime-aged.

Next we consider changes in switching job finding rates, from non-routine unemployment into routine cognitive employment:  $UNRC \rightarrow ERC$  and  $UNRM \rightarrow ERC$ . Again, for brevity, we do not present the results of these decompositions in detail, and instead summarize as follows. As can be seen in Figure 5, the  $UNRC \rightarrow ERC$  transition rate has experienced significant declines throughout the polarization era. The falls in this switching job finding rate are unexplained by demographics, and are particularly strong among females and singles. By contrast, the  $UNRM \rightarrow ERC$  rate rose during job polarization, due both to explained and unexplained factors. Rising post-secondary education rates among the unemployed non-routine manual accounts for the explained effect; rising propensities of the young and non-whites to switch from  $UNRM \rightarrow ERC$  account for the unexplained effects.

### Inflows from Non-participation

For brevity, we do not present the regression results for the  $NLF \rightarrow ERC$  rate, and make them available upon request. Table 11 summarizes the results of the OB decomposition for the transition rate from labor force non-participation to routine cognitive employment.

As with  $NLF \rightarrow ERM$ , the  $NLF \rightarrow ERC$  rate displays a sharp decline following the Great Recession. This change is entirely accounted for by a fall in the propensity of all individuals to find employment in routine cognitive jobs. The effect was particularly pronounced for the young (16-24

Table 12: Oaxaca Decomposition:  $ERC \rightarrow NLF$ 

	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
Baseline Expansion (1982m12-1990m6): 2.96%			
Difference:	-0.071%*** (0.026)	+0.106%*** (0.030)	-0.081%** (0.037)
<b>Composition</b>	-0.133%*** (0.007)	-0.094%*** (0.010)	-0.094%*** (0.013)
male	-0.014%*** (0.002)	-0.047%*** (0.003)	-0.069%*** (0.003)
education	-0.035%*** (0.003)	-0.032%*** (0.003)	-0.084%*** (0.005)
<b>Propensities</b>	+0.062%** (0.025)	+0.201%*** (0.030)	+0.013% (0.037)
male	+0.137%*** (0.018)	+0.203%*** (0.022)	+0.297%*** (0.028)
age	+0.206%*** (0.045)	+0.290%*** (0.049)	+0.137%** (0.059)
constant	-0.124% (0.098)	-0.088% (0.114)	-0.319%** (0.139)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

year olds) and whites. As with routine manual occupations, this unexplained change is a key factor for the malaise in routine cognitive employment since 2009.

Prior to the Great Recession,  $NLF \rightarrow ERC$  rates exhibit modest increases relative to the pre-polarization period of the 1980s. This increase is due to explained factors; important changes include rising educational attainment and the increasing share of 16-24 year olds in the non-participant pool. During the expansions of the 1990s and early-2000s, these compositional changes mask unexplained factors that predict declines in the transition to routine cognitive employment. Hence, since job polarization, there have been consistent falls in the propensity to transition from  $NLF$  to  $ERC$ .

### Outflows Towards Non-Participation

Finally, Table 12 summarizes the results for the transition rate from routine cognitive employment to labor force non-participation; as above, we do not present the results of the linear probability regressions for brevity, and make them available upon request. As is evident, there is little change in the  $ERC \rightarrow NLF$  transition rate across pre- and post-polarization periods. Moreover, whether the rate increases or decreases is not consistent across post-polarization expansions.

However, what is consistent across periods is the fact that explained and unexplained factors operate in opposite directions. Demographic changes predict that the exit rate from routine cognitive employment to non-participation should have fallen. This is due primarily to rising education and the rising share of males amongst routine cognitive workers. By contrast, propensity changes predict

increased exit from the labor force among routine cognitive workers. This change is particularly strong for males and the young (16-24 year olds).

## Summary

To summarize, the return job finding rate into routine cognitive employment fell in each post-polarization expansion relative to the pre-polarization 1980s benchmark. This fall is driven primarily by unexplained factors, with propensity changes strongest for whites, females, the highly educated, and prime-aged. The finding rate from non-participation to routine cognitive employment also fell following the Great Recession. Propensity change accounts for this, and predicts a decrease in the  $NLF \rightarrow ERC$  rate throughout the job polarization era. Finally, propensity change also predicts an increase in the exit rate from routine cognitive employment to non-participation in each post-polarization expansion; this is driven by the effect of males and the young.

## 4.3 Contrast with Transition Rates for Non-Routine Workers

Our analysis identifies a number of important changes in the transition patterns in and out of routine occupations that are key in accounting for the long run decline of per capita routine employment. This subsection discusses the extent to which these changes are unique to routine occupations by contrasting them with non-routine occupations. For brevity, we present the results for the OB decomposition analysis in Appendix A, and highlight the key findings here.<sup>26</sup> We focus on the period prior to the Great Recession in this section, and analyze the patterns for the most recent expansion period in Subsection 4.4.

We begin with entry rates into employment from unemployment and non-participation. As discussed above, the post-polarization era has featured sharp falls in the return job finding rate from unemployment for both routine cognitive and routine manual occupations. These falls are driven primarily by propensity changes, as opposed to simply changes in demographic composition. By contrast, both the  $UNRC \rightarrow ENRC$  and  $UNRM \rightarrow ENRM$  transition rate have increased since job polarization, notably during the expansions of the 1990s and early-2000s. The rise in return job finding rates into non-routine jobs is due to an increased propensity.

The  $NLF \rightarrow ENRC$  transition rate has also increased in the post-polarization era; this is true even for the period since the Great Recession. This increase in the entry rate into non-routine cognitive employment is driven by unexplained factors, as opposed to change in demographics. Prior to the Great Recession, the  $NLF \rightarrow ENRM$  rate is essentially unchanged relative to the period prior to job polarization. However, this lack of change masks an increase in propensity to transition to non-routine manual employment. This unexplained effect is offset by the opposing explained effect, stemming primarily from the increased educational attainment amongst labor force non-participants. These increases in propensity to transition into non-routine employment contrast starkly with the fall in propensity to transition from non-participation into routine employment.

Finally, we discuss briefly the outflow rates from non-routine employment towards non-participation. The  $ENRC \rightarrow NLF$  transition rate exhibits no consistent pattern of change relative to the pre-

---

<sup>26</sup>The full decomposition results, as well as estimation results of equation (3) for the non-routine transition rates, are available from the authors upon request.

polarization period. Moreover, the changes are quantitatively small. By contrast, the  $ENRM \rightarrow NLF$  rate has fallen since job polarization. These changes are large and statistically significant, owing to both explained and unexplained factors. Indeed, this decreased tendency to transition to non-participation is the primary factor accounting for the rise in non-routine manual employment. Again, this change contrasts sharply with the rise in the  $ERC \rightarrow NLF$  and  $ERM \rightarrow NLF$  rates, and especially the rise in the propensities to exit from routine employment.

#### 4.4 Finding Rates since the Great Recession

As is clear from the previous results, much of the long-run decline in per capita routine employment can be attributed to the lack of recovery in the four years since the end of the Great Recession. Moreover, as indicated in Section 3 along with the decomposition results above, this decline can be attributed largely to the fall in finding rates into routine employment, from both unemployment and labor force non-participation since 2009. In this subsection, we make clear that the failure of these finding rates to recover since the recession is quantitatively unique to routine occupations. That is, while all finding rates at the occupational level have fallen, the effect is much more pronounced for routine cognitive and routine manual occupations. Hence, the malaise in aggregate employment and “jobless recovery” observed since the Great Recession is disproportionately due to the disappearance of routine jobs.

To demonstrate this, Panel A of Table 13 presents return job finding rates for all four occupational groups:  $URM \rightarrow ERM$ ,  $URC \rightarrow ERC$ ,  $UNRM \rightarrow ENRM$ , and  $UNRC \rightarrow ENRC$ . The first row presents these rates for the benchmark, pre-polarization expansion; the second row presents the return job finding rates for the 2009-2012 expansion period. The return job finding rates into routine employment have fallen precipitously since the end of the Great Recession, by approximately 8 or 9 percentage points. These compare to modest return job finding rate declines of around 3 percentage points for either of the non-routine occupation groups. Hence, while return job finding rates in all occupations have fared poorly since 2009, the large declines observed for routine jobs are not simply attributable to economy-wide forces. The stark difference across routine and non-routine occupations points to the importance of job polarization forces.

Panel B of Table 13 presents changes in switching job finding rates, from the pre-polarization expansion to the past four years. Because of the large number of switching job finding rates—3 per occupation group (e.g.,  $UNRC \rightarrow ERM$ ,  $UNRC \rightarrow ERC$ ,  $UNRC \rightarrow ENRM$ ) times 4 occupation groups—we simplify our analysis as follows. We consider job finding rates for unemployed individuals from each non-routine occupation group into employment in either routine occupation (cognitive or manual), and vice-versa.

Consider, the switching job finding rate for the unemployed with previous employment in a non-routine manual job to employment in a routine (cognitive or manual) occupation,  $UNRM \rightarrow ER$ , displayed in the first column. Comparing across expansion periods, this transition rate has fallen by 3.97%. This fall is even greater, at 5.34%, for the rate at which unemployed non-routine cognitive workers switch into routine employment. In fact, these are larger than the falls of approximately 3 percent in their return job finding rates into non-routine jobs from Panel A. Hence, the fall in the “total” job finding rate for the unemployed non-routine (into employment of any occupation) since the end of the Great Recession is disproportionately due to the reduced rate at which these workers find

Table 13: Changes in Return Job Finding Rates

<i>Panel A: Return Job Finding Rates</i>				
	$URM \rightarrow$ $ERM$	$URC \rightarrow$ $ERC$	$UNRM \rightarrow$ $ENRM$	$UNRC \rightarrow$ $ENRC$
Pre-Polarization Expansion	23.12%	15.80%	13.98%	14.80%
2009-2012 Expansion	13.87%	7.91%	11.30%	11.68%
Difference	-9.25%	-7.89%	-2.68%	-3.12%
<i>Panel B: Switching Job Finding Rates</i>				
	$UNRM \rightarrow$ $ER$	$UNRC \rightarrow$ $ER$	$URM \rightarrow$ $ENR$	$URC \rightarrow$ $ENR$
Pre-Polarization Expansion	9.72%	10.35%	4.35%	6.51%
2009-2012 Expansion	5.75%	5.01%	3.30%	4.97%
Difference	-3.97%	-5.34%	-1.05%	-1.54%
<i>Panel C: Non-Participation to Employment Transition Rates</i>				
	$NLF \rightarrow$ $ERM$	$NLF \rightarrow$ $ERC$	$NLF \rightarrow$ $ENRM$	$NLF \rightarrow$ $ENRC$
Pre-Polarization Expansion	1.18%	1.58%	1.57%	0.972%
2009-2012 Expansion	0.801%	1.22%	1.31%	1.20%
Difference	-0.379%	-0.359%	-0.256%	+0.227%

employment in routine occupations.

This contrasts with the change in the switching job finding rates for the unemployed with previous employment in routine jobs. Across the pre-polarization period and the period since the Great Recession, for both *URM* or *URC*, the transition rate into non-routine employment has fallen much less, in the range of 1 percent. This contrasts dramatically with the declines in the return job finding rates into routine employment displayed in Panel A. Again, the observed falls in the “total” job finding rate for unemployed routine workers is disproportionately due to the reduced rate at which these workers find routine employment. The findings of Panel B underscore our emphasis on job polarization forces, and the disappearance of routine jobs, in understanding aggregate employment dynamics since the end of the Great Recession.

Panel C presents transition rates from non-participation into employment for all four occupational groups. The fall in the finding rates from non-participation into employment since the Great Recession is not shared by all occupation groups. In fact, the transition rate from non-participation into non-routine cognitive employment has risen in the recent period. Thus, the declines in finding rates for routine jobs since 2009 are not simply attributable to recessionary, economy-wide forces. Job polarization has led to much more pronounced effects on routine employment since the Great Recession.

## 4.5 Further Analysis of the Transition Rates

As documented above, unemployed workers previously employed in routine jobs have experienced sharp declines in the rate at which they return to employment in routine occupations. Here, we investigate the implication of this change in the return job finding rates to routine employment. Specifically, we determine whether these falls have been offset by increased transition rates into non-routine employment, or simply led to longer periods of non-employment.<sup>27</sup>

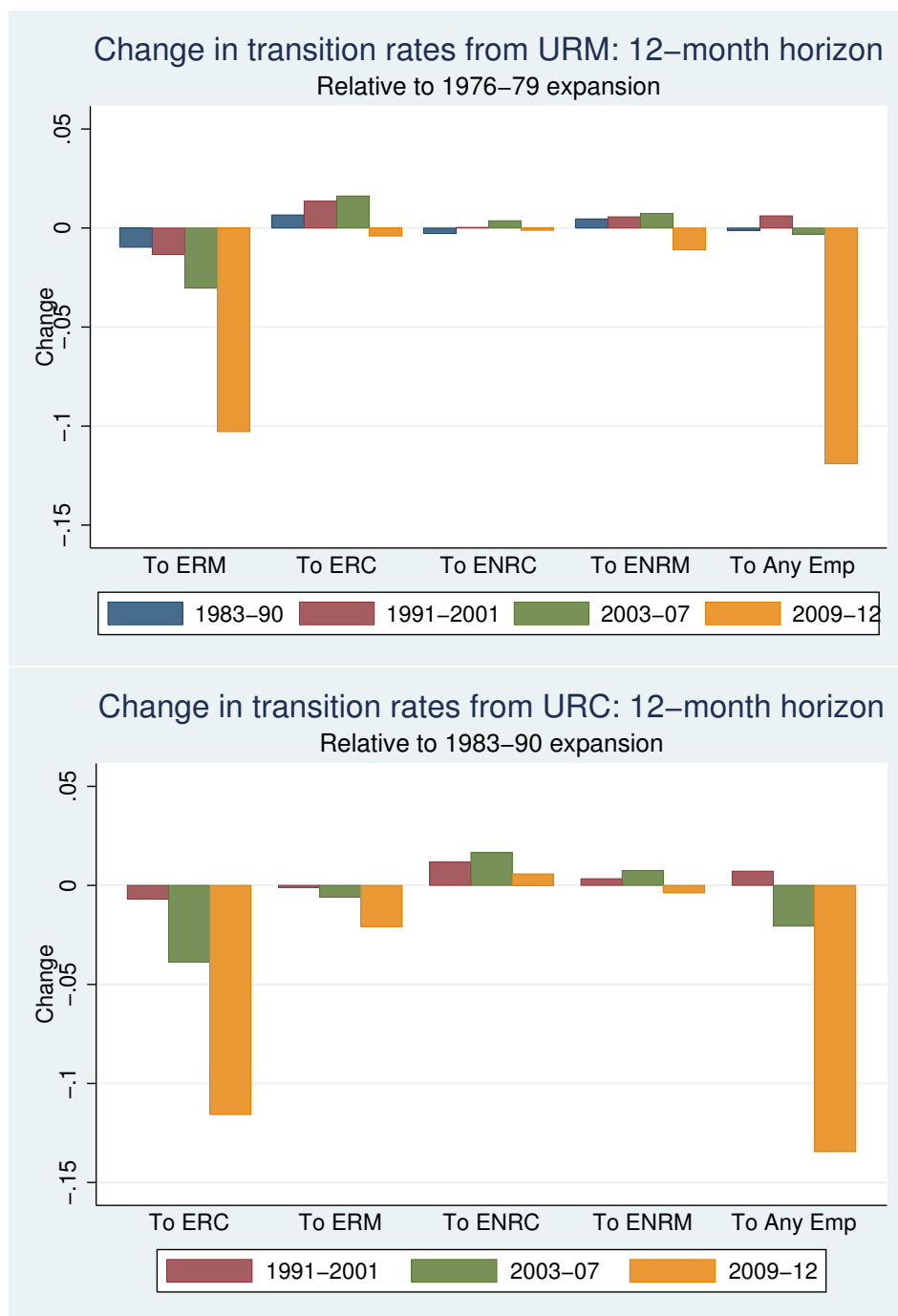
Figure 11 displays the changes in the job finding rates from routine unemployment observed between the pre-polarization expansion, and each subsequent expansion since job polarization. We consider transition rates into each occupational group (return and switching job finding rates), as well as the rate into employment of any occupation (the total job finding rate). Since occupational switching takes time, with potential intervening spells of non-participation, Figure 11 displays changes in 12-month job finding rates (i.e., transitions from unemployment at date  $t$  to employment at date  $t + 12$ ).<sup>28</sup>

Changes in the transition rates from *URM* are in the top panel, changes for *URC* in the bottom. Comparing the pre-polarization expansion with the period since the Great Recession, declines in the 12-month *URM*  $\rightarrow$  *ERM* rate were accompanied by declines in the switching job finding rate into all other occupation groups (though these were of much smaller magnitude). Hence, unemployed routine manual workers have experienced a pronounced fall in job finding probability into any occupation. Similarly, unemployed routine cognitive workers have experienced a larger fall in their total job finding

<sup>27</sup>As discussed in Section 2, the CPS redesign of 1994 induced discontinuities in the measured transition rates between unemployment and non-participation in the labor force. As such, we are unable to determine whether changes in return job finding rates have led to longer spells of unemployment or increased transition to non-participation separately.

<sup>28</sup>We can observe transition rates up to a 15-month horizon; however we prefer to consider the 12-month horizon as this affords approximately four times as many observations (individuals in their first four months-in-sample, rather than only individuals in their first month-in-sample). Moreover, because we are interested in changes during business cycle expansions, we do not consider 12-month transition rate observations which straddle both booms and recessions. For reference, we include the analogous figure for monthly job finding rate changes in Appendix A.

Figure 11: Change in transition rates for unemployed routine workers across expansionary phases (12-month horizon)





rate compared to their return job finding rate, following the Great Recession. This, however, masks a slight increase in the 12-month  $URC \rightarrow ENRC$  rate since 2009, when compared to the pre-polarization benchmark.

Prior to the Great Recession, falls in the  $URM \rightarrow ERM$  rate were offset by higher switching rates in the 1980s, 1990s, and early-2000s expansions. This can be seen by the near zero change in the total job finding rate from  $URM$  in the top panel. This increased occupational switching for unemployed routine manual workers, however, did not go into high-wage, non-routine cognitive jobs. Instead,  $URM$  workers switched primarily into routine cognitive work, and also into non-routine manual occupations.

Similarly, falls in the return job finding rate for the unemployed routine cognitive were largely offset by higher switching rates prior to the Great Recession. This is particularly evident in the  $URC \rightarrow ENRC$  rate, though increased switching into non-routine manual occupations was also observed. Hence, to the extent that non-routine cognitive occupations represent higher wage jobs relative to the other occupation groups, unemployed routine cognitive workers have fared better than routine manual workers in the job polarization era.

To summarize, since the Great Recession, falls in return job finding rates have been accompanied by longer spells of non-employment for unemployed routine workers. Prior to this, falls in return job finding rates during the job polarization era have been largely offset by increased occupational switching. Unemployed routine manual workers switched primarily into routine cognitive occupations, while unemployed routine cognitive workers have switched primarily into non-routine cognitive jobs.

## 5 Demographics or Propensities: Detailed Counterfactuals

In this section, we investigate the role of demographic change and changes in transition propensities in accounting for the disappearance of per capita routine employment. We consider two types of counterfactual experiments. In the first, the demographic composition of the U.S. population is held constant at pre-polarization levels while the transition rates of each demographic group are allowed to evolve over time as observed in the data. In the second, we allow for aggregate demographic change but hold certain demographic group-specific transition rates constant at their pre-polarization levels.

Recall that in Section 4 the Oaxaca-Blinder decomposition results suggested that the changes in the key transition rates were mainly due to changes in propensities rather than changes in explained factors. However, note that in the Oaxaca-Blinder decomposition the term attributed to demographics is given by:

$$\left(\overline{X}_0^A - \overline{X}_1^A\right) \widehat{\beta}_0$$

This is the difference between the observed aggregate transition rate in period 0,  $\left(\overline{X}_0^A \widehat{\beta}_0\right)$ , and the counterfactual transition rate that would be observed if we use the transition propensities from period 0 and the *observed* demographic composition of period 1,  $\left(\overline{X}_1^A \widehat{\beta}_0\right)$ . This ignores the fact that, if transition propensities had remained at their period 0 levels, the demographic composition of labor market state  $A$  in period 1 would potentially differ dramatically from that observed in the data. To address this, the experiments in this section allow the counterfactual demographic composition within each labor market state to evolve in a manner consistent with the transition rates being used.

We proceed as follows. In each period we divide the sample into a total of 144 bins according to

the demographic characteristics of: gender (2 groups), age (6 groups), education (3 groups), race (2 groups) and marital status (2 groups). We then calculate the time series of transition rates across the ten labor market states *for each demographic bin*; this is equivalent to the matrix  $\rho_t$  in equation (1), except computed at the demographic group-specific level, as opposed to at the aggregate level considered in Sections 2 and 3. For each of the 144 demographic groups, we track their distribution across the ten states over time using either true or counterfactual transition rates by applying a law-of-motion analogous to equation (2). This gives us the labor market evolution for each demographic group that is consistent with the transition rates being considered.

Next, in order to account for demographic change observed in the U.S. population (e.g. rising educational attainment, population aging), we apply the following re-weighting procedure. At each point in time we assign a weight to each demographic group that is equal to their share in the *population* as observed in the data. This re-weighting of demographic groups ensures that we accurately match the aggregate demographic composition in each period, while simultaneously ensuring that the distribution of each demographic group *across* the ten labor market states is determined endogenously.<sup>29</sup>

Figure 12 displays the various series for per capita employment in routine occupations constructed using the observed demographic group-specific transition rates, along with our re-weighting procedure. It also displays the series for routine employment based on the aggregate law-of-motion as shown in Figure 2. One might be worried that the fact that we have a very large number of demographic bins leads to noisy group-specific transition rates. However, the fact that the two series track each other very closely implies that our procedure works well in replicating aggregate dynamics. The series that use the demographic-specific rates represent our benchmark throughout this section of the paper.

## 5.1 The overall role of demographics

Our first counterfactual experiments analyze the role of demographic change in the U.S. population in accounting for the decline of routine employment. We do this by allowing each demographic group's transition rates to evolve as they do in the data, but hold the relative size of each demographic group constant at its pre-polarization level. Any decline in routine employment mitigated by the counterfactual is therefore due to demographic change.

Due to the fact that routine manual (*ERM*) and routine cognitive (*ERC*) employment peak at different times, we perform slightly different counterfactuals for each of the two series. In the left panel of Figure 13 we plot the benchmark stocks of *ERM* in the solid blue line; the counterfactual holding aggregate demographics constant at their 1976:1 levels (allowing transition rates to evolve as they do in the data) is plotted in the hatched green line. The two series have been smoothed to remove seasonality.

If demographic composition had remained constant at pre-polarization levels, routine manual employment would have risen further leading up to the 1980 recession. Following the peak, *ERM* would

---

<sup>29</sup>An analogous interpretation of our re-weighting approach would be in terms of entry and exit from the sample, by assuming that entry and exit occurs proportionately to the size of each labor market state for individuals within each demographic bin. That is, if the size of a particular group is increasing, we assume that these additional workers are distributed across the ten states in the same way as the incumbents from that group. Hence, entry and exit does not change the labor force composition *within a given demographic group*. However, different entry and exit rates across demographic groups change the relative size of each group in the population, thus changing the composition across the ten labor market states *in the aggregate*.

Figure 12: Routine Employment: Stocks based on Law of Motion using Aggregate and Demographic-Group Specific Transition Rates

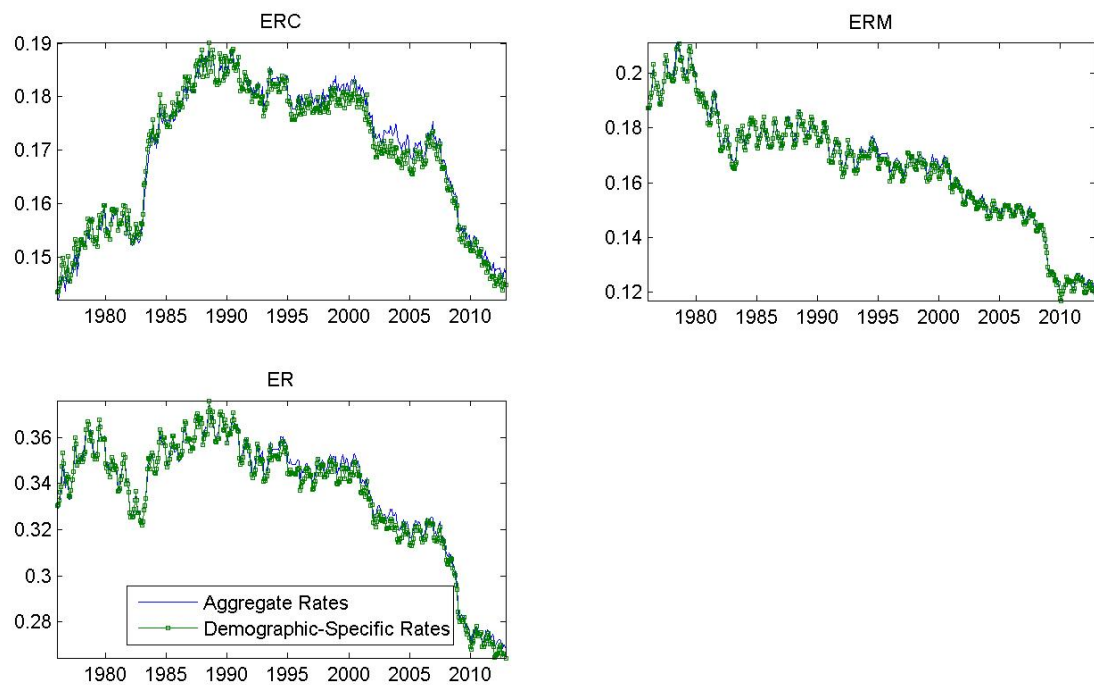
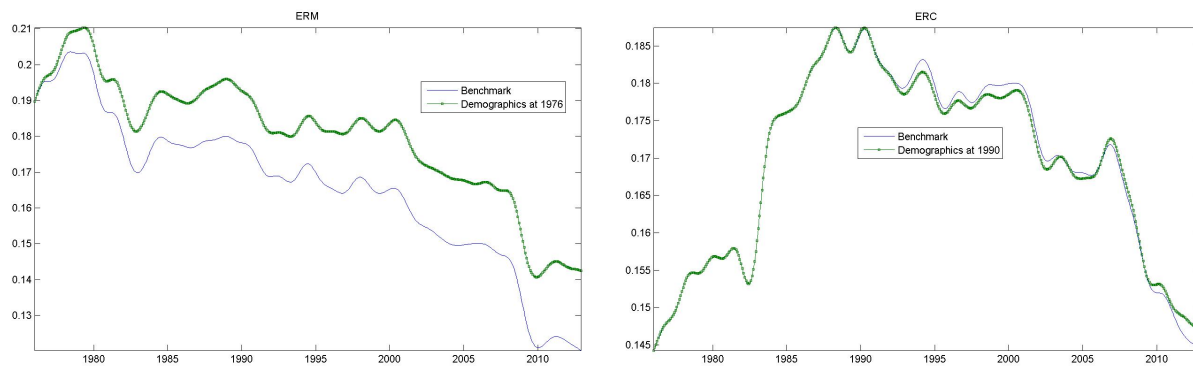


Figure 13: Counterfactual Experiment: No aggregate demographic change



have fallen to 16.61 per cent of the population (rather than 14.83) by early 2007, and to 14.24 by the end of 2012 (rather than 12.02). Thus, relative to the pre-1980 peak of 20.36, holding demographics constant mitigates about 32% of the fall up to early 2007, and about 27% of the fall up to the end of 2012. Hence, demographic change in the U.S. population—principally in terms educational composition and age structure—explains a small, though not insignificant, portion of the decline in routine manual employment. The remainder is accounted for by changes in demographic-specific transition rates.

For routine cognitive employment, given that it peaks at a later date, we perform a counterfactual where we hold the relative size of each demographic bin constant at their 1989:12 levels. The right panel of Figure 13 plots the benchmark and counterfactual stocks of *ERC*. As is clear from the figure, holding demographics constant at pre-polarization levels has little effect on the fall of routine cognitive employment. By the end of 2012 the counterfactual *ERC* reaches 14.77 per cent of the population (rather than 14.48), thus mitigating less than 7% of the total fall. We can conclude that changes in group-specific transition rates account for the vast majority of the total fall in *ERC*.

## 5.2 The role of inflows to routine employment

### Inflows from unemployment

Following the same logic as in Section 3, our next experiment holds constant the transition rates from all categories of unemployment into routine employment, for each of the 144 demographic bins, at their pre-job polarization levels.<sup>30</sup> As is the case in the remaining counterfactuals, all other transition rates and the demographic composition of the population evolve as observed in the data. Note that there are two key differences relative to the analysis in Subsection 3.1. First, when holding transition propensities at their pre-polarization levels, we do this individually *for each demographic group*, rather than at the aggregate level; thus aggregate transition rates will change over time because of changes in the demographic composition in each labor market state. Second, we allow for aggregate demographic change by using the re-weighting procedure outlined above.

The results for this counterfactual experiment are displayed in Figure 14. Holding the inflow propensities from unemployment constant at their pre-polarization levels does not mitigate the fall in routine employment prior to the Great Recession, but does mitigate approximately 16% of the fall to the end of 2012. Looking separately at the two types of routine employment, unemployment to routine employment propensities account for about 10% of the fall in routine manual occupations, and 17% of the fall in routine cognitive occupations.

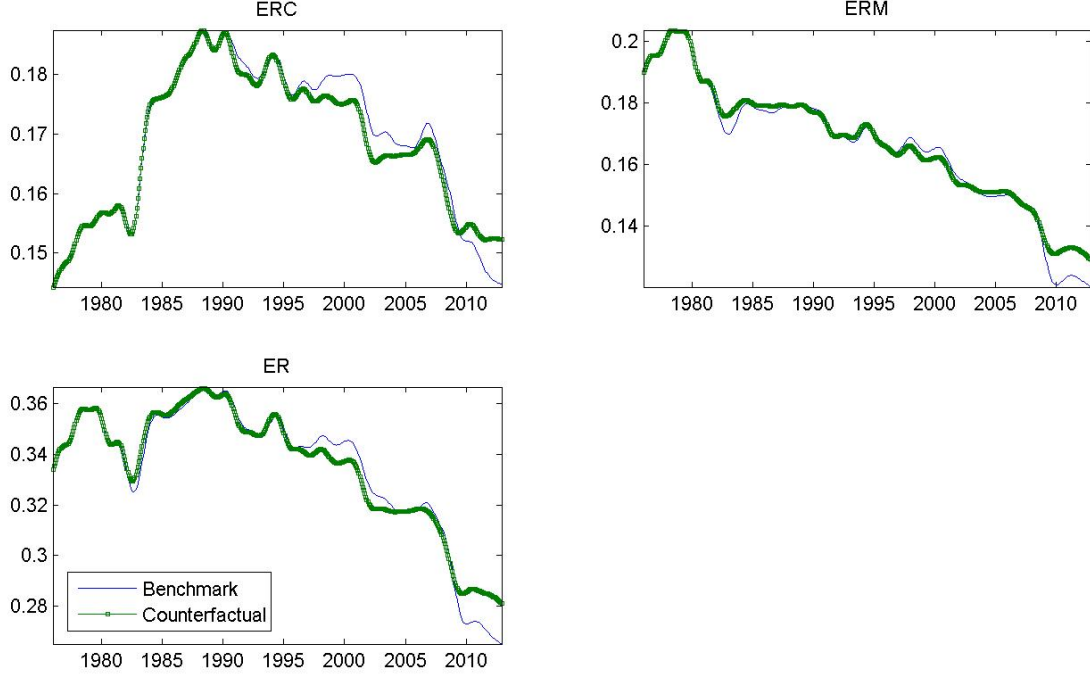
### Inflows from non-participation

Figure 15 displays the counterfactual experiment where the transition propensities from non-participation into routine employment are held constant at their pre-job polarization levels for all demographic

---

<sup>30</sup>As in Section 3, whenever we hold a particular transition rate to its pre-job polarization level, this entails holding it at the phase average for phases R1 and E1 (R2 and E3) in subsequent recessions and expansions, respectively, for *ERM* (*ERC*). As in Section 3, we adjust the diagonal elements (i.e. the “staying” rates) in our counterfactuals to ensure that transition rates from a given source add up to one.

Figure 14: Routine Employment - Inflow Rates from Unemployment to Routine Employment at their pre-polarization levels



groups. This experiment leads to a stronger recovery of routine manual and, especially, routine cognitive employment after the 2001 recession. It also generates a slight recovery following the Great Recession, as opposed to continued decline observed in the data. Overall, 18% of the fall up to early 2007, and 29% of the fall up to the end of 2012 is mitigated. As such, changes in  $NLF \rightarrow ER$  propensities play an important role in the disappearance of routine employment.

### 5.3 The role of outflows from routine employment to non-participation

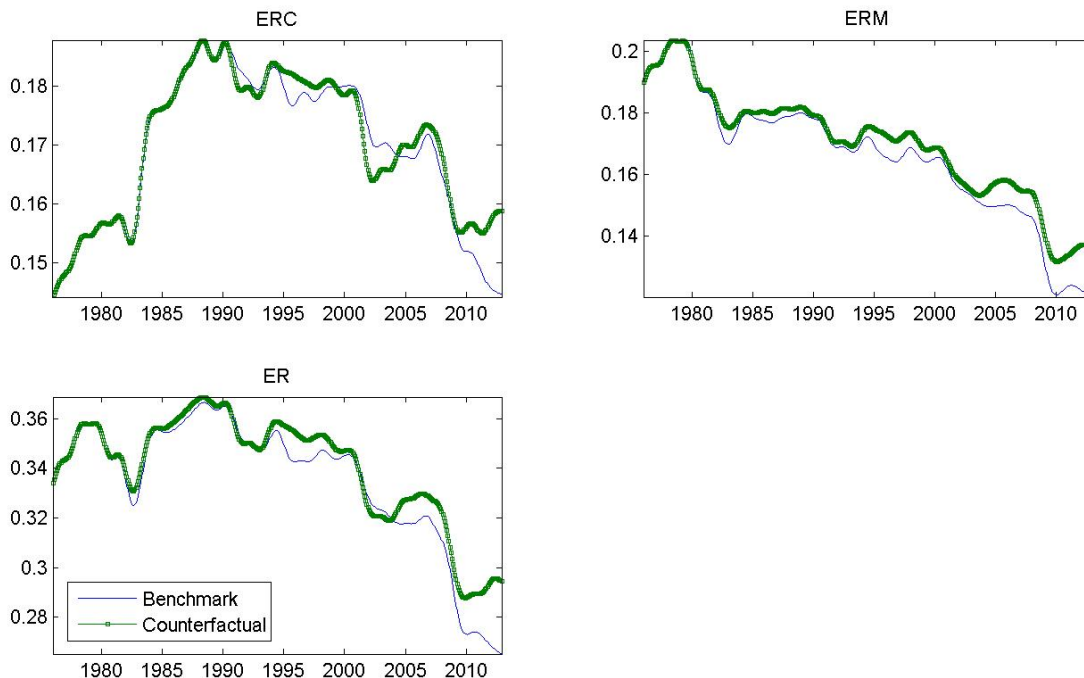
The next experiment holds the demographic group-specific transition propensities from routine employment to labor force non-participation constant at their pre-job polarization levels. Again, all other transition rates and demographic composition evolve as they do in the data.

As displayed in Figure 16, this transition propensity is particularly important before the onset of the Great Recession. Of the fall in routine employment experienced up to 2007, 36% is mitigated by holding these propensities constant. The role of this channel in more recent years is smaller, mitigating 7% of the fall to the end of the sample. This is due entirely to its effect on routine manual employment, as the counterfactual series for *ERC* is essentially indistinguishable from the actual series by 2012.

### 5.4 Other switching rates

Our final experiment investigates the role of direct transitions across occupations for workers who report being employed from one month to the next, so called “job-to-job” transition rates across

Figure 15: Routine Employment - Inflow Rates from Non-Participation to Routine Employment at their pre-polarization levels



occupational groups. Unfortunately, due to the 1994 redesign of the CPS and the discontinuities induced in the measurement of such transitions, we only investigate the role of these propensity changes for a much shorter time frame. For this experiment, we hold the job-to-job transition propensities across occupation groups constant for all demographic groups at their values during the earliest post-redesign phase, namely the 1994:1-2001:2 expansion.

As such, this experiment investigates the role of changes in occupational mobility from the 2001 recession onward in accounting for the decline in routine employment. The results are plotted in Figure 17. Changes in occupational mobility rates since the 1990s play a small role in the fall in routine employment after the Great Recession: the counterfactual mitigates 12% of the decline to the end of 2012.

## 5.5 Summary

The results from the counterfactual experiments in this section are summarized in Table 14.<sup>31</sup> In short, we find that changes in the demographic composition of the US population can account for approximately 30% of the fall in routine manual employment and less than 10% of the fall in routine cognitive employment. The remainder of the fall is due to changes in transition propensities, and their interaction with demographic change. Transition propensities between employment and labor force

<sup>31</sup>As in Section 3, we find that changes in the separation rate from routine employment to unemployment have essentially no quantitative impact on the decline in routine employment and do not report them here.

Figure 16: Routine Employment - Outflow Rates to Non-Participation from Routine Employment at their pre-polarization levels

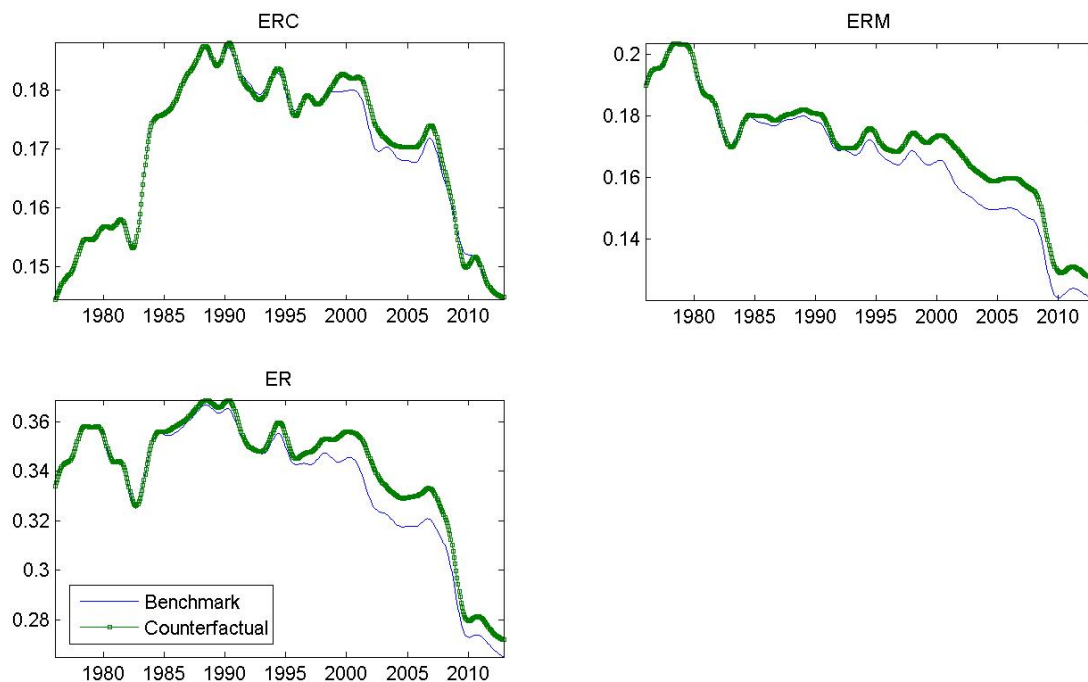


Figure 17: Routine Employment - Switching Rates between Employment Categories fixed

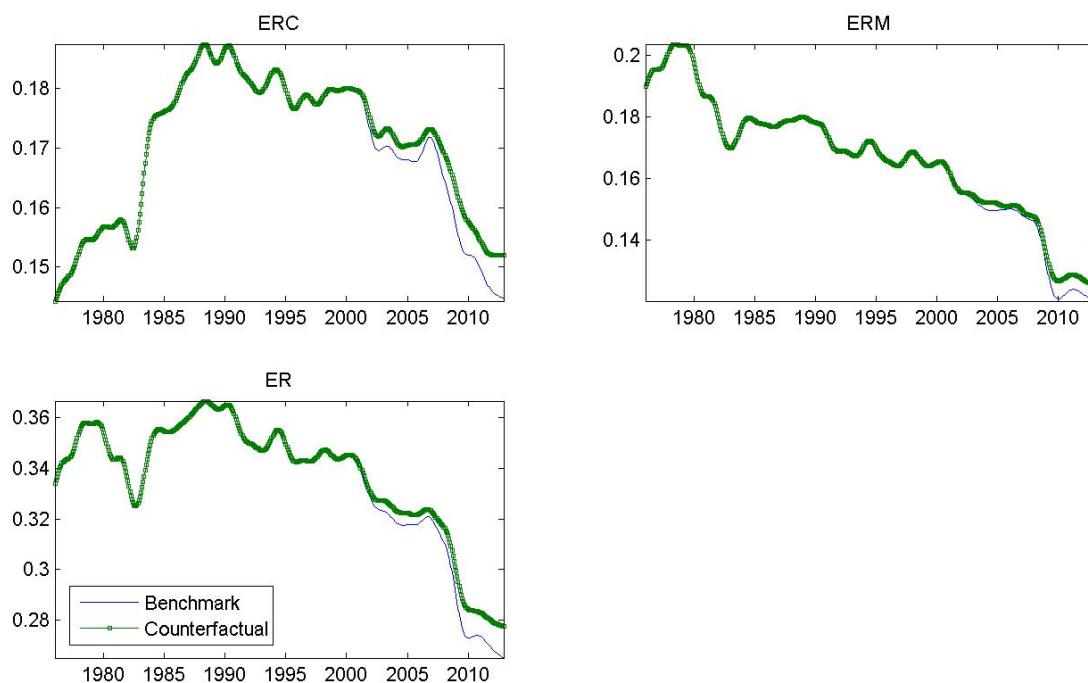


Table 14: Summary of Results from Counterfactual Experiments

	ER		ERM		ERC	
	Peak: 36.67		Peak: 20.36		Peak: 18.74	
	2007:1	2012:12	2007:1	2012:12	2007:1	2012:12
<b>Baseline</b>	31.99	26.51	14.83	12.02	17.16	14.48
<b>Counterfactual where demographic composition is held at pre-polarization levels:</b>						
Counterfactual	n/a	n/a	16.61	14.24	17.25	14.77
<i>Mitigated %</i>			<i>32.2%</i>	<i>26.6%</i>	<i>5.6%</i>	<i>6.6%</i>
<b>Counterfactual where transition rates are held at pre-polarization levels for:</b>						
Inflows from Unemployment	31.67	28.12	14.78	12.89	16.89	15.22
<i>Mitigated %</i>	<i>-6.8%</i>	<i>15.9%</i>	<i>-0.9%</i>	<i>10.5%</i>	<i>-17.0%</i>	<i>17.4%</i>
Inflows from Non-Participation	32.82	29.43	15.50	13.55	17.32	15.87
<i>Mitigated %</i>	<i>17.7%</i>	<i>28.7%</i>	<i>12.2%</i>	<i>18.4%</i>	<i>9.9%</i>	<i>32.6%</i>
Outflows to Non-Participation	33.26	27.20	15.85	12.72	17.40	14.48
<i>Mitigated %</i>	<i>27.0%</i>	<i>6.8%</i>	<i>18.6%</i>	<i>8.4%</i>	<i>15.1%</i>	<i>-0.1%</i>
All Three Above	33.68	31.60	16.40	15.09	17.28	16.51
<i>Mitigated %</i>	<i>36.1%</i>	<i>50.1%</i>	<i>28.4%</i>	<i>36.8%</i>	<i>7.3%</i>	<i>47.6%</i>

non-participation, in both directions, are important in accounting for the dynamics of routine employment up to 2007. Starting in the Great Recession, the inflow propensities from non-participation and unemployment become the key determinants of the decline, and lack of recovery, of routine employment.

To illustrate the overall importance of these key propensity channels, we conduct a comprehensive counterfactual experiment in which we simultaneously hold all of the key transition propensities at their pre-polarization values. The results are plotted in Figure 18. Relative to the benchmark time series of per capita routine employment, holding these transition propensities fixed mitigates 35% of the decline leading into the Great Recession, and 50% of the decline to the end of the sample.

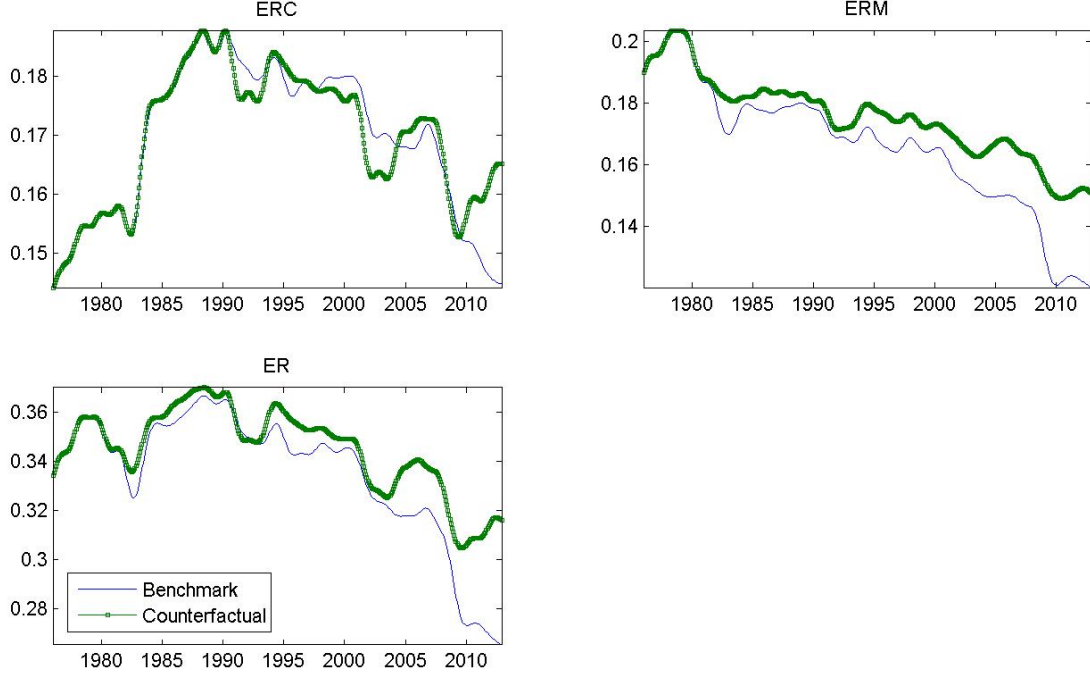
## 5.6 Further details on counterfactual results

### Which are the “key” demographic groups?

In this subsection, we provide further analysis on the results of the counterfactual exercises presented above. We first ask: of all demographic groups considered in the counterfactual analysis, whose propensity change is most important in accounting for the decline of per capita routine employment? To investigate this, we recompute the comprehensive counterfactual, this time holding constant only the transition rates for specific demographic groups. For instance, to isolate the role of transition propensities for males, we hold constant only those for the 77 (out of 144) demographic bins belonging to men. For brevity, we perform this exercise along three dimensions: (i) gender (male, female), (ii)



Figure 18: Routine Employment - All Key Transition Rates

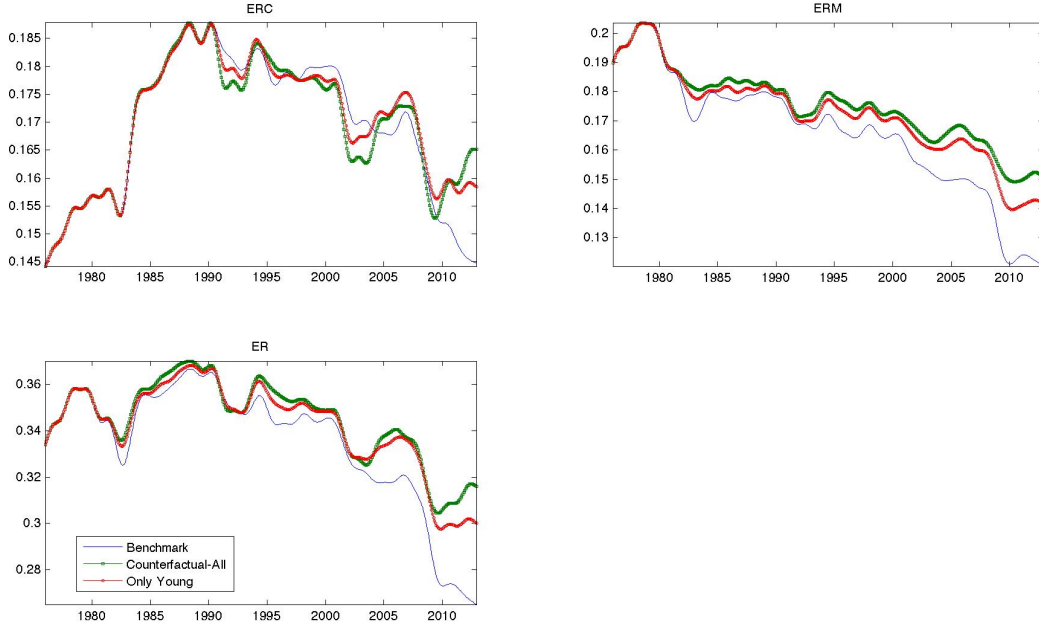


education (less than high school, high school diploma or some college, college graduates), and (iii) age (16-34 year olds, 35-54 year olds, over 55).

Figure 19 illustrates our principal finding. The blue solid line displays the benchmark time series for routine employment. The green hatched line repeats the counterfactual series from Figure 18, in which the key transition propensities for all demographic groups are held at pre-polarization levels. The red hatched line displays the counterfactual when only the transition propensities for 16-34 year olds are held constant. As is evident, much of the mitigating effect of the full counterfactual exercise is achieved by the counterfactual performed only with the propensities of the young. In analysis not presented here for brevity (and available from the authors upon request), we find that this is due primarily to the fact that 16-34 year olds have experienced disproportionately large changes in transition rates; this is especially true for the return job finding rates from unemployment ( $UR \rightarrow ER$ ) and finding rates from non-participation ( $NLF \rightarrow ER$ ) into routine employment.

Finally, though we do not depict this in Figure 19, we find that much of the mitigating effect of the full counterfactual on  $ERM$  is achieved by a counterfactual performed only with the propensities of males. Similarly, much of the effect of the full counterfactual on  $ERC$  is achieved by a counterfactual performed only with the propensities of females. These final two results are, perhaps, not surprising given the evidence reported in Table 2. Specifically, routine manual occupations are predominantly male occupations, and routine cognitive occupations are predominantly female.

Figure 19: Routine Employment - The Role of Demographic Groups



### Understanding the differences with the aggregate counterfactuals

Finally, we note that the fraction of the long-run decline in routine employment accounted for by the key transition propensities, as summarized in Table 14, is smaller than that accounted for by the same transition rates in Section 3, and summarized in Table 4.

To understand the source of this difference, recall that in Section 5, the sample of individuals is divided into 144 bins according to demographic characteristics (age, education, gender, marital status, race). As such, the aggregate switching rate from labor market state  $A$  to state  $B$  is given by:

$$\rho_t^{AB} = \sum_{j=1}^{144} s_{tj}^A \rho_{tj}^{AB} \quad (5)$$

where  $s_{tj}^A$  is the share of demographic group  $j$  within state  $A$ , and  $\rho_{tj}^{AB}$  is the transition rate for demographic group  $j$  between states  $A$  and  $B$ .

In Section 3, *aggregate* transition rates are held at their pre-polarization levels in the counterfactual experiments. In terms of equation (5), this can be interpreted as replacing *both* the demographic composition (i.e., the shares,  $s_{tj}^A$ ) and the group-specific transition rates ( $\rho_{tj}^{AB}$ ) with their pre-polarization values. By contrast, in Section 5, when holding transition propensities at their pre-polarization levels, we do this individually for each demographic group. The counterfactual values of the aggregate transition rate,  $\rho_t^{AB}$ , then vary over time because of changes in the demographic composition, i.e., changes in  $s_{tj}^A$ .

To visualize this, Appendix Figure A.2 plots the key transition rates identified as accounting for

the bulk of the fall in routine employment. For each transition rate, we plot (i) the benchmark series, which corresponds to the phase averages as observed in the data, (ii) the counterfactual transition rates used in Section 3, and (iii) the implied counterfactual transition rates from Section 5.

To summarize briefly, Appendix Figure A.2 shows that in the counterfactuals of Section 5, outflow rates from routine employment to non-participation are lower than in Section 3, while inflow rates from non-participation to routine employment are slightly higher. This explains why, in comparing Tables 4 and 14, these labor market transitions account for a *larger* fraction of the fall in routine employment in Section 5.

However, the return job finding rates from routine unemployment are lower in the Section 5 counterfactuals compared to Section 3. The quantitative effect of the return job finding rate dominates, implying that transition *propensities* account for less of the fall in routine employment when compared to transition *rates* overall. The difference in the counterfactual return job finding rates between Sections 3 and 5 are due to the difference in the implied composition of the unemployment pool.

For the return job finding rate into routine manual jobs, the key difference in demographic composition is the reduction in the share of white males, 16-35 year olds, with less than college education in the Section 5 counterfactuals. This group accounted for about a third of the pool of unemployed routine manual workers in the pre-polarization era, and its share almost halved (to 17%) by the final phase in the sample. Importantly, such individuals had an average return job finding rate of 32% compared to an average of 11% for unemployed routine manual workers from other demographic groups. For the return job finding rate into routine cognitive employment, the key difference is the fall in the share of white females, 16-35 years old, with less than college education. This group accounted for approximately 30% of the routine cognitive unemployment pool in the pre-polarization era, and halved to 15% by the final phase in the sample. Moreover, this group had an average return job finding rate of 18% compared to an average of 8% for unemployed routine cognitive workers from other demographic groups.

To summarize, the results of Section 5 attribute less importance to changes in transition propensities, relative to the importance attributed to transition rates in Section 3. This is because the counterfactual exercises performed with transition propensities allow for demographic change—specifically, for the increased educational attainment and aging observed in the U.S. population.

## 6 Conclusions

In this paper, we use matched individual-level data from the monthly Current Population Survey (CPS) to analyze transitions into and out of employment in routine occupations at the “micro” and “macro” levels. At the macro level, we find that changes in three transition rate categories are of primary importance in accounting for the disappearance of per capita routine employment. The first is a fall in transition rates from unemployment to routine employment. This includes falls in both “return” job finding rates and “switching” job finding rates, with the former being quantitatively most important. The second change is a fall in transition rates from labor force non-participation to routine employment. The third is a rise in transition rates from routine employment to non-participation. Changes in the finding rates into routine employment (the first and second factors) are important in

accounting for the decline both leading into the Great Recession and, especially, thereafter. Changes in the separation rate from routine employment to non-participation matter primarily prior to 2007.

At the “micro” level, we study how these transition rates have changed across the pre- and post-job polarization eras, and the extent to which these changes are accounted for by changes in demographics or by changes in the behavior of individuals with particular demographic characteristics. Using a Oaxaca-Blinder decomposition analysis, we find that the changes are primarily accounted for by changes in transition propensities. With respect to entry and exit rates to and from routine manual employment, changes in propensities have been particularly acute for males, the young, and those with lower levels of education. With respect to the fall in the propensity to switch from unemployment to routine cognitive employment, this is particularly strong for females, the prime-aged, and those with higher levels of education. In terms of the rise in the propensity to transition out of the labor force from routine cognitive employment, the effect is strongest for men and the young.

Our final contribution is to quantify the relative importance of demographic change and transition propensity changes in accounting for the disappearance of routine employment. We find that demographic composition change in the U.S. population can account for at most 30% of the fall in per capita routine manual employment, and less than 10% of the fall in per capita routine cognitive employment. As such, the primary factor in the decline of routine employment is propensity change, that is, change in demographic-group specific transition rates. Moreover, we find that it is the change in transition propensities of the young that are of primary importance.

The results in this paper provide a much richer picture of the way in which polarization has occurred over recent decades. Our findings suggest that changes in the occupational choices of young workers play a prominent role in accounting for the decline of routine employment. A further empirical analysis of these changes and their implications for entry wages and future career progression would be an interesting direction for future research.

## References

- Acemoglu, Daron and David Autor (2011), “Skills, tasks and technologies: Implications for employment and earnings.” *Handbook of Labor Economics*, 4, 1043–1171.
- Autor, David and David Dorn (2009), “This job is “getting old”: Measuring changes in job opportunities using occupational age structure.” *American Economic Review*, 99, 45–51.
- Autor, David H. and David Dorn (2013), “The growth of low skill service jobs and the polarization of the U.S. labor market.” *American Economic Review*, 103, 1553–1597.
- Autor, David H, David Dorn, and Gordon H Hanson (2013), “Untangling trade and technology: Evidence from local labor markets.” *Working Paper, National Bureau of Economic Research*.
- Autor, D.H., L.F. Katz, and M.S. Kearney (2006), “The Polarization of the US Labor Market.” *The American Economic Review*, 96, 189–194.
- Autor, D.H., F. Levy, and R.J. Murnane (2003), “The Skill Content of Recent Technological Change: An empirical exploration.” *Quarterly Journal of Economics*, 118, 1279–1333.
- Cortes, G.M. (2014), “Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data.” *Working Paper*.
- Elsby, M.W.L., R. Michaels, and G. Solon (2009), “The ins and outs of cyclical unemployment.” *American Economic Journal: Macroeconomics*, 1, 84–110.
- Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux (2011), “Occupational tasks and changes in the wage structure.” *University of British Columbia*.
- Foote, C.L. and R.W. Ryan (2014), “Labor-market polarization over the business cycle.” *Working Paper*.
- Frazis, Harley J, Edwin L Robison, Thomas D Evans, and Martha A Duff (2005), “Estimating gross flows consistent with stocks in the CPS.” *Monthly Labor Review*, 128, 3.
- Goos, M. and A. Manning (2007), “Lousy and lovely jobs: The rising polarization of work in Britain.” *The Review of Economics and Statistics*, 89, 118–133.
- Goos, M., A. Manning, and A. Salomons (2010), “Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions.” *Center for Economic Performance Discussion Paper No 1026*.
- Goos, Maarten, Alan Manning, and Anna Salomons (2009), “Job polarization in Europe.” *American Economic Review*, 99, 58–63.
- Hall, Robert E (2006), “Job loss, job finding and unemployment in the US economy over the past 50 years.” In *NBER Macroeconomics Annual 2005, Volume 20*, 101–166, MIT Press.
- Jaimovich, N. and H.E. Siu (2012), “The trend is the cycle: Job polarization and jobless recoveries.” *National Bureau of Economic Research Working Paper*.

- Kambourov, G. and I. Manovskii (2013), “A Cautionary Note on Using (March) CPS and PSID Data to Study Worker Mobility.” *Macroeconomic Dynamics*, 17, 172–194.
- Meyer, PB and AM Osborne (2005), “Proposed Category System for 1960-2000 Census Occupations.” *Bureau of Labor Statistics Working Paper*, 383.
- Moscarini, Giuseppe and Kaj Thomsson (2007), “Occupational and job mobility in the US.” *Scandinavian Journal of Economics*, 109, 807–836.
- Nekarda, Christopher J (2009), “A Longitudinal Analysis of the Current Population Survey: Assessing the Cyclical Bias of Geographic Mobility.” *Federal Reserve Board of Governors*.
- Shimer, Robert (2012), “Reassessing the ins and outs of unemployment.” *Review of Economic Dynamics*, 15, 127–148.
- Smith, Christopher L. (2013), “The dynamics of labor market polarization.” *Finance and Economics Discussion Series 2013-57. Board of Governors of the Federal Reserve System*.

## Appendix A Additional Tables and Figures

Table A.1: Mapping of detailed occupation codes to broad groups

Broad Occupation	Census Coding System			
	1970	1980 and 1990	2002	2010
Non-Routine Cognitive	001-100, 102-162, 165, 171, 173-216, 222-225, 230, 235-245, 321, 326, 363, 382, 426, 506, 801-802, 924, 926	003-225, 228-229, 234-235, 473-476	0010-3540	0010-3540
Non-Routine Manual	101, 505, 740, 755, 901-923, 925, 931-984	403-469, 486-487, 773	3600-4650	3600-4650
Routine Cognitive	220, 231-233, 260-285, 301-305, 310-320, 323-325, 330-362, 364-381, 383-395	243-389	4700-5930	4700-5940
Routine Manual	163-164, 170, 172, 221, 226, 401-425, 430-446, 452-504, 510-575, 601-624, 626-715, 750-751, 753-754, 760, 762-785	226-227, 233, 503-769, 774-799, 803-869, 873-889	6200-9750	6200-9750
Farming, Military	450, 580, 600, 625, 752, 761, 821-824	477-485, 488-499, 905	6000-6130, 9800-9840	6005-6130, 9800-9840

Figure A.1: Change in transition rates for unemployed routine workers across expansionary phases

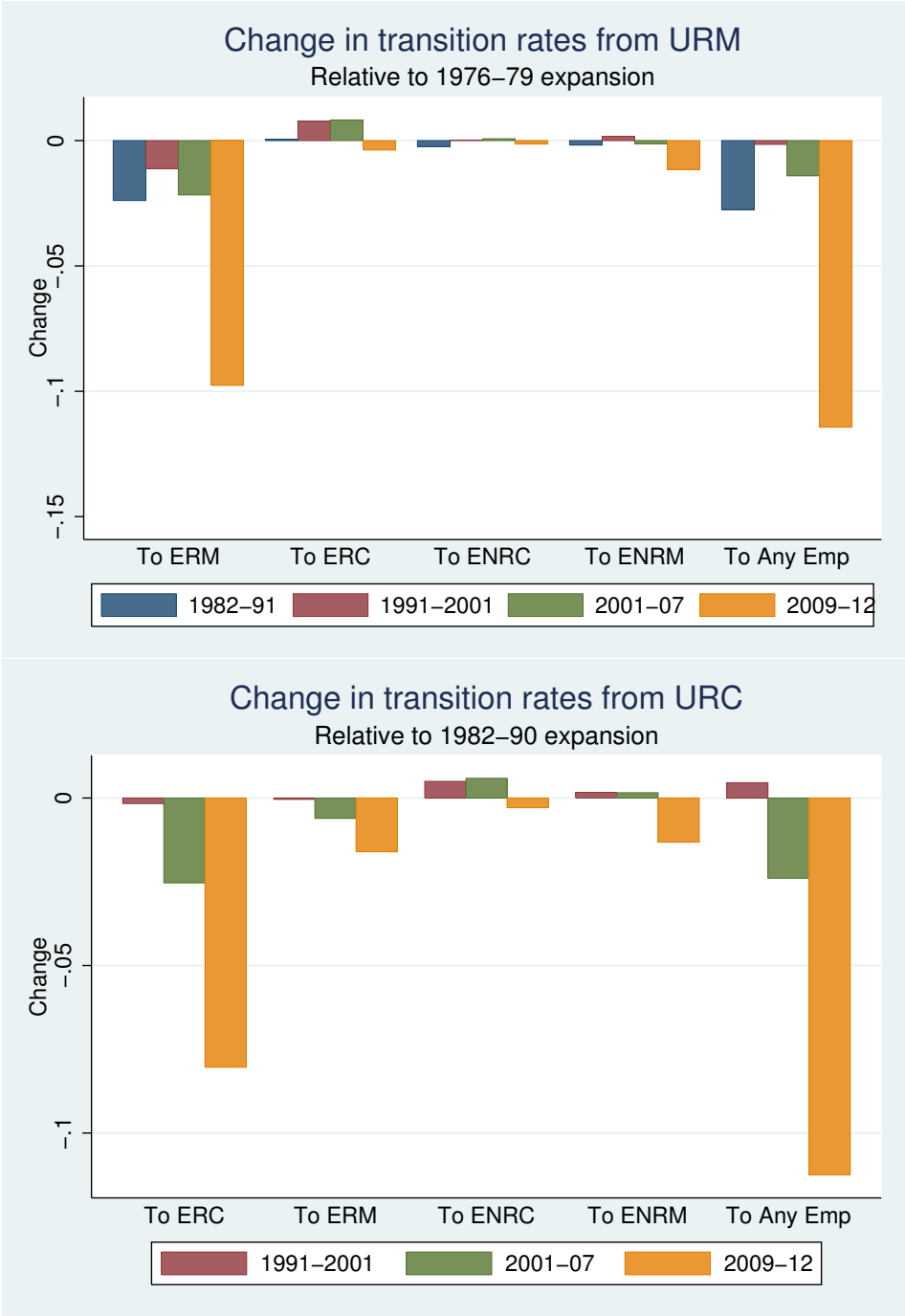




Table A.2: Linear Probability Regression:  $NLF \rightarrow ERM$ 

	1976m1- 1979m12	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
constant	0.0061*** (0.0005)	0.008*** (0.0004)	0.0081*** (0.0004)	0.0085*** (0.0005)	0.0068*** (0.0005)
married	-0.0048*** (0.0003)	-0.0032*** (0.0002)	-0.0016*** (0.0002)	-0.0008*** (0.0002)	0.0004 (0.0003)
non-white	-0.0032*** (0.0004)	-0.0031*** (0.0003)	-0.0024*** (0.0002)	-0.0025*** (0.0003)	-0.0018*** (0.0003)
male	0.0269*** (0.0004)	0.0218*** (0.0002)	0.0207*** (0.0002)	0.0199*** (0.0003)	0.0142*** (0.0003)
16-24 yrs	0.0105*** (0.0005)	0.0070*** (0.0004)	0.0047*** (0.0004)	-0.0006 (0.0004)	-0.0024*** (0.0005)
25-34 yrs	0.0061*** (0.0004)	0.0060*** (0.0004)	0.0081*** (0.0004)	0.0073*** (0.0005)	0.0043*** (0.0006)
35-44 yrs	0.0045*** (0.0004)	0.0048*** (0.0004)	0.0062*** (0.0004)	0.0046*** (0.0005)	0.0029*** (0.0006)
55-64 yrs	-0.0062*** (0.0003)	-0.0078*** (0.0003)	-0.0073*** (0.0003)	-0.0076*** (0.0004)	-0.0054*** (0.0004)
65+ yrs	-0.0127*** (0.0003)	-0.0129*** (0.0003)	-0.0122*** (0.0003)	-0.0124*** (0.0003)	-0.0090*** (0.0004)
low educ	0.0004 (0.0003)	-0.0007*** (0.0002)	-0.0011*** (0.0002)	-0.0014*** (0.0003)	-0.0019*** (0.0003)
high educ	-0.0068*** (0.0003)	-0.0071*** (0.0002)	-0.0086*** (0.0002)	-0.0083*** (0.0002)	-0.0056*** (0.0002)
$R^2$	0.0194	0.0156	0.014	0.0124	0.0082
no of obs	1049124	1999447	2148793	1430639	886410

Notes: Table presents regression coefficients; excluded group is single, white, female, 45-54 years old, middle education level; see text for complete list of variables included in analysis. \* :  $p < 0.10$ ,

\*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table A.3: Linear Probability Regression:  $ERM \rightarrow NLF$ 

	1976m1- 1979m12	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
constant	0.0344*** (0.0010)	0.0269*** (0.0007)	0.0259*** (0.0007)	0.0302*** (0.0010)	0.0269*** (0.0015)
married	-0.0159*** (0.0006)	-0.0099*** (0.0004)	-0.0086*** (0.0003)	-0.0092*** (0.0005)	-0.0083*** (0.0006)
non-white	0.0045*** (0.0007)	0.0046*** (0.0005)	0.0077*** (0.0005)	0.0096*** (0.0007)	0.0083*** (0.0010)
male	-0.0204*** (0.0007)	-0.0149*** (0.0005)	-0.0129*** (0.0005)	-0.0149*** (0.0007)	-0.0119*** (0.0010)
16-24 yrs	0.0303*** (0.0007)	0.0297*** (0.0006)	0.0318*** (0.0007)	0.0367*** (0.0010)	0.0408*** (0.0015)
25-34 yrs	0.0032*** (0.0005)	0.0003 (0.0004)	0.0007* (0.0004)	0.0012** (0.0005)	0.0030*** (0.0008)
35-44 yrs	0.0005 (0.0005)	-0.0009** (0.0004)	-0.0004 (0.0004)	-0.0012*** (0.0005)	0.00006 (0.0007)
55-64 yrs	0.0105*** (0.0007)	0.0126*** (0.0006)	0.0141*** (0.0006)	0.0110*** (0.0007)	0.0107*** (0.0009)
65+ yrs	0.1013*** (0.0034)	0.1070*** (0.0027)	0.0898*** (0.0023)	0.0640*** (0.0023)	0.0549*** (0.0026)
low educ	0.0106*** (0.0005)	0.0122*** (0.0004)	0.0146*** (0.0004)	0.0155*** (0.0006)	0.0151*** (0.0009)
high educ	0.0081*** (0.0012)	0.0047*** (0.0007)	0.0021*** (0.0006)	0.00003 (0.0007)	0.0011 (0.0010)
$R^2$	0.0242	0.0209	0.0179	0.0159	0.0141
no of obs	591724	1104625	1202173	750645	366382

Notes: Table presents regression coefficients; excluded group is single, white, female, 45-54 years old, middle education level; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table A.4: Oaxaca Decomposition: Transition Rates into Non-Routine Cognitive Occupations

	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
<i>Panel A: UNRC → ENRC</i>		Baseline Expansion (1982m12-1990m6): 14.80%	
Difference:	+1.50%*** (0.337)	+1.40%*** (0.359)	−3.12%*** (0.333)
Composition	−0.089% (0.102)	−0.077% (0.143)	−0.315%* (0.180)
Propensities	+1.59%*** (0.336)	+1.48%*** (0.370)	−2.80%*** (0.360)
<i>Panel B: NLF → ENRC</i>		Baseline Expansion (1982m12-1990m6): 0.972%	
Difference:	+0.168%*** (0.012)	+0.381%*** (0.015)	+0.227%*** (0.016)
Composition	+0.151%*** (0.004)	+0.336%*** (0.006)	+0.409%*** (0.007)
Propensities	+0.018% (0.013)	+0.045%*** (0.016)	−0.182%*** (0.019)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Table A.5: Oaxaca Decomposition: Transition Rates into Non-Routine Manual Occupations

	1982m12- 1990m6	1991m4- 2001m2	2001m12- 2007m11	2009m7- 2012m12
<i>Panel A: UNRM → ENRM</i>		Baseline Expansion (1976m1-1979m12): 13.98%		
Difference:	−0.528%* (0.299)	+1.61%*** (0.306)	+1.51%*** (0.331)	−2.68%*** (0.320)
Composition	−0.128% (0.103)	−0.016% (0.125)	+0.246%* (0.149)	+0.339%* (0.204)
Propensities	−0.399% (0.310)	+1.63%*** (0.326)	+1.27%*** (0.362)	−3.02%*** (0.381)
<i>Panel B: NLF → ENRM</i>		Baseline Expansion (1976m1-1979m12): 1.57%		
Difference:	−0.061%*** (0.017)	−0.087%*** (0.017)	−0.006% (0.018)	−0.256%*** (0.020)
Composition	−0.129%*** (0.005)	−0.136%*** (0.007)	−0.053%*** (0.009)	−0.029%*** (0.010)
Propensities	+0.069%*** (0.016)	+0.049%*** (0.016)	+0.047%** (0.019)	−0.227%*** (0.022)

Notes: Table presents detailed decomposition for selected variables; see text for complete list of variables included in analysis. \* :  $p < 0.10$ , \*\* :  $p < 0.05$ , \*\*\* :  $p < 0.01$

Figure A.2: Counterfactuals Comparison

