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THE TREND IS THE CYCLE:
JOB POLARIZATION AND JOBLESS RECOVERIES

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Working Paper 18334
<http://www.nber.org/papers/w18334>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2012

We thank Mark Aguiar, Susanto Basu, Paul Beaudry, Larry Christiano, Matias Cortes, Marcelo Veracierto, as well as numerous conference and seminar participants for helpful discussions. Domenico Ferraro provided expert research assistance. Siu thanks the Social Sciences and Humanities Research Council of Canada for support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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The Trend is the Cycle: Job Polarization and Jobless Recoveries
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NBER Working Paper No. 18334
August 2012
JEL No. E0,J0

ABSTRACT

Job polarization refers to the recent disappearance of employment in occupations in the middle of the skill distribution. Jobless recoveries refers to the slow rebound in aggregate employment following recent recessions, despite recoveries in aggregate output. We show how these two phenomena are related. First, job polarization is not a gradual process; essentially all of the job loss in middle-skill occupations occurs in economic downturns. Second, jobless recoveries in the aggregate are accounted for by jobless recoveries in the middle-skill occupations that are disappearing.

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1 Introduction

In the past 30 years, the US labor market has seen the emergence of two new phenomena: “job polarization” and “jobless recoveries.” Job polarization refers to the increasing concentration of employment in the highest- and lowest-wage occupations, as job opportunities in middle-skill occupations disappear. Jobless recoveries refer to periods following recessions in which rebounds in aggregate output are accompanied by much slower recoveries in aggregate employment. We argue that these two phenomena are related.

Consider first the phenomenon of job polarization. [Acemoglu \(1999\)](#), [Autor et al. \(2006\)](#), [Goos and Manning \(2007\)](#), and [Goos et al. \(2009\)](#) (among others) document that, since the 1980s, employment is becoming increasingly concentrated at the tails of the occupational skill distribution. This hollowing out of the middle has been linked to the disappearance of jobs focused on “routine” tasks – those activities that can be performed by following a well-defined set of procedures. [Autor et al. \(2003\)](#) and the subsequent literature demonstrates that job polarization is due to progress in technologies that substitute for labor in routine tasks.¹

In this same time period, [Gordon and Baily \(1993\)](#), [Groshen and Potter \(2003\)](#), [Bernanke \(2003\)](#), and [Bernanke \(2009\)](#) (among others) discuss the emergence of jobless recoveries. In the past three recessions, aggregate employment continues to decline for years following the turning point in aggregate income and output. No consensus has yet emerged regarding the source of these jobless recoveries.

In this paper, we demonstrate that the two phenomena are connected to each other. We make two related claims. First, job polarization is not simply a gradual phenomenon: the loss of middle-skill, routine jobs is concentrated in economic downturns. Specifically, 92% of the job loss in these occupations since the mid-1980s occurs within a 12 month window of NBER dated recessions (that have all been characterized by jobless recoveries). In this sense, the job polarization “trend” is a business “cycle” phenomenon. This contrasts to the existing literature, in which job polarization is oftentimes depicted as a gradual phenomenon, though a number of researchers have noted that this process has been accelerated by the Great Recession (see [Autor \(2010\)](#); and [Brynjolfsson and McAfee \(2011\)](#)). Our first point is that routine employment loss happens almost entirely in recessions.

Our second point is that job polarization accounts for jobless recoveries. This argument is based on three facts. First, employment in the routine occupations identified by [Autor et al. \(2003\)](#) and others account for a significant fraction of aggregate employment; averaged over the jobless recovery era, these jobs account for more than 50% of total employment. Second, essentially all of the contraction in aggregate employment during NBER dated recessions can

¹See also [Firpo et al. \(2011\)](#), [Goos et al. \(2011\)](#), and the references therein regarding the role of outsourcing and offshoring in job polarization.

be attributed to recessions in these middle-skill, routine occupations. Third, jobless recoveries are observed only in these disappearing, middle-skill jobs. The high- and low-skill occupations to which employment is polarizing either do not experience contractions, or if they do, rebound soon after the turning point in aggregate output. Hence, jobless recoveries can be traced to the disappearance of routine occupations in recessions. Finally, it is important to note that jobless recoveries were not observed in routine occupations (nor in aggregate employment) prior to the era of job polarization.

In Section 2, we present data on employment to document our two principal findings. In Section 3, we present a search-and-matching model of the labor market in which “routine-biased technological change” is a trend phenomenon. Nonetheless, job polarization is concentrated in downturns, and recoveries from these events are jobless. Section 4 concludes.

2 Labor Market Data

2.1 Jobless Recoveries

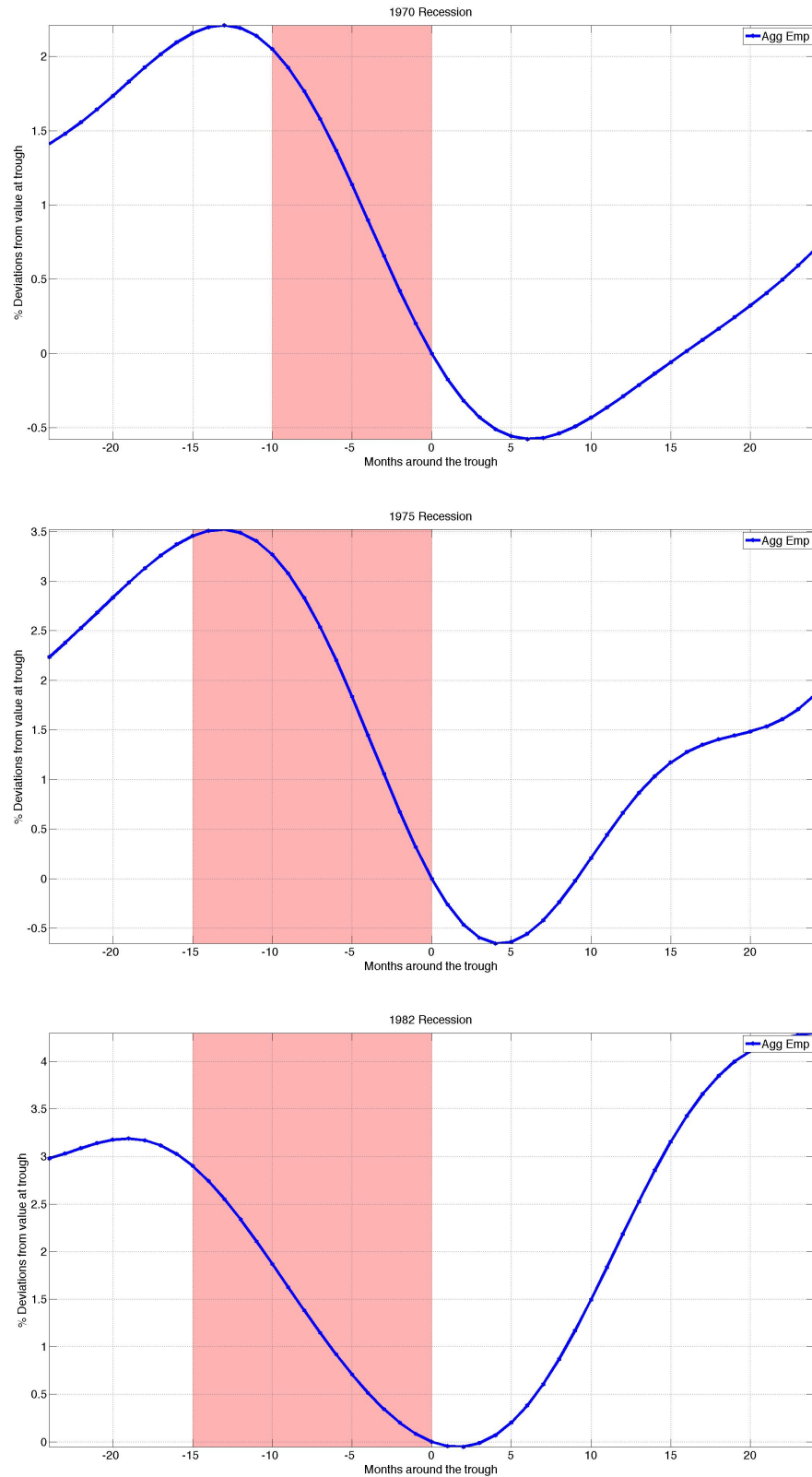
Figures 1 and 2 plot the cyclical behavior of aggregate per capita employment in the US during the past six recessions and subsequent recoveries.² Aggregate per capita employment is that of all civilian non-institutionalized individuals aged 16 years and over (seasonally adjusted), normalized by the population.³ Because the monthly employment data are “noisy,” the data are logged and band pass filtered to remove fluctuations at frequencies higher than 18 months (business cycle fluctuations are traditionally defined as those between frequencies of 18 and 96 months). On the x -axis of each figure, the trough of the recession, as identified by the NBER, is indicated as date 0; we plot data for two years around the trough date. The shaded regions indicate the NBER peak-to-trough periods. Employment is normalized to zero at the trough of each recession. Hence, the y -axis measures the percent change in employment relative to its value in the trough.

Figure 1 displays the 1970, 1975, and 1982 recessions. In each case, aggregate employment begins to expand within six months of the trough. The fact that employment recovers within two quarters of the recovery in aggregate output and income is typical of the business cycle prior

²The 1980 recession is omitted since it is followed by a recession in 1982, limiting our ability to study its recovery. Throughout the paper, recessions are addressed by their trough year, e.g., the recession that began in December 2007 and ended in June 2009 is referred to as the 2009 recession.

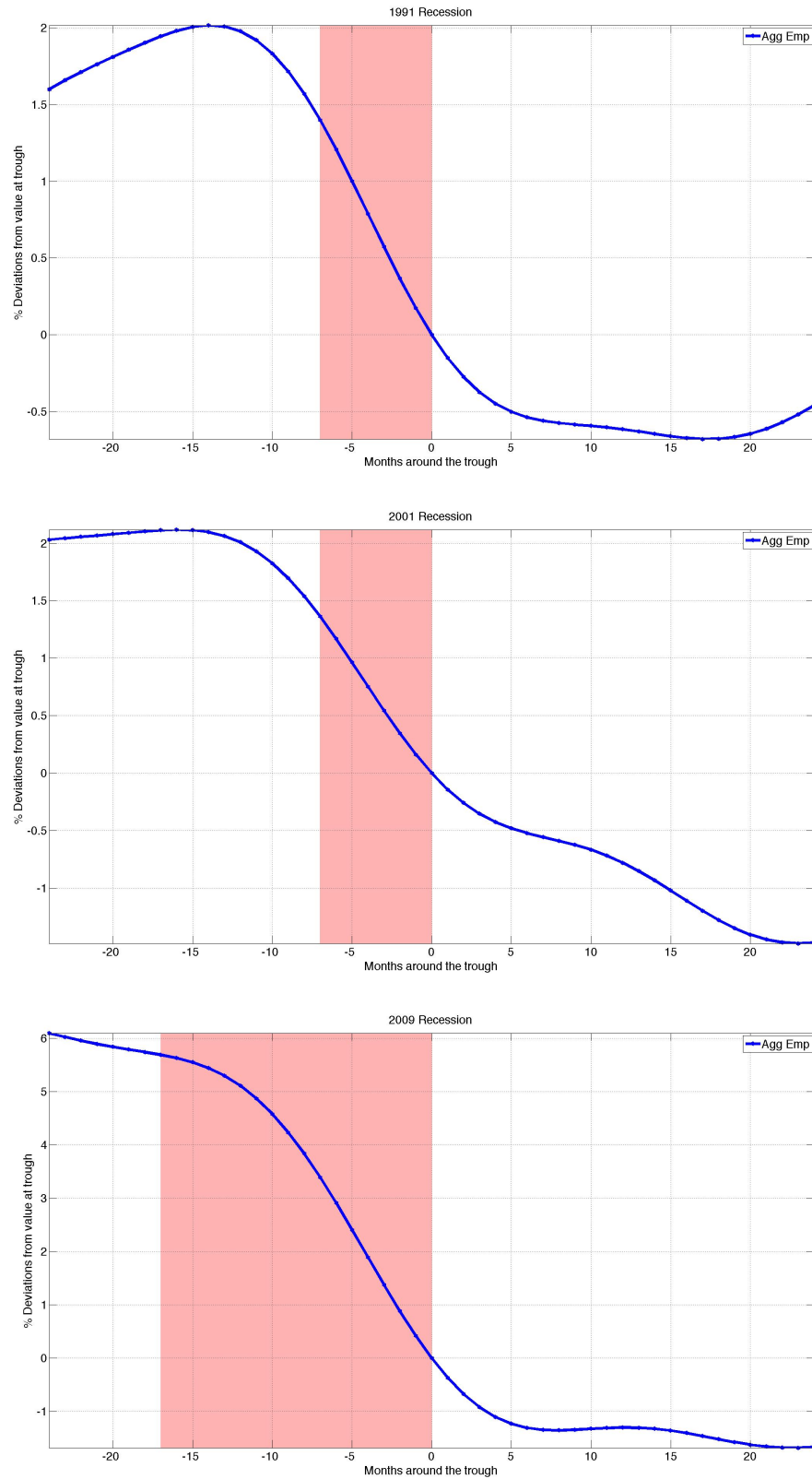
³Data are taken from the Labor Force Statistics of the CPS, downloaded from the BLS website (<http://www.bls.gov/data/>) on February 2, 2012. See Appendix A for detailed description of all data sources. Employment data at the aggregate and occupational level are available dating back to 1959. However, there are well-documented issues with the early CPS data, especially during the 1961 recession; see, for instance, the 1962 report of the President’s Committee to Appraise Employment and Unemployment Statistics entitled “Measuring Employment and Unemployment.” The recommendations of this report (commonly referred to as the Gordon report) led to methodological changes adopted by the BLS beginning in 1967 (see Stein (1967)). As such, our analysis uses data beginning in July 1967.

Figure 1: Aggregate Employment around Early NBER Recessions



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details.

Figure 2: Aggregate Employment around Recent NBER Recessions



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details.

Table 1: Measures of Recovery following Early and Recent Recessions

	<i>Early</i>			<i>Recent</i>		
	1970	1975	1982	1991	2001	2009
<i>A. Employment</i>						
months to turn around	6	4	2	18	23	23
months to trough level	16	10	4	31	55	NA
half-life (in months)	27	23	10	38	NA	NA
<i>B. Output</i>						
months to turn around	0	0	0	0	0	0
months to trough level	0	0	0	0	0	0
half-life (in months)	7	10	5	9	3	15

Notes: Data from the Bureau of Labor Statistics, Current Population Survey; Bureau of Economic Analysis, National Income and Product Accounts; and James Stock and Mark Watson. See Appendix A for details.

to the mid-1980s (see for instance, [Schreft and Singh \(2003\)](#); [Groshen and Potter \(2003\)](#)).

This contrasts sharply from the 1991, 2001, and 2009 recessions. As is obvious in Figure 2, these recoveries were jobless: despite expansions in other measures of economic activity (such as RGDP and real gross domestic income) following the trough, aggregate per capita employment continued to contract for many months. In 1991, employment continues to fall for 18 months past the trough before turning around; employment does not reach its pre-recession level until five years later, in 1996. In 2001, employment falls for 23 months past the trough before turning around; it does not return to its pre-recession level before the subsequent recession. Following the Great Recession of 2009, employment again takes 23 months to begin recovery. Hence, the jobless recovery is a phenomenon characterizing recent recessions (see also [Groshen and Potter \(2003\)](#) and [Bernanke \(2003\)](#)).

Table 1 summarizes these differences, presenting several measures of the speed of recovery following early and recent recessions. Panel A concerns the recoveries in aggregate per capita employment. The first row lists the number of months it takes for employment to turn around, relative to the NBER trough date. The second row indicates the number of months it takes following the trough date for employment to return to its level at the trough. The third row lists a “half-life” measure: the number of months it takes from the trough date to regain half of the employment lost during the NBER-defined recession.

As is obvious, there has been a marked change in the speed of employment recoveries. Averaged over the three early recessions, employment turns around four months after the NBER trough date; in the recent recessions, the average turnaround time is 21 months. Averaged over

the early recessions, employment returns to its trough level within 10 months. In the 1991 and 2001 recessions, this takes 31 and 55 months, respectively; employment has yet to return to the trough level since the end of the 2009 recession. Finally, while it takes *at most* 27 months from the trough date to regain half of the employment lost in the three early recessions, it takes *at least* 38 months in the recent recessions; indeed, employment never regained half of its loss following the 2001 recession, and has yet to do so after the Great Recession.

This contrasts with the nature of recoveries in aggregate output. Panel B presents the same recovery measures for per capita RGDP; to obtain monthly measures, we use the monthly data of Stock and Watson (see Appendix A for details). Given the NBER Dating Committee’s emphasis on RGDP and real gross domestic income in determining cyclical turning points, it is perhaps not surprising that aggregate output begins recovery on the NBER trough dates;⁴ this is true for both the early and recent recessions, as indicated by the first two rows of Panel B. In the early recessions, it takes on average seven months from the trough date for output to regain half of its recessionary loss; in the recent recessions, the average time taken is nine months, only slightly greater.⁵ Hence, there has been no marked change in the speed of recovery for aggregate output across early and recent recessions. The differences in the speed of recovery in employment following recent recessions – without corresponding differences in the recovery speed of output – characterize the jobless recovery phenomenon.

2.2 Job Polarization

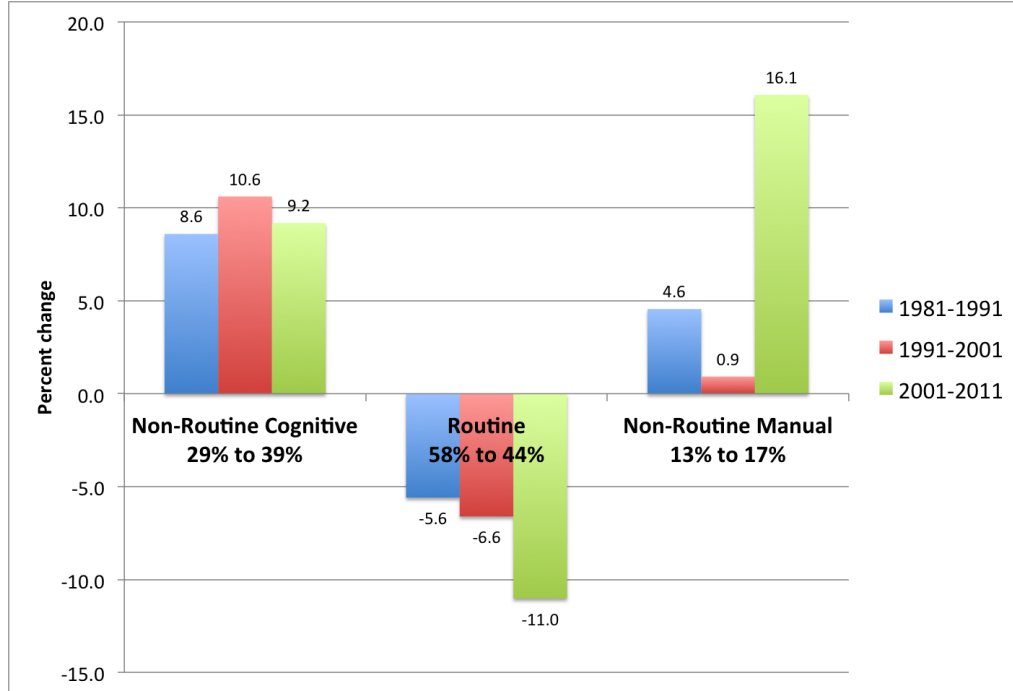
The structure of employment has changed dramatically over the past 30 years. One of the most pervasive aspects of change has been within the skill distribution: employment has become polarized, with employment shifting away from middle-skill occupations towards both the high- and low-skill tails of the distribution (see, for instance, [Acemoglu and Autor \(2011\)](#), and the references therein).

To see this, we disaggregate total employment by occupational groups. Following [Acemoglu and Autor \(2011\)](#), we delineate occupations along two dimensions: “cognitive” versus “manual”, and “routine” versus “non-routine”. These delineations are based on the skill content of the tasks performed in the occupation. The distinction between cognitive and manual jobs is straightforward, characterized by differences in the extent of mental versus physical activity. The distinction between routine and non-routine jobs is based on the work of [Autor et al. \(2003\)](#). If the tasks involved can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures, the occupation is considered routine. If instead the

⁴See http://www.nber.org/cycles/recessions_fa.html.

⁵Because the monthly RGDP estimates of Stock and Watson are “noisy,” the data are band pass filtered to remove fluctuations at frequencies higher than 18 months (as with the employment data) in producing the half-life statistics.

Figure 3: Percent Change in Employment Shares by Occupation Group



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details.

job requires flexibility, creativity, problem-solving, or human interaction skills, the occupation is non-routine.

In this delineation, non-routine cognitive occupations include managerial, professional and technical workers, such as physicians, public relations managers, financial analysts, computer programmers, and economists. Routine cognitive occupations are those in sales, and office and administrative support; examples include secretaries, bank tellers, retail salespeople, travel agents, mail clerks, and data entry keyers. Routine manual occupations are “blue collar” jobs, such as machine operators and tenders, mechanics, dressmakers, fabricators and assemblers, cement masons, and meat processing workers. Non-routine manual occupations are service jobs, including janitors, gardeners, manicurists, bartenders, and home health aides.⁶

These classifications, not surprisingly, correspond to rankings in the occupational income distribution. Non-routine cognitive occupations tend to be high-skill occupations and non-routine manual occupations low-skilled. Routine occupations – both cognitive and manual – tend to be middle-skill occupations (see, for instance, Autor (2010); and Firpo et al. (2011)). Given this, we combine the routine cognitive and routine manual occupations into one group.⁷

⁶Our matching of occupations to occupational groups follows the approach of Acemoglu and Autor (2011); see that paper and Cortes (2011) for further discussion. See Appendix A for details.

⁷For brevity, the analogs of all of our figures with the routine occupations split into two groups can be found in an earlier version of this paper, available at <http://faculty.arts.ubc.ca/hsiu/research/polar20120331.pdf>. None

Figure 3 displays data relating to job polarization. We present data by decade, as is common in the literature (see, for instance, Autor (2010)). Each bar represents the percent change in an occupation group’s share of total employment. Over time, the share of employment in high-skill (non-routine cognitive) and low-skill (non-routine manual) jobs has been growing. This has been accompanied by a hollowing out of the middle-skill, routine occupations. This process has accelerated in the past 10 years, as both routine cognitive and routine manual occupational groups have seen noticeable losses in employment share. Hence, there has been a polarization in employment away from routine, middle-skill jobs toward non-routine cognitive and manual jobs. In 1981, routine occupations accounted for 58% of total employment; in 2011, this share has fallen to 44%.

2.3 Occupational Employment: The Bigger Picture

In this subsection, we ask how the process of job polarization has unfolded over time. In particular, has it occurred gradually, or is polarization “bunched up” within certain time intervals? To investigate this, Figure 4 displays time series for per capita employment in the three occupational groups at a monthly frequency from July 1967 to December 2011.

As is obvious from the figure, both of the non-routine occupational groups are growing over time. Non-routine cognitive employment displays a 52 log point increase during this period. After declining from 1967 to 1972, non-routine manual employment displays a 26 log point increase. Recessions have temporarily halted these occupations’ growth to varying extents, but have not abated the trends.⁸

This stands in stark contrast to the routine occupational group. Relative to total population, routine employment has been falling. Employment has fallen 28 log points from the local peak in 1990 to present. Hence, job polarization does not simply represent a *relative* decline in routine employment due to the growth of the low- and high-skill tails; in *absolute* terms, per capita routine employment is disappearing.

What is equally clear in Figure 4 is that routine job loss has not occurred steadily during the past 30 years. The decline in routine occupations is concentrated in economic downturns. This occurred in essentially three steps. Following the peak in 1990, per capita employment in these occupations fell 3.5% to the trough of the 1991 recession, and a further 1.8% during the subsequent jobless recovery. After a minor rebound, employment was essentially flat until the 2001 recession. In the two year window around the 2001 trough, this group shed 6.3% of its employment, before leveling off again. Routine employment has plummeted again in the Great Recession – 12.0% in the two year window around the trough – with no subsequent recovery.

of our substantive results are altered when considering the routine cognitive and routine manual occupations separately.

⁸The obvious caveat being that it is too early to speak definitively following the most recent recession.

Figure 4: Employment in Occupational Groups: 1967 – 2011



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details.
NR COG = non-routine cognitive; NR MAN = non-routine manual; R = routine.

To state this slightly differently, 92% of the 28 log point fall in routine employment that occurred in this period occurred within a 12 month window of NBER recessions (six months prior to the peak and six months after the trough). Hence, this stark element of job polarization is observed during recessions; it is a business cycle phenomenon.

2.4 Occupational Employment: Business Cycle Snapshots

During the polarization period, per capita employment in routine occupations disappeared during recessions. Moreover, as Figure 4 makes clear, prior to job polarization, routine employment always recovered following recessions. In this subsection, we investigate whether job polarization has contributed to the jobless recoveries following the three most recent recessions. This is quantitatively plausible since routine occupations account for a large fraction of the total; as of 2011, routine jobs still account for 44% of aggregate employment.

To do this, we “zoom in” on recessionary episodes; Figures 5 and 6 plot per capita employment for the three occupational groups around NBER recessions. These figures are constructed in the same manner as Figures 1 and 2.

Figure 5 displays the earlier recessions of 1970, 1975, and 1982. Contractions in employment are clearly observed in the routine occupations. In the non-routine occupations, employment was either flat or growing through these recessions and recoveries.⁹ Hence, the contractions in aggregate employment displayed in Figure 1, are due almost exclusively to the routine occupations. Measuring from NBER peak to trough, 97% of all job loss in both the 1970 and 1975 recessions was accounted for by job loss in routine occupations; in the 1982 recession, job loss in routine occupations accounted for more than 100% of the aggregate, as employment was actually growing in the non-routine groups.

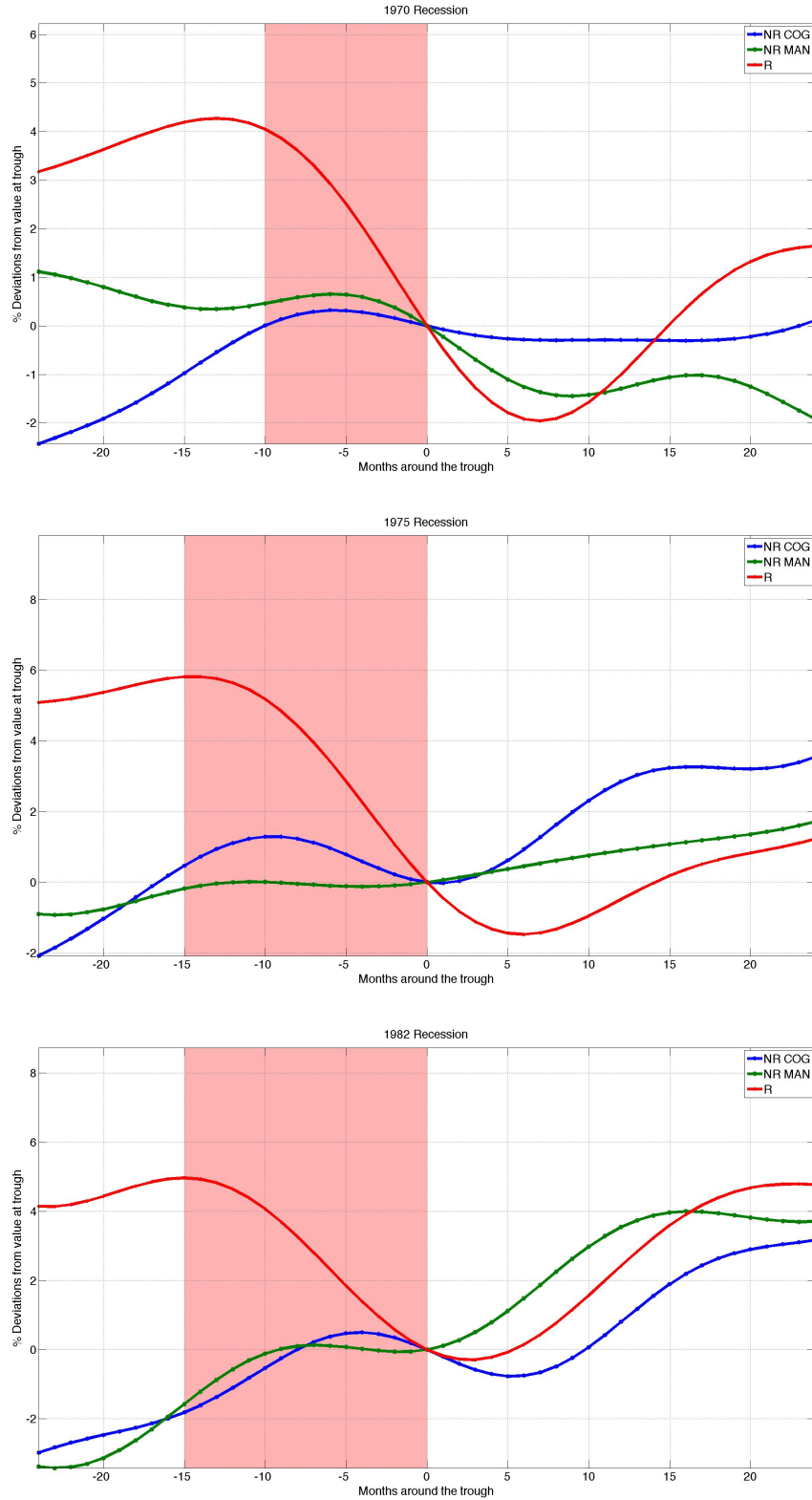
Moreover, no jobless recoveries were observed in the routine occupational group. Following these recessions, employment begins recovering within 7 months of the trough. This mirrors the lack of jobless recoveries at the aggregate level displayed in Figure 1.

This contrasts sharply with the three recent recessions. As is clear from Figure 6, jobless recoveries are not experienced in all occupations. Consider first the non-routine occupations, both cognitive and manual. No severe contractions are observed in the 1991, 2001, or 2009 recessions. Per capita employment in these occupations is either flat or display mild contractions. Employment in routine occupations experience clear contractions. As with the early recessions, these occupations account for the bulk of the contraction in aggregate employment. In 1991, 2001, and 2009, routine occupations account for 87%, 89%, and 93% of all job loss, respectively.

More importantly, routine occupations show no recoveries in Figure 6. In 1991, employment

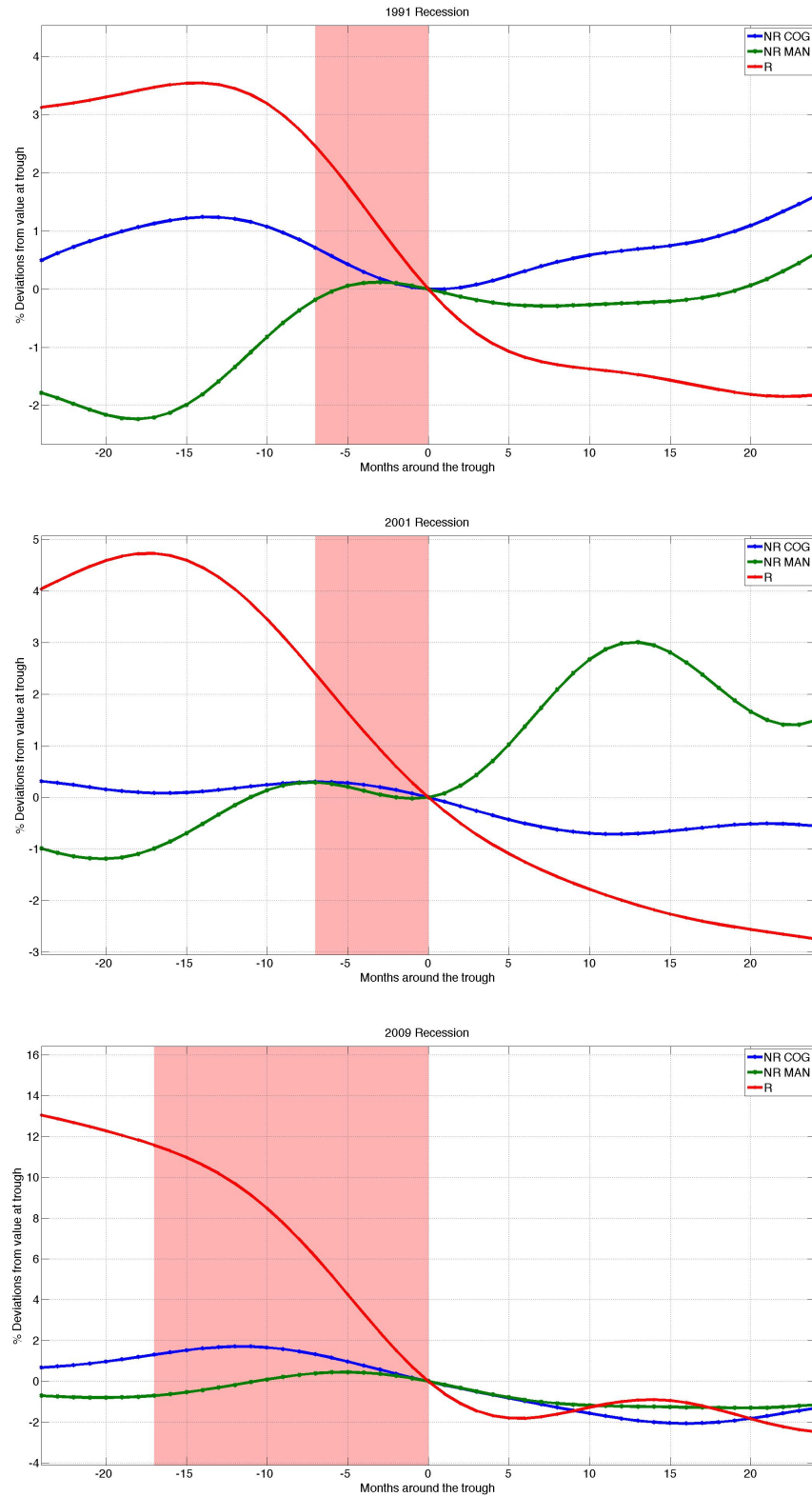
⁹An exception is employment in non-routine manual occupations in 1970. As is clear from Figure 4, this was a medium-run phenomenon, and not due to the recession.

Figure 5: Occupational Employment around Early NBER Recessions



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details. NR COG = non-routine cognitive; NR MAN = non-routine manual; R = routine.

Figure 6: Occupational Employment around Recent NBER Recessions



Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See Appendix A for details. NR COG = non-routine cognitive; NR MAN = non-routine manual; R = routine.

in routine occupations falls 3.5% in the 12 months leading up to the recession’s trough; employment falls a further 1.8% in the following 24 months. A similar picture emerges for the 2001 recession: large employment losses leading up to the trough are followed by further large losses afterward. In 2009, these occupations are hit especially hard, falling 11.8% from the NBER peak to trough. Routine employment shows no recovery to date, down a further 2.5% from the recession’s trough.

To summarize, jobless recoveries are evident in only the three most recent recessions and they are observed only in routine occupations. In this occupational group, employment never recovers – in the short-, medium- or long-term. These occupations are disappearing. In this sense, the jobless recovery phenomenon is due to job polarization.

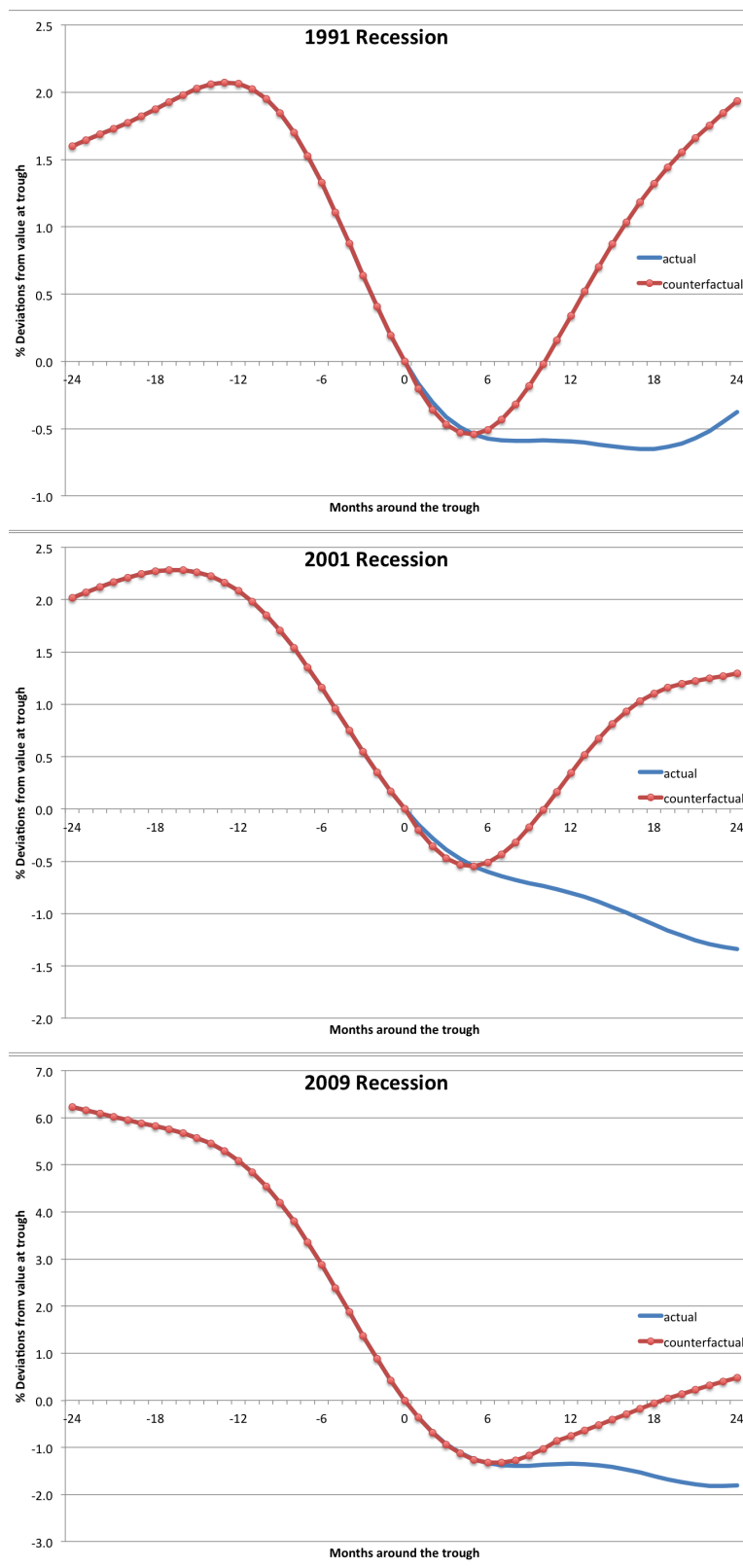
2.5 A Counterfactual Experiment

To make this final point clear, we perform a simple counterfactual experiment to document the role of job polarization in accounting for jobless recoveries. This is an informative exercise since recessions in aggregate employment are due almost entirely to recessions in routine occupations, as discussed above. We ask what would have happened in recent recessions if the post-recession behavior of employment in routine occupations had looked more similar to the early recessions. Would the economy still have experienced jobless recoveries in the aggregate?

For the 1991, 2001, and 2009 recessions, we replace the per capita employment in routine occupations following the trough with their average response following the troughs of the 1970, 1975, and 1982 recessions. We do this in a way that matches the magnitude of the fall in employment after each recent recession, but follows the time pattern of the early recessions. In particular, we ensure that the turning point in routine employment comes 5 months after the trough, as in the average of those recoveries. We then sum up the actual employment in non-routine occupations with the counterfactual employment in routine occupations to obtain a counterfactual aggregate employment series. The behavior of these counterfactual series around the recent NBER trough dates are displayed in Figure 7. Further details regarding the construction of the counterfactuals is discussed in Appendix B.

Figure 7 makes clear that had it not been for the polarization of routine jobs that occurs during recessions, we would not have observed jobless recoveries. Aggregate employment would have experienced clear turning points 5, 5, and 7 months after the troughs of the 1991, 2001, and 2009 recessions, respectively. In the 1991 and 2001 recessions, employment would have exceeded its value at the NBER-dated trough within 12 months. In the case of the much more severe Great Recession, recovery back to the trough level would have taken 18 months; this is due to the fact that the most recent recession was experienced more broadly across occupations. Nonetheless, employment would have recovered, as opposed to declining in the 24 months following the end

Figure 7: Actual and Counterfactual Employment around Recent NBER Recessions



Notes: Actual data from the Bureau of Labor Statistics, Current Population Survey; counterfactuals described in Appendix B.

of the recession.

2.6 Further Discussion

In this subsection, we offer a few points of clarification regarding job polarization and jobless recoveries. We first clarify the role of the manufacturing sector in accounting for these two phenomena; we then discuss the role played by educational composition.

It is well-known that employment in manufacturing is more “routine-intensive” compared to the economy as a whole.¹⁰ Moreover, employment dynamics in manufacturing, during both early and recent recessions, follow a similar pattern to that of routine occupations (across all sectors). Namely, manufacturing employment displayed strong cyclical rebounds prior to the mid-1980s; in the three recent recessions, employment has failed to recover following rebounds in manufacturing (and aggregate) output.

Here, we first demonstrate that job loss in manufacturing accounts for only a fraction of job polarization. Secondly, we show that the jobless recoveries experienced in the past 30 years cannot be explained by jobless recoveries in the manufacturing sector.

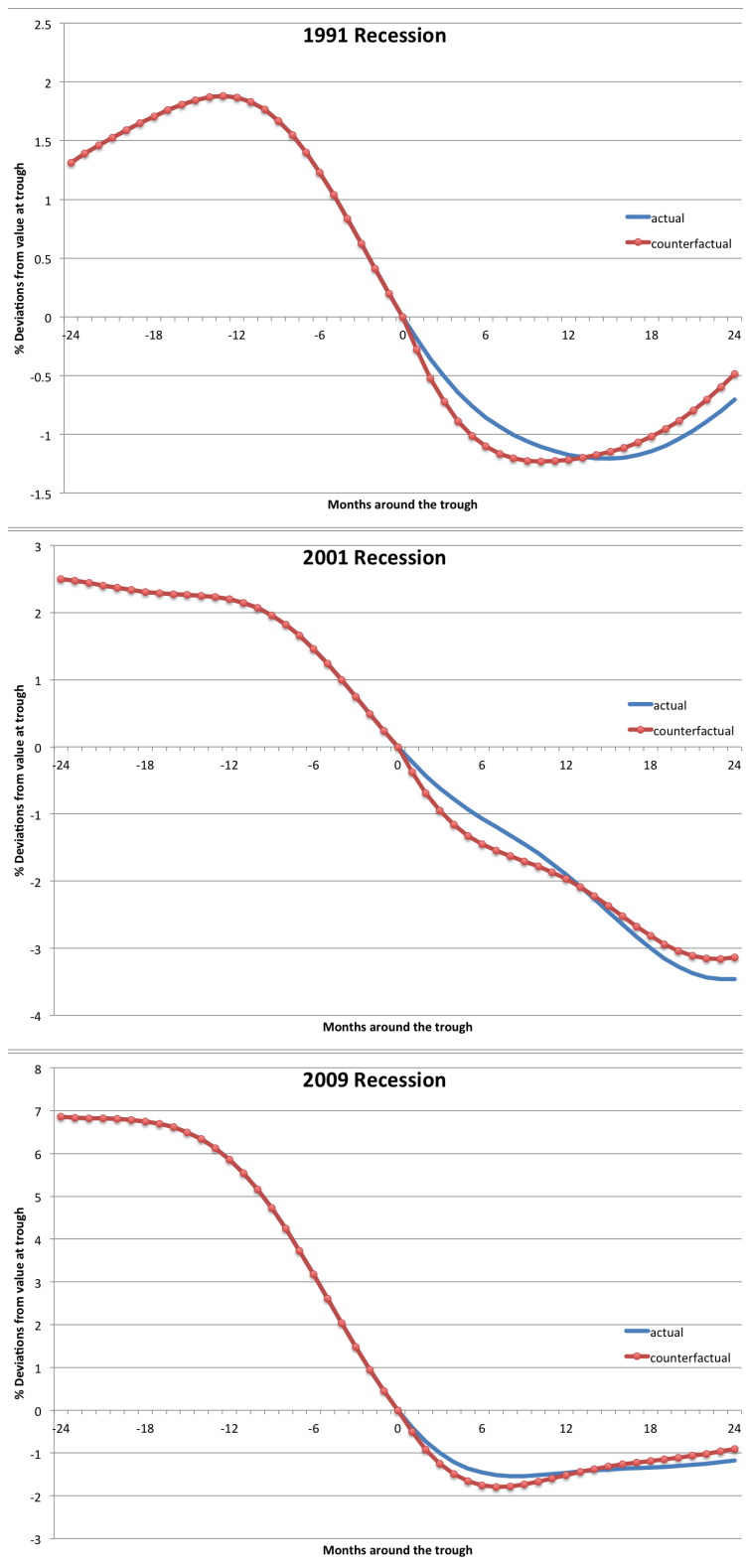
Regarding the first point, we note that across all sectors, routine employment has fallen 28 log points from 1990 to present, as displayed in Figure 4. In levels, this reflects a per capita employment loss of 0.081. But manufacturing aside, all other sectors of the economy have also experienced a pronounced polarization. Routine employment in sectors outside of manufacturing has fallen 21 log points during the same period. This represents a per capita employment loss of 0.050. Hence, manufacturing accounts for only $0.031/0.081 = 38\%$ of the observed job polarization.¹¹

With respect to the second point, while the post-recession behavior of employment in manufacturing mimics that of routine occupations, jobless recoveries in aggregate employment cannot be attributed to the manufacturing sector. This is due to the fact that manufacturing accounts for a quantitatively small share of total employment (approximately 18% in the mid-1980s and 9% in 2011). To demonstrate this, Figure 8 performs the same counterfactual experiment for the manufacturing industry as Figure 7 does for routine occupations. In each of the three jobless recoveries, we replace the employment in manufacturing following the trough with their average response following the troughs of the early recessions. We then sum up the actual employment in non-manufacturing industries with the counterfactual employment in manufacturing to obtain a counterfactual aggregate employment series.

¹⁰For instance, as of 2011, routine occupations account for 68% of total employment in manufacturing, as compared to 44% economy-wide.

¹¹See also Autor et al. (2003) and Acemoglu and Autor (2011) who demonstrate that job polarization is due largely to shifts in occupational composition (away from routine, towards non-routine jobs) within industries; in contrast, shifts in industrial composition (from routine-intensive to non-routine-intensive industries) explain less.

Figure 8: Actual and Counterfactual Employment around Recent NBER Recessions: the Manufacturing case



Notes: Actual data from the Bureau of Labor Statistics, Current Employment Statistics Survey; counterfactuals described in Appendix B.

Figure 8 displays the behavior of these counterfactual series around the 1991, 2001, and 2009 NBER trough dates.¹² The figure makes clear that eliminating the jobless recoveries in manufacturing has little impact on the post-recession dynamics in aggregate employment. That is, jobless recoveries would still have been observed following each recessionary episode. Aggregate employment would still have been below the value at the trough, a full 24 months after the recession ended.¹³

Finally, we clarify the role of education in accounting for job polarization and jobless recoveries. The share of low educated workers in the labor force (i.e., those with high school diplomas or less) has declined in the last three decades, and these workers exhibit greater business cycle sensitivity than those with higher education. It is thus reasonable to conjecture that the terms “routine” and “low education” are interchangeable. In what follows, we show that this is not the case.

In particular, it is true that education is correlated with occupation. However, as discussed in [Acemoglu and Autor \(2011\)](#), educational attainment is more closely aligned with the distinction between cognitive versus manual occupations, with high (low) educated workers tending to work in cognitive (manual) jobs. As such, job polarization – the disappearance of employment in *routine* occupations relative to *non-routine* occupations – cannot be explained simply by the change in educational composition. To make this clear, consider the case of high school graduates, who make up the vast majority of low educated workers. In levels, their per capita employment has fallen 0.057 from 1990 to present. However, this fall is highly concentrated, with 91% of the loss occurring in routine occupations. In contrast, employment among high school graduates in non-routine jobs has remained essentially constant, falling by only 0.005 during the polarization period.¹⁴

Similarly, jobless recoveries are not simply a phenomenon reflecting the post-recession dynamics of low education employment. In particular, business cycle fluctuations for high school educated workers differ greatly across occupational groups. In routine occupations, per capita employment fell 3.6%, 4.0%, and 13.2% in the 1991, 2001, and 2009 recessions, respectively.¹⁵ And indeed, it is this group that is disappearing and not recovering: averaged across the three recessions, employment is down a further 1.5% from the level at the NBER trough, a full 24

¹²Note that the behavior of actual aggregate employment differs slightly from that depicted in Figure 7. This is due to the fact that Figure 7 is constructed using CPS data, whereas Figure 8 is constructed using CES data.

¹³See also [Aaronson et al. \(2004\)](#) for evidence that the recent jobless recoveries cannot be explained by “structural change” at the sectoral or industry level occurring around recessions.

¹⁴The importance of the routine/non-routine distinction is further illustrated by the “some college” group – those with more than high school attainment, but less than a college degree. Per capita employment in this group has risen 7% since 1990. However, it has only risen in non-routine occupations (by 24%); routine employment has actually fallen 7% for the some college group, reflecting polarization among these relatively high educated workers. See also the discussion in [Autor et al. \(2003\)](#).

¹⁵Hence, while high school, routine occupational employment accounts for roughly 20% of aggregate employment during this period, it accounts for roughly 44% of total job loss across the three recent recessions.

months into the economic recovery. In contrast, employment of high school graduates in non-routine occupations experience extremely mild contractions – of 0.9%, 0.2%, and 0.5% in the three recent recessions – and no polarization. Thus, among these low educated workers, jobless recoveries are only to be found in routine occupations.

3 A Simple Model

In this section, we present a simple analytical model to highlight the key mechanisms in relating the phenomena of job polarization and jobless recoveries. Specifically, we show how a simple model can qualitatively capture the following observations: (a) routine biased technological change (RBTC) leading to job polarization, (b) polarization being “bunched” in recessions despite a “smooth” RBTC process, (c) recessionary job losses being concentrated in routine occupations, (d) jobless recoveries caused by the disappearance of routine employment, and (e) absent RBTC, non-jobless recoveries in routine and aggregate employment.

Our analytical framework is a search-and-matching model of the labor market with occupational choice and RBTC. RBTC is modelled as a trend increase in the productivity of non-routine occupations relative to routine occupations.¹⁶ The search-and-matching framework of [Diamond \(1982\)](#), [Mortensen \(1982\)](#), and [Pissarides \(1985\)](#) (hereafter, the DMP framework) is well-suited for our analysis since it emphasizes the dynamic, multi-period nature of employment and occupational choice.¹⁷

We first present a model with only non-routine cognitive (or “high-skill,” hereafter) occupations and routine (“middle-skill”) occupations. In the face of RBTC, middle-skill workers choose whether to remain in a routine occupation for which they are currently well-suited, or attempt to become a high-skill worker. If middle-skill workers choose to leave the market for routine work, then we have a disappearance of middle-skill occupations, in favour of high-skill occupations.¹⁸ We use this simple model to illustrate how a temporary, recessionary shock can accelerate this disappearance, and how job polarization in recessions can lead to jobless recoveries. We then discuss how the model can be extended to have middle-skill workers switch out

¹⁶See, for instance, [Acemoglu and Autor \(2011\)](#) who document a widening wage gap between high- and middle-skill earnings since about 1980, and a narrowing gap between middle- and low-skill earnings since the 1990s.

¹⁷As is well-known, the standard calibration of the DMP model does not succeed quantitatively at generating sizeable unemployment fluctuations in response to productivity/output fluctuations of business cycle magnitude (see, for example, [Andolfatto \(1996\)](#), [Shimer \(2005\)](#), and [Costain and Reiter \(2008\)](#)). As such we find our model informative, qualitatively, regarding the link between job polarization and jobless recoveries in employment, and less so regarding the quantitative business cycle properties of unemployment.

¹⁸Our analytical framework emphasizing occupational switching is motivated by our ongoing work. Specifically, in [Cortes et al. \(2012\)](#), using high-frequency longitudinal data, we find that the majority of routine employment loss since the mid-1980s is attributable to workers moving from routine to non-routine occupations (as opposed to the occupational choices of labor market entrants, or the participation decisions of displaced routine workers). See also [Cortes \(2011\)](#) for evidence on the quantitative importance of switching from routine occupations to both high- and low-skill occupations, and the rise in switching probabilities during the job polarization period.

of routine occupations for both high- and low-skill (i.e. non-routine manual) work.

3.1 Description

As emphasized in the DMP framework, the labor market features a search friction in the matching process between unemployed workers and vacancy posting firms. The ratio of vacancies to unemployed workers determines the economy's match probabilities. Workers differ in their proficiency in performing occupational tasks, and this proficiency is reflected in the output in a worker-firm match. Workers are of three types: (1) "high-skill" workers who have the ability to perform non-routine cognitive tasks, (2) "middle-skill" workers who have the ability to perform routine task but currently lack the ability to perform non-routine cognitive tasks, and (3) middle-skill workers who are in the process of acquiring the skills to do non-routine cognitive work. The process of gaining the proficiency to do high-skill work requires experience on the job, as emphasized in the learning-by-doing literature. Firms post vacancies for workers of different types in separate markets.

We begin by describing the market for high-skill workers, which is identical to the standard DMP model. Firms maintain (or "post") vacancies in order to recruit these workers. Vacancy posting must satisfy the following free entry condition:

$$\kappa_H = \beta q(\theta_H) J_{Ht+1}. \quad (1)$$

Here, κ_H is the cost of maintaining such a vacancy, β is the one-period discount factor, $q(\theta_H)$ is the probability that the firm is matched with a worker (the job filling probability), θ_H is the number of vacancies seeking high-skill workers relative to the number of unemployed high-skill workers (the so-called "tightness ratio") in the H market, and J_H is the firm's surplus from being matched with a high-skill worker. We adopt the usual timing convention whereby matches formed at date t become productive at date $t + 1$.

Firm surplus is given by:

$$J_{Ht} = f_{Ht} - \omega_{Ht} + \beta(1 - \delta)J_{Ht+1}, \quad (2)$$

where f_H is the output (or revenue) produced in a high-skill worker-firm match, ω_H is the compensation paid to the worker, and δ is the exogenous separation rate.

An unemployed, high-skill worker receives a flow value of unemployment, z , and matches with a firm with job finding probability, $\mu(\theta_H)$.¹⁹ If a match occurs, the worker begins employment in the following period; otherwise she remains unemployed. The present discounted value of being unemployed for such a worker is:

$$U_{Ht} = z + \beta [\mu(\theta_H)W_{Ht+1} + (1 - \mu(\theta_H))U_{Ht+1}], \quad (3)$$

¹⁹We assume that the matching process has the usual properties, so that $\mu(\theta)$ is a strictly increasing function of the tightness ratio, θ ; $q(\cdot)$ is a strictly decreasing function of θ ; and $q(\theta) = \mu(\theta)/\theta$.

where W_H is the value of being a matched, high-skill worker. This latter value is given by:

$$W_{Ht} = \omega_{Ht} + \beta [(1 - \delta)W_{Ht+1} + \delta U_{Ht+1}]. \quad (4)$$

Worker compensation in a match is determined via generalized Nash bargaining. Letting τ represent the worker's bargaining power, this implies that in equilibrium, firm surplus is a fraction, $(1 - \tau)$, of total match surplus; worker surplus, defined as $W_H - U_H$, is the complementary fraction, τ . Total surplus is defined simply as $TS_H \equiv J_H + W_H - U_H$; this imposes the free entry condition, with the firm's value of being unmatched set to zero. We maintain the assumption of Nash bargaining over compensation in all markets in the model.

In the market for routine, middle-skill workers, firms post vacancies such that the free entry condition holds:

$$\kappa_M = \beta q(\theta_{Mt}) J_{Mt+1}. \quad (5)$$

Note that we allow the vacancy cost in the routine market, κ_M , to differ from that of the high-skill occupation. Also, the tightness ratio and firm surplus in this market is marked with an M to reinforce the fact that the M market is distinct from the H market. Middle-skill workers have the choice to search either in the routine market or in an alternative, "switching market" to become a high-skill worker (described below).

Firm surplus in such a match is given by:

$$J_{Mt} = \max \{f_{Mt} - \omega_{Mt} + \beta(1 - \delta)J_{Mt+1}, 0\}. \quad (6)$$

Here, f_M is the output produced in a middle-skill match, and ω_M is the compensation paid to the worker. The firm may choose to separate from the match, if the surplus is non-positive.²⁰

The value function for a middle-skill worker while employed is:

$$W_{Mt} = \max \{\omega_{Mt} + \beta [(1 - \delta)W_{Mt+1} + \delta U_{Mt+1}], U_{Mt}\}. \quad (7)$$

The worker can choose to separate from the match if the value of being an unemployed job searcher, U_M , exceeds the value of remaining in the match. With Nash bargaining, separations are efficient since firm and worker surplus in a match are proportional.

When unemployed, the middle-skill worker faces an occupational choice. First, it may choose to remain in the market for routine work. In this case, the value of unemployment is given by:

$$U_{MMt} = z + \beta [\mu(\theta_{Mt})W_{Mt+1} + (1 - \mu(\theta_{Mt}))U_{Mt+1}], \quad (8)$$

where $\mu(\theta_M)$ is the job finding rate in the market for routine work. On the other hand, the worker may choose to search for a job which allows for the switching from routine to non-routine occupations:

$$U_{MSt} = z + \beta [\mu(\theta_{St})W_{St+1} + (1 - \mu(\theta_{St}))U_{Mt+1}]. \quad (9)$$

²⁰This is technically a possibility in the high-skill market as well; however, we assume parameter values are such that this uninteresting case does not occur.

Here, $\mu(\theta_S)$ is the job finding rate in the “switching market,” and W_S is the value of being employed in such a match. The unemployed middle-skill worker chooses where to search according to:

$$U_{Mt} = \max \{U_{MMt}, U_{MSt}\}. \quad (10)$$

Note that in the case of an unsuccessful job search at date t , the worker is free to search in either market at date $t + 1$.

It remains to define the value functions associated with the switching market.²¹ The value of being employed is given by:

$$W_{St} = \omega_{St} + \beta [(1 - \delta)W_{Ht+1} + \delta U_{Ht+1}]. \quad (11)$$

When employed in a switching match, workers receive compensation ω_S and acquire skills towards becoming a high-skill worker. For simplicity, we assume the worker becomes proficient at performing non-routine cognitive tasks after one period on the job. If the match remains intact, with probability $(1 - \delta)$, the worker continues as a high-skill worker with value W_H . If the match is separated, with probability δ , she enters the next period as an unemployed high-skill worker, with value U_H . Skills that the worker acquires on-the-job are retained when unemployed and can be applied to future matches; in other words, occupational skill is not firm- or match-specific.

To close the model, the free entry condition in the switching market is given by:

$$\kappa_S = \beta q(\theta_{St}) J_{St+1}, \quad (12)$$

where

$$J_{St} = f_{St} - \omega_{St} + \beta(1 - \delta)J_{Ht+1}. \quad (13)$$

Again, κ_S is the vacancy cost, and f_S is match output in the learning market, which can differ from those in the H -market and M -market.

3.2 Results

Occupational choice, job polarization, and jobless recoveries in this model are straightforward. To understand the implications of the model, we begin with an analysis of the model’s steady state. We then analyze the model’s perfect foresight dynamics.

3.2.1 Steady State

To begin, consider a steady state equilibrium. Equilibrium in any market is summarized by the free entry condition:

$$\kappa_i = q(\theta_i)\beta(1 - \tau)TS_i, \quad (14)$$

²¹For a detailed analysis of labor market dynamics in a model with on-the-job learning very similar to that presented here, see [Gervais et al. \(2011\)](#).

for $i \in \{H, M, S\}$. The term $(1 - \tau)TS_i$ is simply firm surplus (given Nash bargaining). Hence, the number of vacancies firms post per unemployed worker today, θ_i , is increasing in the profit conditional on being matched tomorrow, $\beta(1 - \tau)TS_i$.

High-Skill Market The steady state in the high-skill market is identical to a standard DMP model. Steady state total surplus in a high-skill match is given by:

$$TS_H = \frac{f_H - z - \hat{\tau}\kappa_H\theta_H}{1 - \beta(1 - \delta)}, \quad (15)$$

with $\hat{\tau} \equiv \tau/(1 - \tau)$. The contemporaneous surplus from a match consists of the output (f_H), net of the flow value (z) and option value ($\hat{\tau}\kappa_H\theta_H$) that is foregone when a worker is employed relative to being unemployed. The total surplus is simply the present discounted value of contemporaneous surpluses. The value of being an unemployed high-skill worker in steady state is given by:

$$U_H = \frac{z + \hat{\tau}\kappa_H\theta_H}{1 - \beta}. \quad (16)$$

Middle-Skill Markets For middle-skill workers, the total surplus and the value of being unemployed depend on which market the unemployed search in. Consider the case when middle-skill workers search in the routine market, so that $U_M = U_{MM}$. Steady state total surplus in a routine match is:

$$TS_M = \frac{f_M - z - \hat{\tau}\kappa_M\theta_M}{1 - \beta(1 - \delta)}, \quad (17)$$

and the value of unemployment is:

$$U_M = \frac{z + \hat{\tau}\kappa_M\theta_M}{1 - \beta}. \quad (18)$$

These have the same interpretations given above for the H market.

In a steady state with unemployed middle-skill workers searching in the switching market ($U_M = U_{MS}$), the value of unemployment is:

$$U_M = \frac{z + \hat{\tau}\kappa_S\theta_S}{1 - \beta}. \quad (19)$$

The expression for total surplus in a switching match is best understood in the following form:

$$TS_S = f_S - z - \hat{\tau}\kappa_S\theta_S + \beta[(1 - \delta)TS_H + (U_H - U_M)]. \quad (20)$$

Relative to the expressions for TS_H and TS_M , TS_S differs in two ways. First, the continuation value is $\beta(1 - \delta)TS_H$, reflecting the learning of high-skill tasks that takes place during the first period of a switching match. Second, total surplus involves the additional term, $\beta(U_H - U_M)$;

this reflects a capital gain due to the learning of high-skill tasks that occurs in the first period of a switching match.²²

Unemployed workers will search in the routine market if $U_{MM} > U_{MS}$. From equations (18) and (19), this occurs in steady state when the option value of unemployment in that market, $\hat{\tau}\kappa_M\theta_M$, exceeds the option value in the switching market, $\hat{\tau}\kappa_S\theta_S$. Conversely, workers will search in the switching market whenever $\hat{\tau}\kappa_S\theta_S > \hat{\tau}\kappa_M\theta_M$.

It is easy to see that either steady state can emerge, depending on parameter values. To illustrate this most simply, suppose that $f_S = f_H$ and $\kappa_S = \kappa_H$. This way, the high-skill and switching markets are identical, so that the equilibrium conditions summarizing the switching market are identical to equations (15) and (16), simplifying the analysis. To see how unemployed middle-skill workers would choose to search in the switching market is straightforward. Suppose that $\kappa_M = \kappa_S (= \kappa_H) = \kappa$ and $f_S > f_M$. In this case, output in a switching match exceeds that in a routine match. Since vacancy costs are the same, the free entry condition implies that market tightness in the switching market must be greater: $\theta_S > \theta_M$. It follows that $\hat{\tau}\kappa\theta_S > \hat{\tau}\kappa\theta_M$, so that the value of search in the switching market exceed that in the routine market.

It is also possible that unemployed middle-skill workers would search in the routine market, even when $f_S > f_M$. This occurs when the vacancy cost in the routine market is sufficiently smaller than that in the switching market. We discuss this in detail in Appendix C. Intuitively, $f_S > f_M$ implies that the value of being employed in a switching match exceeds that in a routine match. However, the value of being unemployed also depends on the probability of entering into a match, the job finding rate. If κ_S is sufficiently large relative to κ_M , this implies a low incentive for job creation in the S market, translating into a low job finding rate for workers. Hence, when $f_S > f_M$, there exists a cutoff value of the relative vacancy costs such that for all values of κ_M/κ_S less than the cutoff, $U_{MM} > U_{MS}$.

3.2.2 Dynamics

We now consider dynamics in an economy that experiences RBTC. Specifically, we consider an economy that starts in a steady state where middle-skill workers work and search in the routine market. At some date, agents learn that, due to RBTC, productivity in a high-skill match rises to a new value over time relative to a routine match; as a result, middle-skill workers eventually prefer to search in the S market and the labor market polarizes. Given the recursive nature of

²²Specifically, after one period on the job, there is an upgrade to a high-skill match in the next period. Hence, the total surplus includes the change in the worker's and firm's values, weighted by β . With probability $(1 - \delta)$ the match survives, so that upgrading reflects a change in the matched value of both the worker and the firm. With probability δ the match is separated, and the upgrading is reflected only in a change in the unemployed worker's value.

the model, we can map out the model's perfect foresight dynamics.²³

For simplicity, assume that at each point in time, productivity in a switching match is identical to that in a high-skill match, $f_S = f_H = f$, and greater than in a routine match, $f > f_M$. Since we are interested in an economy that begins in a steady state where middle-skill workers work and search in the routine market, $U_{MM} > U_{MS}$, we follow the logic of the Subsection 3.2.1 and assume that κ_M is sufficiently smaller than κ_S so that, initially, the S market is not operative even though $f > f_M$.²⁴

At some date, agents learn that f rises over time to a new value due to RBTC, while f_M remains unchanged. As f rises, so too does the total surplus in S matches. From the free entry condition, this implies that the tightness ratio, θ_S , rises too. This in turn implies a rise in the value of unemployed search in the switching market, U_{MS} . Given that RBTC has no effect on productivity in routine matches, f_M , there is little effect on total surplus, TS_M , early on and unemployed middle-skill workers continue to search in that market, $U_M = U_{MM}$. But as RBTC progresses, and the value of unemployed search in the switching market rises, we reach a point when $U_{MS} > U_{MM}$; unemployed middle-skill workers begin searching in the switching market. This initiates the disappearance of routine employment. As θ_S continues to rise, so too does the job finding rate in that market, $\mu(\theta_S)$, and the upgrading of middle-skill to high-skill workers. In the long-run, routine employment disappears, and the entire workforce becomes high-skill.

An Example of Polarization In what follows we illustrate these dynamics in an example. The initial steady state has half of all workers (working or searching) in the H market, and the remaining half in the M market (again, the S market is initially not operative).

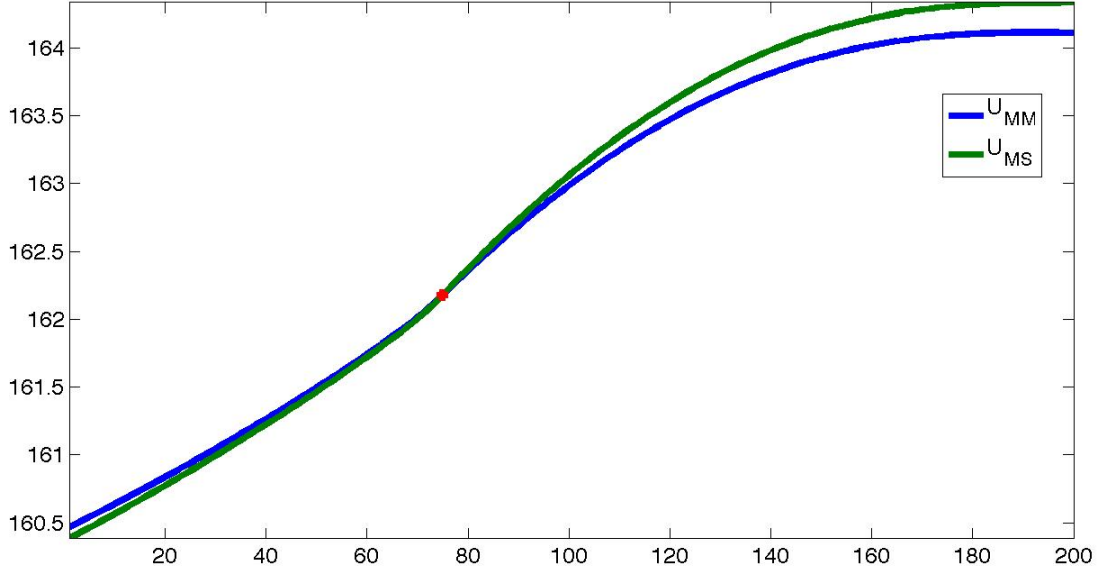
Figure 9 depicts the perfect foresight paths for U_{MMt} and $U_{MS t}$. Agents in this example learn at period 1 that RBTC causes f to grow at a constant rate over time, reaching a new steady state level in period 200. Initially, unemployed middle-skill workers prefer to search for work in the routine market. In period 75, this switches and unemployed middle-skill workers begin searching in the switching market. In this example, total surplus in routine matches, TS_M , remains positive even in the terminal steady state. Hence, from period 76 to 200, middle-skill workers gradually move to the S market at rate δ , as they exogenously separate from routine matches (and choose to search for a switching match).

Figure 10 depicts the share of H -, S -, and M -type workers in the economy. In periods

²³Specifically, we first solve for the terminal, post-RBTC steady state. We then work backwards, period-by-period, to the initial steady state, solving for the various value functions and tightness ratios along the transition path.

²⁴Unlike the steady state example discussed in Subsection 3.2.1, we set $\kappa_H < \kappa_S$. Since $f_S = f_H = f$, if $\kappa_H = \kappa_S$, the H and S markets would be identical. Hence, the initial steady state would feature $U_{MM} > U_{MS} = U_H$: unemployed high-skill workers would prefer to search in the routine market. Since we are interested in an example where high-skill workers prefer to remain high-skill and yet maintain simplicity, we set $\kappa_H < \kappa_S$ so that the job finding rate in the H market is high.

Figure 9: Middle-Skill Worker's Value of Unemployment



Notes: The blue line denotes the value of an unemployed middle-skill worker searching for routine employment. The green line denotes the value of an unemployed middle-skill worker searching in the switching market. The red dot indicates the period in which the value of unemployment in the switching market crosses above that in the routine market.

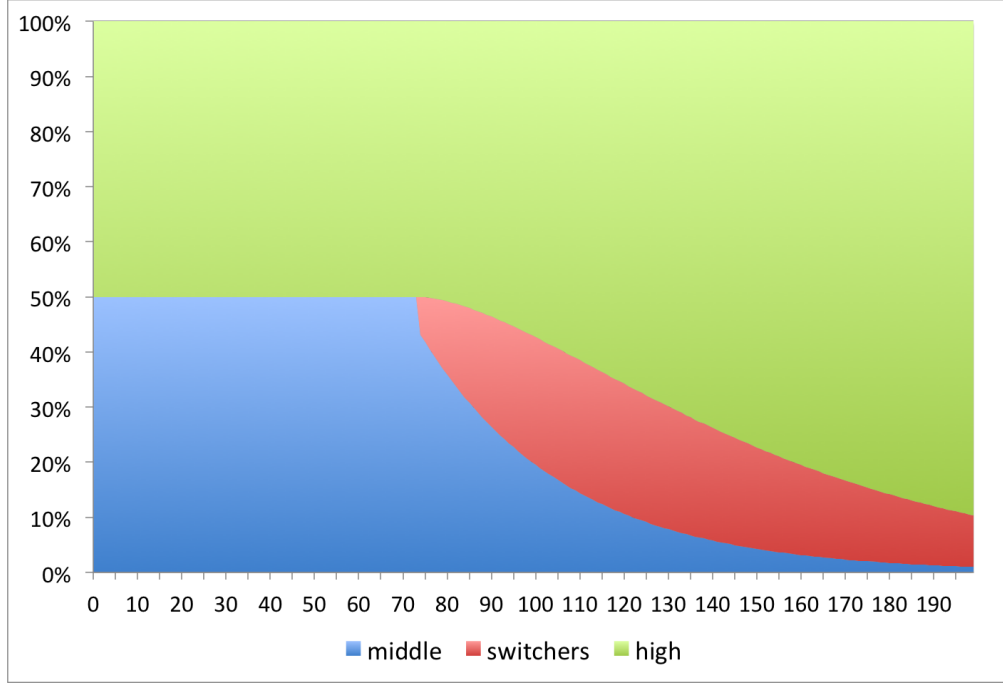
1 through 75, the composition of worker types remains unchanged: high-skill workers remain as such, and routine workers have no incentive to switch. But in period 75, all unemployed middle-skill workers leave the routine market and begin searching in the switching market. In all subsequent periods, workers who separate from routine matches also choose to search in the switching market; the market for routine workers gradually disappears.²⁵

It is also possible to see how a recession accelerates the disappearance of routine employment. In the context of our model, a recession can be viewed as an unanticipated, temporary fall in aggregate productivity (i.e., a fall in the productivity of all matches).

Suppose the process of RBTC is at a stage where $U_M = U_{MS} > U_{MM}$, so that unemployed middle-skill workers prefer to search in the switching market. If the fall in productivity is sufficiently large, total surplus in routine matches becomes non-positive, $TS_M \leq 0$, while total

²⁵In this example, total surplus in routine matches, TS_M , remains positive during the entire transition path, so that in the long-run, exit from the routine market occurs at the constant rate, δ , due to the exogenous separation of routine matches. Note that it is also possible that TS_M becomes non-positive along the transition path. In this case, there would be a sudden exit out of the routine market due to endogenous separation of routine matches.

Figure 10: Evolution of Worker Types During Job Polarization



Notes: The process of RBTC begins in period 1. Job Polarization begins in period 75, as middle-skill workers leave the routine market for the switching market, and eventually become high-skill workers.

surplus in all other matches remain positive.²⁶ This is the case that we consider. When $TS_M \leq 0$, workers in routine matches endogenously separate to unemployment. Middle-skill workers previously employed in these matches switch occupations, and start searching for a match in the S market.

This is depicted in Figure 11. As in Figures 9 and 10, the disappearance of the routine market begins in period 75. To make things exceedingly clear, we introduce a temporary, negative shock to aggregate productivity in exactly period 75 that lasts for 10 periods. At this point, all middle-skill workers move to the switching market.

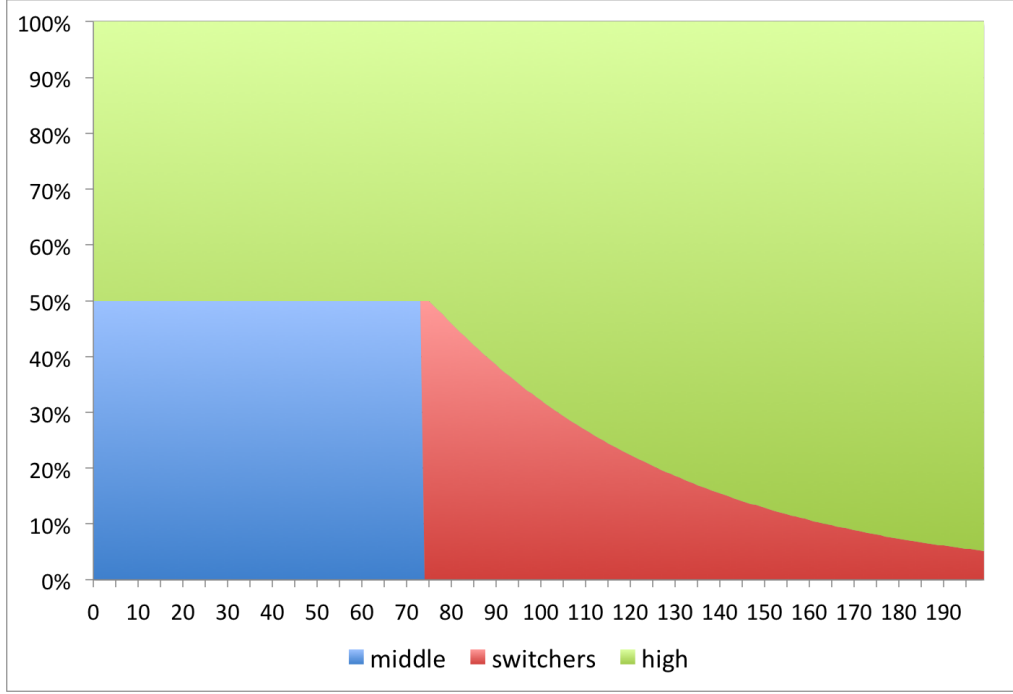
Productivity returns to its non-recession level in period 85. At this point, the values of

²⁶It is easy to see that there always exists a negative productivity shock such that this happens. For simplicity, consider a one-period shock that occurs in the last period before the $U_{MS} > U_{MM}$ switch. This allows us to disregard the S market, which is not yet operative. The total surplus in the two active markets is given by:

$$\begin{aligned} TS_M &= f_M - z - \hat{\tau}\kappa\theta_M + \beta(1-\delta)TS'_M, \\ TS_H &= f_H - z - \hat{\tau}\kappa\theta_H + \beta(1-\delta)TS'_H. \end{aligned}$$

The fact that $f_H > f_M$ (and that the gap is increasing due to RBTC) implies that $TS_H > TS_M$ at all points in time. Hence, for an additive productivity shock (dropping f_H and f_M by the same amount in level terms), it is easy to find a shock that causes $TS_M \leq 0$, leaving $TS_H > 0$. In the case of a multiplicative shock, one simply needs to find a factor, x , such that $xf_M - z - \hat{\tau}\kappa\theta_M + \beta(1-\delta)TS'_M = 0$. Applied to the H -type match, it must be that $xf_H - z - \hat{\tau}\kappa\theta_H + \beta(1-\delta)TS'_H > 0$.

Figure 11: Job Polarization Accelerated by Recession



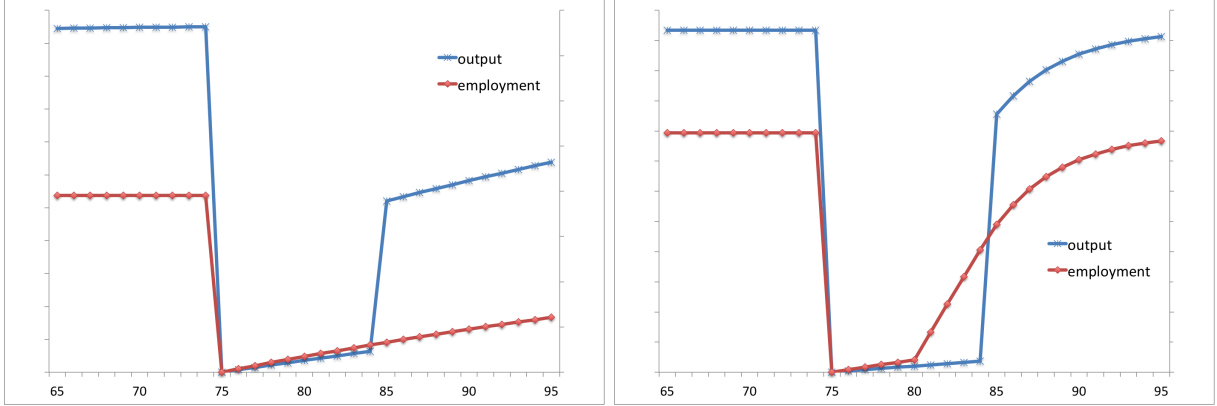
Notes: The process of RBTC begins in period 1. Job Polarization begins in period 75, and is accelerated by a temporary recession that begins in period 75.

employment, unemployment, firm surplus, and total surplus in all markets return to their non-recession, perfect foresight paths. In particular, total surplus in routine matches returns to positive. However, this is irrelevant as the economy has already entered the job polarization phase where $U_{MS} > U_{MM}$. Despite positive total surplus in routine matches, there are no employed routine workers and, importantly, no unemployed middle-skill workers who choose to search in the M market. Hence, in this simple example, all of the disappearance of routine employment occurs in recessions. More generally, during an era of job polarization (i.e., after period 75 in our example), recessions accelerate the disappearance of routine jobs. This is obvious in comparing Figure 11 to Figure 10.

Moreover, the recovery from such a recession can be jobless. In period 85, aggregate productivity returns to its pre-recession level. This implies an immediate jump in output in non-routine matches; as a result, there is an immediate rebound in aggregate output.

However, this is not accompanied by a jump in employment. In the recession, job separations were concentrated among the middle-skill, routine workers. The recovery in aggregate employment then depends on the post-recession job finding rate of these workers now searching in the S market. If this job finding rate is low, the rebound in employment will be sluggish: the economic recovery is jobless.

Figure 12: Recoveries With and Without Job Polarization



Notes: The blue line denotes aggregate output, the red line aggregate employment. Both are normalized to 1 in the initial period of recession. A temporary fall in aggregate productivity in period 75 generates a recession; productivity returns in period 85. The left panel displays the case with job polarization, leading to a jobless recovery. The right panel displays the case with no job polarization, leading to a recovery in both output and employment.

This is precisely the case in our example. The left panel of Figure 12 depicts the dynamics of aggregate output and employment around the recession. Both are normalized to unity in the initial period of the recession, period 75. When productivity rebounds in period 85, output recovers. However, there is no corresponding rebound in employment, as the middle-skill workers who became unemployed in the recession face low job finding rates in their preferred search market, the S market.

This low job finding rate is achieved in our model in a very straightforward way: by setting the vacancy cost, κ_S , high.²⁷ We view this as a simple, yet informative, stand-in for the many real-world factors that cause workers – whose jobs have disappeared due to job polarization – to have difficulty in finding employment in new occupations. For example, firms may be risk-averse (as opposed to risk neutral, as in the DMP framework) and reluctant to create vacancies to attract workers without experience in the advertised occupation following a recession. Alternatively, imperfect information may cause workers to spend time searching in vain for employment in occupations that are no longer hiring, before eventually moving on to search for a new occupation. More broadly, a jobless recovery involves a slow transition into employment from any source of non-employment. Hence, we view the middle-skill worker's move from the M -market, to the S -market, to eventual employment also as a stand-in for temporary spells of labor force non-participation that may arise from time spent relocating or re-training in order to switch occupations.

It is worth noting that our model is consistent with the facts regarding the cyclical behavior

²⁷Note that this is the same mechanism that ensures $U_{MM} > U_{MS}$ in the initial steady state, despite the fact that $f_S > f_M$.

of aggregate labor market flows. First, as documented in Section 2.4, the bulk of the job loss in recessions is in routine occupations. In our model, this is precisely the case as all endogenous separations occur in M -type matches in the recession. Second, as documented in Fujita and Ramey (2009) and Elsby et al. (2009), the onset of US recessions feature a spike in the aggregate separation rate; this too occurs in our model. Finally, after the initial spike in separations, unemployment dynamics are determined by those of the job finding rate. In the data, as in our model, jobless recoveries are characterized by slow recoveries in the aggregate job finding rate, ones that are much more persistent than the recoveries following the recessions of the 1970s and early 1980s.²⁸

An Example with No Polarization It is also interesting to analyze the effects of a recessionary shock absent job polarization. In such an economy, middle-skill workers would not switch to the S market in a recession. As a result, the recovery would not be jobless.

This is illustrated in the right panel of Figure 12. Here we consider an identical model, except there are no underlying trends in f . As a result, unemployed high-skill workers search in the H market and unemployed middle-skill workers search in the M market. No workers choose to search in the low job finding rate S market. As the right panel makes clear, absent the force for job polarization, there would be no jobless recovery. Employment rebounds along with output; and indeed, employment leads output out of the recession due to the fact that we are studying perfect foresight paths, and job creation is forward-looking.

Summary Our model makes clear the two mechanisms required to generate a jobless recovery. First, it requires a rebound in productivity among the employed following a recession. In our model, this occurs in the H - and S -type matches.²⁹ The second feature is a low job finding rate among those who are displaced following a recession. Indeed, absent job polarization, workers would not switch to the S market in a recession. As a result, the recovery would not be jobless.

In summary, we find that our simple model generates a number of the key features characterizing the US labor market in the past 30 years. The model predicts that job polarization is bunched in recessions despite a gradual, trend process in RBTC. In recessions, job losses are concentrated in routine occupations. And following recessions, recoveries are jobless and caused by the disappearance of routine employment.

²⁸See, for instance, Figure 5 of Shimer (2005), and Sahin et al. (2012).

²⁹Of course, this is not the only way to achieve this; any heterogeneity among routine workers (e.g., in the form of individual-level match productivities) could prevent a complete disappearance of routine employment in recessions. And indeed, such a feature is obviously relevant empirically since we do not observe complete polarization in the data. In such a case, the productivity rebound would affect the H -, S -, and remaining M -type matches.

Finally, we note that because our simple model considers only two skill levels (middle and high), we do not obtain true “polarization,” with workers moving to both high- and low-skill occupations. However, it is easy to extend the model in such a direction, by incorporating heterogeneity among middle-skill workers. Specifically, assume there is heterogeneity in the ability to acquire the skills to become a non-routine cognitive worker: suppose some people find it impossible to become proficient at high-skill tasks. Then, RBTC, modelled as a trend increase in the productivity in both high- and low-skill matches relative to routine matches, would generate polarization in both directions. None of the substantive implications of our model would be altered.

4 Conclusions

In the last 30 years the US labor market has been characterized by job polarization and jobless recoveries. In this paper we demonstrate how these are related. We first show that the loss of middle-skill, routine jobs is concentrated in economic downturns. In this sense, the job polarization *trend* is a business *cycle* phenomenon. Second, we show that job polarization accounts for jobless recoveries. This argument is based on the fact that almost all of the contraction in aggregate employment during recessions can be attributed to job losses in middle-skill, routine occupations (that account for a large fraction of total employment), and that jobless recoveries are observed only in these disappearing routine jobs since job polarization began. We then propose a simple search-and-matching model of the labor market with occupational choice to rationalize these facts. We show how a trend in routine-biased technological change can lead to job polarization that is concentrated in downturns, and recoveries from these recessions that are jobless.

A Data Sources

The population measure is the civilian non-institutional population, 16 years and over, taken from the *Current Population Survey*, Bureau of Labor Statistics. Aggregate employment is total employment within this population. Estimates of RGDP at a monthly frequency are those of James Stock and Mark Watson (http://www.princeton.edu/~mwatson/mgdp_gdi.html). These data end in June 2010; data for July 2010 to December 2011 are interpolated from quarterly RGDP data, taken from the *FRED* Database, Federal Reserve Bank of St. Louis.

Data on employment at the occupational group level from July 1967 to December 1982 is taken from the *Employment and Earnings*, Bureau of Labor Statistics, various issues. Non-routine cognitive workers are those employed in “professional and technical” and “managers, officials, and proprietors” occupations. Routine cognitive workers are those classified as “clerical workers” and “sales workers”. Routine manual workers are “craftsmen and foremen”, “operatives”, and “nonfarm labourers”. Non-routine manual workers are “service workers”. “Farm workers” (farmers, farm managers, farm labourers and farm foremen) are excluded from the employment data at the occupational level. Data for January 1983 to December 2011 are taken from *FRED*. Non-routine cognitive workers are those employed in “management, business, and financial operations occupations” and “professional and related occupations”. Routine cognitive workers are those in “sales and related occupations” and “office and administrative support occupations”. Routine manual occupations are “production occupations”, “transportation and material moving occupations”, “construction and extraction occupations”, and “installation, maintenance, and repair occupations”. Non-routine manual occupations are “service occupations”.

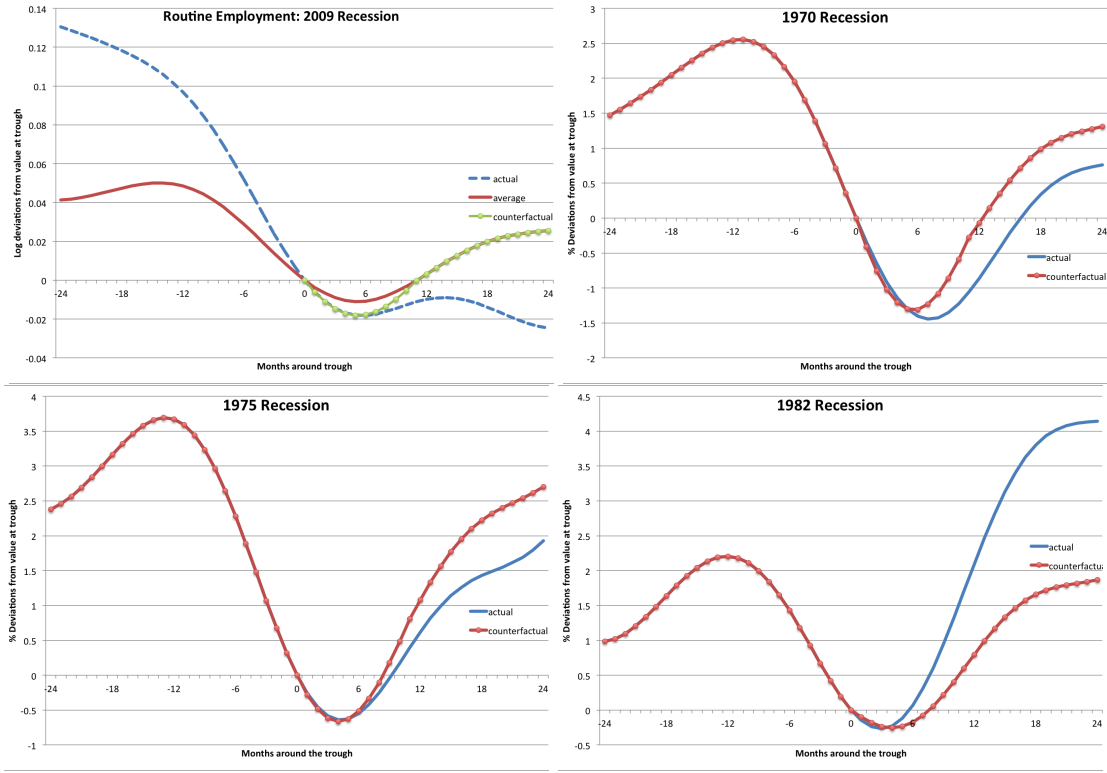
In subsection 2.6, data for industrial employment are from the Current Employment Statistics survey of the BLS, taken from the *FRED* Database. Aggregate employment refers to “all employees: total nonfarm” and manufacturing employment is “all employees: manufacturing”. Data for employment delineated by education and occupation from 1989 to 2011 are from the Basic Monthly Files of the CPS, taken from the NBER website.

B Counterfactuals

Using the data for routine occupations displayed in Figure 5, we derive the average percentage deviation in employment for the 24 months following the trough. We refer to this as the “average response”, and this is displayed as (last half of) the solid line in the upper-left panel of Figure 13. In the 1991, 2001, and 2009 recessions, we replace the post trough dynamics of routine occupational employment with a re-scaled version of the average response. In particular, we re-scale the average response to match the magnitude of the fall in actual employment within the first 5 months of the trough. We choose 5 months, since this is the turning point of the average response.

The counterfactual for routine employment is displayed for the example of the 2009 recession as the hatched line in the upper-left panel of Figure 13. Because the actual fall after the 2009 trough was greater than that observed in the average of the early recessions, the average response had to be magnified. After 11 months, the average response turns positive. The magnification factor would then imply a very sharp rebound in the counterfactual. Hence, to be conservative, we set the counterfactual for months 12 through 24 to be exactly the average response. In the

Figure 13: Constructing Counterfactual Employment



cases of the 1991 and 2001 recessions, the average response fell more sharply than did actual routine employment. In these cases, the counterfactual was derived by attenuating the average response by the appropriate factor. To be conservative on the strength of the recovery, after the average response turns positive, we maintained the attenuation factor.

These counterfactuals in log deviations were then used to derive counterfactuals for routine employment levels. These were then added to the actual employment levels in non-routine occupations to obtain counterfactual aggregate employment series. These counterfactuals in the aggregate were then expressed as log deviations from their value at the recession troughs to obtain Figure 7.

Finally, in the upper-right, lower-left panel, and lower-right panels of Figure 13, we present the results of the same counterfactual experiment for the 1970, 1975, and 1982 recessions. These panels demonstrate that the nature of the early recoveries – which were not jobless – are not fundamentally altered by the exercise. That is, they continue to display recoveries in aggregate employment with roughly the same magnitude and timing.

C Vacancy Costs and the Tightness Ratio

Here we demonstrate how variation in the vacancy cost affects the equilibrium tightness ratio. From equations (14) and (17), the zero profit condition in steady state can be expressed as:

$$\kappa_M = q(\theta_M)\beta(1 - \tau) \left[\frac{f_M - z - \hat{\tau}\kappa_M\theta_M}{1 - \beta(1 - \delta)} \right]. \quad (21)$$

Assuming a Cobb-Douglas matching function (as is standard in the literature), $q(\theta_M) \equiv \theta_M^{\alpha-1}$, $0 < \alpha < 1$. With this, the zero profit condition can be rewritten as:

$$\kappa_M \theta_M = \theta_M^\alpha \beta (1 - \tau) \left[\frac{f_M - z - \hat{\tau} \kappa_M \theta_M}{1 - \beta(1 - \delta)} \right]. \quad (22)$$

Consider a fall in κ_M . Condition (22) requires a rise in θ_M : in equilibrium, a lower vacancy cost induces a fall in the firm's job filling probability through a rise in the tightness ratio, θ_M .

Moreover, maintaining zero profits requires a larger than proportionate rise in θ_M . To see this, suppose to the contrary that the rise in θ_M is proportionate to the fall in κ_M , so that the product $\kappa_M \theta_M$ remains unchanged. This would imply that the LHS of (22) remains unchanged, as does the total surplus (the term in square brackets) on the RHS. Hence, equality would not be maintained as θ_M^α on the RHS would rise. Given that $\alpha < 1$, this implies that θ_M must rise more than proportionately to the fall in κ_M , i.e. that $\kappa_M \theta_M$ rises.

As a result, a lower vacancy cost results in a higher option value of unemployment, $\hat{\tau} \kappa_M \theta_M$, and thus, a higher value of unemployed search in the routine market. Hence, holding the option value of unemployment in the S -market constant, there exists a κ_M such that $\hat{\tau} \kappa_M \theta_M = \hat{\tau} \kappa_S \theta_S$. For any values of κ_M smaller than this, unemployed middle-skill workers would search in the routine market, even when $f_S > f_M$.

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