The Micro and Macro of Job Polarization

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Abstract

In recent decades, the U.S. labor market has become increasingly polarized with the share of employment in middle-wage jobs shrinking over time. This job polarization process has been associated with the disappearance in per capita employment in occupations focused on *routine tasks*. We use matched individual-level data from the CPS to study labor market flows 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. We find that changes in three transition rate categories are of primary importance: (i) the unemployment to routine employment transition rate, (ii) the labor force non-participation to routine employment rate, and (iii) the routine employment to non-participation rate. 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 are due to changes in the propensity of individuals to make such transitions, and relatively little is due to demographics.

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 also the *level* of per capita employment in such occupations.[1]

[1] 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. (2013), and the references therein regarding the role of outsourcing

In spite of the growing literature on polarization, relatively little is known regarding how the decline of routine employment has occurred, both in terms of "when" these jobs disappear over the business cycle, and "who" the disappearance is affecting at the micro-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, at which points in the business cycle, can account for the disappearance of routine employment over the past 30 years. At the "micro" level, we study how these transition rates have changed and the extent to which these changes are accounted for by changes in demographic composition or by changes 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 our 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 jobs is accounted for by occupational switching of employed workers than if it were due to increasing exit rates of prime-aged workers from routine jobs to out of the labor force.

By using data from the matched CPS we are able to analyze nationally-representative transition rates into and out of routine employment at a monthly frequency from 1976 until 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 across consecutive months.

We first investigate which changes in transition rates account for the decline of routine employment in the past 30 years. We perform a series of counterfactual experiments 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.[2] The results indicate that the bulk of the disappearance of routine employment is accounted for by three changes. The first is a fall in transition rates from unemployment to routine employment. This includes falls in both "return" job finding rates – for the unemployed with most recent employment in a routine job, transitioning to employment in a routine job – and "switching" job finding rates – for the unemployed with most recent employment in a non-routine job, switching to employment in a 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 matter prior to 2007.

Our second contribution involves a detailed, micro-level analysis of the key changes in transition rates across the pre- and post-job polarization eras. In particular, we ask whether the observed

and offshoring in job polarization.

[2] 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 variability 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, while also distinguish between employment in different types of occupation groups.

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 involves the estimation of standard Oaxaca-Blinder decompositions in order to separate these two effects.[3]

The results indicate that the changes are primarily accounted for by changes in the propensities to switch, 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 for transition out of routine manual employment to non-participation. With respect to all of these changes in propensity, the effects have been particularly acute for males, the young, and those with low levels of education. These behavioral changes also emerge for routine cognitive occupations: falls in the propensity to transition into employment from unemployment and non-participation, and rises in the propensity to transition out of employment into non-participation, conditional on demographic characteristics. With respect to the fall in unemployment to routine cognitive employment propensity, this is particularly strong for females and the prime-aged. In terms of the rise in propensity to transition out of the labor force from routine cognitive employment, the effect is strongest for men and the young.

Finally, we revisit our counterfactual exercises in greater detail. In accounting for the decline in routine employment, the quantitatively important changes in transition rates may be driven by either demographic change or changes in propensity for given demographic groups. Our final contribution is to disentangle the relative importance of these channels. We find that demographic composition change in the US 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. By contrast, we find that changes in the propensity to transition from routine employment to non-participation, and from unemployment and non-participation into routine employment are primarily responsible for the disappearance of routine jobs.

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 CPS survey are sampled for four consecutive months, then leave the sample for eight months, and then return 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 that can be matched is lower, primarily due to attrition. In particular, the CPS is an address-based survey, so 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 households across these modifications. Details about the algorithm used to match individuals across months can

[3]Previous work analyzing the role of demographics in explaining the changes in transition rates have typically focused on differences across different points of the business cycle, e.g. Shimer (2012), Bachmann and Sinning (2012). We analyze changes across time periods in similar phases of the business cycle (e.g., expansionary periods in the 1970s relative to expansionary periods in the 2000s).

be found in Nekarda (2009).

The main advantage of the CPS is its large sample size and the fact that it is explicitly 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 monthly transitions. A final, and important, advantage is its time coverage, spanning periods both prior to the onset of job polarization and afterward.[4]

In using the CPS, the main data challenge is the fact that the survey experienced a major redesign in 1994, inducing certain discontinuities. The fact that the occupation coding system used in the survey has changed approximately every ten years provides additional minor challenges. We discuss both 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 data 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. Following the literature (e.g. Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), Goos and Manning (2007), Acemoglu and Autor (2011)) occupations are grouped into four broad categories which are labeled according to the main type of task performed by workers in each category.[5] The four broad categories are: non-routine cognitive, routine cognitive, routine manual and non-routine manual, and the types of occupations included in each of these categories are:

- Non-Routine Cognitive: Management, Professional, and Related Occupations
- Routine Cognitive: Sales and Office Occupations
- Routine Manual: Production Occupations and all other Blue-Collar Occupations
- Non-Routine Manual: Service Occupations

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.[6] The occupation coding system has changed over time, specifically in 1983, 1992, 2003 and 2011. In order to aggregate the detailed occupation codes available in the CPS in a consistent way into the four broad occupation categories, we rely on the crosswalk from Autor and Dorn (2013), which converts all the different 3-digit occupation codes that have been used over time to a common coding system.[7] These

[4]By contrast, while the Panel Study of Income Dynamics (PSID) tracks individuals over a longer time period, its sample size 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 (making it problematic for business cycle analysis). While the Survey of Income and Program Participation (SIPP) is at a monthly frequency and has, in certain waves, sample sizes comparable to the CPS, it begins after the onset of job polarization.

[5]We exclude observations with occupation codes corresponding to Farming, Fishing, Forestry and Military.

[6]For matched people 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.

[7]We develop our own crosswalk to convert the occupation codes from the post-2011 period to the common codes from Autor and Dorn (2013). As the changes between the 2003 and 2011 coding systems were relatively minor, this procedure is fairly straightforward.

common codes can then be aggregated to broad categories, and labeled according to the extent to which they involve routine, non-routine, cognitive and manual tasks.

Individuals who are classified as being out of the labor force do not report their most recent occupation.[8] We are therefore constrained in our analysis to consider only one labor force non-participation category that does not distinguish based on previous occupation. This implies that in total 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.

The average monthly fraction of the sample in each of the categories for the period before and after 1990 is presented in Table 1, and Table 2 presents descriptive statistics for the full sample, and for each of the four employment groups and for non-participants. We will discuss the changes over time in the size of the different occupations in more detail below. The main message from the descriptive statistics in Table 2 is that there is important heterogeneity across occupations in their 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). Similarly, there is heterogeneity in gender composition across occupation groups; while routine cognitive occupations are predominantly female, routine manual occupations are predominantly male.

Figure 1 displays the evolution over time of each of the four stocks of per capita employment in our monthly CPS sample. Although the Autor and Dorn (2013) crosswalk is used in order to define consistent occupational groups, there are two obvious discontinuities in the employment stocks. These occur in 1983 and 2003 with the introduction of the 1980 and 2000 occupation codes, respectively, which re-allocate per capita employment from the non-routine cognitive group to routine cognitive. In spite of these breaks, the figure clearly illustrates the obvious rise in per capita non-routine employment. The dynamics of routine manual and routine cognitive employment are quite different. Per capita routine manual employment begins to disappear in the early 1980s. The business cycle dimension discussed in Jaimovich and Siu (2012) is evident: employment in these occupations falls during recessions, and fails to recover during the subsequent expansion periods. On the other hand, routine cognitive employment continues to grow through the 1980s, before reversing in the early 1990s. Its decline begins in the 1991 recession when per capita employment falls and fails to recover in the subsequent expansion. This pattern is repeated in a dramatic manner beginning in 2007: a sharp disappearance in the Great Recession with no recovery in the four years since. Our analysis focuses on the factors contributing to the fall in the two types of routine employment, taking into account the subtle differences in timing across the two.

2.2 Construction of Switching Rates and the Flows Approach

Using information on the labor force status and occupation for matched individuals who are observed across two consecutive months, we can construct monthly transition rates across our ten labor market

[8] The exception is when they are in the 'outgoing rotation group' (i.e. in their fourth or eight month in the sample) but this information is not useful for our purposes as we no longer observe these individuals in the following month.

states. This gives us a 10x10 matrix of switching rates ρ_t for each month t in our sample. This matrix can be split into different subgroups as follows:

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

where:

- ρ_t^{EE} (4x4): Employment 'stayers' and transitions across occupations for employed workers
- ρ_t^{EU} (4x5): Job destruction rates[9]
- ρ_t^{EN} (4x1): Exit rates to non-participation from employment
- ρ_t^{UE} (5x4): Job finding rates
- ρ_t^{UU} (5x5): Unemployment 'stayers'
- ρ_t^{UN} (5x1): Exit rates to non-participation from unemployment
- ρ_t^{NE} (1x4): Entry rates from non-participation into employment
- ρ_t^{NU} (1x5): Entry rates from non-participation into unemployment
- ρ_t^{NN} (1x1): Non-participation 'stayers'

The evolution over time of the stock of people in each of the ten labor market states will be governed by the following law of motion equation:

$$\underbrace{Stocks_t}_{(10,1)} = \underbrace{\rho_{t-1}}_{(10,10)} * \underbrace{Stocks_{t-1}}_{(10,1)} \tag{2}$$

where $Stocks_t$ is a 10x1 vector with the number of people in each of our ten labor force categories in month t.

To understand the dynamics implied by Equation (2), consider for example the evolution of the stock of employed workers in routine-manual occupations. The change in this stock across two months will depend on the "inflows" of individuals from unemployment, out of the labor force, and from other occupations, relative to the reverse "outflows" to unemployment, out of the labor force, and to other occupations. These inflows and outflows in turn depend on the size of each of the stocks, and on the corresponding transition rates within the matrix ρ_t.

Our main goal in this paper is to understand the change over time in the stocks of workers employed in routine occupations by focusing on the changes that have occurred in the different switching rates in the matrix ρ_t. This will allow us to determine which types of transitions are particularly important in accounting for the decline in routine employment observed in recent decades. We will do this by performing a number of counterfactual experiments which will be discussed in detail in the next section.

[9]The fifth column represents transitions into the unemployment category with unknown previous occupations. All entries in this column are equal to zero in all periods.

Before proceeding to the counterfactual experiments, it is important to determine whether the law of motion in Equation (2) provides a good approximation of the stocks observed in the data for each of the ten labor market states. This may not be the case as the stocks constructed using Equation (2) rely only on an initial composition of stocks and on the subsequent flow data, and due to entry and exit from the sample, the flow data for matched individuals may not necessarily replicate the stock data. Figure 2 plots the fraction of the population in each of the four employment states from 1976:1 to 2012:12, as observed in the full data (blue line) and as estimated when we use the law of motion in Equation (2) initialized with the observed stocks in 1976:1 and using the measured transition rates for all consecutive months (green line).[10] Figure 3 is an analogous plot for the fraction of the population who is out of the labor force.

As has been documented elsewhere, for example in Frazis et al. (2005), stock data constructed from flows in the matched CPS sample tend to underestimate the fraction of employed workers, and overestimate the fraction of individuals who are out of the labor force. This has been referred to in the literature as 'margin error'. We confirm this with our stocks based on the law of motion. By the end of our sample period, the fraction of the population who is out of the labor force is overestimated by approximately two percentage points. Interestingly, we find that the gap in employment that arises when using the flow data is due entirely to an underestimation of the fraction of people working in non-routine occupations, whereas the fraction of people working in routine occupations is estimated quite accurately.[11] Overall, a comparison of the series depicted in Figure 2 indicates that the stocks based on the law of motion follow similar paths in the long term to those based on the full data, so margin error is not a major concern in terms of the overall long-term patterns observed for the different stocks. This justifies our approach of focusing on the flow data in order to understand the long-term dynamics for the stock of routine employment.

The main data challenge that arises when analyzing the evolution over time of transition rates across labor market states using the CPS data is the discontinuity induced by the redesign of the survey which occurred in 1994. Starting in that year, the CPS switched to a method of dependent interviewing. This means that information collected in the previous month's interview is imported into the current interview to ease respondent burden and improve the quality of the labor force data. For the collection of occupation data, interviewers began asking whether the interviewee still had the same job and if the answer was yes, the individual would receive the same occupation code as in the previous month. This made it unnecessary for the interviewer to re-enter the detailed occupation description. This method of dependent coding has been shown to substantially reduce the amount of spurious transitions in the month-to-month transitions across occupations (see Kambourov and Manovskii (2013) and Moscarini and Thomsson (2007)). However, this means that there is a break in 1994 in the switching rates across occupational groups for employed workers, with a substantial fall in the measured rate of mobility, even at the aggregation level that we are interested in. To visualize some examples of these discontinuities, Figure 4 plots the transition rates from non-routine cognitive employment to employment in other occupations in the top panel, and the transition rates

[10] For the 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 stocks constant.

[11] Another interesting finding (not shown) is that there is no evidence of differential rates of attrition across labor force categories, so this does not seem to be the reason behind margin error.

from routine manual employment to employment in other occupations in the bottom panel. In addition to the transition rates across employment categories, the CPS redesign also induces a discontinuity in the measured monthly switching rates between inactivity and unemployment.

That being said, Figure 2 shows that even when we use certain noisy transition rate measures from the pre-redesign period and the cleaner measures from the post-redesign period in our law of motion, we build stocks that replicate the dynamics over time of the true stocks quite well. However, we will still be cautious when analyzing changes over time that involve the rates that have these discontinuities.

3 What has changed?

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 by performing a number of counterfactual experiments where we analyze the effect of holding certain transition rates fixed on the evolution of the stock of routine employment.

It is worth emphasizing why we perform these counterfactual experiments rather than simply looking at the evolution of different 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 no quantitative effect on the stock of 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 quantitative 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, and given that certain transition rates (such as job finding rates and separation rates) vary significantly over the business cycle, we divide the time series into 17 cyclical phases. Specifically, we split the sample into recessions, based on NBER dates; recoveries, defined as the 24-month period following the end of a recession; and expansions, defined as starting at the end of the recovery period and ending at the time of the business cycle peak. Table 3 lists the 17 individual phases in our sample. We denote the five recessions as R1 through R5, the six recovery periods as V1 through V6, and the six expansion periods as E1 through E6.[12]

We calculate the average of each transition rate during each of these 17 phases and determine the evolution of the stocks of routine employment when using the phase-by-phase averages (for each of the 17 phases) in the law of motion from Equation (2), instead of their observed month-by-month values. We call these the *stocks based on average rates*. They are plotted in Figure 5 for routine cognitive, routine manual, and total routine employment, along with 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. The fact that the two series track each other well indicates that the *stocks based on average rates* provide a good approximation of the data.

[12] Due to the redesign of the CPS and the discontinuities that it induces in certain transition rates, we split the expansion period 1993:4-2001:2 into the periods before and after the January 1994 redesign.

Consider the stock, based on average rates, of per capita routine manual employment. The forces of job polarization become evident beginning around 1980. Per capita routine manual employment declines from a pre-1980 peak of 20.45 to 12.08 percent in 2012:12, representing a fall of 41%. As discussed in Section 2, job polarization does not become evident in routine cognitive occupations until around 1990. From the pre-1990 peak of 18.61 percent of the population, this stock falls to 15.44 percent in 2012:12. As a result, per capita employment in all routine occupations falls from 36.50 percent – regardless of whether you consider the pre-1980 or pre-1990 peak – to 27.50 percent in 2012:12, a fall of 9 percentage points.[13] As a fraction of its peak value, this represents a 25% decline. These are the benchmark falls in the stocks of routine employment that we will seek to explain.

The falls in per capita routine employment shown in Figure 5 are driven by the changes in the transition rates. Our goal is to investigate which particular transition rates are, from an accounting standpoint, primarily responsible for these declines. To do this, we perform a number of counterfactual experiments. To understand our experiments, recall that the vector of labor market stocks at any point in time can be determined recursively by the law-of-motion (2), given an initialization of the vector and the (10×10) transition matrix, ρ. The transition matrix contains 90 off-diagonal elements, determining the rate at which the population transitions across labor market states (e.g., $NLF \rightarrow ERM$). The diagonal elements represent "non-transition" rates: rates at which the population within a labor market state remain within the same state in the following period (e.g., $NLF \rightarrow NLF$).

In the experiments we consider, we let all of the average transition rates evolve phase-by-phase as observed in the data *except* for certain ones that are held constant at their pre-polarization averages. To make sure that the transition rates out of any given source category add up to one, the difference between the observed and the counterfactual transition rates is allocated to the corresponding diagonal elements.[14] A switching rate is considered to be important in accounting for the fall in routine employment if, by holding it constant at pre-polarization levels, a substantial fraction of the observed fall in employment is mitigated.[15] When analyzing the results we will particularly focus on the fall in routine employment up until two key points in time: early 2007, in order to understand the period before the onset of the Great Recession, and the end of 2012, to understand the full sample period including the Great Recession and its aftermath.

In principle, there are 90 counterfactual experiments to consider, one for each of the off-diagonal transition rates in the matrix, ρ. Unsurprisingly, not all of these counterfactuals have quantitatively relevant impacts on the dynamics 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 size of source pools of individuals that may eventually transition into routine employment), and we find that they are of negligible importance. As such, our reporting of findings will focus on transition rates that correspond directly to inflows and outflows to and from per capita routine employment. Moreover, for the sake of brevity, we will not report results for all of these direct transition rates, and discuss only those of quantitative importance.

[13] Note that the total fall in the stock of routine employment using the full CPS sample is equal to 9.31 percentage points, so using the average rates by phase gives us a good approximation of the total true fall.

[14] 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.

[15] Shimer (2012) performs a similar style of counterfactuals to determine the contribution of changes in different transition rates to fluctuations in the unemployment rate.

As mentioned, our counterfactual experiments will involve holding certain transition rates constant at their pre-polarization averages. We therefore have to make a decision about which time period we consider to be representative of the pre-polarization era. Because of the time when the two types of routine employment peak as a share of the population, we consider the 1970s and early-1980s as the pre-polarization period for routine manual occupations (ERM), and the years up until the end of the 1980s as the pre-polarization period for routine cognitive occupations (ERC). In any counterfactual experiment where we hold a particular inflow or outflow rate from ERM fixed, we will replace: (i) its average value during recession R2 through R5 with the average for recession R1 (1980:1-1980:7), (ii) its average value during recoveries V2 through V6 with the average for recovery V1 (1976:1-1977:3), and (iii) its average value during expansions E2 through E6 with the average for expansion E1 (1977:4-1979:12). For any counterfactual experiment where we hold a particular inflow or outflow rate from ERC fixed, we will replace: (i) its average value during recession R3 through R5 with the average for recession R2 (1981:7-1982:11), (ii) its average value during recoveries V4 through V6 with the average for recovery V3 (1982:12-1984:11), and (iii) its average value during expansions E3 through E6 with the average for expansion E2 (1984:12-1990:6).

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 routine employment 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; to 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.

The results for this counterfactual experiment are displayed in Figure 6. In the counterfactual, the fall in routine manual employment is mitigated from 1980 onward. Per capita routine manual employment falls only to 0.1554 in 2007 (instead of 0.1483), and 0.1407 in 2012 (instead of 0.1208). Hence, holding the various $U \rightarrow ER$ rates – the so called "job finding rates" into routine employment – at pre-polarization levels mitigates 13% and 24% of the fall, in the two time periods respectively.

In the case of routine cognitive occupations, job finding rates were, in actuality, slightly higher during the boom of the 1990s (E3 and E4) relative to that of the 1980s (E2); hence, the counterfactual predicts slightly lower employment during this period. By 2007, the counterfactual time series falls to 0.1781, essentially the same level as the benchmark series, so this implies that prior to the Great Recession, $U \rightarrow ER$ rates explain none of the overall decline. However, in the subsequent recovery and boom period, counterfactual routine cognitive employment falls only to 0.1661 (instead of 0.1544). Hence, job finding rates into routine employment account for a sizeable 37% 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 $U \rightarrow ER$ not changed from their pre-polarization values, routine employment (in manual and cognitive occupations taken together) would have remained higher. This is especially true since 2002. The counterfactual stock of routine employment reaches a level of 0.3335 in 2007 as opposed to 0.3264, implying that approximately 18% of the fall before the Great

Recession is mitigated by this experiment. By the end of the sample period, the counterfactual reaches a level of 0.3068 as opposed to 0.2752. Thus, approximately 35% of the total fall observed since 1980 is mitigated.

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 55% 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 will pay particular attention to these two 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. As in the previous experiment, we set the average transition rates into routine manual employment (in this case, $NLF \rightarrow ERM$) from the early 1980s onwards to those observed in the late 1970s and early 1980s, and the average transition rates into routine cognitive employment (in this case, $NLF \rightarrow ERC$) from the early 1990s onwards to those observed in the 1980s.

Figure 7 displays the results. For routine manual occupations, this counterfactual mitigates the per capita employment decline throughout the polarization period. The effect is particularly evident from the expansion period of 2003:12-2007:11 onward, when observed $NLF \rightarrow ERM$ rates are much lower than those observed in the 1970s. In the counterfactual, per capita routine manual employment falls only to 0.1551 in 2007, and 0.1336 in 2012. Hence, this experiment mitigates 12% and 15% of the fall in routine manual employment, respectively.

For routine cognitive occupations, the $NLF \rightarrow ERC$ rate was actually higher during much of the 1991-2007 period, relative to the 1980s. As such, the counterfactual predicts lower per capita routine cognitive employment during this period. However, in the recovery and boom period following the Great Recession, the actual $NLF \rightarrow ERC$ rate has been much lower than in the benchmark pre-polarization period. This implies that counterfactual routine cognitive employment falls only to 0.1661 as opposed to 0.1544 in the data. Hence, changes in the $NLF \rightarrow ERC$ rate account for 34% of the total per capita employment decline in routine cognitive occupations, concentrated exclusively in the period since the Great Recession.

Overall, the counterfactual stock of per capita routine employment falls to 0.3297 by 2007, and 0.2989 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 9% and 26%, in each of the time periods respectively.

3.2 The role of outflows from routine employment

Outflows towards non-participation

Our next experiment sets the transition rates from routine employment to labor force non-participation at their pre-job polarization levels. As Figure 8 indicates, this experiment has a modest mitigating effect on the decline in per capita routine employment. For routine manual occupations, the counterfactual series falls from a pre-1980 peak of 0.2045 to 0.1514 in 2007, just prior to the Great Recession; employment falls again to 0.1235 by the end of 2012. Hence, holding the $ERM \rightarrow NLF$ transition rate constant at pre-polarization values mitigates 6% and 3% of the fall, respectively.

For routine cognitive occupations, the counterfactual time series falls to 0.1535 by the end of the time period, just below the actual level of 0.1544. Hence, the change in the $ERC \rightarrow NLF$ explains none of the decline observed in the whole time period. However, the counterfactual falls only to 0.1807 in 2007, as opposed to 0.1781 in the data. Hence, prior to the Great Recession, the employment to non-participation rate accounts for a sizeable 33% of the decline in per capita routine cognitive employment.

Overall, holding the employment to non-participation rates constant to their pre-polarization values has essentially no mitigating effect on the decline in per capita routine employment. However, this experiment does indicate that changes in these transition rates since job polarization are relevant to understanding the decline prior to the Great Recession. From the pre-1980 peak to 2007, approximately 15% of the decline in routine employment is accounted for by such changes, principally in the $ERC \rightarrow NLF$ rate.

3.3 Conclusion

To summarize, we find that changes in the average transition rates from: (i) labor force non-participation to routine employment, $NLF \rightarrow ER$, (ii) unemployment to routine employment, $U \rightarrow ER$ (and, in particular, "return" job finding rates $URM \rightarrow ERM$ and $URC \rightarrow ERC$), 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. On the other hand, changes in the "separation rate" from routine employment to non-participation matter prior to 2007.[16]

To further explore the quantitative role of these changes, we conduct a comprehensive counterfactual in which we simultaneously hold all of these key transition rates to their pre-polarization values. From a pre-1980 peak of 0.3650, the counterfactual series falls to 0.3427 in 2007, and to 0.3342 in 2012. Relative to the actual time series for per capita routine employment, holding these transition rates fixed mitigates 42% of the decline leading into the Great Recession, and 66% of the decline to the end of the sample.

[16]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 in detail.

4 Demographics or propensities?

The previous section identifies the fall 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 the state of 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, people in their prime working ages are less likely to leave the labor force than those who are younger or older, and 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 that have occurred over time in the transition rates into and out of routine employment.

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

To the extent that changes in transition rates are due principally to the former, one might argue that polarization has occurred as a natural consequence of demographic change (e.g., population aging, declining marriage rates). 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 easily 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. By contrast, if changes in transition rates are due principally to changes in propensities or behavior by individuals within demographic groups, a stronger case can be made that such change is due, in part, to the forces responsible for job polarization. Another advantage of this analysis is that it will allow us to determine which demographic groups in particular have experienced the most important changes in their transition rates.

We perform a Oaxaca-Blinder (OB) decomposition of the switching rates. Specifically, let ρ_{it}^{AB} be a dummy 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 category A to category B between month t and month $t+1$, and equal to zero otherwise. Consider then the following linear probability model for ρ_{it}^{AB}:

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

Here, X_{it}^{A} includes a set of key demographic variables available in the CPS, as well as macroeconomic controls for seasonality. The demographic variables we include are age (a set of six age bin dummies), education (dummies for less than high school, high school graduate, and college graduate), gender, race, and marital status.

We estimate Equation (3) for each of the transition rates in the matrix ρ 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 routine employment. We perform the estimation separately for each of the 17 recession, recovery and expansion phases listed in Table 3. This means that the estimated vector of coefficients β is allowed to vary across different business cycle phases and over time.

Consider two different time periods from the same phase of the business cycle, 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 mid to late-1990s. We can use the estimated coefficients $\widehat{\beta}$ for each of these two time periods, along with information on the evolution over time of the demographic variables included in X^A to decompose the change across the two periods in the average switching rate as follows:

$$\begin{aligned}\overline{\rho}_0^{AB} - \overline{\rho}_1^{AB} &= \left(\overline{X}_0^A \widehat{\beta}_0\right) - \left(\overline{X}_1^A \widehat{\beta}_1\right) \\ &= \left(\overline{X}_0^A - \overline{X}_1^A\right)\widehat{\beta}_0 + \left(\overline{X}_1^A\right)\left(\widehat{\beta}_0 - \widehat{\beta}_1\right) \end{aligned} \tag{4}$$

The change in the average switching rate over time across the two phases (on the left-hand side of the equation) can be decomposed into two parts. The first part, given by the first term in Equation (4), is the component that can be attributed to changes over time in the demographic composition of individuals in category A (as well as changes in the macroeconomic variables included in X). The second part can be attributed to changes over time in the vector of coefficients $\widehat{\beta}$. This latter portion reflects changes over time in the propensities to switch for particular demographic groups. We can thus decompose the changes in switching rates from the pre-polarization to the post-polarization era into changes that are "explained" or "unexplained" by observables. Moreover, by analyzing the changes in the estimated coefficients on specific covariates, we can determine which demographic groups have experienced the largest changes in switching propensities across particular labor market states.

We can perform the OB decomposition in Equation (4) to analyze changes across comparable phases of the cycle, such as early versus late recessions, or early versus late expansions. In what follows, we do not discuss the results of the exercise for recessions. This is because the transition rates that we focus on do not tend to feature much systematic change across different recessions. Moreover, because recessions are short events (lasting, on average, 11 months during our sample period), it is the behavior of transition rates out of recession (during recovery and boom phases) that dictate the long-run dynamics of the employment stocks of interest.

As discussed in Section 3, we consider the relevant pre-polarization period for routine manual employment to be represented by the late 1970s, specifically phases V1 and E1. For all of the switching rates into or out of routine manual employment, our OB decomposition will analyze the change in each recovery phase relative to phase V1, and each expansion phase relative to phase E1. For routine cognitive employment, we consider the relevant pre-polarization phases to be given by the 1980s phases V3 and E2. Therefore, our OB decomposition of the changes in the switching rates into or out of routine cognitive employment will analyze the change in each recovery phase relative to phase V3, and each expansion phase relative to phase E2.

4.1 Inflows to Routine Employment

Return Job Finding Rates

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 ($U \to ER$). The most important of these is the rate at which unemployed individuals who previously held routine jobs transition back to a routine job ($UR \to ER$), what we refer to as the "return job finding rate." We begin by decomposing the change in this transition rate that has occurred since job polarization.

Table 4 summarizes the results of the OB decomposition for the return job finding rate for routine manual occupations ($URM \to ERM$). Results for recovery periods are displayed in Panel A, expansion periods in Panel B. As mentioned above, we take the recovery and expansion periods of the 1970s as the pre-polarization baseline period ("Period 0" in our discussion of the previous subsection), and compare subsequent recoveries and expansions to them. In each panel, 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). Because of space constraints, we do not present the detailed decomposition results for all explanatory variables, but instead, report results for selected covariates.[17]

As is obvious from the rightmost columns, there has been a precipitous fall in the $URM \to ERM$ rate since the end of the Great Recession. In the two years following the end of the recession (2009-2011), the return job finding rate was 13.77%. In the expansion period since then (2011-2012), it has been 14.09%. This compares to average rates of 21.17% and 24.33% in the recovery and expansion phases of the 1970s. The steep decline in this return job finding rate is one of the key contributors to the lack of recovery in routine manual employment since the recession. As we discuss below, this fall is not unique to routine manual occupations. Indeed, it is shared by the return job finding rate for all occupation groups, though the fall is much larger for routine occupations relative to non-routine ones. Moreover, the fall in all of the return job finding rates is unexplained by observables. Given this, it is clear that the Great Recession and its aftermath is a unique episode in terms of postwar business cycles. As such, the fall in the $URM \to ERM$ transition rate since 2009 may only be partly due to job polarization forces.[18]

However, even prior to the Great Recession, we see that the average $URM \to ERM$ transition rate is lower during all periods after the late 1970s. Aside from the recovery period of 2001-2003, these differences are large and statistically significant at the 1% level. These falls occurred despite compositional changes generally predicting a rise in the return job finding rate. In particular, the increasing fraction of males among the pool of unemployed workers from routine manual occupations predicts an increase in this rate, given that males are more likely to make this transition relative to females.

Hence, the fall in observed return job finding rates is driven by the "unexplained" change in all expansion and recovery periods since the onset of job polarization. The OB decomposition reveals that in most periods, individuals of all demographic groups experienced a fall in their propensity to

[17] The full detailed decomposition is available from the authors upon request.

[18] Likewise, from a macroeconomic perspective, the jobless recovery (and subsequent jobless expansion) following the Great Recession cannot be solely attributed to the forces underlying job polarization.

transition to routine manual employment. This effect was particularly acute for males and both the youngest age group (16-24 year olds) and the prime-aged (35-44 year olds).

Table 6 summarizes the results for the $URC \rightarrow ERC$ transition rate. As mentioned above, we take the recovery and boom of the 1980s as the baseline, pre-polarization period.

Until 2003, the average return job finding rate for unemployed routine cognitive workers displays relatively small differences compared to the pre-polarization era, though in five of the six periods, it is lower. From the expansionary phase of 2003m12-2007m11 onward, the falls are large and statistically significant. These are especially noticeable following the Great Recession. Aside from the expansion of the 1990s, the fall in observed return job finding rates is driven by both explained and unexplained effects, with the latter typically being more important. The unexplained component predicts falls in the $URC \rightarrow ERC$ rate for all demographic groups. This decrease in the propensity to return to employment in a routine cognitive occupation is strongest for whites, females, and the prime-aged 45-54 year olds.

To summarize, we observe falls in the the return job finding rate into routine employment after the Great Recession. This is also true of the return job finding rate into routine manual employment throughout the job polarization period, and into routine cognitive employment during the 2000s. In all of these cases, the falls are driven by unexplained factors, namely the propensity of individuals to return to routine employment. For the $URM \rightarrow ERM$ transition rate, this fall in propensity was stronger for both very young and prime-aged males; for the $URC \rightarrow ERC$ transition rate, this fall in propensity was stronger for whites, females, and the prime-aged.

These results can be contrasted with those observed for the return job finding rate into non-routine employment. Not surprisingly, these transition rates also exhibit sharp declines since the Great Recession, driven primarily by unexplained factors. However, prior to 2007, the return job finding rate for non-routine occupations was higher during the job polarization era, relative to the 1970s. Moreover, the increases in these transition rates were due to unexplained factors. For the return job finding rate into non-routine cognitive jobs, the rise in propensity was strongest for females and those with college education or greater. For non-routine manual occupations, the rise in propensity was strongest for males and married individuals.

Unemployed Workers Switching Occupations

Next we consider the changes in transition rates from unemployment for those who were previously working in a non-routine occupation, into routine employment. The four transition rates are: $UNRC \rightarrow ERM$, $UNRM \rightarrow ERM$, $UNRC \rightarrow ERC$, and $UNRM \rightarrow ERC$. We refer to these as "switching job finding rates." For brevity, we do not present the results of these OB decompositions in detail, and instead summarize as follows. As with return job finding rates, all of the switching job finding rates display large falls following the Great Recession, again indicating the important impact of this event on the recent evolution of routine employment. However, even prior to 2007, important changes occurred.

With respect to both the $UNRC \rightarrow ERM$ and $UNRM \rightarrow ERM$ rates, these 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 workers previously working in non-routine cognitive jobs (since older and more educated individuals are less likely to switch into a routine manual occupation). By contrast, the fall in the $UNRM \rightarrow ERM$ is almost entirely due to unexplained changes: the fall in propensity is concentrated among the very young (16-24 years old), high school graduates, and males.

Similarly, the $UNRC \rightarrow ERC$ transition rate has experienced significant declines, with the exception of the 1991-1993 recovery (when it shows a statistically insignificant rise). The falls in this switching job finding rate are essentially all unexplained by demographics, and are particularly strong among females and the non-married. By contrast, the $UNRM \rightarrow ERC$ rate rose during job polarization (of course, with the exception of the periods following the Great Recession). This was 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

Next, we decompose the change observed since the onset of job polarization in the transition rates from out of the labor force to routine employment ($NLF \rightarrow ER$). As discussed in Section 3, changes in these transition rates account for about one-quarter of the decline in per capita routine employment.

Table 6 summarizes the results of the Oaxaca-Blinder decomposition for the switching rate from non-participation to routine manual employment ($NLF \rightarrow ERM$). Again, we take the recovery and expansion periods of the 1970s as the pre-job polarization baseline periods, and compare subsequent recoveries and expansions to them.

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. Not surprisingly, this fall in the non-participation to employment transition rate is shared by the $NLF \rightarrow E$ transition rate into employment in all occupational groups. The fall in all of these finding rates is unexplained by observables. Given this shared pattern, the fall in the $NLF \rightarrow ERM$ rate cannot be solely attributed to job polarization forces.

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, except one. This is particularly strong during the expansion phases, where the fall in the transition rate relative to the baseline period is statistically significant. Moreover, we find that the unexplained effect consistently predicts a fall in the transition rate, across all periods. That is, across all expansions and recoveries, the propensity to make the $NLF \rightarrow ERM$ transition is significantly lower. This fall in propensity is concentrated among individuals who are male, young (under the age of 25), and single.

In all periods, these negative unexplained changes are offset by changes in the composition of labor force non-participants. Specifically, the rising proportion of males in non-participation predicts a rise in the $NLF \rightarrow ERM$ rate (since these individuals, relative to females, have a higher probability of transiting to routine manual employment).

Table 7 summarizes the results of the OB decomposition for the switching rate from labor force non-participation to routine cognitive employment ($NLF \rightarrow ERC$). As with $NLF \rightarrow ERM$, the

$NLF \rightarrow ERC$ transition rate displays a sharp decline following the Great Recession. Moreover, this decline is entirely accounted for by a fall in the propensity of all individuals to transition to this type of employment. As with routine manual occupations, this unexplained change accounts for the malaise in routine cognitive employment since 2009.

Prior to the Great Recession, $NLF \rightarrow ERC$ rates exhibit modest increases relative to the baseline period of the 1980s, during both recoveries and booms. This increase is largely accounted for by explained factors. The rising educational attainment of the non-participant pool is one important factor, as those with greater education are more likely to be employed in cognitive occupations. The other important factor is the increasing fraction of young, 16-24 year olds among non-participants, as this age group is more likely (relative to other age groups) to transition to routine cognitive employment. In all cases, these changes are highly statistically significant.

Interestingly, these explained changes are offset by unexplained factors predicting a fall in the $NLF \rightarrow ERC$ rate in four of the six periods. This is especially strong from the expansion phase of 2003m12-2007m11 onward, when the propensity of non-participants to transition into routine cognitive employment was significantly lower than in the 1980s. From that period on, the fall in propensity was experienced by all demographic groups, and was strongest for the highly educated (those with post-secondary education) and the prime-aged (those aged 45-54).

To summarize, changes in the demographic composition of the non-participant pool would generally have predicted an increase over time in the inflow rate to routine employment. Falls in the inflow rates observed since the Great Recession were driven entirely by changes in transition propensities. But even prior to 2007, changes in the propensities of non-participants to switch into routine employment were visible. In the case of $NLF \rightarrow ERM$ transitions, this fall in propensity – concentrated among the young, the single, and males – was strong enough to result in lower transition rates relative to the baseline, pre-polarization period. In the case of $NLF \rightarrow ERC$ transitions, the fall in propensity – experienced across all demographic groups, but stronger for the highly educated and prime-aged – served to mitigate the rise due to compositional change beginning in 2003.

4.2 Outflows from Routine Employment

Outflows Towards Non-Participation

Finally, we investigate the change in transition rates from employment in routine occupations to labor force non-participation ($ER \rightarrow NLF$). Table 8 summarizes the decomposition results for the switching rate from routine manual employment to out of the labor force ($ERM \rightarrow NLF$). 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 a rise in the transition rate that begins during the expansion of 1994m1-2001m2 and continues through the end of the sample period. This rise in the rate at which employed routine manual workers leave the labor force has occurred despite compositional changes that predict a fall. 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 shift in the age composition of such workers away from the very young (16-24 year olds), toward prime-aged workers (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 exclusively to unexplained factors. Indeed, the increased exit propensities are observed in all four expansion periods since job polarization. As is clear from the decomposition result, this positive unexplained effect is not shared by all demographic groups. Indeed the increased propensity to exit the labor force is concentrated among males, those who are married, and those with less than high school education.

Table 9 summarizes the results for the switching rate from routine cognitive employment to non-participation ($ERC \to NLF$). As with $ERM \to NLF$, the average $ERC \to NLF$ transition rate begins to rise relative to the benchmark in the boom of 1994m1-2001m2. The increase is statistically significant during the 2003m12-2007m11 boom. The OB decomposition indicates that this increase occurred despite compositional changes with the opposite effect. In particular, the increasing educational attainment, aging, and increasing fraction of males in the pool of routine cognitive employment predict a fall in the rate at which such workers leave the labor force.

Hence, the rise in the $ERC \to NLF$ rate between 1994 and 2007 is due entirely to unexplained factors. As evidenced by the decomposition results, the unexplained effect is not shared by all demographic groups. The increase in the propensity of routine cognitive workers to transition to non-participation is concentrated especially among males and those aged 16-34 years old.

Since the Great Recession, the $ERC \to NLF$ rate has actually fallen relative to the pre-polarization benchmark. This is due principally to a significant weakening of the unexplained effect since 2009 relative to 1994-2007.

4.3 Summary

The decomposition results presented in this section help us understand whether the observed changes in transition rates which have been identified as contributing to the disappearance of routine employment can be explained by changes in the demographic composition of individuals in different labor market states, or are due to changes in transition propensities for people with given demographic characteristics. The results overwhelmingly point towards the latter. There have been falls since the 1980s in the rate at which unemployed routine manual workers return to routine manual jobs, and since the 2000s in the rate at which unemployed routine cognitive workers return to routine cognitive jobs. There have also been falls in the rate at which unemployed non-routine workers find jobs in routine manual occupations. This is particularly true of young men with high school degrees. The rate at which individuals who are out of the labor force enter routine manual occupations, conditional on their demographic characteristics, has fallen since the 1980s among young, single men. The same is true for the entry rate into routine cognitive occupations particularly for the highly educated and prime aged. Finally, in terms of outflows from routine employment, married men without a high school diploma have experienced particularly strong increases in the propensity with which they transition from routine manual employment to labor force non-participation. The same is true about transitions out of routine cognitive employment for men aged 16 to 34.

5 Decomposed Transition Rate Counterfactuals

In Section 3 we found that changes in three categories of transition rates were of primary importance in accounting for the long-run decline of employment in routine occupations. The results in Section 4 suggest that the changes in these key transition rates are predominantly due to changes in propensities to switch rather than changes in demographic composition of particular employment states. In this section, we investigate the role of aggregate demographic change and changes in transition propensities in more detail. The OB decomposition attributes to demographics the changes that would have occurred in the transition rate given the observed changes in the demographic composition of the source labor market state, and given the transition propensities from the baseline period (see Equation (4)). However, this ignores the fact that, had demographic-specific transition rates remained at pre-polarization levels, the demographic composition within each labor market state would potentially be quite different from what is actually observed in the data.

In this section we perform a new set of experiments where we account for the counterfactual demographic composition within each labor market state that would have been observed if certain transition rates had remained at their pre-polarization levels. At the same time, we allow for changes in the aggregate demographic composition of the economy such as increases in education and population aging. This will allow us to make a more transparent distinction between the changes in per capita routine employment that can be attributed to demographic change, and the ones that can be attributed to changes in transition propensities. Distinguishing between these two factors is relevant, for example, in the consideration of policy implications. If the decline in routine employment were attributable to population aging, for example, the desirability of policy intervention might be very different than if it were due to a reduced ability of prime-aged, married individuals with low education to return to employment in their previous occupations.

We proceed as follows. In each period we divide the sample into a total of 144 bins according to their demographic characteristics, as given by gender (2 groups), age (6 groups), education (3 groups), race (2 groups) and marital status (2 groups). We obtain from the data the time series of transition rates for each demographic bin across the ten labor market states. Given the initial distribution of each demographic group across the ten labor market states, we track their distribution over time across these ten states using either true or counterfactual transition rates by applying a law of motion analogous to Equation (2).

To account for demographic change over time in the aggregate population, we adjust in each period the relative weights of each of the 144 bins in the aggregate population. For example, over time the relative size of the college-educated groups is increasing. When building our stocks of each of the ten labor market states, we take this into account by increasing the weight of these demographic groups as observed in the data. This re-weighting of demographic groups ensures that we accurately match the aggregate demographic composition of the economy in each period. At the same time, because the composition across the ten labor market states for each demographic group is driven by the laws of motion, we account for how different assumptions about transition rates would counterfactually influence the demographic composition of individuals in any given labor market state over time.[19]

[19] 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 within each demographic bin occurs proportionately to the size of each of the ten labor force states for individuals from that demographic group, as given by the law of motion. That is, if the size of a particular bin is increasing, assume that these additional workers are distributed across the ten labor force states in the same way as the incumbents from the same demographic group. Under this assumption, entry and exit will not change the composition of the ten labor market states *for a given demographic group.* There are however different entry and exit rates for different demographic groups, so as the relative size of each demographic group changes in the population, this will change the *aggregate share* of each of the ten labor market states.

Figure 9 displays the series of per capita stocks based on the law of motion using the observed aggregate transition rates period by period (as in Figure 2), and using the observed demographic-group specific transition rates period by period along with our re-weighting procedure. The two series track each other very closely, which demonstates that our procedure works well. The same would be true if we plotted routine cognitive and routine manual employment separately. The series that use the demographic-specific rates will be our benchmark throughout this section of the paper.

We now proceed to our counterfactual experiments. We begin by analyzing the overall role of demographic composition change in the population in accounting for the disappearance of routine employment. We then perform a number of counterfactual experiments where, following a logic similar to Section 3, we hold particular transition propensities at their pre-polarization levels. Note that there are two key differences between the analysis in this Section and the analysis in Section 3. First, when holding transition "propensities" at their pre-polarization levels, we do this by holding transition rates *for each demographic group* constant rather than at the aggregate level. Hence, aggregate transition rates change over time, because of changes in the demographic composition of individuals in each labor market state. The second difference is that we allow for aggregate demographic change by using the re-weighting procedure outlined above.

5.1 The overall role of demographics

Our first counterfactual experiments analyze the overall role of demographic change 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 we hold the relative size of each demographic group constant at its pre-polarization value. This is a counterfactual experiment where we are not allowing for any aggregate demographic change. Therefore, any decline in routine employment arises solely from changes in group-specific transition rates.

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 stocks. In Figure 10 we plot the benchmark stocks of ERM along with the counterfactual where we hold the relative size of each demographic cell in the aggregate economy at their 1976:1 levels, while allowing transition rates to evolve as they do in the data. The two series have been smoothed to remove seasonality. If demographic composition had remained constant at 1976 levels, routine manual employment would have risen further in the lead-up to the 1980 recession. Following the peak, ERM would have fallen to 16.59 per cent of the population (rather than 14.92) by early 2007, and to 14.15 by the end of 2012 (rather than 12.07). Thus, relative to the pre-1980 peak of 20.31, holding demographics constant mitigates about 31% of the fall up to early 2007, and about 25% of the fall up to the end of 2012. This means that aggregate demographic change, principally in terms of changes in the age structure and educational composition of the population, explain a small, though non insignificant portion of the shift away from routine employment. However, changes in demographic-specific transition rates alone (i.e. without changes in demographics) account for between 70% and 75% of the total fall in ERM.

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 cell in the aggregate economy at their 1989:12 levels (while allowing transition rates to evolve as they do in the data). Figure 11 plots the benchmark and counterfactual stocks of ERC. The counterfactual stock of ERC falls to 18.03 by early 2007 (rather than 17.95) and to 15.51 by the end of 2012 (rather than 15.25). Therefore, relative to the pre-1990 peak of ERC of 18.85, holding demographics constant mitigates about 10% of the (very small) fall up to early 2007, and only 7% of the fall up to the end of 2012. Changes in group-specific transition rates alone, without changes in demographics, can therefore explain the vast majority of the total fall in ERC.

We conclude from these two experiments that demographic change alone can account for up to 30% of the fall in routine manual employment, and less than 10% of the fall in routine cognitive employment. Therefore, changes in transition rates, rather than aggregate demographic change, are the primary drivers of the fall in routine employment per capita.

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 demographic cell at their pre-job polarization levels.[20] Recall that the differences with Subsection 3.1 are that (i) instead of using aggregate transition rates we use transition rates specific to each demographic cell, and (ii) we allow for aggregate demographic change by re-weighting the different cells to match the aggregate demographic data.

The results for this counterfactual experiment for total routine employment are displayed in Figure 12. Holding these transition rates constant does not mitigate the fall in routine employment prior to the Great Recession, but they do mitigate over 17% of the fall up to the end of 2012. Looking separately at the two types of routine employment, we see that particularly for routine cognitive employment, holding the job finding rates at their pre-polarization levels tends to exacerbate the fall in the stocks up to around 2007. By the end of the period, however, 10% of the fall in routine manual employment and 18% of the fall in routine cognitive employment is avoided.

Inflows from non-participation

Next, we consider the role of changes in the propensity to switch into routine employment for individuals who are outside of the labor force. This experiment allows all of the demographic group-specific transition rates to evolve as they do in the data, except those for the two transition rates from non-participation into routine employment, which are held constant at their pre-job polarization levels for each demographic group. The results, displayed in Figure 13, show that holding these transition rates constant leads to a stronger recovery of routine employment after the 2001 recession, a smaller fall in routine employment during the 2008 recession, and some recovery since late 2011. Overall, 17% of the fall up to early 2007 is mitigated, and 31% of the fall up to the end of 2012. The pattern is very

[20] 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, V1 and E1 in subsequent recessions, recoveries and expansions respectively, except if it is a transition rate which directly involves ERC, in which case we hold it at the phase average for phases R2, V3 and E2 respectively. Note that the phase averages in this section are specific to each of our demographic bins. As in Section 3, we adjust the diagonal elements (i.e. the "staying" transition rates) in our counterfactuals to ensure that switching rates from a given source category for each demographic group add up to one.

similar for routine manual employment, with 12% of the fall to 2007 and 18% of the fall to the end of 2012 being mitigated. For routine cognitive employment, none of the fall to 2007 is mitigated, but 34% of the fall to the end of 2012 is.

5.3 The role of outflows from routine employment

Outflows towards unemployment

For the next experiment we hold the transition rates from routine employment to unemployment constant for each demographic group at their pre-polarization levels. In this case, displayed in Figure 14 none of the fall in routine employment before the Great Recession is avoided. The counterfactual series reaches a level of 0.2796 at the end of the sample period. This means that holding the transition rates from routine employment to unemployment constant mitigates only about 7% of the fall in the stock. Changes in transition rates from routine employment to unemployment therefore play only a relatively small role in accounting for the fall in routine employment, and only since the Great Recession, when increased propensities to 'separate' into unemployment can explain some of the fall. This is true both for routine manual and routine cognitive employment.

Outflows towards non-participation

The next experiment holds the transition rates from routine employment to labor force non-participation constant at their pre-job polarization levels for each demographic group, while allowing all other transition rates to evolve as they do in the data, and allowing for aggregate demographic change. As seen in Figure 13, this channel is particularly important before the onset of the 2008 recession. 37% of the fall in routine employment up to 2007 is mitigated by holding this pair of transition rates constant. The role of this channel in more recent years is relatively smaller, mitigating 7% of the fall to the end of 2012. This effect in recent years is entirely due to a mitigating effect on routine manual employment, which does not occur for the routine cognitive stock.

5.4 Other switching rates

Our final experiment investigates the role of occupational transitions for employed workers. Unfortunately, due to the 1994 redesign of the CPS and the discontinuities induced in this set of switching rates, we can only investigate the role of this channel for a much shorter time frame. For this experiment, we hold the transition rates across all employment categories (i.e. across occupation groups for workers who are employed in two consecutive months) constant for each demographic group at their corresponding values for the first post-redesign phase – the 1994:1-2001:2 expansion – during all subsequent periods (regardless of the phase of the cycle). This experiment investigates the role of changes in occupational mobility rates from the 2001 recession onwards in accounting for the fall in routine employment. We can see in Figure 16 that changes in occupational mobility rates play some role in accounting for the fall in routine employment after the Great Recession, but their role is relatively modest. Holding them constant at their mid to late 1990s levels mitigates 11% of the fall in routine employment to the end of 2012.

5.5 Summary

To summarize, we find that aggregate changes in the demographic composition of the US population can account for 25 to 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. For routine manual employment, we have identified transitions between employment and labor force non-participation as being the most important drivers of the fall in this stock up to 2007. For routine cognitive employment, increased exit to labor force non-participation can account for a substantial fraction of the fall in this stock up to 2007. In the years since the 2008 recession, the role of outflows from routine employment to non-participation has become much more modest. During this period, the key flows responsible for the decline (and lack of recovery) of routine employment are the inflow rates from unemployment and particularly from labor force non-participation.

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. 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 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 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 low 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 and the prime-aged. 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 aggregate importance of demographic change and transition propensity changes in accounting for the disappearance of routine employment. We find that demographic composition change in the US 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 changes in propensities, that is, changes in demographic-group specific transition rates.

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Figure 1: Employment Stocks per Capita in Monthly CPS data

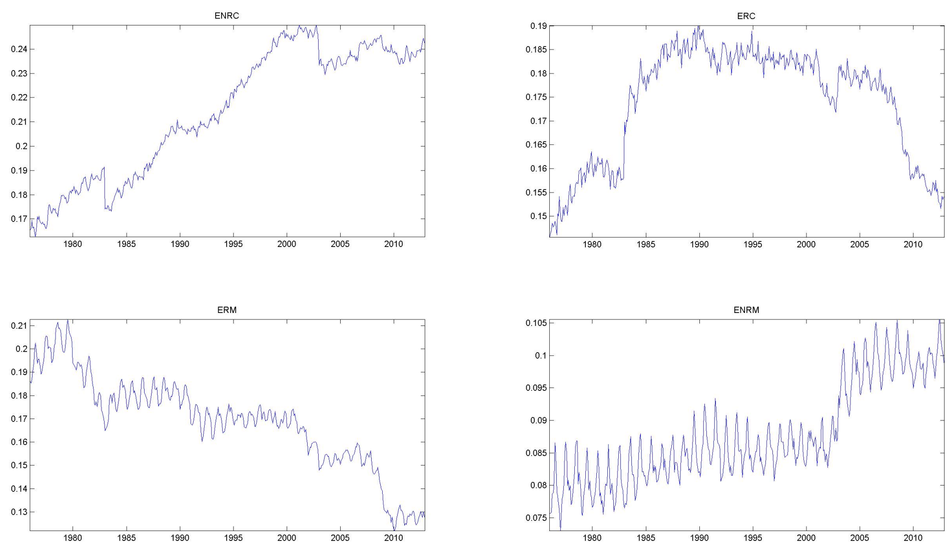

Figure 2: Stocks from Full Sample and based on Law of Motion, by Occupation

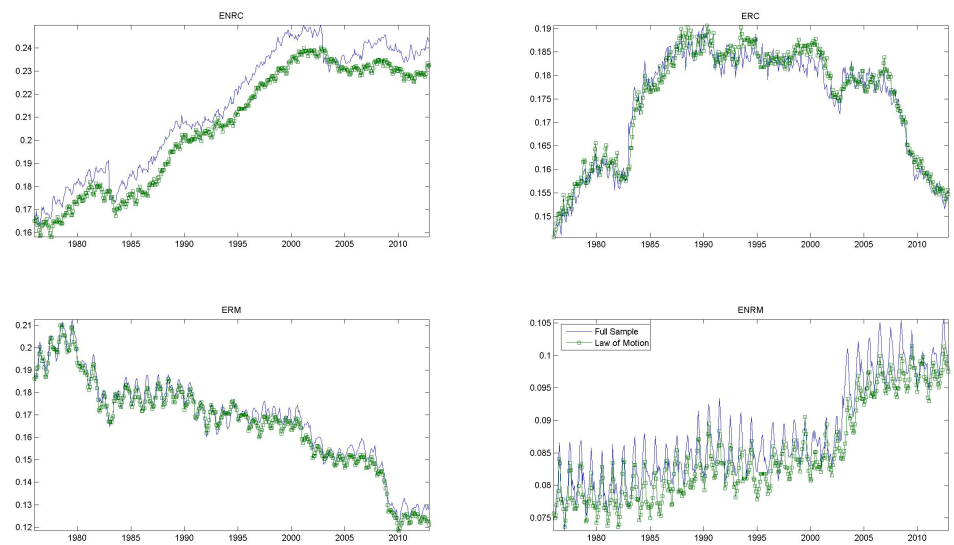

Figure 3: Non-Participation Stocks from Full Sample and based on Law of Motion

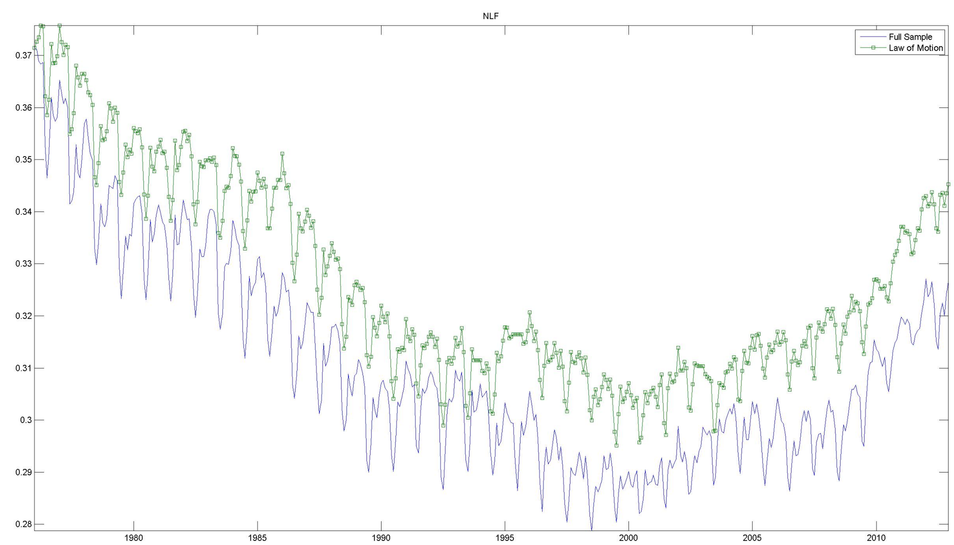

Figure 4: Transition Rates across Employment Groups

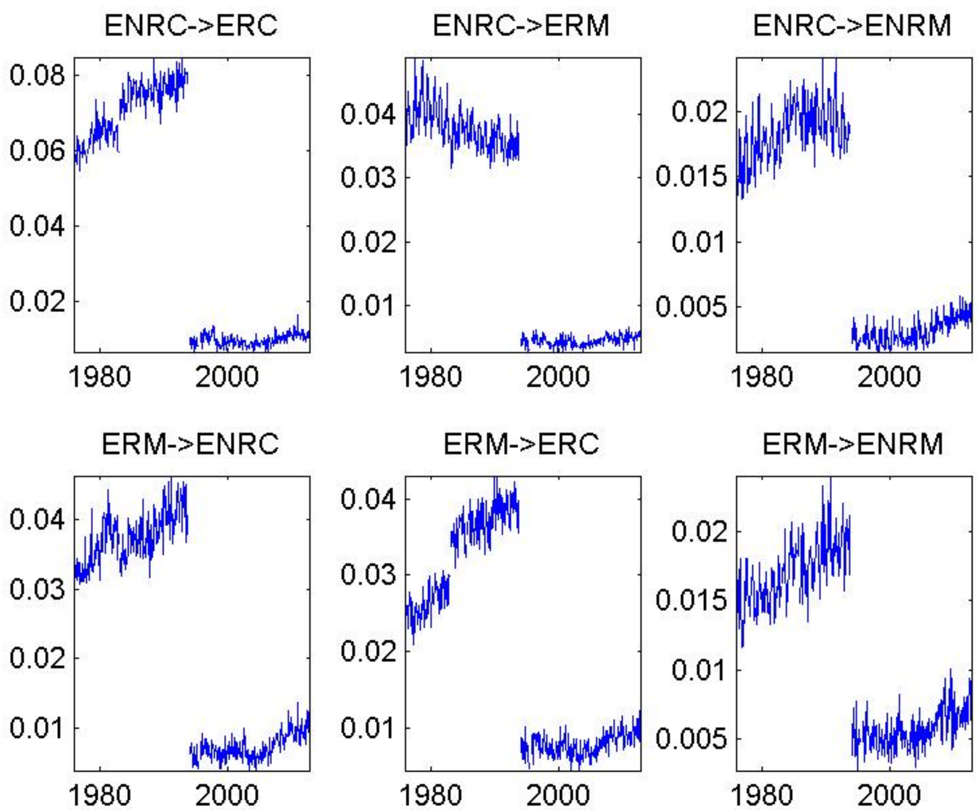

Figure 5: Stocks Based on Law of Motion using Monthly Rates and Phase Averages

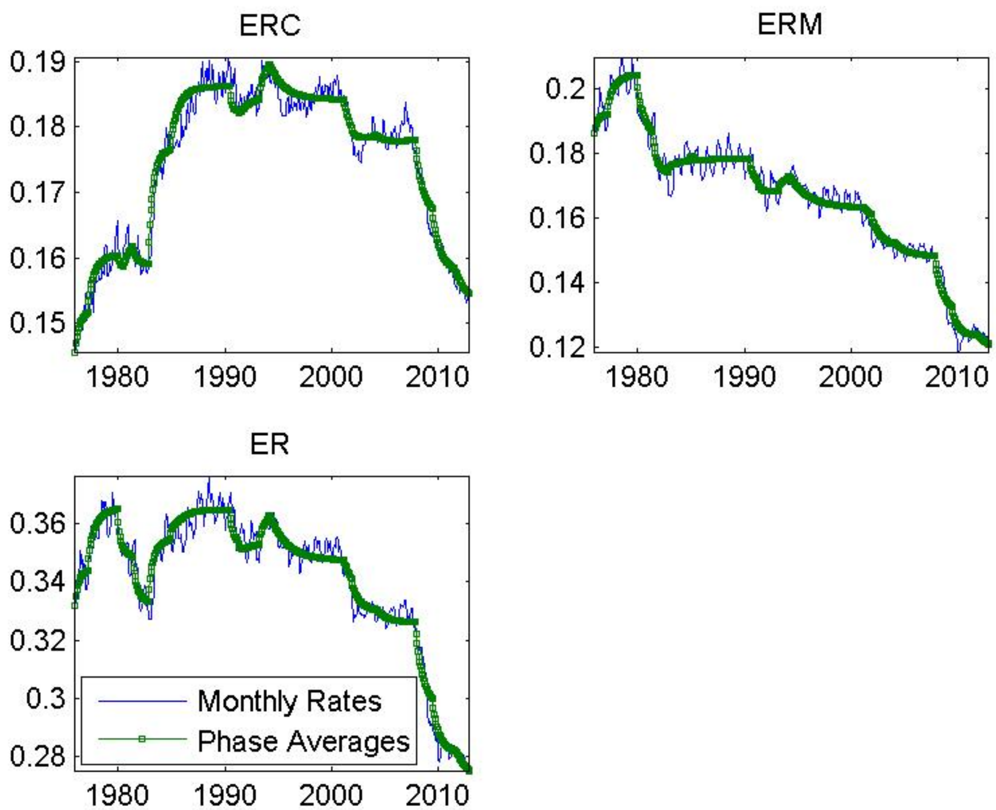

Figure 6: Counterfactual Routine Employment: Inflow rates from Unemployment to Routine Employment at their pre-polarization levels

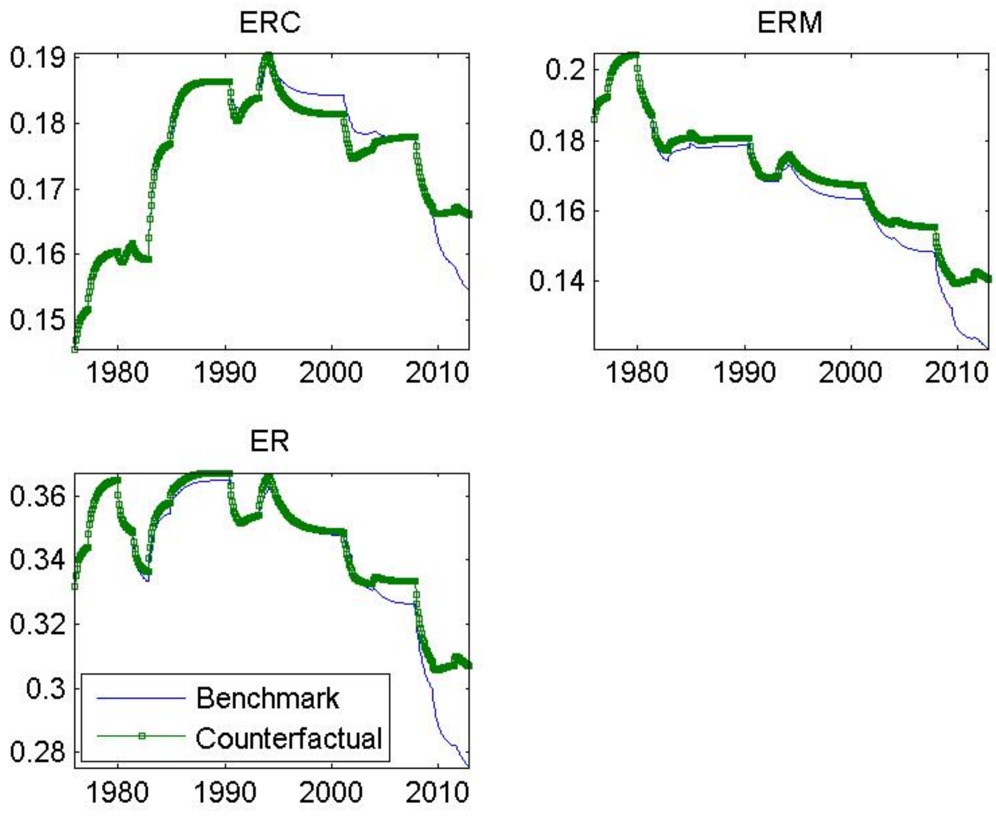

Figure 7: Counterfactual Routine Employment: Inflow rates from Non-Participation to Routine Employment at their pre-polarization levels

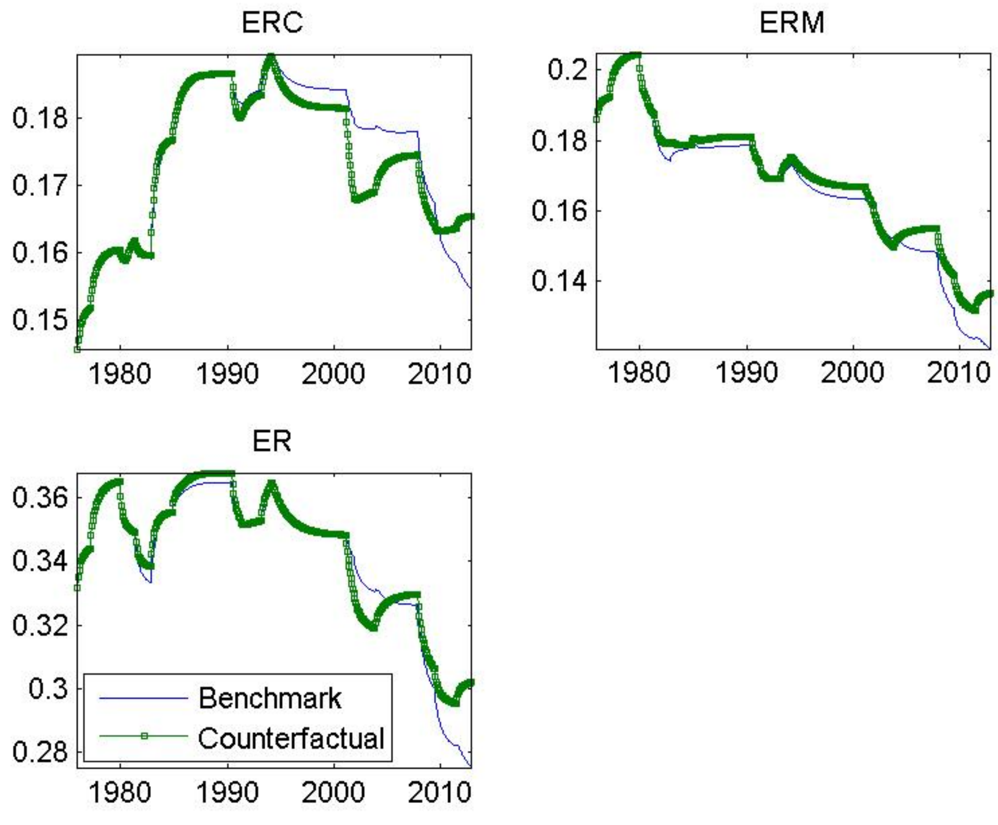

Figure 8: Counterfactual Routine Employment: Outflow rates to Non-Participation from Routine Employment at their pre-polarization levels

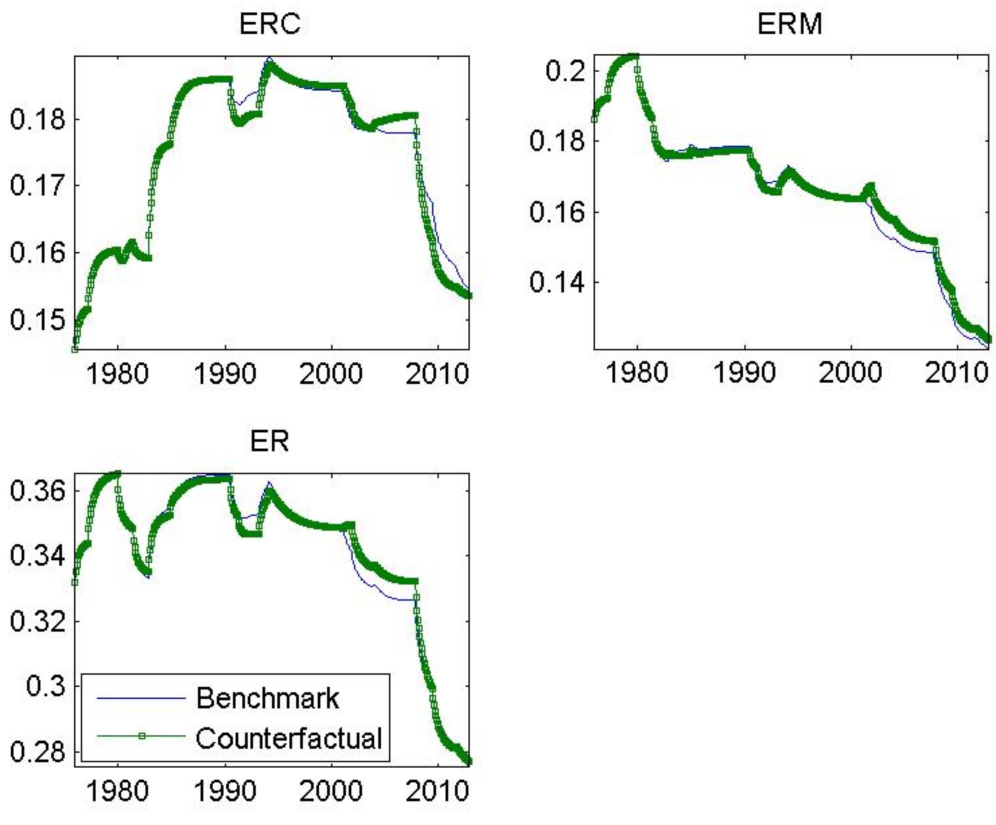

Figure 9: Routine Employment: Stocks based on Law of Motion using Aggregate and Demographic-Group Specific Transition Rates

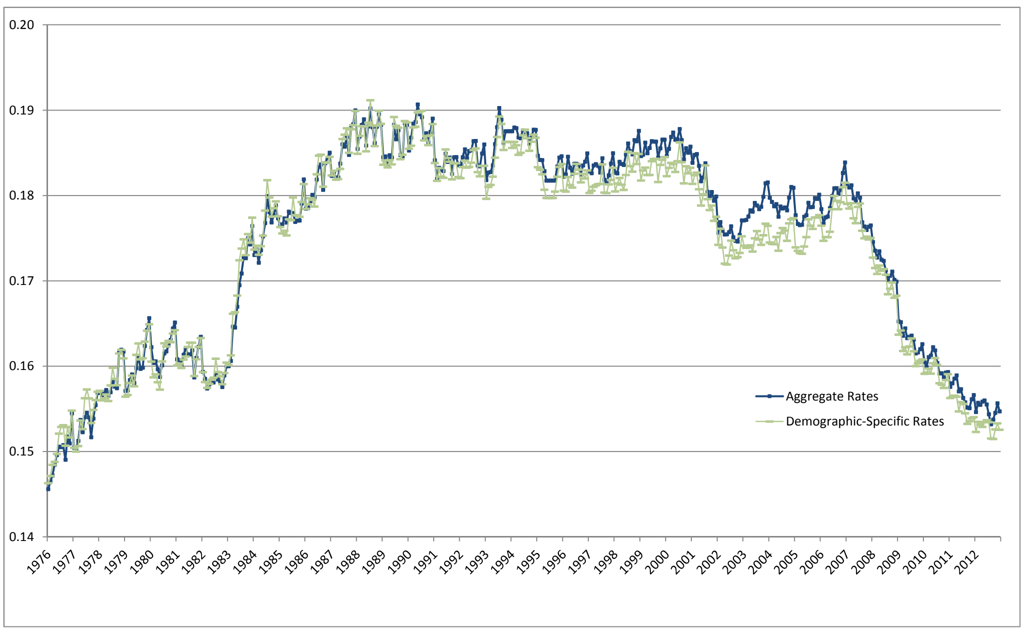

Figure 10: Routine Manual Employment - Counterfactual Experiment: No aggregate demographic change relative to 1976:1

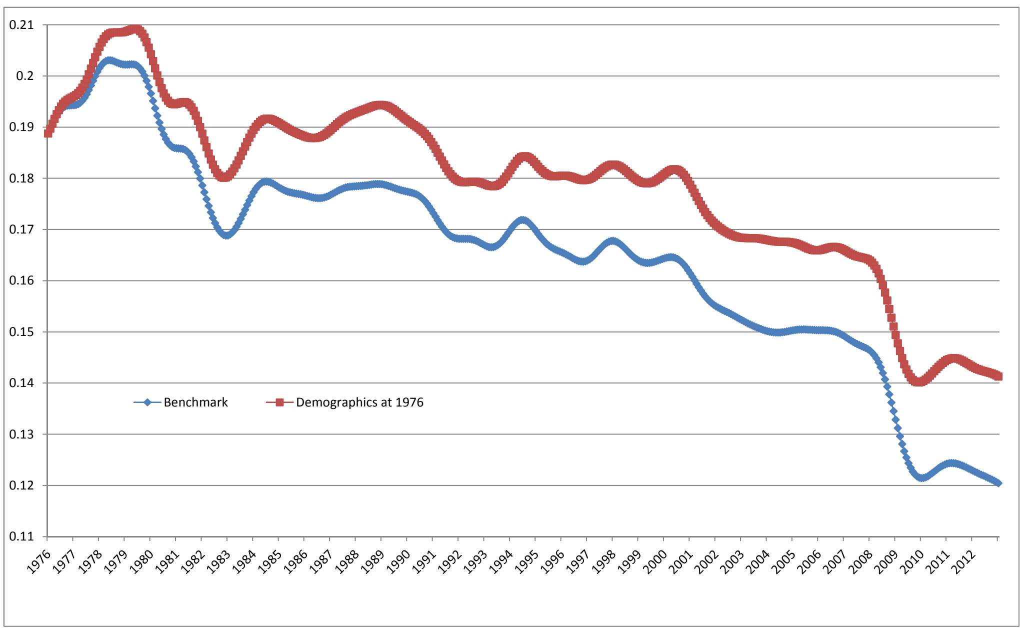

Figure 11: Routine Cognitive Employment - Counterfactual Experiment: No aggregate demographic change relative to 1989:12

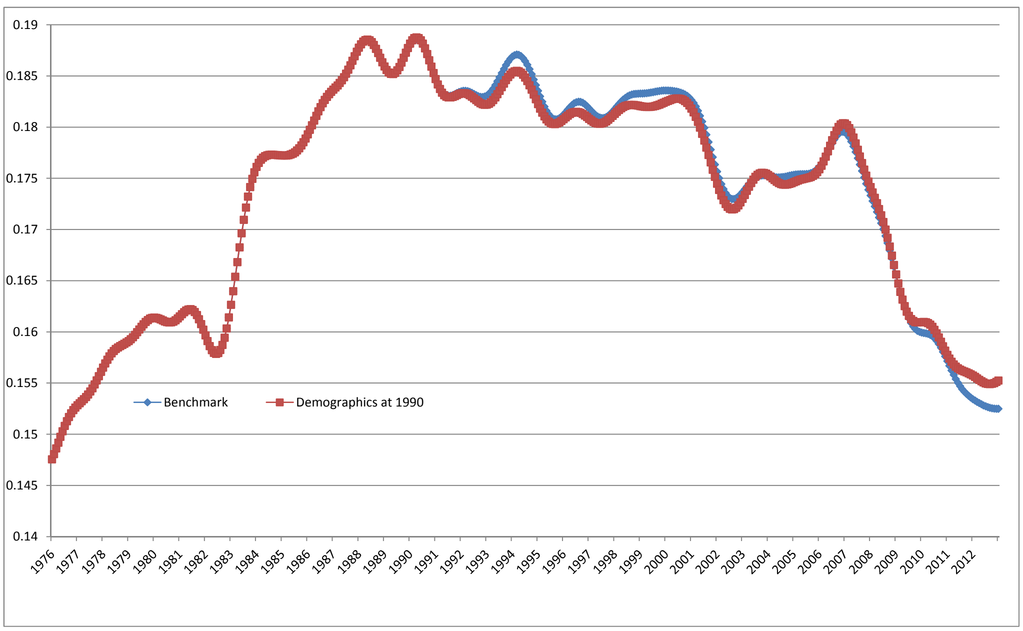

Figure 12: Routine Employment - Inflow Rates from Unemployment to Routine Employment at their pre-polarization levels

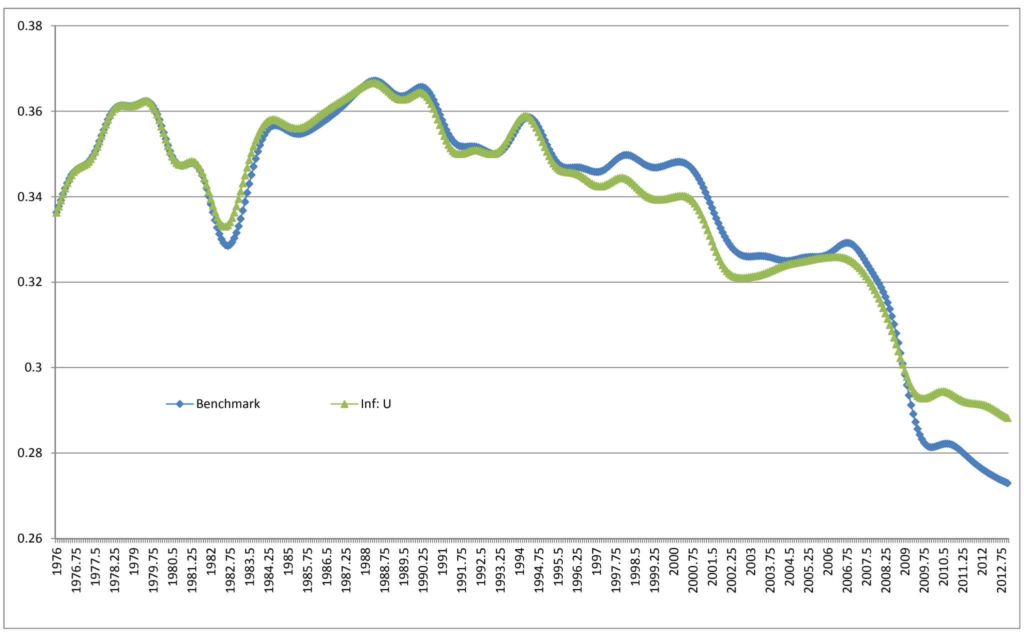

Figure 13: Routine Employment - Inflow Rates from Non-Participation to Routine Employment at their pre-polarization levels

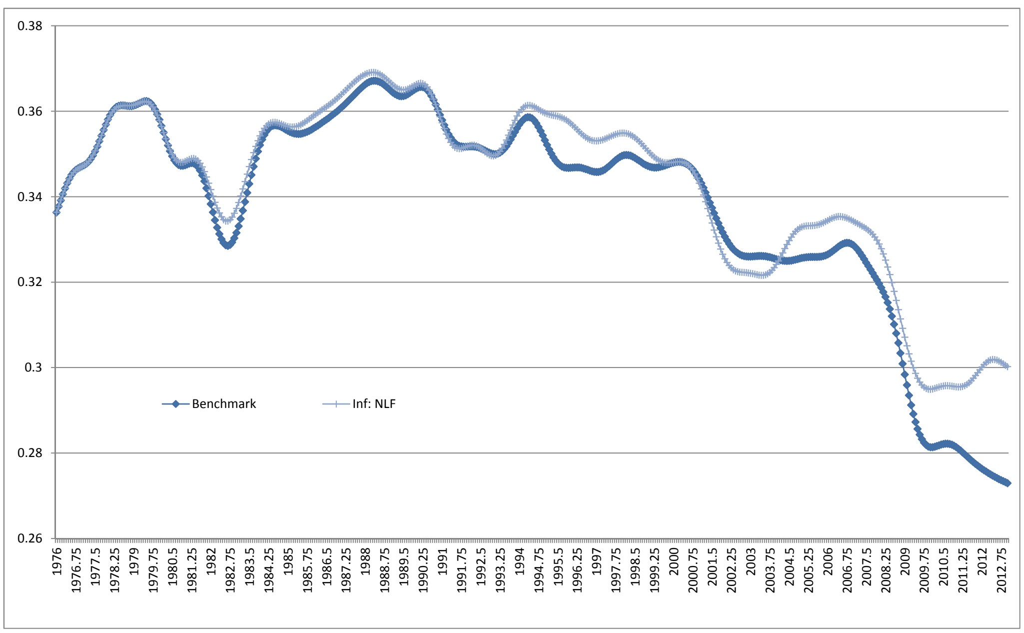

Figure 14: Routine Employment - Outflow Rates to Unemployment from Routine Employment at their pre-polarization levels

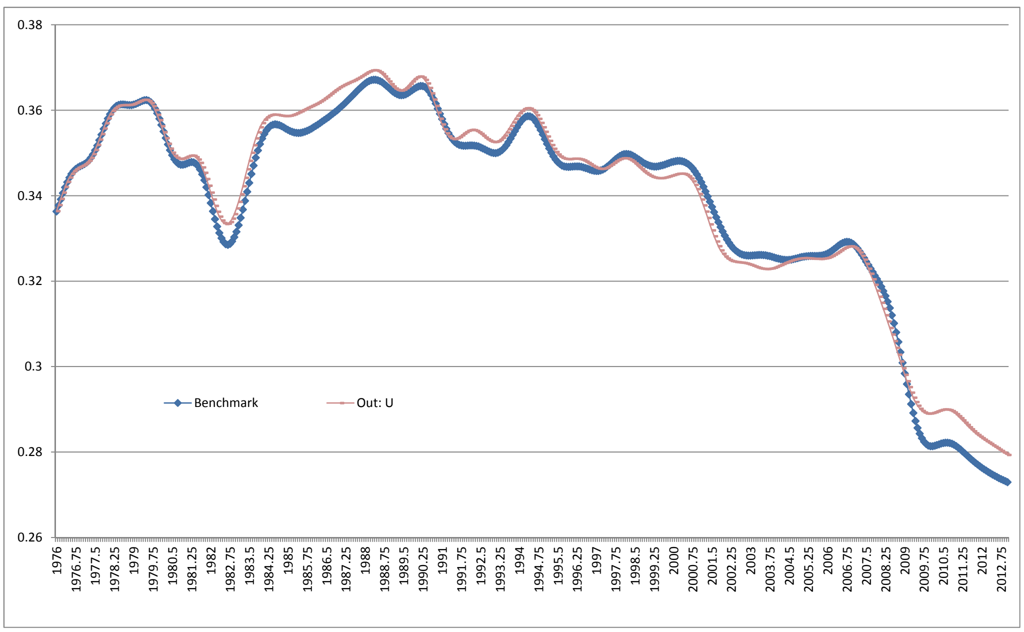

Figure 15: Routine Employment - Outflow Rates to Non-Participation from Routine Employment at their pre-polarization levels

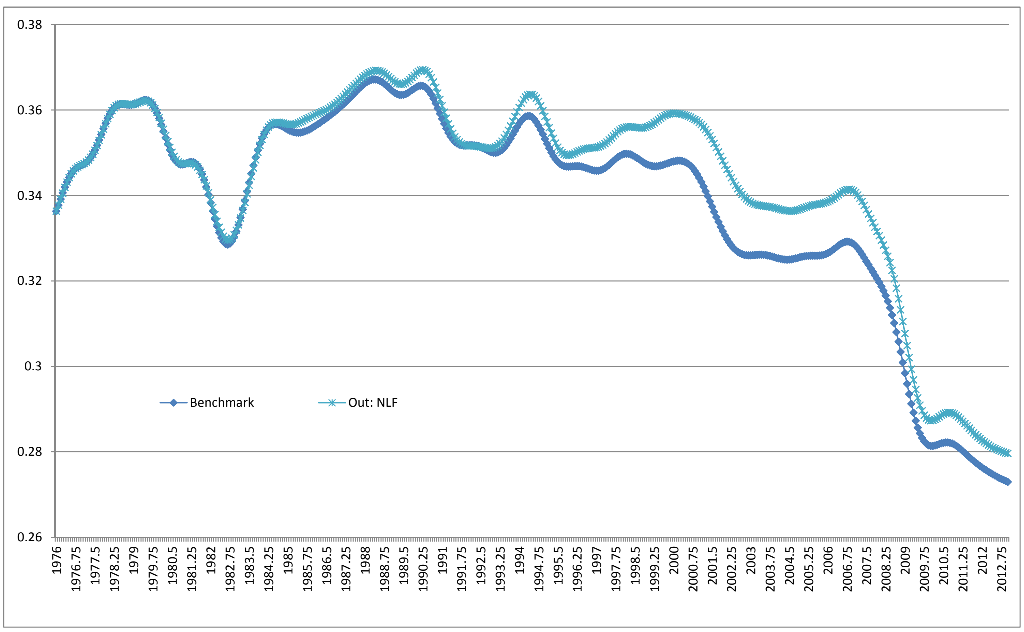

Figure 16: Routine Employment - Switching Rates between Employment Categories fixed

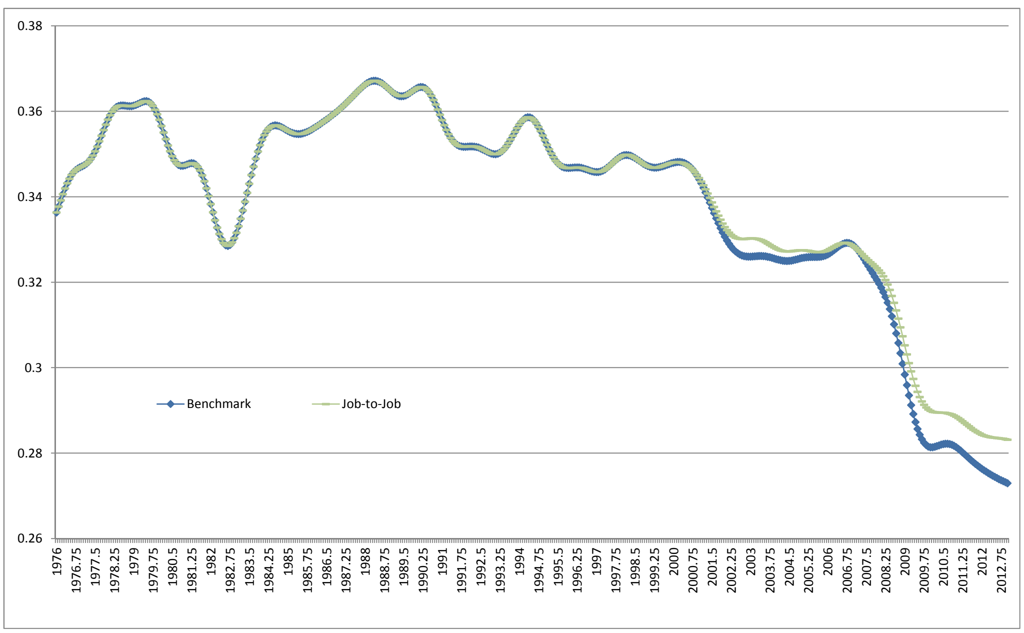

Table 1: Employment/Occupation categories and average monthly fraction of sample [To be updated – Numbers in this table currently based on a 10% random sub-sample]

Category	1976-1989	1990-2012
Employed: Non-Routine Cognitive	18.5%	23.1%
Employed: Routine Cognitive	16.9%	17.8%
Employed: Routine Manual	18.7%	15.8%
Employed: Non-Routine Manual	8.2%	9.1%
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	0.5%	0.3%
Not in the labor force	33.0%	29.9%

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

Table 2: Descriptive Statistics [To be updated – Numbers in this table currently based on a 10% random sub-sample]

	1976-1989					
	Full	ENRC	ERC	ERM	ENRM	NLF
Average age	40.01	39.35	36.44	36.59	35.23	46.69
Fractions within the occupation group						
HS dropouts	0.281	0.050	0.104	0.326	0.387	0.430
HS graduates	0.557	0.435	0.749	0.635	0.569	0.484
College graduates	0.162	0.516	0.148	0.039	0.044	0.086
Male	0.479	0.606	0.315	0.820	0.363	0.301
Non-White	0.135	0.091	0.104	0.135	0.202	0.147
Married	0.634	0.721	0.617	0.683	0.495	0.623
Total number of observations (millions)						
Unweighted	1.771	0.320	0.291	0.318	0.145	0.573
Weighted	2,730	497	453	499	220	880

	1990-2012					
	Full	ENRC	ERC	ERM	ENRM	NLF
Average age	41.59	41.76	39.01	39.03	36.57	46.89
Fractions within the occupation group						
HS dropouts	0.183	0.020	0.076	0.213	0.258	0.316
HS graduates	0.580	0.389	0.719	0.727	0.665	0.540
College graduates	0.237	0.590	0.204	0.061	0.076	0.144
Male	0.487	0.520	0.351	0.836	0.384	0.371
Non-White	0.174	0.145	0.156	0.157	0.220	0.193
Married	0.581	0.680	0.574	0.621	0.470	0.544
Total number of observations (millions)						
Unweighted	2.669	0.619	0.470	0.407	0.241	0.785
Weighted	5,550	1,270	972	858	503	1,640

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'.

Table 3: List of individual business cycle phases

Recessions:	Recoveries:	Expansions:
	1976m1-1977m3 (V1)	1977m4-1979m12 (E1)
1980m1-1980m7 (R1)	1980m8-1981m6 (V2)	
1981m7-1982m11 (R2)	1982m12-1984m11 (V3)	1984m12-1990m6 (E2)
1990m7-1991m3 (R3)	1991m4-1993m3 (V4)	1993m4-1993m12 (E3)
		1994m1-2001m2 (E4)
2001m3-2001m11 (R4)	2001m12-2003m11 (V5)	2003m12-2007m11 (E5)
2007m12-2009m6 (R5)	2009m7-2011m6 (V6)	2011m7-2012m12 (E6)

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

Table 4: Oaxaca Decomposition: $URM \rightarrow ERM$

Panel A: Recovery Periods

	1982m12-1984m11	1991m4-1993m3	2001m12-2003m11	2009m7-2011m6
	Baseline (1976m1-1977m3): 21.17%			
Difference:	$-2.82\%^{**}$	$-1.41\%^{**}$	-0.740%	$-7.39\%^{**}$
	(0.403)	*(0.43)*	*(0.478)*	*(0.403)*
Composition	$+0.364\%^{*}$	$+0.320\%$	-0.052%	$+0.125\%$
	(0.174)	*(0.236)*	*(0.276)*	*(0.331)*
male	$+0.157\%^{**}$	$+0.413\%^{**}$	$+0.260\%^{**}$	$+0.721\%^{**}$
	(0.046)	*(0.058)*	*(0.055)*	*(0.079)*
age	$+0.277\%^{**}$	$+0.402\%^{**}$	$+0.291\%^{*}$	$+0.164\%$
	(0.105)	*(0.150)*	*(0.155)*	*(0.198)*
Propensities	$-3.18\%^{**}$	$-1.73\%^{**}$	-0.688%	$-7.52\%^{**}$
	(0.431)	*(0.484)*	*(0.539)*	*(0.511)*
male	$-1.96\%^{**}$	$+0.272\%$	$+0.957\%$	-0.436%
	(0.689)	*(0.769)*	*(0.822)*	*(0.742)*
age	$+0.565\%$	$+1.35\%$	$+0.821\%$	$+1.81\%^{*}$
	(1.09)	*(1.13)*	*(1.11)*	*(0.885)*
constant	$+0.088\%$	$-4.66\%^{*}$	$+0.953\%$	$-8.50\%^{**}$
	(1.86)	*(1.96)*	*(2.10)*	*(1.76)*

Panel B: Expansion Periods

	1984m12-1990m6	1994m1-2001m2	2003m12-2007m11	2011m7-2012m12
	Baseline (1977m4-1979m12): 24.33%			
Difference:	$-2.22\%^{**}$	$-0.991\%^{**}$	$-2.24\%^{**}$	$-10.24\%^{**}$
	(0.333)	*(0.349)*	*(0.393)*	*(0.426)*
Composition	$+0.608\%^{**}$	$+0.027\%$	$+0.244\%$	$+0.542\%$
	(0.156)	*(0.195)*	*(0.225)*	*(0.282)*
male	$+0.531\%^{**}$	$+0.609\%^{**}$	$+0.906\%^{**}$	$+1.23\%^{**}$
	(0.056)	*(0.059)*	*(0.072)*	*(0.089)*
age	$+0.197\%^{*}$	$+0.231\%^{*}$	$+0.022\%$	-0.276%
	(0.099)	*(0.113)*	*(0.132)*	*(0.177)*
Propensities	$-2.83\%^{**}$	$-1.02\%^{**}$	$-2.48\%^{**}$	$-10.78\%^{**}$
	(0.359)	*(0.388)*	*(0.440)*	*(0.499)*
male	$-1.85\%^{**}$	-0.947%	$+0.793\%$	$-3.14\%^{**}$
	(0.527)	*(0.557)*	*(0.650)*	*(0.745)*
age	-0.888%	-1.27%	-1.36%	-0.306%
	(0.940)	*(0.925)*	*(0.923)*	*(0.937)*
constant	$+1.82\%$	$+1.09\%$	-1.59%	$-7.37\%^{**}$
	(1.67)	*(1.69)*	*(1.83)*	*(2.04)*

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

Table 5: Oaxaca Decomposition: $URC \rightarrow ERC$

Panel A: Recovery Periods

	1991m4-1993m3	2001m12-2003m11	2009m7-2011m6
	Baseline (1982m12-1984m11): 13.56%		
Difference:	$-0.775\%^{*}$	-0.475%	$-6.02\%^{**}$
	(0.406)	*(0.425)*	*(0.348)*
Composition	-0.198%	$-0.466\%^{**}$	$-0.836\%^{**}$
	(0.106)	*(0.134)*	*(0.189)*
male	$-0.100\%^{**}$	$-0.247\%^{**}$	$-0.370\%^{**}$
	(0.032)	*(0.051)*	*(0.068)*
age	-0.076%	0.000%	$-0.542\%^{**}$
	(0.049)	*(0.062)*	*(0.119)*
Propensities	-0.577%	-0.008%	$-5.18\%^{**}$
	(0.408)	*(0.432)*	*(0.378)*
male	-0.032%	-0.108%	$+0.889\%^{**}$
	(0.255)	*(0.299)*	*(0.273)*
non-white	$+0.152\%$	$+0.657^{*}\%$	$+1.19\%^{**}$
	(0.216)	*(0.262)*	*(0.212)*
constant	$-3.75\%^{*}$	$+2.38\%$	$-7.02\%^{**}$
	(1.77)	*(1.97)*	*(1.53)*

Panel B: Expansion Periods

	1994m1-2001m2	2003m12-2007m11	2011m7-2012m12
	Baseline (1984m12-1990m6): 16.78%		
Difference:	$+0.362\%$	$-2.57\%^{**}$	$-7.75\%^{**}$
	(0.309)	*(0.332)*	*(0.354)*
Composition	$-0.474\%^{**}$	$-0.550\%^{**}$	$-0.496\%^{**}$
	(0.079)	*(0.111)*	*(0.182)*
male	$-0.103\%^{**}$	$-0.359\%^{**}$	$-0.416\%^{**}$
	(0.028)	*(0.045)*	*(0.054)*
age	$+0.093\%^{*}$	-0.074%	$-0.455\%^{**}$
	(0.038)	*(0.060)*	*(0.105)*
Propensities	$+0.837\%^{**}$	$-2.02\%^{**}$	$-7.25\%^{**}$
	(0.308)	*(0.339)*	*(0.388)*
male	$+0.078\%$	$+0.419\%^{*}$	$+1.23\%^{**}$
	(0.192)	*(0.202)*	*(0.260)*
non-white	$+0.540\%^{**}$	$+0.946^{**}\%$	$+1.41\%^{**}$
	(0.189)	*(0.202)*	*(0.223)*
constant	-1.16%	$-5.64\%^{**}$	$-11.1\%^{**}$
	(1.39)	*(1.48)*	*(1.69)*

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

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

Panel A: Recovery Periods

	1982m12- 1984m11	1991m4- 1993m3	2001m12- 2003m11	2009m7- 2011m6
		Baseline (1976m1-1977m3): 1.03%		
Difference:	-0.008%	-0.021%	$+0.093\%^{**}$	$-0.198\%^{**}$
	(0.024)	*(0.025)*	*(0.026)*	*(0.024)*
Composition	$+0.062\%^{**}$	$+0.101\%^{**}$	$+0.232\%^{**}$	$+0.298\%^{**}$
	(0.009)	*(0.011)*	*(0.015)*	*(0.017)*
male	$+0.091\%^{**}$	$+0.175\%^{**}$	$+0.252\%^{**}$	$+0.312\%^{**}$
	(0.005)	*(0.007)*	*(0.008)*	*(0.009)*
age	$-0.071\%^{**}$	$-0.099\%^{**}$	$-0.041\%^{**}$	$-0.025\%^{**}$
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*
Propensities	$-0.070\%^{**}$	$-0.122\%^{**}$	$-0.139\%^{**}$	$-0.497\%^{**}$
	(0.026)	*(0.028)*	*(0.032)*	*(0.032)*
male	$-0.086\%^{**}$	$-0.160\%^{**}$	$-0.136\%^{**}$	$-0.370\%^{**}$
	(0.024)	*(0.026)*	*(0.029)*	*(0.029)*
age	-0.070%	-0.122%	$-0.175\%^{**}$	$-0.229\%^{**}$
	(0.062)	*(0.068)*	*(0.068)*	*(0.062)*
constant	$+0.123\%$	$+0.267\%^{*}$	$+0.268\%^{*}$	$+0.156\%$
	(0.100)	*(0.108)*	*(0.110)*	*(0.101)*

Panel B: Expansion Periods

	1984m12- 1990m6	1994m1- 2001m2	2003m12- 2007m11	2011m7- 2012m12
		Baseline (1977m4-1979m12): 1.22%		
Difference:	$-0.097\%^{**}$	$-0.061\%^{**}$	$-0.146\%^{**}$	$-0.454\%^{**}$
	(0.018)	*(0.018)*	*(0.019)*	*(0.022)*
Composition	$+0.019\%^{**}$	$+0.114\%^{**}$	$+0.232\%^{**}$	$+0.256\%^{**}$
	(0.007)	*(0.009)*	*(0.011)*	*(0.013)*
male	$+0.140\%^{**}$	$+0.246\%^{**}$	$+0.291\%^{**}$	$+0.343\%^{**}$
	(0.004)	*(0.005)*	*(0.006)*	*(0.008)*
age	$-0.090\%^{**}$	$-0.060\%^{**}$	$+0.004\%$	-0.000%
	(0.003)	*(0.003)*	*(0.003)*	*(0.004)*
Propensities	$-0.116\%^{**}$	$-0.175\%^{**}$	$-0.378\%^{**}$	$-0.710\%^{**}$
	(0.018)	*(0.020)*	*(0.023)*	*(0.026)*
male	$-0.181\%^{**}$	$-0.239\%^{**}$	$-0.305\%^{**}$	$-0.564\%^{**}$
	(0.018)	*(0.019)*	*(0.021)*	*(0.025)*
age	$-0.141\%^{**}$	$-0.099\%^{*}$	$-0.274\%^{**}$	$-0.217\%^{**}$
	(0.048)	*(0.046)*	*(0.050)*	*(0.061)*
constant	$+0.224\%^{**}$	$+0.209\%^{**}$	$+0.246\%^{**}$	$+0.041\%$
	(0.080)	*(0.079)*	*(0.087)*	*(0.110)*

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

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

Panel A: Recovery Periods

	1991m4-1993m3	2001m12-2003m11	2009m7-2011m6
	Baseline (1982m12-1984m11): 1.44%		
Difference:	$+0.044\%$	$+0.249\%^{**}$	$-0.170\%^{**}$
	(0.028)	*(0.030)*	*(0.026)*
Composition	-0.013%	$+0.114\%^{**}$	$+0.148\%^{**}$
	(0.007)	*(0.009)*	*(0.012)*
education	$+0.057\%^{**}$	$+0.118\%^{**}$	$+0.158\%^{**}$
	(0.003)	*(0.006)*	*(0.007)*
age	$-0.027\%^{**}$	$+0.055\%^{**}$	$+0.081\%^{**}$
	(0.004)	*(0.005)*	*(0.005)*
Propensities	$+0.057\%^{*}$	$+0.134\%^{**}$	$-0.318\%^{**}$
	(0.028)	*(0.031)*	*(0.029)*
education	-0.037%	$-0.090\%^{**}$	$+0.002\%$
	(0.026)	*(0.029)*	*(0.025)*
age	$+0.051\%$	$+0.103\%$	-0.061%
	(0.085)	*(0.083)*	*(0.075)*
constant	$+0.121\%$	$+0.351\%^{*}$	$-0.312\%^{**}$
	(0.130)	*(0.138)*	*(0.121)*

Panel B: Expansion Periods

	1994m1-2001m2	2003m12-2007m11	2011m7-2012m12
	Baseline (1984m12-1990m6): 1.62%		
Difference:	$+0.058\%^{**}$	$+0.063\%^{**}$	$-0.367\%^{**}$
	(0.018)	*(0.020)*	*(0.025)*
Composition	$+0.061\%^{**}$	$+0.200\%^{**}$	$+0.238\%^{**}$
	(0.005)	*(0.007)*	*(0.010)*
education	$+0.064\%^{**}$	$+0.115\%^{**}$	$+0.159\%^{**}$
	(0.002)	*(0.004)*	*(0.005)*
age	$+0.049\%^{**}$	$+0.133\%^{**}$	$+0.140\%^{**}$
	(0.003)	*(0.004)*	*(0.005)*
Propensities	-0.004%	$-0.137\%^{**}$	$-0.605\%^{**}$
	(0.02)	*(0.022)*	*(0.027)*
education	$-0.076\%^{**}$	$-0.098\%^{**}$	-0.042%
	(0.017)	*(0.019)*	*(0.023)*
age	$+0.175\%^{**}$	$+0.115\%^{*}$	$+0.067\%$
	(0.052)	*(0.056)*	*(0.069)*
constant	-0.114%	$-0.211\%^{*}$	$-0.731\%^{**}$
	(0.081)	*(0.093)*	*(0.124)*

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

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

Panel A: Recovery Periods

	1982m12- 1984m11	1991m4- 1993m3	2001m12- 2003m11	2009m7- 2011m6
		Baseline (1976m1-1977m3): 2.26%		
Difference:	−0.136%**	−0.169%**	+0.267%**	+0.154%**
	(0.049)	*(0.050)*	*(0.054)*	*(0.055)*
Composition	+0.015%	−0.129%**	−0.115%**	−0.116%**
	(0.021)	*(0.027)*	*(0.032)*	*(0.038)*
education	−0.102%**	−0.162%**	−0.180%**	−0.207%**
	(0.010)	*(0.015)*	*(0.017)*	*(0.022)*
age	−0.082%**	−0.231%**	−0.217%**	−0.182%**
	(0.010)	*(0.014)*	*(0.016)*	*(0.020)*
Propensities	−0.151%**	−0.041%	+0.382%**	+0.270%**
	(0.051)	*(0.053)*	*(0.060)*	*(0.064)*
male	+0.330%*	+0.602%**	+0.684%**	+1.02%**
	(0.132)	*(0.134)*	*(0.148)*	*(0.153)*
married	+0.442%**	+0.704%**	+0.538%**	+0.641%**
	(0.091)	*(0.087)*	*(0.086)*	*(0.085)*
constant	−0.723%**	−1.15%**	−0.762%**	−1.31%**
	(0.228)	*(0.232)*	*(0.246)*	*(0.250)*

Panel B: Expansion Periods

	1984m12- 1990m6	1994m1- 2001m2	2003m12- 2007m11	2011m7- 2012m12
		Baseline (1977m4-1979m12): 2.34%		
Difference:	−0.102%**	+0.004%	+0.144%**	+0.154%**
	(0.032)	*(0.032)*	*(0.038)*	*(0.055)*
Composition	−0.236%**	−0.322%**	−0.301%**	−0.124%**
	(0.014)	*(0.018)*	*(0.020)*	*(0.027)*
education	−0.095%**	−0.145%**	−0.147%**	−0.169%**
	(0.006)	*(0.009)*	*(0.011)*	*(0.014)*
age	−0.194%**	−0.275%**	−0.249%**	−0.155%**
	(0.008)	*(0.010)*	*(0.011)*	*(0.017)*
Propensities	+0.134%**	+0.326%**	+0.445%**	+0.278%**
	(0.032)	*(0.033)*	*(0.039)*	*(0.059)*
male	+0.451%**	+0.615%**	+0.487%**	+0.701%**
	(0.086)	*(0.085)*	*(0.104)*	*(0.152)*
married	+0.422%**	+0.429%**	+0.421%**	+0.337%**
	(0.054)	*(0.050)*	*(0.055)*	*(0.075)*
constant	−0.864%**	−0.951%**	−0.624%**	−0.527%
	(0.165)	*(0.164)*	*(0.187)*	*(0.298)*

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

Table 9: Oaxaca Decomposition: $ERC \rightarrow NLF$

Panel A: Recovery Periods

	1991m4-1993m3	2001m12-2003m11	2009m7-2011m6
	Baseline (1982m12-1984m11): 2.98%		
Difference:	$-0.252\%^{**}$	$+0.043\%$	$-0.146\%^{**}$
	(0.051)	*(0.054)*	*(0.054)*
Composition	$-0.150\%^{**}$	$-0.166\%^{**}$	$-0.191\%^{**}$
	(0.014)	*(0.017)*	*(0.024)*
male	$+0.002\%$	$-0.029\%^{**}$	$-0.055\%^{**}$
	(0.004)	*(0.005)*	*(0.005)*
education	$-0.055\%^{**}$	$-0.045\%^{**}$	$-0.098\%^{**}$
	(0.005)	*(0.007)*	*(0.010)*
Propensities	$-0.102\%^{*}$	$+0.209\%^{**}$	$+0.045\%$
	(0.050)	*(0.053)*	*(0.056)*
male	$+0.157\%^{**}$	$+0.192\%^{**}$	$+0.305\%^{**}$
	(0.034)	*(0.038)*	*(0.040)*
age	$+0.252\%^{**}$	$+0.338\%^{**}$	$+0.219\%^{*}$
	(0.096)	*(0.091)*	*(0.091)*
constant	-0.359%	-0.266%	-0.312%
	(0.200)	*(0.205)*	*(0.204)*

Panel B: Expansion Periods

	1994m1-2001m2	2003m12-2007m11	2011m7-2012m12
	Baseline (1984m12-1990m6): 2.96%		
Difference:	$+0.030\%$	$+0.141\%^{**}$	-0.019%
	(0.029)	*(0.036)*	*(0.053)*
Composition	$-0.117\%^{**}$	$-0.076\%^{**}$	$-0.044\%^{*}$
	(0.009)	*(0.012)*	*(0.019)*
male	$-0.011\%^{**}$	$-0.047\%^{**}$	$-0.071\%^{**}$
	(0.002)	*(0.003)*	*(0.005)*
education	$-0.023\%^{**}$	$-0.034\%^{**}$	$-0.088\%^{**}$
	(0.003)	*(0.004)*	*(0.006)*
Propensities	$+0.147\%^{**}$	$+0.216\%^{**}$	$+0.025\%$
	(0.029)	*(0.036)*	*(0.054)*
male	$+0.121\%^{**}$	$+0.195\%^{**}$	$+0.305\%^{**}$
	(0.021)	*(0.026)*	*(0.040)*
age	$+0.195\%^{**}$	$+0.287\%^{**}$	$+0.212\%^{**}$
	(0.052)	*(0.057)*	*(0.082)*
constant	-0.051%	-0.017%	$-0.521\%^{*}$
	(0.112)	*(0.136)*	*(0.210)*

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