The Trend is the Cycle: Job Polarization and Jobless Recoveries

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**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.

**Keywords:** job polarization; jobless recovery; business cycle

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1 Introduction

In the past 25 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 jobs 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 employment is becoming concentrated at the tails of the occupational skill distribution. This process has accelerated since the 1980s, as per capita employment in middle-skill jobs disappears. This hollowing out of the middle is linked to the disappearance of occupations 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.

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 (of 1991, 2001, and 2009), 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 related. We report two related findings. First, the disappearance of per capita employment in routine occupations is not simply a gradual phenomenon: the loss 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), Autor and Dorn (2012), 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

\[\text{See also Firpo et al. (2011), Goos et al. (2011), and the references therein regarding the role of outsourcing and offshoring in job polarization.}\]
employment. Second, essentially all of the contraction in aggregate employment during NBER dated recessions can 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 jobless recoveries and job polarization. In Section 3, we present data documenting our two principal findings, that these two phenomena are related. In Section 4, 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 5 concludes.

2 Two Labor Market Phenomena

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. Aggregate per capita employment is that of all civilian non-institutionalized individuals aged 16 years and over (seasonally adjusted), normalized by the population. 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

\footnote{The 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.}

\footnote{Data are taken from the Labor Force Statistics of the CPS, downloaded from the BLS website (http://www.bls.gov/data/). 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.}

\footnote{We implement this using the band pass filter proposed by Christiano and Fitzgerald (2003), who discuss the merits of their method for isolating fluctuations outside the traditional business cycle frequencies and near the endpoints of datasets.}
Figure 1: Aggregate Employment around Early NBER Recessions

Figure 2: Aggregate Employment around Recent NBER Recessions

Table 1: Measures of Recovery following Early and Recent Recessions

<table>
<thead>
<tr>
<th></th>
<th>Early</th>
<th>Early</th>
<th>Early</th>
<th>Recent</th>
<th>Recent</th>
<th>Recent</th>
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<tr>
<td>A. Employment</td>
<td></td>
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<tr>
<td>months to turn around</td>
<td>6</td>
<td>4</td>
<td>2</td>
<td>17</td>
<td>23</td>
<td>23</td>
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<tr>
<td>months to trough level</td>
<td>16</td>
<td>10</td>
<td>4</td>
<td>31</td>
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<td>half-life (in months)</td>
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<td>23</td>
<td>10</td>
<td>38</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>B. Output</td>
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<td></td>
<td></td>
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<tr>
<td>months to turn around</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>months to trough level</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>half-life (in months)</td>
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<td>10</td>
<td>5</td>
<td>9</td>
<td>3</td>
<td>15</td>
</tr>
</tbody>
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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.

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 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 17 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 (stop contracting), relative to the NBER trough date. The second row indicates the number of months it takes from 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; 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. 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 in the past 25 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. In Appendix A, we discuss the occupational classification in detail, as well as robustness of our results to alternative classifications used in the literature. For brevity, we include a summary here. Following Acemoglu and Autor (2011), we delineate occupations along two dimensions: “cognitive” versus

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6Because 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.
“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 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.

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.\(^7\)

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. 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%.

3 Linking the Two Phenomena

3.1 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. Per capita employment in non-routine cognitive occupations 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 upward trends.\(^8\)

This stands in stark contrast to the routine occupational group. In per-capita terms, routine employment was relatively constant until the late 1980s, and has fallen 28 log points from the local peak in 1990 to present. The evolution of routine and non-routine employment makes clear that the share of employment in routine occupations has been in decline since at least 1967. Job polarization refers to the obvious acceleration of this decline in the past 25 years. Hence, job polarization does not simply represent a relative decline in routine employment; in absolute terms, per capita routine employment is disappearing. As such, and given our interest in jobless recoveries in per capita aggregate employment, we focus on the decline of per capita

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\(^7\)For 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 of our substantive results are changed when considering the routine cognitive and manual occupations separately.

\(^8\)The obvious caveat being that it is too early to speak definitively following the most recent recession.
Figure 4: Employment in Occupational Groups: 1967 – 2011

employment in routine occupations.\footnote{While we refer to the decline of routine employment as job polarization for brevity, it should be clear that the polarization phenomenon involves both the decline of routine employment and the rise of non-routine employment.}

What is equally clear in Figure 4 is that routine job loss has not occurred steadily during the past 25 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.

To state this slightly differently, 92\% of the 28 log point fall in per capita 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.

### 3.2 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.\footnote{An 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.} 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 actually grew in the non-routine groups.

Moreover, no jobless recoveries were observed in the routine occupational group. Following
Figure 5: Occupational Employment around Early NBER Recessions

Figure 6: Occupational Employment around Recent NBER Recessions

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 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.

### 3.3 A Counterfactual Experiment

To make this final point clear, we perform a simple accounting experiment to investigate, at a first pass, 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
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.
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 2009 recession, recovery back to the trough level would have taken 18 months. This is due to the fact that the recent, and far more severe, Great Recession was experienced more broadly across occupations. Nonetheless, employment would have recovered, as opposed to declining in the 24 months following the end of the recession.

3.4 Further Discussion

In this subsection, we offer a few points of clarification regarding job polarization and jobless recoveries by clarifying the role of the manufacturing sector and educational composition in accounting for these two phenomena.

3.4.1 Manufacturing

This paper emphasizes the business cycle properties of job polarization. Given this, it is possible that recessionary job losses in routine occupations simply reflect losses in the cyclically sensitive goods-producing industries, namely manufacturing and construction. This, however, is not the case. As discussed above, routine occupations account for approximately 90% of total job loss in recessions since the job polarization era. Of the losses in routine employment, only 62%, 57%, and 56% come from losses in manufacturing and construction during the 1991, 2001, and 2009 recessions, respectively. Hence the disappearance of routine employment in recessions are experienced across both goods- and service-producing sectors of the economy.

More specifically, it is possible that the phenomena of job polarization and jobless recoveries simply reflect the employment dynamics of the manufacturing and construction industries. In manufacturing, it is well-known that employment is more “routine-intensive” compared to the economy as a whole. 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.

11For instance, as of 2011, routine occupations account for 68% of total employment in manufacturing, as compared to 44% economy-wide.
We first note that job loss in manufacturing accounts for only a fraction of job polarization. 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. This point has also been made by 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, as opposed to shifts in industrial composition (away from routine-intensive, towards non-routine-intensive industries).

Secondly, jobless recoveries experienced in the past 25 years cannot be explained simply by jobless recoveries in the manufacturing sector. While the post-recession behavior of employment in manufacturing mimics that of routine occupations, it plays only a small part in generating jobless recoveries. 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.

Figure 8 displays the behavior of these counterfactual series around the 1991, 2001, and 2009 NBER trough dates. Eliminating the jobless recovery in manufacturing implies that following the 1991 recession, aggregate employment returns to its level at the trough after 23 months, as opposed to the 31 months observed in the data. This is still appreciably longer than the average of 10 months required in the early recoveries. Following the 2001 and 2009 recessions, altering the recovery in manufacturing has even less impact. Aggregate employment would still have been below the value at the trough, a full 24 months after the recession ended. Jobless recoveries would still have been observed following each recessionary episode. This evidence is consistent with the findings of Aaronson et al. (2004), who find that jobless recoveries cannot be explained by “structural change” at the sectoral or industry level.

Finally, we note that neither phenomena are due to employment dynamics in construction. With respect to job polarization, of the total job losses in routine occupations from 1990 to present, only 6% are accounted for by construction. With respect to jobless recoveries, construction plays essentially no role since: (i) the industry accounts for a very small share (about 5%) of total employment, and (ii) aside from the 2009 recession, the industry has always expe-
Figure 8: Actual and Counterfactual Employment around Recent NBER Recessions: the Man-
ufacturing case

Notes: Actual data from the Bureau of Labor Statistics, Current Employment Statistics Survey; counterfactuals described in Appendix B.
rienced strong cyclical recoveries in employment.\textsuperscript{12}

### 3.4.2 Education

Here, 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 25 years, and these workers exhibit greater business cycle sensitivity than those with higher education. It is thus possible 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.\textsuperscript{13}

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.\textsuperscript{14} 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 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.

\textsuperscript{12}See also Charles et al. (2013) for a discussion of housing and manufacturing employment during the most recent business cycle boom and bust.
\textsuperscript{13}The 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).
\textsuperscript{14}Hence, 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.
3.5 Transition Rates

Our final exercise in this section is to further investigate the process by which job polarization has resulted in jobless recoveries. To do this, we look at how transition rates across labor market states has changed across pre- and post-job polarization eras.

The “stock” of employed persons in an occupational group at any point in time is governed by the following law-of-motion, displayed for routine manual employment here:

\[ RM_t = RM_{t-1}(1 - \rho_{t-1}^{RM,NRM} - \rho_{t-1}^{RM,RC} - \rho_{t-1}^{RM,NRC} - \rho_{t-1}^{RM,NLF}) \\
+ NRM_{t-1}\rho_{t-1}^{NRM,RC} + RC_{t-1}\rho_{t-1}^{RC,RC} + NRC_{t-1}\rho_{t-1}^{NRC,RC} + URM_{t-1}\rho_{t-1}^{URM,RM} \\
+ UNRM_{t-1}\rho_{t-1}^{UNRM,RC} + URC_{t-1}\rho_{t-1}^{URC,RC} + UNRC_{t-1}\rho_{t-1}^{UNRC,RC} + NLF_{t-1}\rho_{t-1}^{NLF,RM}. \]  

(1)

Here, \( \rho_{t-1}^{X,Y} \) denotes the transition rate between dates \( t - 1 \) and \( t \), from labor market state \( X \) to labor market state \( Y \), and \( RM, NRM, RC, \) and \( NRC \) denote employment in routine manual, non-routine manual, routine cognitive, and non-routine cognitive occupations, respectively. Similarly, \( URM, UNRM, URC, \) and \( UNRC \) denote unemployment in which the last job was in each of the four occupational groups, respectively. Finally, \( NLF \) denotes non-participation in the labor force. Hence, the evolution of employment in the routine manual group is governed by the “inflows” from out of the labor force, and unemployment and employment from each occupation, relative to the reverse “outflows” out of routine manual employment. The evolution of the other employment stocks (\( NRM, RC, \) and \( NRC \)) are given by the analogous laws-of-motion.

Our focus is on how these transition rates (both inflows and outflows) have changed during economic recoveries across the pre- and post-polarization periods. To do this, we use the monthly Current Population Survey (CPS) files from 1976 to 2012. Households are surveyed for four consecutive months, then leave the sample during the next eight months, and then surveyed again for a final four months. Each household member is uniquely identified. As such, we obtain a longitudinal record for each person which allows us to study individual labor market experiences, including occupational information, over time.\(^{15}\)

We track monthly transitions across states of employment and unemployment, along with their current or previous occupation, as well as labor force non-participation.\(^{16}\) This allows us to compare the monthly transition rates averaged over the recoveries following three early recessions (1975, 1980, 1982), and the three recent recessions (1991, 2001, 2009). For brevity, we discuss results for transition rates averaged over the first 12 months of recovery following NBER trough dates; the results are largely unchanged when we consider data from the first 18 or 24 months of recovery.

\(^{15}\)For a complete description of the construction of the longitudinal data, see Nekarda (2009).

\(^{16}\)Specifically, the CPS records the most recent occupation for the unemployed. We do not observe the most recent occupation for those out of the labor force.
Comparing monthly transition rates during recoveries in the pre-polarization era to post-polarization, we find no substantive changes in the rate at which workers flow out from employment. That is, in all occupational groups, the rate at which employed workers separate to unemployment or out of the labor force (e.g., $\rho_{RM,URM}^{t-1}$ and $\rho_{RM,NLF}^{t-1}$ in equation (1)) is unchanged following early and recent recessions.\(^{17}\) Similarly, during recoveries we find no substantive changes in the average monthly transition rate from out of the labor force into employment (e.g., $\rho_{NLF,RM}^{t-1}$) for any of the occupational groups.

Instead, we find significant changes across time periods in the rate at which unemployed workers transition to employment during recoveries, the so-called “job finding rate.” Given the lack of change in the other transition rates, this change in the job finding rate – specifically, its fall – is the proximate cause of jobless recoveries. As we discuss below, job polarization has been accompanied by a significant change in the level and occupation of destination of job finding.

These changes are illustrated in Table 2. The table compares the average monthly job finding rate in early, pre-polarization recoveries, to the recent, post-polarization recoveries. For three of the four occupational groups, the rate at which unemployed workers transition into employment has fallen in the recent recoveries. For example, for unemployed workers who were previously working in a routine cognitive occupation, the average job finding rate has fallen from 22.7% to 18.9%. The exception is among the unemployed whose last occupation was non-routine manual, where the job finding rate has risen slightly, though this is not significant at the 5% level.

The fact that the job finding rate has fallen for both unemployed workers with previous routine occupations and non-routine cognitive occupations might lead one to believe that the routine/non-routine distinction, and thus job polarization, is uninformative with respect to the causes of jobless recoveries. However, this conclusion is misguided because of the non-trivial rates at which workers switch occupational groups following a spell of unemployment.\(^{18}\) What is relevant for understanding the fall in job finding rates and jobless recoveries is not what occupation the unemployed come from, but the occupations to which they are going. That is, the relevant question is whether there has been a fall in the transition rate into employment in routine occupations or into employment in non-routine occupations.

Consider first the unemployment-to-employment transitions for unemployed workers whose last occupation was routine manual. This group has seen a fall in its “total” job finding rate...
Table 2: Unemployment-to-Employment Transition Rates following Early and Recent Recessions

<table>
<thead>
<tr>
<th></th>
<th>Early</th>
<th>Recent</th>
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<th>Early</th>
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<tr>
<td><strong>A. Routine Manual</strong></td>
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<tr>
<td>Job Finding Rate</td>
<td>23.9</td>
<td>22.4*</td>
<td></td>
<td>Job Finding Rate</td>
<td>22.7</td>
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<td>to Routine Cognitive</td>
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<td>1.8*</td>
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<td>to Routine Cognitive</td>
<td>13.9</td>
</tr>
<tr>
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<td>17.0*</td>
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<td>to Routine Manual</td>
<td>3.1</td>
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<td>to Routine</td>
<td>20.5</td>
<td>18.7*</td>
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<td>to Routine</td>
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<tr>
<td>to Non-Routine Cognitive</td>
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<td>1.2*</td>
<td></td>
<td>to Non-Routine Cognitive</td>
<td>2.0</td>
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<tr>
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<td><strong>C. Non-Routine Cognitive</strong></td>
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<tr>
<td>Job Finding Rate</td>
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<td>Job Finding Rate</td>
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<tr>
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<td>to Non-Routine</td>
<td>15.3</td>
<td>14.1*</td>
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<td>to Non-Routine</td>
<td>13.6</td>
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</tbody>
</table>

Notes: Data from the Bureau of Labor Statistics, Current Population Survey. See text for details. Table displays monthly transition rates by occupational group. * indicates difference across early and recent recovery periods is significant at 5% level.
(i.e., into employment in any occupation) from 23.9% to 22.4%. However, the transition rate into non-routine occupations has either remained constant (at 2.4%, in the case of non-routine manual) or increased (from 1.0% in early recoveries to 1.2% in recent ones, in the case of non-routine cognitive). Hence, the fall in the job finding rate for unemployed routine manual workers is due to a fall in the rate at which they return to routine occupations. This can be seen in the rate at which these workers return to employment in routine manual occupations; this has fallen substantially from 19.0% to 17.0%. Hence, more than 100% of the total fall in the job finding rate since job polarization is due to a fall in the transition rate to routine employment, specifically, in the rate that they return to a routine manual job.

This is true for the other routine occupational group as well. Since job polarization and the era of jobless recoveries, the job finding rate for the unemployed whose last occupation was routine cognitive has fallen even more, from 22.7% to 18.9%. Again, this is not due to a fall in the rate at which they switch to employment in non-routine occupations. Overall, the rate at which they switch has remained essentially constant: 5.7% in early recoveries versus 5.6% in recent ones, a difference that is not statistically significant. However, the rate at which they return to employment in routine cognitive occupations has fallen substantially from 13.9% to 10.7%. The rate at which these workers find employment in routine manual jobs has fallen too, from 3.1% to 2.7%. Both of these falls are statistically significant. Hence, 3.7% of the 3.8% (or 98% of the) total fall in the job finding rate for the unemployed whose last occupation was routine cognitive is due to a fall in the rate at which these workers return to routine occupations.

By contrast, the fall in the job finding rate for the non-routine is not due to a fall in the rate at which they return to their previous occupational group. Consider unemployed workers whose last occupation was non-routine cognitive. The rate at which they return to employment in the same occupation group has fallen by only 0.5%, which is statistically insignificant. Instead, this group has seen large and significant falls in the rate at which they switch to other occupations, particularly routine ones. Comparing early to recent recoveries, the rate at which they switch to employment in either routine cognitive or routine manual occupations has fallen from 8.9% to 6.8%. This accounts for approximately two-thirds of the fall in their total job finding rate.

Finally, consider the job finding rate for unemployed whose last occupation was non-routine manual. While this has remained essentially unchanged across early and recent recoveries, this masks important changes in the composition of occupations to which they are finding jobs. The rate at which they transition to both non-routine cognitive and non-routine manual occupations has gone up (though only the latter increase is statistically significant). However, as with the non-routine cognitive, the rate at which they find employment in both routine cognitive and routine manual groups has fallen (though, again, only the latter is significant).

To summarize, we find important falls in the job finding rate for most occupational groups when comparing recent recovery periods to early ones; this is the proximate cause of jobless
recoveries. This fall in the job finding rate is due to a fall in the transition rate of unemployed workers into routine occupations. Unemployed routine workers have experienced a fall in the rate at which they return to employment in a routine occupation. Unemployed non-routine workers have experienced a fall in the rate at which they switch to routine employment. The fall in the transition rate into routine occupations during recoveries, and the consequent disappearance of routine employment, accounts for jobless recoveries in the era of job polarization.

4 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. In addition, our model captures: (f) the fall in the transition rate of unemployed workers into employment in routine occupations in jobless recoveries, relative to non-jobless ones, discussed in subsection 3.5.

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.\textsuperscript{19} 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.\textsuperscript{20} The model’s explicit consideration of frictional unemployment also allows us to address the recent discussion of “mismatch” in the labor market (see, for instance, Kocherlakota (2010) and Sahin et al. (2012)). Specifically, we show how jobless recoveries caused by job polarization need not result in any increased mismatch between vacancies and unemployed workers.

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

\begin{footnote}{See, 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.}
\end{footnote}

\begin{footnote}{As 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.}
\end{footnote}
routine work, then we have a disappearance of middle-skill occupations, in favour of high-skill occupations.\textsuperscript{21} We use this simple model to illustrate how a temporary, recessionary shock can accelerate this disappearance, and how recessions during a phase of job polarization lead to jobless recoveries. We then discuss how the model can be extended to have middle-skill workers switch out of routine occupations for both high- and low-skill (i.e. non-routine manual) work.

4.1 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 tasks 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 to recruit these workers. Vacancy posting must satisfy the following free entry condition:

$$\kappa_H = \beta q(\theta_H) J_{Ht+1}. \quad (2)$$

Here, $\kappa_H$ is the cost of maintaining such a vacancy, $\beta$ is the one-period discount factor, $q(\theta_H)$ is the probability that the firm is matched with a worker (the job filling probability), $\theta_H$ is the number of vacancies for high-skill workers relative to the number of unemployed high-skill workers (the so-called “tightness ratio”), 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:

$$J_{Ht} = f_{Ht} - \omega_{Ht} + \beta(1 - \delta) J_{Ht+1}, \quad (3)$$

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

\textsuperscript{21}Our analytical framework emphasizing occupational switching is motivated by the results of subsection 3.5. See also Cortes (2012) 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.
An unemployed, high-skill worker receives a flow value of unemployment, \( z \), and matches with a firm with job finding probability, \( \mu(\theta_H) \).\(^{22}\) 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:

\[
U_{Ht} = z + \beta \left[ \mu(\theta_H)W_{Ht+1} + (1 - \mu(\theta_H))U_{Ht+1} \right],
\]

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

\[
W_{Ht} = \omega_{Ht} + \beta \left[ (1 - \delta)W_{Ht+1} + \delta U_{Ht+1} \right].
\]

Worker compensation in a match is determined via generalized Nash bargaining. Letting \( \tau \) 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, \( \tau \). 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:

\[
\kappa_M = \beta q(\theta_M)J_{Mt+1}.
\]

We allow the vacancy cost in the routine market, \( \kappa_M \), to differ from that of the high-skill market. 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:

\[
J_{Mt} = \max \left\{ f_{Mt} - \omega_{Mt} + \beta(1 - \delta)J_{Mt+1}, 0 \right\}.
\]

Here, \( f_M \) is the output produced in a middle-skill match, and \( \omega_M \) is the compensation paid to the worker. The firm may choose to separate from the match, if the surplus is non-positive.\(^{23}\)

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

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

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.

\(^{22}\)We assume that the matching process has the usual properties, so that \( \mu(\theta) \) is a strictly increasing function of the tightness ratio, \( \theta \); \( q(\cdot) \) is a strictly decreasing function of \( \theta \); and \( q(\theta) = \mu(\theta)/\theta \).

\(^{23}\)This 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.
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:

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

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

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

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:

$$U_{Mt} = \max \{U_{MMt}, U_{MSt}\}.$$

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. The value of being employed is given by:

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

When employed in a switching match, workers receive compensation $\omega_S$ 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 $\delta$, 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:

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

where

$$J_{St} = f_{St} - \omega_{St} + \beta (1 - \delta)J_{Ht+1}.$$
case, employment in a match allows them to become high-skill). This choice depends on the markets’ relative costs (as summarized by the job finding rates) and benefits (as summarized by the worker’s compensation which, given Nash bargaining, depends on total surplus).

4.2 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.

4.2.1 Steady State

Consider a steady state equilibrium. Equilibrium in any market is summarized by the free entry condition:

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

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, $\theta_i$, 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:

$$TS_H = f_H - z - \hat{\tau}\kappa_H\theta_H$$

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:

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

**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:

$$TS_M = f_M - z - \hat{\tau}\kappa_M\theta_M$$

with $\hat{\tau} \equiv \tau/(1 - \tau)$. The term $(1 - \tau)TS_M$ is simply firm surplus (given Nash bargaining). Hence, the number of vacancies firms post per unemployed worker today, $\theta_i$, is increasing in the profit conditional on being matched tomorrow, $\beta(1 - \tau)TS_i$. 

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and the value of unemployment is:

\[ U_M = \frac{z + \hat{\tau} \kappa M \theta M}{1 - \beta}. \]  

(19)

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:

\[ U_M = \frac{z + \hat{\tau} \kappa S \theta S}{1 - \beta}. \]  

(20)

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

\[ TS_S = f_S - z - \hat{\tau} \kappa S \theta S + \beta [(1 - \delta)TS_H + (U_H - U_M)]. \]  

(21)

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 from the learning of high-skill tasks that occurs in such a match.\(^{24}\)

Unemployed workers will search in the routine market if \( U_{MM} > U_{MS} \). From equations (19) and (20), this occurs 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 (16) and (17), simplifying the analysis. To see how unemployed middle-skill workers would choose to search in the switching market is straightforward. Suppose that \( \kappa_M = \kappa_S = \kappa \) 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 \( \hat{\tau} \kappa S \theta S > \hat{\tau} \kappa M \theta M \), 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

\(^{24}\)Specifically, 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 \( \beta \). 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 \( \delta \) the match is separated, and the upgrading is reflected only in a change in the unemployed worker’s value.
match. However, the value of being unemployed also depends on the probability of entering into a match, the job finding rate. If $\kappa_S$ is sufficiently large relative to $\kappa_M$, 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 $\kappa_M/\kappa_S$ less than the cutoff, $U_{MM} > U_{MS}$.

4.2.2 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 the model, we can map out the model’s perfect foresight dynamics.\footnote{Specifically, 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.}

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 4.2.1 and assume that $\kappa_M$ is sufficiently smaller than $\kappa_S$ so that, initially, the $S$ market is not operative even though $f > f_M$.\footnote{Unlike the steady state example discussed in Subsection 4.2.1, 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.}

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, $\theta_S$, 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, the economy reaches a point when $U_{MS} > U_{MM}$. This initiates the disappearance of routine employment. Once the economy enters this polarization phase, there is a marked change in the “occupation of destination” of unemployed middle-skill workers: they switch from searching solely in the $M$-market and begin searching solely in the $S$-market. As $\theta_S$ continues to rise, so too does the job finding rate in that market, $\mu(\theta_S)$, and the upgrading of middle-skill to
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.

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 $U_{MM}$ and $U_{MS}$. 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 the unemployed prefer searching in the switching market. That is, even though no observable, discrete “shock” has occurred to productivity, all unemployed middle-skill workers switch in response to the “trend” change in relative productivity. This, of course, is accompanied by a change in vacancy creation: firms no longer post vacancies in the $M$-market and begin posting in the $S$-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 $\delta$, as they exogenously separate from routine matches. Upon separation, all unemployed middle-skill workers choose to search for a switching match.

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

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.\textsuperscript{27}

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 all unemployed middle-skill workers search in the switching market. If the recessionary fall in productivity is sufficiently large, total surplus in routine matches becomes non-positive, $TS_M \leq 0$, while total surplus in all other matches remain positive.\textsuperscript{28}

This is the case that we consider. When $TS_M \leq 0$, routine matches endogenously separate.

\textsuperscript{27}In 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, $\delta$, 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.

\textsuperscript{28}It 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
Matched firms prefer to continue as a vacancy, and matched routine workers prefer to be unemployed. In particular, these previously employed workers choose unemployment in the \( S \) market, in order to switch occupations.

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 separate to unemployment and move to the switching market.

Productivity returns to its non-recession level in period 85. At this point, the values of 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 disregard the \( S \) market, which is not yet operative. The total surplus in the two active markets is given by:

\[
TS_M = f_M - z - \hat{\tau} \kappa \theta_M + \beta (1 - \delta) TS'_M,
\]
\[
TS_H = f_H - z - \hat{\tau} \kappa \theta_H + \beta (1 - \delta) TS'_H.
\]

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 \( x f_M - z - \hat{\tau} \kappa \theta_M + \beta (1 - \delta) TS'_M = 0 \). Applied to the \( H \)-type match, it must be that \( x f_H - z - \hat{\tau} \kappa \theta_H + \beta (1 - \delta) TS'_H > 0 \).
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 return to 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.

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, $\kappa_S$, high.\textsuperscript{29} 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. 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 as a high-skill worker 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 of aggregate labor market flows. First, as documented in Section 3.2, 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

\textsuperscript{29}Note that this is the same mechanism that ensures $U_{MM} > U_{MS}$ in the initial steady state, despite the fact that $f_S > f_M$. 34
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.

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.

Third, after the initial spike in separations, unemployment dynamics are determined by the job finding rate. In the data, as in our model, jobless recoveries are characterized by a low aggregate job finding rate, relative to that observed in recoveries of the 1970s and early 1980s. In our model, in the presence of polarization, the low job finding rate is due to unemployed middle-skill workers who are switching occupations, and no longer returning routine employment.\footnote{By construction, this fall is very stark in the model, as workers cease searching in the $M$-market permanently once the economy enters the polarization phase.} By contrast, absent job polarization unemployed middle-skill workers never switch, as we discuss below. As such, the model is consistent with the low transition rates from unemployment to routine employment observed since polarization, presented in subsection 3.5.

Finally, we note that the jobless recovery exhibited in our model is not accompanied by increased “mismatch” in the labor market. Though there are a number of working definitions of mismatch in the literature, the common idea is summarized by Kocherlakota (2010): “Firms have jobs, but can’t find appropriate workers. The workers want to work, but can’t find appropriate jobs.”

This does not occur in our model. While recessions result in a large number of separations in middle-skill matches, these unemployed workers choose to search in the switching market. There are no middle-skill workers searching “inappropriately” for vacancies in the $M$-market that do not exist. Similarly, because firms are free to create vacancies in any markets, firms do not post vacancies in the $M$ market inappropriately to attract unemployed workers who prefer...
to become high-skill workers; new vacancies are created in the $S$ market (until the zero profit condition is satisfied) where unemployed middle-skill workers are searching. Therefore, there is no more mismatch during a jobless recovery than there was before.

Obviously, our simple search-and-matching model is not a wholly accurate representation of the real world. Nonetheless, it presents an example in which equilibrium arguments result in jobless recoveries, driven by RBTC and job polarization, without increased mismatch. As such, the model is consistent with the lack of evidence for increased mismatch following the most recent recession (see, for example, Sahin et al. (2012)).

**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 are not searching in the $S$ when unemployed. As a result, recoveries 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. The second feature is a low job finding rate among those who are displaced following a recession. In our model, this occurs for unemployed middle-skill workers switching occupations. 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 25 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.

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

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31Of 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.
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: some people find it impossible to become proficient at high-skill tasks, and can only perform middle- and low-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. The relative productivities in high- and low-skill matches rise until they cross thresholds, at which point an unemployed middle-skill worker ceases searching for a middle-skill match, in favor of a match in the skill level suited to their ability. None of the substantive implications of our model would be altered.

5 Conclusions

In the last 25 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 employment is concentrated in economic downturns. Second, we show that job polarization accounts for jobless recoveries. This is based on the fact that almost all of the contraction in aggregate employment during recessions can be attributed to job losses in routine occupations (that account for a large fraction of total employment), and that jobless recoveries are observed only in these disappearing jobs since 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.

These findings illustrate how tenuous it can be to dichotomize “trend” and “cycle” in economic analysis. The nature of job polarization – a long-run, or “trend” phenomenon – is informed by an analysis of its business cycle properties. Moreover, an understanding of jobless recoveries – a “cyclical” phenomenon – requires consideration of the job polarization trend in the labor market.
A Data Sources

A.1 Aggregate Data

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.

In subsection 3.4, 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,” manufacturing employment is “all employees: manufacturing,” and construction employment is “all employees: construction.” 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.

A.2 Disaggregated Data

We consider an occupational classification system that proves useful for macroeconomic analysis and ease of data access and replication. Beginning in 1983, our classification is based on the categorization of occupations in the 2000 Standard Occupational Classification system. Specifically, 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”.

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”, “operators”, 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.

The job polarization literature considers a number of alternative ways to classify employment at the occupational level. We have used a number of these and find our results robust to these alternatives. Perhaps the most comprehensive is that of Autor and Dorn (2012). They generate six broad categories based on an occupation’s degree of intensity in abstract (i.e., cognitive), routine, and manual tasks. Based on these categories, routine occupations are those with rou-

\[32\text{Specifically, Autor and Dorn (2012) first take the Census Occupation Codes from 1960, 1970, 1980, 1990, and 2000 and map them into a single, consistent set of occupation codes. This “cross-walk” of occupation codes is based on the work of Meyer and Osborne (2005). These consistent occupations are then allocated to occupational groups.}\]
tine task intensity greater than the average across all occupations. Specifically, we consider the “Production/Craft”, “Transport/Construction/Mechanic/Mining/Farm”, and “Machine Operators/Assemblers” categories to be routine manual occupations, and the “Clerical/Retail Sales” category to be routine cognitive. The “Managers/Professional/Technician/Finance/Public Safety” category constitutes the non-routine cognitive occupations, and the “Service” category the non-routine manual. Using this categorization, we redo the analysis of this paper and find the results to be essentially unchanged.\footnote{This can be understood by comparing Autor and Dorn (2012)’s classification system to ours. In particular, using their consistent occupation codes, the two systems are remarkably similar. Of the 330 occupations considered by Autor and Dorn (2012), the two systems differ with respect to the routine/non-routine delineation for only 15 occupations. Further details are available from the authors upon request.}

Finally, we note that regardless of the classification system, employment at the occupational group level displays a break between 1982 and 1983. This is due to the extensive reclassification of occupations undertaken with the 1980 Census codes (see, for instance, Rytina and Bianchi (1984) and Meyer and Osborne (2005)), and implemented in the CPS beginning in January 1983. As such, we have adjusted the data prior to 1983 to remove the discontinuity. Because the adoption of the 1980 occupation codes occurs only one month from the start of the recovery following the 1982 recession (NBER trough date on November 1982), the timing of the break does not affect our analysis regarding the nature of recoveries in employment.

\section*{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 counter factual for months 12 through 24 to be exactly the average response. In the 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.

\section*{C Vacancy Costs and the Tightness Ratio}

Here we demonstrate how variation in the vacancy cost affects the equilibrium tightness ratio. From equations (15) and (18), the zero profit condition in steady state can be expressed as:

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

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:

\[ \kappa_M \theta_M = \theta_M^{\alpha} \beta (1 - \tau) \left[ \frac{f_M - z - \hat{\tau} \kappa_M \theta_M}{1 - \beta (1 - \delta)} \right]. \] (23)

Consider a fall in \( \kappa_M \). Condition (23) requires a rise in \( \theta_M \): in equilibrium, a lower vacancy cost induces a fall in the firm’s job filling probability through a rise in the tightness ratio, \( \theta_M \).
Moreover, maintaining zero profits requires a larger than proportionate rise in $\theta_M$. To see this, suppose to the contrary that the rise in $\theta_M$ is proportionate to the fall in $\kappa_M$, so that the product $-\kappa_M\theta_M$ remains unchanged. This would imply that the LHS of (23) remains unchanged, as does the total surplus (the term in square brackets) on the RHS. Hence, equality would not be maintained as $\theta_M^k$ on the RHS would rise. Given that $\alpha < 1$, this implies that $\theta_M$ must rise more than proportionately to the fall in $\kappa_M$, 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 $\kappa_M$ such that $\hat{\tau}\kappa_M\theta_M = \hat{\tau}\kappa_S\theta_S$. For any values of $\kappa_M$ smaller than this, unemployed middle-skill workers would search in the routine market, even when $f_S > f_M$. 
References


