Job Flows, Jobless Recoveries, and the Great Moderation

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Abstract:

This paper uses a new, long time-series on job flows within manufacturing to examine their volatility and behavior before and during the Great Moderation. Like many other aggregate statistics, job creation and job destruction had a sharp decline in their volatility in the mid-1980s. At the same time, job reallocation, a measure of the cross-sectional dispersion of employer growth, exhibited a secular decline dating back to 1960. More importantly, the responses of job creation and job destruction to an aggregate shock (conditional on the size of the shock) have changed since the mid-1980s. Their responses are now larger and more persistent, and job creation no longer displays a strong recovery as it did prior to 1984. The altered responses lead to employment growth patterns that resemble a jobless recovery. The results are robust to several counterfactual exercises and underscore the fact that the labor market has fundamentally changed how it responds to aggregate shocks since the start of Great Moderation.

Keywords: gross job flows, jobless recoveries, aggregate volatility, Great Moderation

JEL Codes: E24, E32, J63.

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Contact: jfaberman@ frbchi.org. 230South LaSalle St., Chicago, IL 60604. Phone: (312) 322- 5274. Fax: (312) 322-2357.1 thank Steve Davis, Pablo Guerron, John Haltiwanger, Alejandro Justiniano, Giorgio Primiceri, Scott Schuh, Keith Sill, Tom Stark, Dan Sullivan, and numerous seminar and conference participants for helpful comments. Any remaining errors are my own. The views expressed are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1. Introduction

Starting in the mid-1980s, the volatility of aggregate economic activity declined considerably and remained low until the most recent recession. Most economists refer to this decline, first reported by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000), as the "Great Moderation." A wealth of research has emerged on its sources (whether it is the result of good policies, or simply good luck) and its dynamics (whether the decline is a break in the time series or part of a long-run trend), among other things.[1]

The Great Moderation also affected cyclical patterns within the labor market. The comovement of hours, output, and labor productivity changed considerably (Galí and Gambetti, 2009; Galí and van Rens, 2010). The volatility of employment growth declined concurrent with the volatility of other aggregate variables. "Jobless recoveries," defined as an employment recovery that substantially lags the recovery of output, have followed each of the last three recessions.[2] These labor market changes have occurred at roughly the same time, yet there is little work to date that attempts to link them.[3]

In this paper, I focus on the latter two changes: the decline in employment volatility and the onset of jobless recoveries. I construct a longtime series of gross job flows for the U.S. manufacturing sector that covers the entire postwar period. The series is a synthesis of earlier data constructed by Davis and Haltiwanger (1999) and estimates I generate from the Business Employment Dynamics micro data. By examining gross rather than net employment changes, I am able to perform a richer analysis of

[1] Notable examples of this research include Blanchard and Simon (2001), Stock and Watson (2002), Ahmed, Levin, and Wilson (2004), Ramey and Vine (2006), and Justiniano and Primiceri (2007).
[2] Researchers have put forth several hypotheses on the cause of jobless recoveries, but none fully capture the changes in the labor market over this period. See Groshen and Potter (2003), Schreft and Singh (2003), Aaronson, Rissman, and Sullivan (2004), Koenders and Rogerson (2005), and Bachmann (2007).
[3] A notable exception is Engemann and Owyang (2007), who use a Bayesian approach to study an econometric link between jobless recoveries and the Great Moderation.

the changes in employment dynamics over the postwar period. I begin by establishing several new facts about the behavior of gross job flows over this period:

- Job reallocation, a measure of the cross-sectional dispersion of employment growth at the employer level, experienced a secular decline that started between 1955 and 1960 and continued through 2010. The trend reallocation rate fell by one-third during this time.
- The time-series volatility of job creation and job destruction experienced a sharp, structural decline at the onset of the Great Moderation (identified at 1982-83). The decline was asymmetric, leading to a fall in the relative volatility of job destruction to job creation, and the comovement of job creation and job destruction with output growth, and with each other, became weaker. Job flow volatility increased sharply during the 2008-09 recession, but not quite to the levels preceding the Great Moderation.
- Evidence on job loss across the broader economy from other data sources suggests that these patterns are not unique to manufacturing. If anything, the broader evidence suggests that the manufacturing data overstate the recent resurgence in labor market volatility.

Next, I analyze the behavior of job flows within the structural VAR framework developed by Davis and Haltiwanger (1999). This framework attributes time-series movements in job creation and job destruction to structural shocks that are either aggregate or reallocative in nature. I perform the analysis separately on the pre-1984 and post-1984 periods and focus on two aspects of the data: changes in the volatility of the structural shocks and changes in the response of job flows to these shocks across the two sample periods. Two results stand out in the analysis.

First, the volatility of both aggregate and allocative shocks declined during the Great Moderation. The volatility of aggregate shocks had a substantially larger decline, suggesting that the majority of the decline in job flow volatility was aggregate rather than reallocative in nature. Depending on the

identifying assumptions used, the standard deviation of the aggregate innovations fell between 52 and 62 percent, while the standard deviation of the allocative innovations fell between 23 and 41 percent.

Second, and most importantly, the responses of job creation and job destruction to an aggregate shock are notably different during the Great Moderation period. Compared to the earlier period, the responses after 1984 are larger and more persistent, conditional on the size of the shock. This is especially true of job destruction. Moreover, the response of job creation to a negative aggregate shock does not exhibit a quick, strong recovery from an aggregate shock, as it did in the earlier period. This leads to fairly symmetric responses of job creation and destruction to an aggregate shock after 1984. These altered responses led to *net* employment growth behavior that is consistent with a jobless recovery. Prior to 1984, net employment growth returned to its initial level about 4 quarters after a negative aggregate shock and actually exhibited several quarters of above-trend growth before returning to its initial value. From 1984 onward, it took 8 quarters to return to its initial level, and the period of above-trend growth observed prior to 1984 disappears. Notably, there is no difference in the responses of job creation and destruction to an allocative shock across the early and later periods of the data. Changes in job flow behavior appear to be primarily in response to aggregate shocks. These results hold regardless of the identifying assumptions of the structural VAR.

Thus, the exercise suggests that jobless recoveries, and to some extent the decline in volatility, have come about primarily because job creation no longer exhibits a strong, over-pronounced recovery and because job destruction remains persistently high following the onset of a negative aggregate shock. Net employment losses last longer as a result. The nearly symmetric responses of job flows to an aggregate shock also imply that one is equally likely to observe a jobless recovery driven persistently low job creation or persistently high job destruction. This is something that is evident in the jobless

recoveries following the last three recessions: 1992 was a period of relatively high job destruction, while 2002-03 and 2009-10 were periods of relatively low job destruction.

My structural VAR results are robust to alternative exercises. For instance, one may think that the severity of the Great Recession may distort the results for the post-1984 period. When I replicate my analysis for the 1984-2006 period (excluding the last downturn), the volatility of the structural shocks is somewhat lower, up to 22 percent relative to the 1984-2010 estimates, depending on the identify assumptions, but there is little change in the impulse responses of job creation or job destruction.

One might also think that a structural shift in the labor market away from temporary layoffs and towards temporary help employment accounts for the differing impulse responses before and after 1984. Since the mid-1980s, the cyclically of unemployment due to temporary layoffs has practically disappeared. By their nature, temporary layoffs should generate a less persistent response in job destruction and strong recovery in job creation as those temporarily laid off are recalled. In addition, Dey, Houseman, and Polivka (2012) show that temporary help employment has made up an increasing share of manufacturing, with the share rising from 2 percent in 1989 to nearly 9 percent in 2008. Temporary help employment is much more volatile and exhibits stronger cyclically than manufacturing employment. In establishment-based data, however, temporary help workers at manufacturing plants are counted within the employment services industry. Dey et al. estimate a reasonable allocation of these workers back to manufacturing.

When I generate a counterfactual series of job flows based on the Dey et al. study, I obtain results that are nearly identical to my original estimates. Specifically, I generate a counterfactual job flow series from 1990 forward that allocates a fraction of the job flow rates in the employment services industry to manufacturing each quarter and then replicate the structural VAR analysis. The magnitude of job flows is notably higher, as is their volatility, but the shift to temporary help, however, accounts for

no more than 6 percent of the decline in the volatility of aggregate shocks. It also does almost nothing to change the response of job flows to an aggregate shock.

My results build on the findings of Galí and Gambetti (2009) and others on the changes in the comovement patterns of hours, output, and labor productivity. Specifically, they underscore the fact that the Great Moderation was as much a period of altered responses to shocks within the labor market as it was a period of lower aggregate volatility. Earlier research showed that the cyclical movements in hours and labor productivity went from being essentially uncorrelated to strongly negatively correlated, while labor productivity itself went from being strongly procyclical to roughly acyclical. I add to this by showing that labor adjustments at the establishment level, when analyzed in the aggregate, are now larger and more persistent for a given aggregate shock. These changes in employment adjustment are reflected in a longer period of job destruction and a weaker recovery of job creation following an adverse aggregate shock and it leads to what we observe as jobless recoveries in the data. The changes are also concentrated in the responses to an aggregate shock. Responses of job flows to allocative shocks, which can be interpreted as disturbances that cause labor to reallocate across employers, have not changed much during the entire postwar period. Thus, jobless recoveries have not come about because of a slower or longer labor reallocation process. Finally, while aggregate volatility increased during the Great Recession, the altered responses of job flows to an aggregate shock persisted.

2. Data and Measurement

I use data from two sources on gross job creation and gross job destruction. Gross *job creation* refers to the sum of all employment increases across employers who are either expanding or just starting up. Gross *job destruction* refers to the sum of all employment declines across employers who are either contracting or closing down. Aggregate *net* employment growth is simply the difference between job creation and job destruction.

I use data from the Business Employment Dynamics (BED) data of the Bureau of Labor Statistics (BLS) as well as data on job creation and job destruction within manufacturing from Davis and Haltiwanger (1999). The BED is a linked, longitudinal source of establishment micro data. It is based on administrative unemployment insurance (UI) records, and is therefore a virtual census of all establishments within the U.S.[4] The Davis-Haltiwanger series is a splice of job flow rates calculated from the Census Bureau's Longitudinal Research Database (LRD), which the authors used extensively in earlier work (e.g., Davis and Haltiwanger, 1990, 1992), and predicted job flows from the now-defunct BLS Labor Turnover Survey (LTS).[5] Job flows within the BED and LRD data are measured using employment changes between the third-month of each quarter at the establishment level. They are expressed as rates using the methodology of Davis, Haltiwanger, and Schuh (1996), which divides each flow by the average of third-month employment in the current and previous quarters.[6] Given the nature of the splicing algorithm used by Davis and Haltiwanger, the predicted LTS job flows have the same measurement interpretation. In my analysis I also examine the behavior of the job reallocation rate, which is the sum of the job creation and job destruction rates. It is a useful measure of the cross-sectional dispersion of establishment growth at a point in time. I also examine the excess reallocation rate, which is the job relocation rate minus the absolute value of the net growth rate. It provides a measure of reallocation in excess of what one needs to achieve the observed employment growth rate.

This study involves two innovations to the job flow data. The first extends the BED job flow series back to 1990. Currently, the BLS publishes data on job creation and job destruction using the BED

[4] The primary exclusion from the BED are the self-employed, the military, and select non-profit organizations. I use a subsample of 43 U.S. states that allow access to their UI micro data through BLS confidentiality agreements. The excluded states are Connecticut, Florida, Massachusetts, Michigan, Mississippi, New Hampshire, New York, Pennsylvania, and Wyoming. There is very little difference between the job flow rates derived from this sample and the published BED job flow statistics. For more on the BED data, its scope, its creation, and its measurement of job flows, see Spletzer et al. (2004).

[5] I thank John Haltiwanger for providing me with an updated version of their data.

[6] This produces a symmetric growth rate that is bounded between -200 and 200 percent and allows for a symmetric treatment of employment changes at opening and closing establishments.

data, but because of data issues, these published statistics only begin in 1992Q3. The data issues involve administrative changes that made it difficult to link continuous establishment records across quarters using the standard BLS algorithm. When these linkages are missed, it produces an overstatement of job flows because the un-linked records are counted as closing and opening establishments. I deal with these data issues by generating an algorithm that first identifies establishment openings and closings within detailed industries and counties that have similar firm identifier information and then links records where they most likely represent a continuous establishment. Details of my approach and its effect on the job flow estimates are in the appendix. The approach only adds 9 quarters of earlier data but the period includes a recession and subsequent jobless recovery. The additional quarters also considerably increase the overlap period, as well as the volatility during the overlap period, between the BED series and the LRD-LTS series constructed by Davis and Haltiwanger. This is crucial for the splicing methodology used in my second data innovation, described next.

The second innovation merges the BED job flow rates with the job flow rates from the Davis-Haltiwanger data to produce a single, consistent time series of manufacturing job flow data that covers the entire postwar period (1947-2010). I splice the two series together using a Generalized Method of Moments (GMM) approach that imposes that the mean, volatility and comovement behavior of job flows in the BED data on the LRD-LTS sample during the period when the two series overlap (1990Q2 - 1998Q4). It does so using a predicted relationship between the LRD-LTS job flows, the BED job flows, and net employment growth. This method is similar to the approach Davis and Haltiwanger used to merge the LRD and LTS.[7] The goal of the splicing procedure is to produce a predicted series of the earlier data that behaves as if it was measured as BED data.

[7] Davis and Haltiwanger use OLS to generate the predicted LTS job flow estimates from the series' overlap with the LRD data.

Let JC_t and JD_t represent the job creation and job destruction rate estimates, respectively, at time t from the BED, and let POS_t and NEG_t represent the job creation and job destruction rate estimates, respectively, from the LRD-LTS data. Let NET_t^C be the net growth rate calculated from the Current Employment Statistics (CES) survey. I use the CES net growth rate as part of the splicing procedure because it provides a consistent measure of growth that spans both the early and later periods. In addition, the CES is an establishment-based survey that draws its sample from the same administrative data used to create the BED, so the two data sources have nearly identical growth rates by construction. The predicted relationships used in the estimation process are:

$$JC_t = \alpha_0 + \alpha_1 POS_t + \alpha_2 NET_t^C + u_t^c \text{, and}$$

$$JD_t = \beta_0 + \beta_1 NEG_t + \beta_2 NET_t^C + u_t^d.$$

I estimate the α and β parameters through GMM, using six moments that describe the mean, variability, and comovement patterns of job creation and job destruction in the BED data during the overlap period. I focus on these aspects to ensure consistency in the measurement of the magnitudes, cyclically, and comovement of job flows across both the early and later data. The choice of moments is nontrivial because, due to the definitions of job flows, net growth and job reallocation, many candidate moments are linear combinations of one another, and can therefore lead to an under-identified system.

Table 1 lists the moments used and their values in the BED data. The GMM estimation produces parameter estimates for α and β. I use these estimates along with the data for POS_t, NEG_t, and NET_t^C to derive the out-of-sample predicted estimates of $\widehat{JC}_t$ and $\widehat{JD}_t$ for the 1947Q1 - 1990Q1 period. These estimates, along with the actual BED estimates for the 1990Q2 - 2010Q4 period make up my final spliced series of manufacturing job flow rates. The web appendix details the GMM estimation further, and includes a comparison of the spliced series to the original LRD-LTS series.

3. Job Flows: Reallocation, Cyclicality, Comovement

3.1. Basic Evidence

Figure 1 shows the spliced time series of job creation and job destruction. Several salient features stand out. First, the volatility of job creation and job destruction is higher prior to the 1980s. Second, the magnitudes of job creation and job destruction fall, on average, from the 1980s onward. This secular decline in job flows is especially pronounced during the 2000s. Finally, with the exception of the last recession, spikes in job destruction during recessions get progressively smaller from the 1980s forward.

Table 2 presents the summary statistics that describe job flow behavior in Figure 1. The table splits the data out into two periods: 1947-1983 and 1984-2010. The break represents the date that most studies identify as the start of the Great Moderation.[8] Below, I show that is close to the date of a structural break in the job flow volatility as well. The magnitudes of job creation and job destruction both fell, so that the average job reallocation rate in the 1984-2010 period was 22 percent lower than the average job reallocation rate in the 1947-1983 period. Volatility is also lower in the later period. The standard deviation of job creation fell by 19 percent and the standard deviation of job destruction fell by 29 percent. Thus, the relative volatility of job destruction to job creation fell from 1.31 to 1.14. Relative to the standard deviation of output growth (measured as the difference in the log of real GDP), the volatility of job creation and job destruction actually increased. In general, Table 2 shows that the comovement patterns of job creation, job destruction, and output growth weakened in the later period. Both job creation and job destruction became less correlated with output growth and less correlated with each other. In fact, the correlation between creation and destruction switched in sign, from -0.4 to 0.1. The correlation between job reallocation and net employment growth became weaker as well.

[8] See, for example Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Stock and Watson (2002).

Figures 2 through 4 provide a more detailed picture of the declines in the magnitude, volatility, and comovement patterns of job creation and job destruction. Figure 2 shows the full time series of the job reallocation rate and the excess reallocation rate (job reallocation in excess of what is needed to achieve the net growth rate). It also shows the trend for each estimated using a low-frequency Hodrick-Prescott filter (smoothing parameter = 10^5). The job reallocation trend peaks in 1955 while the excess reallocation trend peaks in 1960. Both trends exhibit a steady decline throughout the remainder of the sample period, only flattening out in the final years of the sample. Between 1960 and 2010, the trends of both reallocation rates declined by about one-third.

Figure 3 reports rolling 20-quarter standard deviations of the job creation and job destruction rates (top panel), and job reallocation and excess reallocation rates (bottom panel). These are comparable to the 20-quarter rolling standard deviations of output growth reported by Blanchard and Simon (2001). The top panel of Figure 3 shows that the volatility of job flows follows a similar pattern to the volatility of output growth documented by Blanchard and Simon. The volatility of both rates begins high and steadily declines between 1952 and the late 1960s. It then rose considerably and remained high until it dropped sharply in the mid-1980s. This was especially true for job destruction. There was a moderate but short-lived rise in volatility around the 2001 recession, followed another rise during the 2008-09 recession. The rise in the volatility of job destruction was particularly sharp, but did not quite reach its peak levels observed during the 1970s and early 1980s.

The bottom panel of Figure 3 shows the volatility of job reallocation and excess reallocation. The volatility of reallocation exhibits a strikingly different pattern. The volatility of the job reallocation rate falls in the early part of the sample and rises during the 1970s and 1980s. Following a drop in volatility in the mid-1980s, however, it continues to exhibit episodes of high volatility following the end of each recession. The volatility of the excess reallocation rate falls more sharply between 1952 and the late

1960s, but it does not exhibit as much of a rise during the 1970s and 1980s. Other than some cyclical movements in the late 1990s and 2000s, the volatility of the excess reallocation rate does not change much thereafter.

Figure 4 reports rolling 20-quarter correlations between the job creation rate and output growth and the job destruction rate and output growth, where output growth is measured as the change in the log of real GDP. For the most part, prior to the mid-1980s, job creation was strongly positively correlated with output growth and job destruction was strongly negatively correlated with output growth. From the late 1980s forward, however, the relationships became weaker, particularly for job creation, and more volatile. During the most recent recession, the correlations with output increased in magnitude to levels observed prior to the late 1980s.

3.2. Testing for Structural Breaks in Volatility

To summarize, the magnitude of job reallocation exhibited a trend decline that started well before the date attributed to the start of Great Moderation, while the volatility of job flows, and to some extent their comovement with output and with each other, declined sharply during the mid-1980s, consistent with the date attributed to the start of the Great Moderation. I now employ methods from previous research on the Great Moderation to formally test for a structural break in the time series of job flow volatility and to examine whether the shift in volatility continues to hold when one allows for changes in the persistence and the trend in job creation and job destruction.

I first test for a structural break in the time series volatility of the job flow data following the approach of McConnell and Perez-Quiros (2000) and Stock and Watson (2002).[9] Specifically, I use the following model:

[9] Stock and Watson test for breaks in both the conditional mean and conditional variance of the time series. Given the job flow evidence in the previous section, I focus only on the variance in this exercise, as McConnell and Perez-

$$y_t = \alpha + \Phi(L)y_{t-1} + \varepsilon_t,$$

where y_t represents one of the job flow rate measures and $\Phi(L)$ is a lag polynomial. I assume that the variance of the residuals follows

$$Var(\varepsilon_t) = \begin{cases} \sigma_1^2 & t \leq \tau \\ \sigma_2^2 & t > \tau \end{cases}$$

The test for a structural break uses the Quandt Likelihood Ratio (QLR) test statistic, also known as the sup-Wald statistic, to test whether σ_1^2 is significantly different from σ_2^2 at some unknown date τ (see Quandt, 1960, and Andrews, 1993). I estimate the model using a lag length of 4 quarters in the regression for each variable of interest. The QLR statistic is then calculated for all potential break dates in the central 70 percent of the time-series sample, defining the conditional variance as the mean of the absolute value of the regression residuals. An estimated potential break date f is the date of the maximum QLR statistic. If the maximum QLR statistic is above a given critical value of the test, one can reject the null of no break in the time-series variance of the given variable.

I perform the test separately for each job flow series (job creation, job destruction, job reallocation, excess reallocation, and net employment growth). For comparison, I also test for a break in the volatility of output growth and in the volatility of the inflow rate into unemployment. I measure the latter variable two ways. The first uses the number of individuals unemployed less than five weeks, as a percentage of employment, from the Current Population Survey (CPS). The second is the total number of UI initial claimants, as a percent of employment. Both inflows are measured as quarterly totals.

My job flow data faces a measurement issue in that the QLR test is implicitly an evaluation of the performance of my splicing methodology. Measurement differences between the predicted LRD-LTS

Quiros do. My second exercise examines whether there were joint changes in the trend, persistence, and volatility of job creation and job destruction.

series and the BED data used in the later part of the sample will appear as a structural break around the splicing date, 1990Q2.1 take this caveat into account when identifying a break date using the maximum QLR statistic. Specifically, when rejecting the null of no break in the variance of the residuals, I take into account the potential for false maxima around the splice date.

Table 3 presents the results of the structural break test. For each variable, I report the maximum value of the QLR statistic and the break date associated with this value. The critical values for the test as specified are 12.35 for significance at the 1 percent level and 8.85 for significance at the 5 percent level. Both job creation and job destruction have significant breaks in their time-series volatility in 1983Q2 and 1982Q2, respectively. Net employment growth is identified to have a significant break in volatility at 1982Q1. These dates are close to the identified break date of 1984Q2 for real GDP growth. Both unemployment inflow measures show a structural break in their volatility around the same time as well (1985Q1 for the CPS-based measure and 1985Q2 for the UI-based measure). All of these break points are within the range of break points identified by Stock and Watson (2002) for a wide array of aggregate economic variables.[10]

Neither the job reallocation rate nor the excess reallocation rate shows a definitive break in their time-series volatility. As shown in the appendix, the QLR statistic for job reallocation is only significant around the point of splicing, 1990Q2. The test statistic is close to zero for most of the remainder of the time series. The QLR statistic for the excess reallocation rate is significant over a range of the time series but its maximum occurs just before the splicing date (1989Q2). The appendix shows that I can reject the null of no break in its time-series volatility sometime between 1983 and 1989, but I cannot determine whether such a rejection is driven by a true structural change in the volatility of excess reallocation or by measurement error in the spliced series.

[10] Stock and Watson (2002) estimate a structural break in output growth and employment growth in 1983Q2, while McConnell and Perez-Quiros (2000) estimate a break in output growth in 1984Q1.

Finally, it is worth noting that the QLR statistics for job creation, job destruction, excess reallocation, and net growth have notably large and significant local maxima between 1959 and 1960 (see appendix). This is not surprising given the sharp shifts in volatility observed in Figure 3 around this period, but it likely warrants further research.

My second exercise examines changes in the behavior of the variance of the residuals relative to potential changes in the trend or persistence of job creation or job destruction. It replicates the exercise Blanchard and Simon (2001) perform on output growth. I estimate an AR(1) model with an intercept term for rolling 20-quarter windows of the job creation rate and job destruction rate. I then report the time series behavior of the coefficients and variance of the residuals from these autoregressions. Figure 5 reports the results. The top two panels report the time series of the trend (i.e., intercept) coefficients for the job creation rate (left) and the job destruction rate (right), the middle two panels report the persistence (i.e., slope) coefficients, and the bottom two panels report the volatility (i.e., variance of the residuals). Only the volatility estimates show any notable change in their time series behavior, and do so for both job creation and job destruction during the mid-1980s. This is consistent with my earlier evidence. There appears to be no major shift in either the trend or persistence of either variable. This is consistent with the patterns Blanchard and Simon found when performing the exercise on output growth.

3.3. (Non-)Uniqueness of Manufacturing

This study focuses exclusively on manufacturing, primarily because a long and current time series of labor turnover data does not exist for the broader economy. There are, however, job flow data for the private sector over a shorter time period and labor market measures that should behave similarly to the private-sector job destruction rate over a longer period. To gauge the representativeness of my manufacturing results, I compare the time-series behavior of the job destruction rate of my

spliced manufacturing series with the behavior of these comparable data series. I focus on the comparability of their magnitudes and their volatility.

Specifically, I compare the spliced manufacturing job destruction rate to (i) the private-sector job destruction rate from the BED, which covers the 1990-2010 period, (ii) the CPS-based unemployment inflow measure, which covers the 1948-2010 period, and the UI claims-based unemployment inflow measure, which covers the 1967-2010 period. All four measures broadly measure the extent of gross job loss.[11] The latter three do so for a much broader measure of the economy than manufacturing. If the spliced manufacturing data are representative of the whole economy, its job destruction rate should behave very similarly to these other measures.

The evidence is in Figure 6. The top panel shows the time-series behavior of each series. All measures are expressed as percentages of employment. While the average magnitudes differ across each series, the cyclical behavior of all four series is strikingly similar. The bottom panel of Figure 6 provides perhaps the most convincing evidence that the findings of this study are likely not unique to manufacturing. It is the analog to Figure 3 and reports the rolling 20-quarter standard deviations for each variable. For the most part, the rolling standard deviations of all four measures of job loss practically lie on top of each other throughout the sample period. If anything, the evidence suggests that the manufacturing job flows may overstate the recent increase in volatility. Only the UI claims data show a similar spike in volatility, while the CPS-based inflows and the private-sector job destruction rate show a notably smaller increase in volatility. I conclude from Figure 6 that the results in this study are likely not unique to the manufacturing industry.

[11] The CPS data includes a direct measure of gross worker flows from employment to unemployment, which is admittedly a superior measure to the short-term unemployment inflow measure. Unfortunately, the gross worker flow data are only calculable back to 1976, and this start date is too close to the identified structural break dates to allow for a meaningful comparison of the data.

4. Changes in the Response to Structural Shocks

Thus far, I have shown that the magnitude of job flows have exhibited a steady secular decline that predated the onset of the Great Moderation while the volatility of job flows exhibited a sharp structural decline at a date consistent with the start of the Great Moderation. Since the start of the Great Moderation, another predominant feature of cyclical fluctuations within the labor market has been the prevalence of jobless recoveries. These are defined as periods following a recession where the recovery of employment growth substantially lags the recovery of output growth.

One interpretation of the reduction in volatility is that the shocks to the labor market have gotten smaller. Given the jobless recoveries that have proceeded the last three recessions, it is also worth examining whether the responses to such shocks, conditional on their size, have changed as well.

4.A. A Structural VAR of Job Creation and Job Destruction

To examine whether the response to underlying shocks to the labor market have changed, I use a structural vector autoregression (SVAR) analysis. I use the SVAR model from Davis and Haltiwanger (1999) and apply it separately to an earlier and later sub-period of data. Davis and Haltiwanger used their SVAR to study how much reallocative versus aggregate shocks accounted for cyclical employment fluctuations. I instead use their SVAR model to compare its behavior before and during the Great Moderation. I focus on two aspects: changes in the volatility of the identified structural shocks, and changes in the impulse responses of job creation and job destruction to these shocks.

The SVAR developed by Davis and Haltiwanger (1999) postulates that movements in job creation and job destruction are the result of two types of structural shocks: *aggregate shocks,* which affect the level of economic activity over the business cycle, and *allocative shocks,* which alter the distribution of economic activity. I use the same nomenclature as Davis and Haltiwanger. One can (very) loosely think of the aggregate shock as cyclical in nature and the allocative shock as a shock to the reallocation

process, but one can obviously have reallocation occur due to cyclical factors as well as changes in the level of economic activity due to reallocative factors. Thus, it is likely better to use their mechanical interpretation: aggregate shocks cause job creation and destruction to move in opposite directions (and therefore mostly affect growth) while allocative shocks cause job creation and job destruction to move in the same direction (and therefore mostly affect churning).

These shocks cannot be immediately recovered from a reduced-form VAR specification. Instead, one must make identifying assumptions that restrict the structural parameters to produce a range of plausible results. Let $\mathbf{Y}_t = [JC_t, JD_t]'$ e a vector of the job creation and job destruction rates observed in the data. Let $\varepsilon_t = [\varepsilon_{at}, \varepsilon_{rt}]'$ be a vector containing the structural disturbances that drive the movements in job creation and job destruction, where ε_{at} represents the structural disturbances due to aggregate shocks and ε_{rt} represents the structural disturbances due to allocative shocks. The relationship between the innovations and the observed outcomes is assumed to have a linear moving average representation,

$$\mathbf{Y}_t = \mathbf{B}(L)\varepsilon_t, \qquad \mathbf{B}(0) = \mathbf{B}_0, \tag{1}$$

where $\mathbf{B}(L)$ is an infinite-order matrix lag polynomial. Without loss of generality, one can normalize the diagonal elements of the contemporaneous response matrix, $\mathbf{B}_0$, to one.

Equation (1) depicts the structural representation of job flows and the structural shocks. The VAR, however, estimates the parameters of a reduced-form model,

$$\mathbf{Y}_t = \mathbf{D}(L)\eta_t, \qquad \mathbf{D}(0) = I,$$

where $\mathbf{D}(L)$ is the infinite-order lag polynomial implied by the estimated coefficients of the reduced-form VAR and $\eta_t = [\eta_{ct}, \eta_{dt}]'$ is the vector of reduced-form innovations, where η_{ct} represents innovations to job creation and η_{dt} represents innovations to job destruction. The structural and reduced-form representations are related by the following:

$$\eta_t = \mathbf{B}_0 \varepsilon_t, \quad \text{and} \quad \mathbf{B}(L) = \mathbf{D}(L)\mathbf{B}_0.$$

Therefore, full knowledge of $\mathbf{B}_0$ allows one to recover the structural estimates and innovations from the reduced-form VAR.

Full knowledge of $\mathbf{B}_0$ is impossible from the data alone, so one must restrict the range of its parameter values based on a set of plausible identifying assumptions. Let by denote the element in the ith row and the jth column of $\mathbf{B}_0$, where $i = c$ (job creation) or d (job destruction), and $j = a$ (aggregate innovation) or r (allocative innovation). Davis and Haltiwanger (1999) discuss in depth the relevant spectrum of possible short-run and long-run restrictions and the implications that these restrictions have for the estimated role of the structural shocks. Rather than take a stand on a particular set of identifying assumptions, I focus on a relatively tight set of restrictions from their identification approach to produce a range of plausible estimates. My identifying assumptions are:

(i) $b_{da} \leq -1$,

(ii) $0 < b_{cr} \leq 1$,

(iii) $\text{corr}(\varepsilon_{at}, \varepsilon_{rt}) = 0$.

The first assumption postulates that aggregate disturbances cause job creation and job destruction to move in opposite directions and that the response of job destruction is at least as large as the response of job creation. The boundary case of $b_{da} = -1$ is one where job creation and job destruction have symmetric (though opposite) responses to an aggregate shock. The second assumption states that allocative disturbances cause job creation and job destruction to move in the same direction and that the response of job creation is no larger than the response of job destruction. The boundary case of $b_{cr} = 1$ is the one where job creation and job destruction have a symmetric response to an allocative

disturbance. The final assumption imposes zero covariance between the aggregate and allocative disturbances. This is a common, though critical, assumption for the structural VAR identification.[12]

The zero covariance restriction produces the following mapping between the variances and covariances of the reduced-form and structural innovations:

$$\sigma_c^2 = \sigma_a^2 + b_{cr}^2 \sigma_r^2,$$

$$\sigma_d^2 = b_{da}^2 \sigma_a^2 + \sigma_r^2,$$

$$\sigma_{cd} = b_{da} \sigma_a^2 + b_{cr} \sigma_r^2$$

These three equations present four unknowns: the structural parameters b_{da} and b_{cr}, and the variances of the structural innovations, σ_a^2 and σ_r^2. This leaves the system under-identified, but presents a one-to-one mapping between b_{da} and b_{cr}:

(2) $$b_{cr} = \frac{\sigma_{cd} - b_{da}\sigma_c^2}{\sigma_d^2 - b_{da}\sigma_{cd}}$$

Using a given value of b_{da} and the covariance matrix of the reduced-form innovations, one can use equation (2) to calculate the corresponding value of b_{cr}. This fully characterizes $\mathbf{B}_0$ and subsequently allows one to recover the variances of the structural innovations and as well the structural coefficients of the model.

To provide bounds for the plausible range of results, I perform the SVAR analysis using the extreme versions of the assumptions in (i) and (ii) above. Specifically, I examine the case where $b_{da} = -1$ (symmetric responses to an aggregate shock), and solve for b_{cr} using (2). I then examine the

[12] One could argue that a true aggregate shock (e.g., a productivity shock) will have both an aggregate and allocative component. Davis and Haltiwanger (1999) discuss in detail the justification of the orthogonality condition, as well as the potential interpretation of the sources of these shocks. The argument in favor of the condition is that identified aggregate shocks will tend to depend on both the magnitude and direction of the true underlying shock while allocative shocks will tend to depend only on its magnitude. Thus, over a long time series (like the two subperiods I have here), the two will be essentially uncorrelated. Davis and Haltiwanger also perform their analysis relaxing the orthogonality assumption and find that it has little effect on their results.

case where $b_{cr} = 1$ (symmetric responses to an allocative shock) and solve for b_{da} using (2). I also examine a third, intermediate case. Since I perform the SVAR analysis on two subperiods of the data, the reduced-form covariance matrix in the early period will, in general, not equal the reduced-form covariance matrix in the later period. Consequently, the previous two identification strategies will generally produce different values for b_{da} and b_{cr} in each subperiod. My third identification approach examines the case where these values are constant across subperiods. This assumption provides an additional identifying equation because there are now two versions of equation (2) used, one associated with each subperiod, but still only four parameters to identify. Thus, b_{da} and b_{cr} are uniquely identified by setting the early-period version of equation (2) equal to its late-period version.

4.B. Identification and Estimation of Structural Innovations

I split the spliced manufacturing series into two periods: an early period that covers 1948Q1 - 1983Q4 and a later period that covers 1984Q1 - 2010Q4. This is roughly the start date generally attributed to the Great Moderation and falls within the 1982Q1 - 1985Q2 range of dates reported in Table 3.1 then run the reduced-form VAR estimation separately on each subperiod, using a lag length of four in the autoregressions.

Figure 7 illustrates the estimated relationship between b_{da} and b_{cr} for each subperiod as well as the implied standard deviations of the aggregate and allocative disturbances. It also notes the points for the two limiting sets of identifying assumptions (i.e., $b_{da} = -1$ and $b_{cr} = 1$). The top panel depicts the mapping between b_{da} and b_{cr} for the early and later subperiods based on their estimated reduced-form covariance matrix. Note that my third identification approach (i.e., equal parameter values across the subperiods) occurs where the two curves intersect. An assumption of symmetric responses to an allocative shock ($b_{cr} = 1$) implies that b_{da} equals -1.61 in the early period and -2.05 in the later period.

An assumption of symmetric responses to an aggregate shock ($b_{da} = -1$) implies that b_{cr} equals 0.02 in the early period and 0.23 in the later period. The curves intersect where $b_{cr} = 0.45$ and $b_{da} = -1.37$.

The early subperiod shows a strongly nonlinear, decreasing relationship between the two parameters, while the later period shows a flatter, more linear, decreasing relationship. This is because the estimated covariance of job creation and job destruction is fairly negative in the early period (-0.23) and close to zero in the later period (-0.03). Equation (2) shows that, as the estimated covariance between the two goes to zero, the relationship between b_{da} and b_{cr} becomes linear, and the slope of the relationship depends (negatively) on the relative volatility of job creation to job destruction.

The bottom panel shows the estimated standard deviations of the aggregate and allocative innovations for the early and later periods as a function of b_{da}. The panel shows stark differences, in both absolute and relative terms, in the estimated standard deviations of the early and later periods. The differences *between* periods are generally robust to the identifying assumption for b_{da}. The estimated standard deviations of the disturbances are lower in the later subperiod for most of the relevant range of parameter values. Only the standard deviation of allocative disturbances is lower in the earlier subperiod for $b_{da} < -1.65$. Results *within* each period, particularly the early subperiod, are more sensitive. In the earlier period, the estimated volatility of allocative disturbances increases substantially with b_{da}, but the estimated volatility of aggregate disturbances does not, so identification affects their relative volatility considerably. Under the assumptions of a symmetric response to allocative shocks or an identical contemporaneous response matrix across subperiods, the volatility of aggregate shocks is greater than the volatility of allocative shocks. The volatility of allocative shocks, however, is slightly higher under the assumption of a symmetric response to aggregate shocks. In the later period, the volatilities of aggregate and allocative disturbances are not particularly sensitive to the identifying assumptions, primarily because of the near-linear estimated relationship between b_{da} and

b_{cr}. In all cases, the allocative disturbances are relatively more volatile, with the relative volatility increasing as b_{da} approaches -1 from below.

Table 4 quantifies the differences between the early and later periods under the three identification approaches. Under the assumption of a symmetric response to aggregate shocks, the standard deviation of aggregate disturbances falls by 52 percent, while the standard deviation of allocative disturbances falls by 40 percent. This leads the relative volatility of aggregate to allocative disturbances to fall from 0.91 to 0.73. Under the assumption of a symmetric response to allocative shocks, the standard deviation of aggregate disturbances falls by 59 percent, while the standard deviation of allocative disturbances falls by 28 percent, leading to fall in the relative volatility from 1.77 to 1.00. Finally, under the assumption of a constant contemporaneous response matrix, the standard deviation of aggregate disturbances falls by 62 percent, while the standard deviation of allocative disturbances falls by 23 percent, leading to fall in the relative volatility from 1.29 to 0.81. All three cases suggest that the majority of the decline in volatility was due to a reduction in the volatility of aggregate shocks. All three cases also suggest a shift to a paradigm where allocative disturbances are relatively more important for employment fluctuations.

4.C. Job Flow Responses to Structural Innovations

My main goal in using the SVAR analysis is to examine whether the responses of job creation and job destruction to structural shocks changed during the Great Moderation period. I do so by calculating the impulse response functions of each job flow rate to a unit change in each structural disturbance for each subperiod. I repeat the exercise using each of my three identification approaches. I use a unit change to study the responses of job creation and job destruction so that the known declines in the volatility of the structural innovations do not complicate the analysis. The estimated impulse responses are in Figure 8.

The left column of Figure 8 shows the response to a unit *decrease* in the aggregate disturbance while the right column shows the response to a unit increase in the allocative disturbance. The top two panels of Figure 8 show the results under the assumption of a symmetric response to an aggregate shock, the middle two panels show the results under the assumption of a symmetric response to an allocative shock, and the bottom two panels show the results under the assumption of a constant contemporaneous response matrix across subperiods. Each panel shows the response of the job creation rate and the job destruction rate in both the early period (pre-1984) and later period (1984 and later).

Several features of the impulse responses stand out across all three identification approaches. First, the responses of job creation and destruction to an aggregate shock appear larger in magnitude than a response to an allocative shock. This is consistent with the findings of Davis and Haltiwanger (1999). Second, the responses of job creation and job destruction to an allocative shock are very similar across the two subperiods. Third, and most importantly, there are clear differences in the responses of job creation and destruction to an aggregate shock across the two subperiods.[13] Relative to the earlier period, the response of the job destruction rate is larger on impact and more is persistent in the later period. Relative to the earlier period, the response of the job creation rate is quite different as well. It also has a larger response on impact and is more persistent. Furthermore, in the early period, the job creation rate responded to a negative aggregate shock with a decline followed by a relatively strong recovery. Under all three identification approaches, the response rises above its initial value and exhibits a hump-shaped pattern before finally leveling off. In the later period, there is no such strong recovery

[13] To provide a sense of statistical significance of these differences, I report the impulse responses in separate figures for the early and later periods and include bootstrapped 67 percent confidence intervals derived from 1,000 random draws of each subperiod in the appendix. This approach also produces bootstrapped 67 percent confidence intervals for the implied response of the net growth rate in Figure 9.

and the hump-shaped pattern disappears. Instead, the job creation rate recovers more slowly in a pattern that appears symmetric with the response of the job destruction rate.

Since the net employment growth rate is the difference between the job creation and job destruction rates, one can derive the implied impulse response functions of the net growth rate from the impulse responses in Figure 8. I report the corresponding implied responses of net growth in Figure 9. To illustrate the significance of the differences across subperiods, I report the bootstrapped 67 percent confidence intervals for each response. As one might expect, there is little difference in the response of the net growth rate to an allocative shock between the early and later subperiods. In contrast, the difference in the response of the growth rate to an aggregate shock is clear. Prior to 1984, employment growth fell following an aggregate shock but then rebounded strongly. It returned to positive growth within four quarters and even exhibited several quarters above its initial growth rate before returning to its steady state. From 1984 onward, employment growth exhibited a larger decline in response to the shock and a slower recovery. It does not return to nonnegative growth until 8 quarters after the shock and there is no strong employment expansion that precedes its return to steady state.

The evidence on the response to an aggregate shock in Figure 9 is consistent with a pattern of jobless recoveries in the later subperiod but not in the earlier subperiod. Figures 8 and 9 together shed new light on the mechanics of how jobless recoveries have come about. Both job creation and job destruction now have larger and more persistent responses to an aggregate shock. There is no longer a strong recovery in employment growth following a negative aggregate shock because the job creation rate no longer exhibits a strong recovery that had, prior to 1984, lead to several quarters of relatively strong employment growth before returning to steady state, and because job destruction remains relatively high for longer following a negative aggregate shock. Furthermore, the responses of the job

creation rate and job destruction rate to an aggregate shock are now roughly symmetric. This implies that, within the later period, it will be equally likely to observe a jobless recovery due to persistently high job destruction or persistently low job creation. This a pattern observed in the raw data: Figure 1 shows that the 1992 recovery was a period of relatively high job destruction while the 2002-03 and 2008-09 recoveries were periods of relatively low job creation. Finally, these changes are driven almost entirely by changes in the response of job flows to an aggregate, rather than allocative, shock. Thus, it is not the case that jobless recoveries have come about because of a relatively slower or longer process of labor reallocation.

It is worth noting that the inclusion or exclusion of the Great Recession does little to alter these results. In the appendix, I repeat the analysis using only 1984Q1 - 2006Q4 for the later subperiod. I report the results in the appendix. As one might guess, there is generally a reduction in the volatility of structural shocks once the most recent recession is excluded. Depending on the identifying assumptions, the standard deviation of aggregate shocks are 15 to 23 percent lower than those reported in Table 4, while the standard deviation of allocative shocks are anywhere from 19 percent lower to 6 percent higher. Most importantly, there is almost no difference in the implied impulse response functions of the net growth rate.

5. The Role of Temporary Help and Temporary Layoffs

Figures 8 and 9 present new evidence on the mechanics of how jobless recoveries have come about but they do not explain what has caused these mechanical changes. One potential candidate is the apparent shift in the labor market from the use of temporary layoffs to temporary help employment as a labor adjustment tool in response to cyclical fluctuations in the economy. This hypothesis is appealing for several reasons. First, the flow into unemployment due to temporary layoffs was highly cyclical until the mid 1980s. Now, most of the cyclical fluctuations in the inflow into unemployment are

driven by permanent layoffs. Second, the nature of temporary layoffs should lead to impulse response patterns like those observed for the earlier subperiod in Figure 8: a sharp spike in job destruction (as workers are laid off) followed by a strong recovery of job creation (as workers are recalled). Third, temporary help employment (or, employment from the employment services industry more broadly) has become an increasing share of the labor market, particularly in manufacturing. Temporary help employment is also highly cyclical and volatile relative to other industries. Finally, if one believes that search frictions play an important role in driving the behavior of gross job flows, then temporary help employment represents an outsourcing of the search process to firms that plausibly have a comparative advantage in recruiting. The implicit reduction in search frictions could plausibly account for some of the secular decline in the trend of job reallocation.

To examine whether this shift towards temporary help employment has caused the observed change in job flow behavior, I generate a counterfactual manufacturing series based on recent research by Dey, Houseman, and Polivka (2012, henceforth DHP). They use establishment micro data with detailed occupational and industry information to generate a plausible time-series estimate of the allocation temporary help employment, which is counted as part of the employment services industry, to the industry where temporary help workers are actually employed. They find that their exercise allocates an increasing share of temporary help employment to manufacturing. Temporary help makes up 2 percent of manufacturing employment in 1989 and 9 percent of manufacturing employment in 2009. They argue that this has had a significant impact on the measurement of employment growth and productivity in manufacturing. Here, I test whether it may have affected labor market dynamics within manufacturing as well.

I generate the counterfactual manufacturing series as a weighted average of job flows from my spliced manufacturing data and the employment services industry. The latter data come from the

extended series of BED data I created. The weights are based on the share of the employment services industry working in manufacturing estimated by DHP.[14] The DHP shares are annual rather than quarterly and appear to follow a cyclical pattern. They are also missing estimates for 1995 and 2010. Therefore, I use a predicted time-series of employment shares obtained from regressing the log of the DHP employment services share on the log of total employment in the employment services industry, a constant, and an annual time trend. I run the regression on quarterly data. I then use the predicted shares over the 1990Q2 to 2010Q4 period as my weights. Figure 10 reports the original DHP share and predicted share of employment services in manufacturing. The predicted and DHP estimates track each other very closely.[15] I also report the employment growth rate of the employment services industry in Figure 10. It illustrates the cyclically apparent in both the DHP and predicted employment shares.

Figure 11 compares the job flow rates from my spliced manufacturing series with the job flow rates generated from the counterfactual exercise. Since there is much more churning in the employment services industry, the magnitudes of job creation and job destruction are higher in the counterfactual series. This becomes more evident in the later part of sample when the employment services share of manufacturing is higher. The counterfactual series also appears to show more cyclically. Despite this behavior, however, the counterfactual series produces nearly identical results to the original manufacturing series in the SVAR analysis. Table 5 shows almost no change in the estimated volatility of the structural innovations. Accounting for the reallocation of temporary help workers increases the volatility of aggregate shocks by only 4 to 7 percent, depending on the identifying assumptions, and has essentially no effect on the volatility of allocative shocks. Furthermore, Figure 12 shows that the implied impulse response of the net growth rate to either structural shock is practically identical for the two data series. The figure only reports the results that assume a constant contemporaneous response

[14] I thank Anne Polivka for providing me with these data.
[15] The regression used to generate the predicted series has an R-squared value of 0.98 and the coefficient on (log) employment services employment has a t-statistic of 27.1.

matrix across the both subperiods, but I obtain the same results using the other two identifying assumptions.

One might think that performing the counterfactual in the other direction, i.e., adding back the counterfactual behavior of temporary layoffs to generate a counterfactual series, might provide different results. After all, this exercise was partly motivated by the hypothesis that the recall of workers on temporary layoff could generate the strong response of the job creation rate observed in the earlier subperiod. This is a more difficult and subjective counterfactual to create, though, because it involves assumptions for both the behavior of temporary layoffs and how that behavior would translate into job flow patterns in the later period. The counterfactual based on the DHP findings only required assumptions on the allocation of existing job flows. Furthermore, Figure 12 shows first-order evidence that a counterfactual based on temporary layoffs may fail to account for the change in job flow behavior.

The figure reports actual temporary layoffs, as a percentage of employment, from the CPS. It also reports a counterfactual temporary layoff series. The counterfactual exercise estimates how temporary layoffs would have behaved from 1984 forward, given their cyclical behavior during the earlier period. I construct it by regressing the temporary layoff rate on the current-period value and four lags each of the unemployment rate (as a percentage of employment) and the net employment growth rate, all measured from the CPS, over the 1968-83 period. All variables are quarterly averages of their monthly values. I then use the coefficients obtained from this regression to predict the out-of-sample behavior of the temporary layoff rate over the 1984-2010 period. Comparing the actual and predicted series over the within-sample period shows an exceptionally tight fit. The main point to take away from the exercise is that the predicted temporary layoff rate, despite being derived from earlier-period data, exhibits behavior consistent with a jobless recovery. While the spikes in the temporary layoff rate are

large but relatively short-lived prior to 1984, the predicted spikes from 1984 forward continue to exhibit much greater persistence. This is true even during the Great Recession, when the predicted spike in temporary layoffs is much larger than what is observed in the data. This spike remains high through the end of 2010, six quarters after the official end of the Great Recession.

Thus, while the switch from temporary layoffs to temporary help employment provided a compelling hypothesis for explaining the altered job flow response to an aggregate shock, I find that the effects of the switch are quantifiably negligible.

6. Conclusions

This paper studies the cyclical behavior of job creation and job destruction before and during what economists refer to as the Great Moderation. I use a longtime-series on manufacturing job flows generated from the extension of the time series of existing BED data and the splicing of these data with a time-series constructed by Davis and Haltiwanger (1999). I find that the magnitude of job flows have been trending downward, so that job reallocation, on average, is about one-third lower in 2010 than it was in 1960. I also find that the volatility of job flows exhibited a sharp decline in the mid-1980s, consistent with the date commonly attributed to the start of the Great Moderation. Comovement patterns changed at this time as well. Some, but not all of the volatility returned with the onset of the Great Recession. While these results are for manufacturing, a comparison to similar measures of labor market dynamics suggests that they likely hold for the broader economy.

I then replicate the structural VAR analysis of Davis and Haltiwanger (1999) on the pre-1984 and post-1984 periods of my data. I find that a disproportionate amount of the reduction in the volatility of job flows is due to a reduction in the volatility of aggregate rather than allocative shocks. Furthermore, I find that the responses of job creation and job destruction to these aggregate shocks changed during

the Great Moderation period. The responses of both are now more persistent and job creation no longer exhibits a strong recovery from a negative shock as it did prior to 1984. The result is an implied response of employment growth that resembles a jobless recovery. Prior to 1984, it took about 4 quarters for net growth to return to its initial value following a negative aggregate shock. Now, it takes about 8 quarters.

The altered responses of job flows to an aggregate shock hold regardless of whether one includes the most recent recession. Thus, while volatility may have returned during the most recent recession, it still holds that job flows respond to an adverse aggregate shock with behavior that resembles a jobless recovery. These results underscore earlier work by Galí and Gambetti (2009) and others who document a change in the comovement patterns of hours, output, and labor productivity since the start of the Great Recession. Specifically, it highlights the fact that, for the labor market, the Great Moderation has been a period of altered responses to shocks as much as it has been a period of lower aggregate volatility.

The change in job flow responses to an aggregate shock is also not due to the move away from temporary layoffs to temporary help employment as a cyclical labor adjustment mechanism. Instead, other factors, perhaps related to changes in labor market institutions or policy, have caused the change in job flow behavior. For example, McConnell and Tracy (2005) examine the role of changes in UI tax incentives on the declining role of temporary layoffs. They find a small effect, though Card and Levine (1994) find larger and cyclically varying effects. The increased use of disability insurance may also play a role, as Autor and Duggan (2003) find a link between changes in disability insurance laws in 1984 and subsequent unemployment. Further research along these lines could shed light on the reasons behind the altered behavior of gross job flows since the Great Moderation. It could also provide a better understanding of the causes of jobless recoveries.

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Table 1. Moments Used in GMM Estimation of the Spliced Job Flow Series

Moment	Value
Mean Job Creation, C_t	5.081
Mean Job Destruction, D_t	5.068
Variance of Excess Reallocation, $\mathrm{var}(XR_t)$	0.502
Relative Volatility of Destruction to Creation, $\mathrm{var}(D_t)/\mathrm{var}(C_t)$	5.272
Correlation of Job Creation and Growth, $\mathrm{corr}(C_t, NET_t)$	-0.070
Correlation of Job Destruction and Growth, $\mathrm{corr}(D_t, NET_t)$	-0.901

Source: Author's calculations using the BED data from 1990Q2 - 1998Q4.

Table 2. Job Flows in Manufacturing : Summary Statistics

Period	1947-1983	1984 - 2010
Job Creation Rate		
Mean	6.03	4.51
Standard Deviation	0.84	0.68
Std. Dev. Relative to Std. Dev. Of Output Growth	0.71	1.10
Correlation with Output Growth	0.62	0.44
Job Destruction Rate		
Mean	6.09	4.96
Standard Deviation	1.10	0.78
Std. Dev. Relative to Std. Dev. Of Output Growth	0.93	1.26
Correlation with Output Growth	-0.52	-0.35
Other Statistics		
Std. Dev. Of JD_t Relative to Std. Dev. of JC_t	1.31	1.14
$\mathrm{corr}(JC_t, JD_t)$	-0.38	0.11
$\mathrm{corr}(JR_t, NET_t)$	-0.28	-0.13

Source: Author's calculations a spliced series of job flows from BED data and the spliced LRD-LTS data of Davis and Haltiwanger (1999). Rates are percentages of employment. Output growth is measured as the change in (log) real GDP.

Table 3. Estimated Structural Breaks in Time-Series Volatility

	Job Creation	Job Destruction	Job Reallocation	Excess Reallocation
Estimated Break	1983Q2	45.94	1982Q1	18.83	None*	None*
QLR Test Statistic			---	---
	Employment Net Growth	**Change in log Real GDP**	**Unemployment Inflows, CPS**	**UI Initial Claims Inflows**
Estimated Break	1982Q1	1984Q2	1985Q1	1985Q2
QLR Test Statistic	36.88	46.65	29.03	28.32

Source: Estimated using the spliced series of BED and LRD-LTS job flow rates and other listed variables. Unemployment inflows are the short-term unemployment as a fraction of employment. UI Initial Claims inflows are total initial claims as a fraction of employment. All data are quarterly. The critical values for the QLR statistic given the regression specification are 12.35 at the 1 percent level and 8.85 at the 5 percent level.
* Due to the splicing methodology, I cannot reject the null of no structural break in volatility for the job reallocation rate or the excess reallocation rate.

Table 4. Summary of Structural Innovation Statistics

	b_{da}	b_{cr}	Std. Deviation, Aggregate Shock	Std. Deviation, Allocative Shock	Ratio of Std. Deviations
Assumption 1: Symmetric response to aggregate shocks					
1948Q1 - 1983Q4	-1.0	0.02	0.481	0.527	0.912
1984Q1 - 2010Q4	-1.0	0.23	0.231	0.314	0.734
Ratio, late period to early period			0.479	0.595	
Assumption 2: Symmetric response to allocative shocks					
1948Q1 - 1983Q4	-1.61	1.0	0.419	0.236	1.772
1984Q1 - 2010Q4	-2.05	1.0	0.171	0.171	0.997
Ratio, late period to early period			0.407	0.724	
Assumption 3: Identical contemporaneous responses across periods					
1948Q1 - 1983Q4	-1.37	0.45	0.454	0.353	1.288
1984Q1 - 2010Q4	-1.37	0.45	0.211	0.261	0.808
Ratio, late period to early period			0.379	0.771	

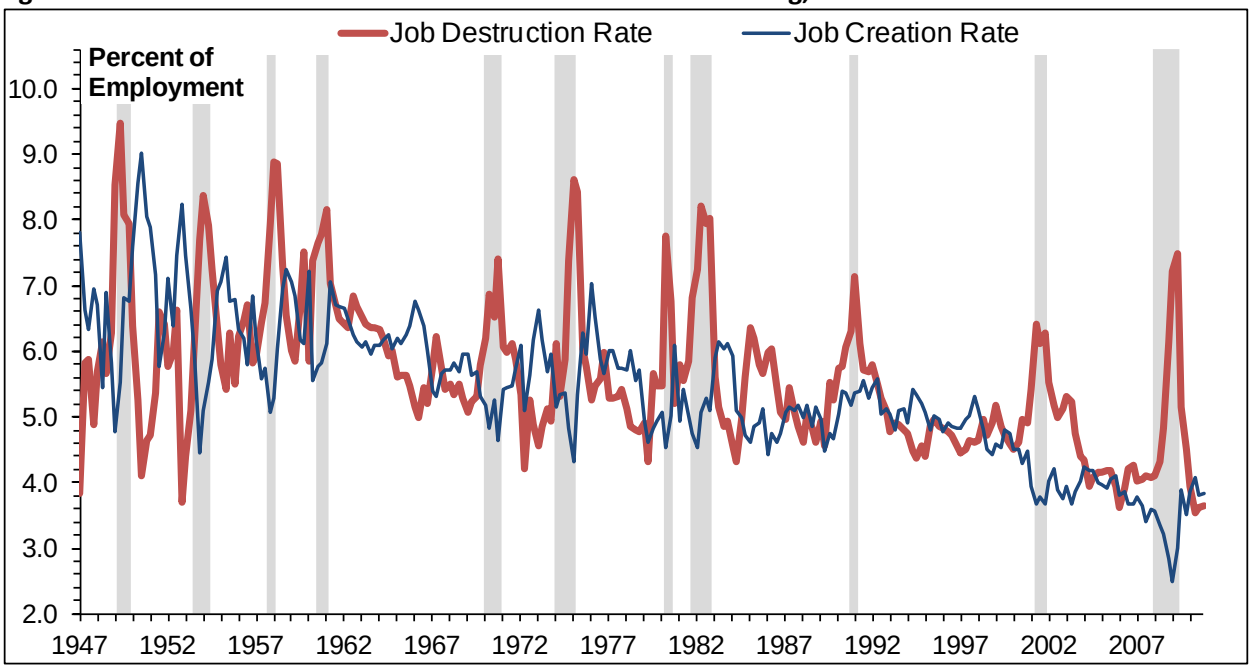
Source: Data are job flows from LTS, LRD, and BED data. Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1948-1983 and 1984-2010 subperiods See text for details.

Table 5. Structural Innovation Statistics with and without Employment Services Added, 1984-2010

	b_{da}	b_{cr}	Std. Deviation, Aggregate Shock	Std. Deviation, Allocative Shock	Ratio of Std. Deviations
Assumption 1: Symmetric response to aggregate shocks					
Original Spliced Series	-1.0	0.23	0.231	0.314	0.734
Including Emp. Services	-1.0	047	0.243	0.319	0.761
Percent Change in Std. Deviation			5.3	1.6	
Assumption 2: Symmetric response to allocative shocks					
Original Spliced Series	-2.05	1.0	0.171	0.171	0.997
Including Emp. Services	-1.94	1.0	0.183	0.177	1.033
Percent Change in Std. Deviation			7.2	3.5	
Assumption 3: Identical contemporaneous responses across periods					
Original Spliced Series	-1.37	0.45	0.211	0.261	0.808
Including Emp. Services	-1.38	0.48	0.220	0.258	0.862
Percent Change in Std. Deviation			4.1	-1.2	

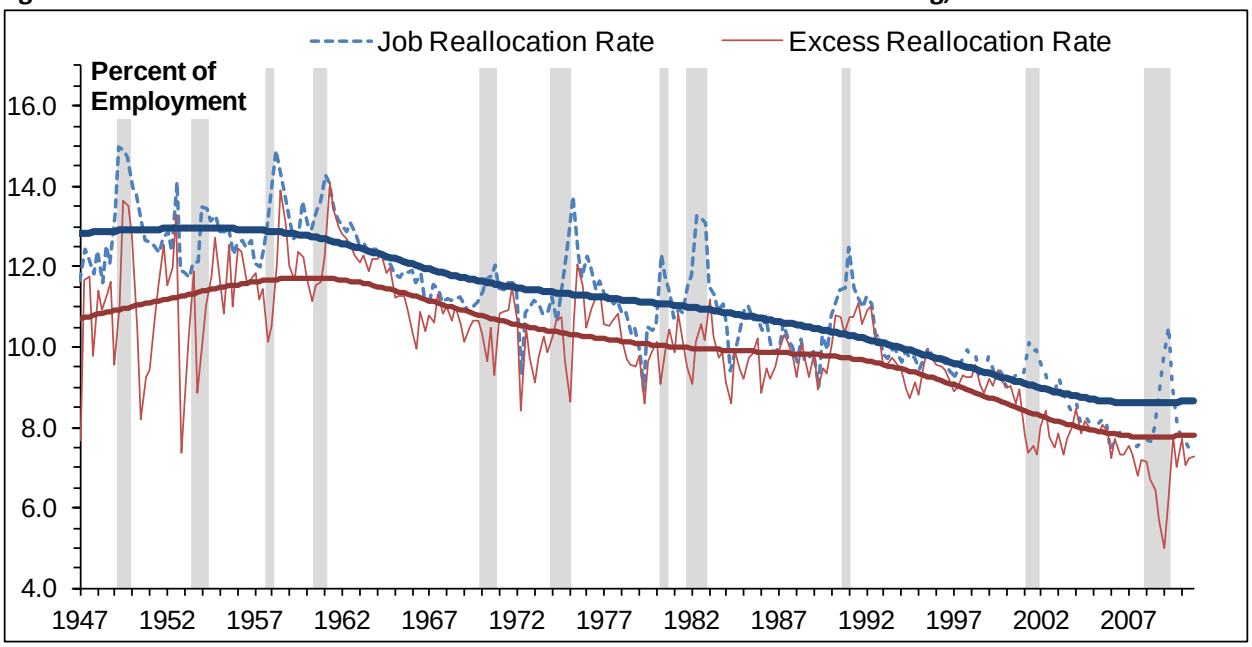
Source: Data are job flows from LTS, LRD, and BED data, with job flows from employment services added according to Dey, Houseman, and Polivka (2012) where noted. Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1948-1983 and 1984-2010 sub-periods for each data source. See text for details of the data construction and VAR analysis. Results are all for the 1984Q1 - 2010Q4 sample period.

Figure 1. Job Creation and Job Destruction Rates in Manufacturing, 1947-2010



Source: Author's estimates using BED data and the spliced LRD-LTS data from Davis and Haltiwanger (1999). Rates are percentages of employment. Shaded areas represent NBER-dated recessions.

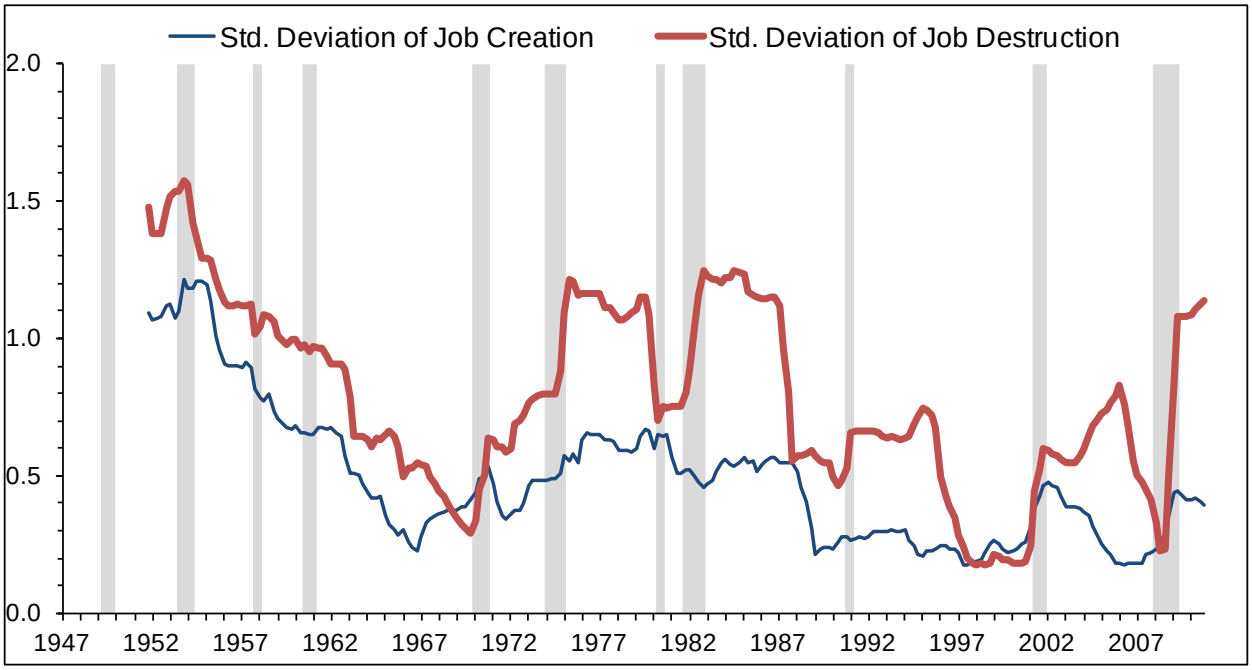
Figure 2. Job Reallocation and Excess Job Reallocation Rates in Manufacturing, 1947-2010



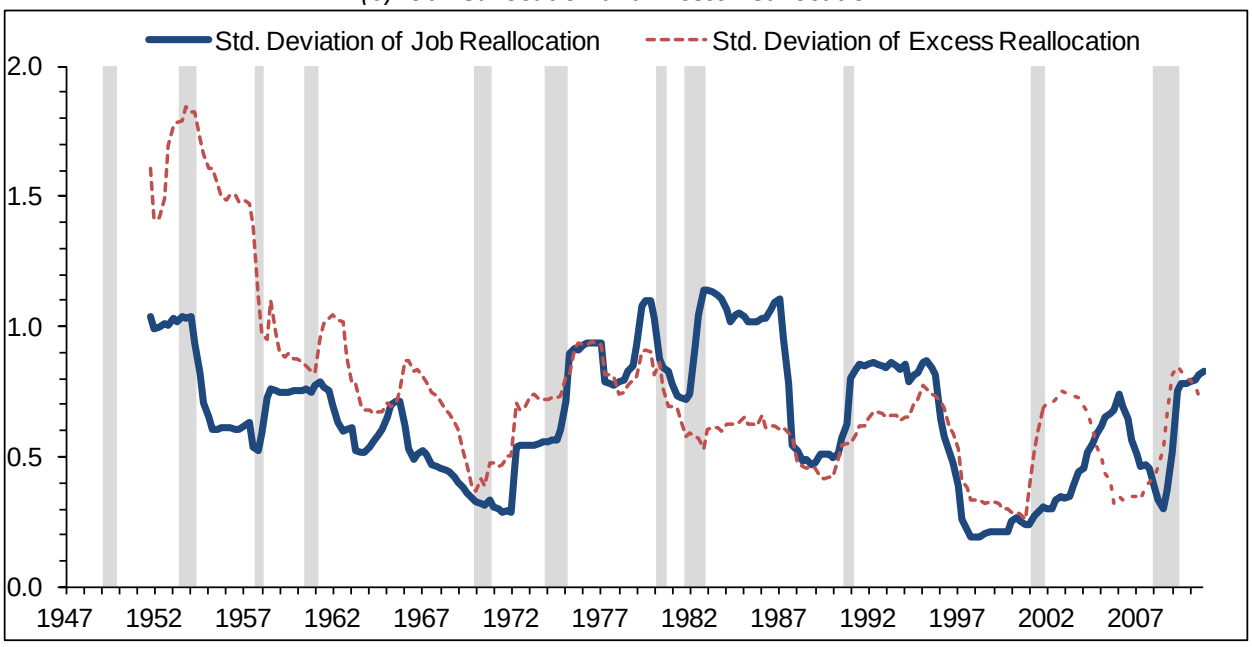
Source: Author's estimates using BED data and the spliced LRD-LTS data from Davis and Haltiwanger (1999). Rates are percentages of employment. Shaded areas represent NBER-dated recessions. Thick solid lines represent trend lines estimated using a low-frequency (10^5) Hodrick-Prescott filter.

Figure 3. Rolling Standard Deviations of Job Flow Rates, 1952-2010

(a) Job Creation and Job Destruction

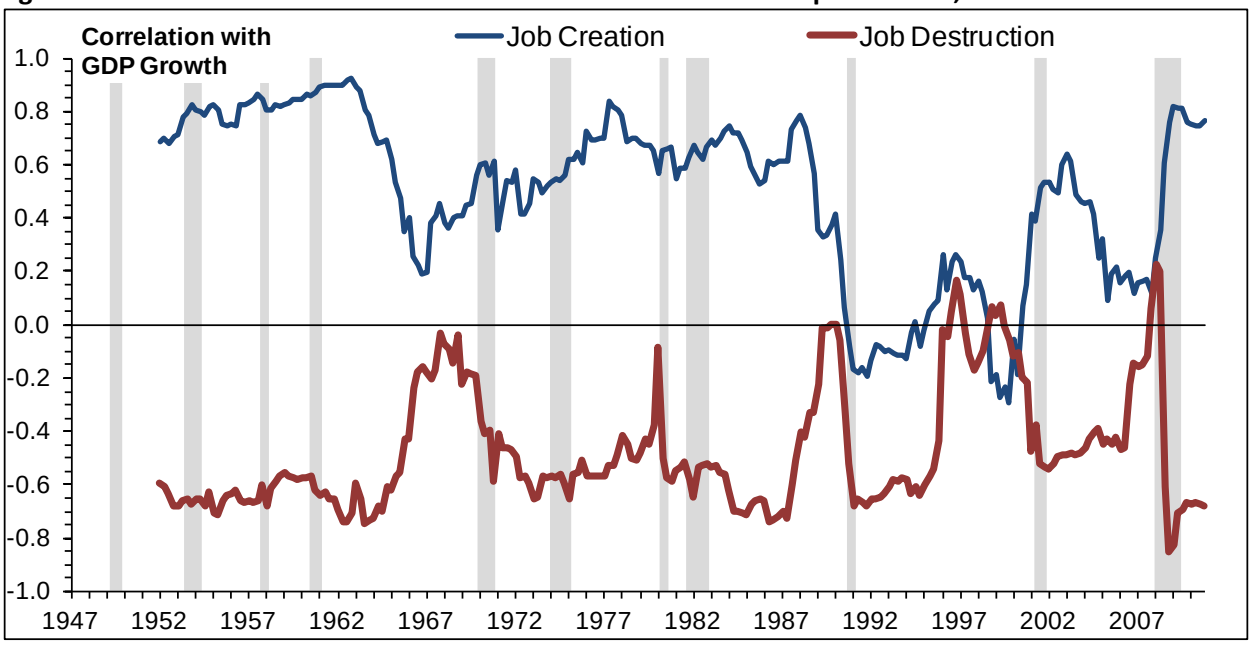


(b) Job Reallocation and Excess Reallocation



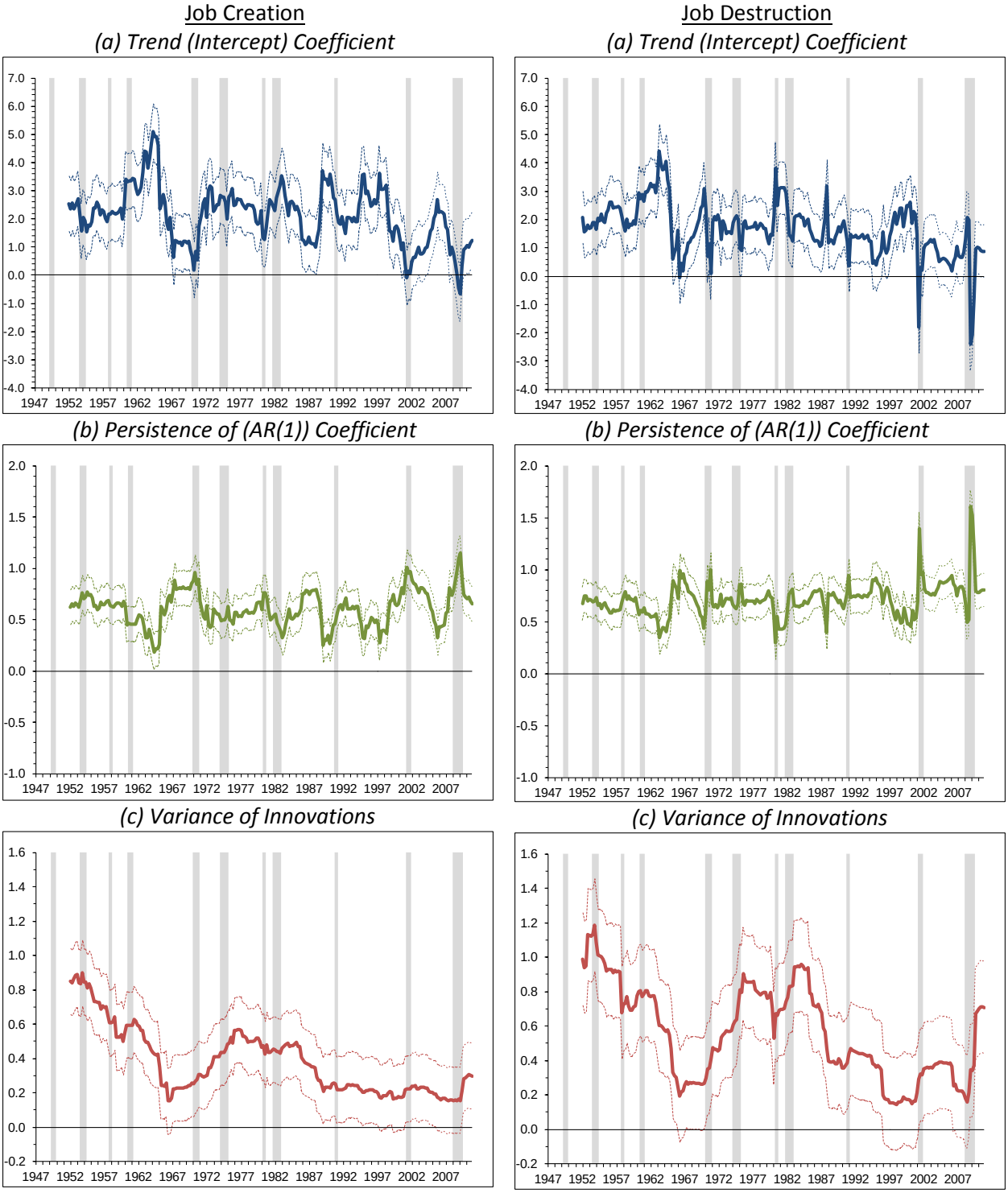
Source: Author's calculations using the spliced series of BED and LRD-LTS data. Rolling standard deviations use a moving window of the current and 19 preceding quarters.

Figure 4. Correlations of Job Creation and Job Destruction with Output Growth, 1952-2010



Source: Author's calculations using the spliced series of BED and LRD-LTS data. Rolling correlations are with the log difference in real GDP and use a moving window of the current and 19 preceding quarters.

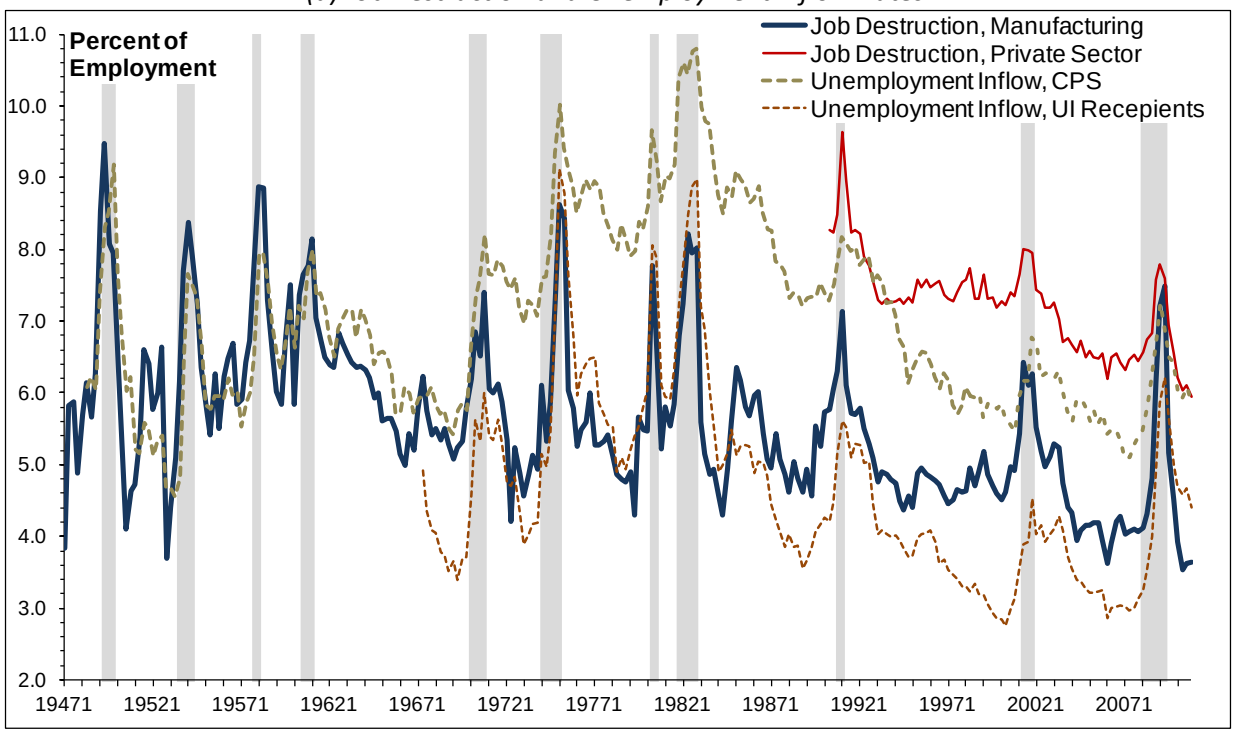
Figure 5. Rolling Autoregression Estimates for Job Creation and Job Destruction Rates, 1952-2010



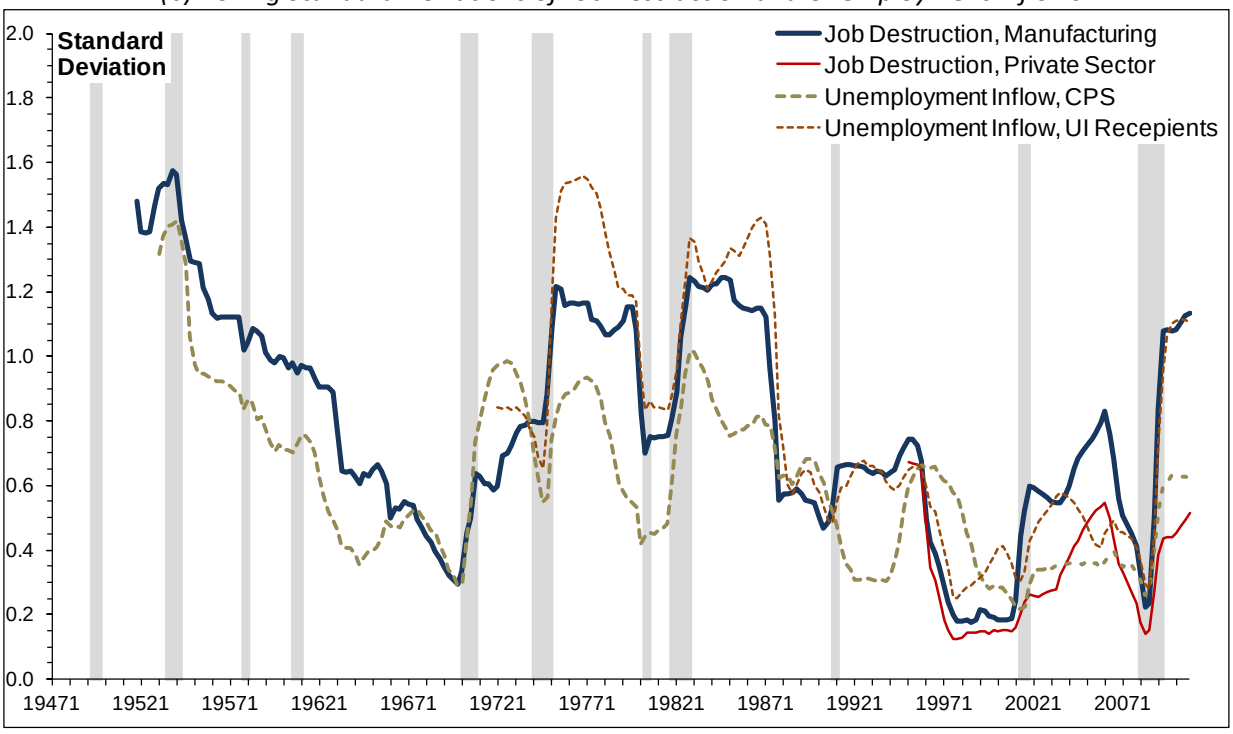
Source: Estimates are from rolling autoregressions of the job creation rate (left panels) and job destruction rate (right panels) that use the current quarter and preceding 19 quarters of data. The top panels report the intercept coefficient, the middle panels report the AR(1) coefficient, and the lower panels report the variance of the residuals of each autoregression. Dashed lines represent 95 percent confidence intervals.

Figure 6. Job Destruction and Unemployment Inflow Rates across Data Sources

(a) Job Destruction and Unemployment Inflow Rates



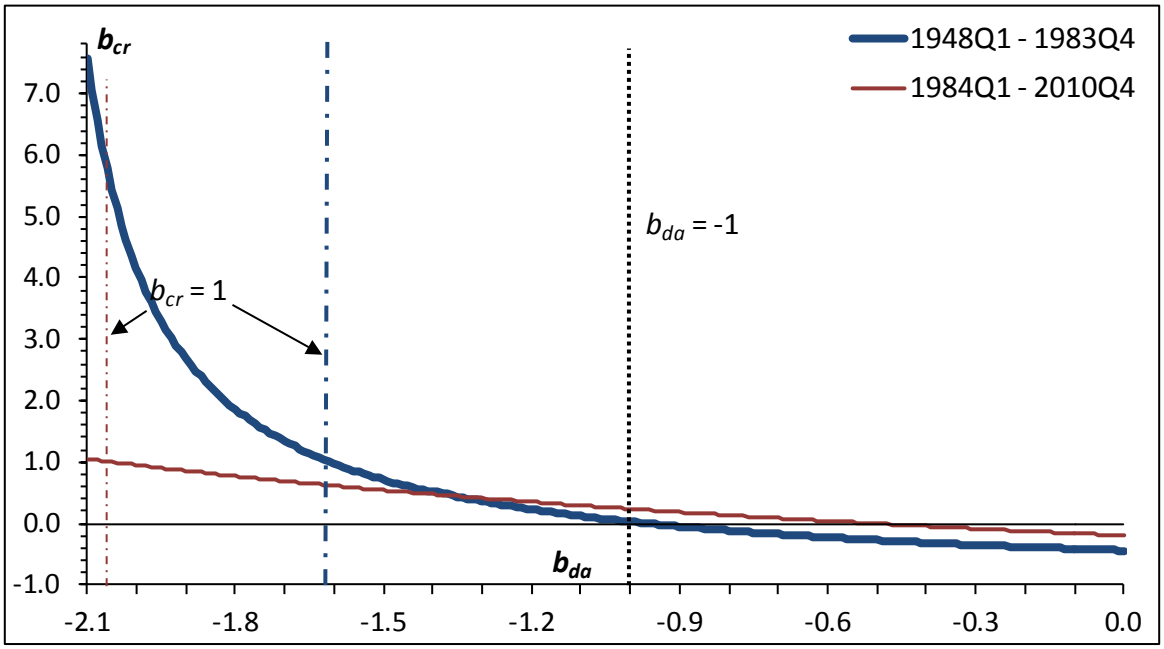
(b) Rolling Standard Deviations of Job Destruction and Unemployment Inflows



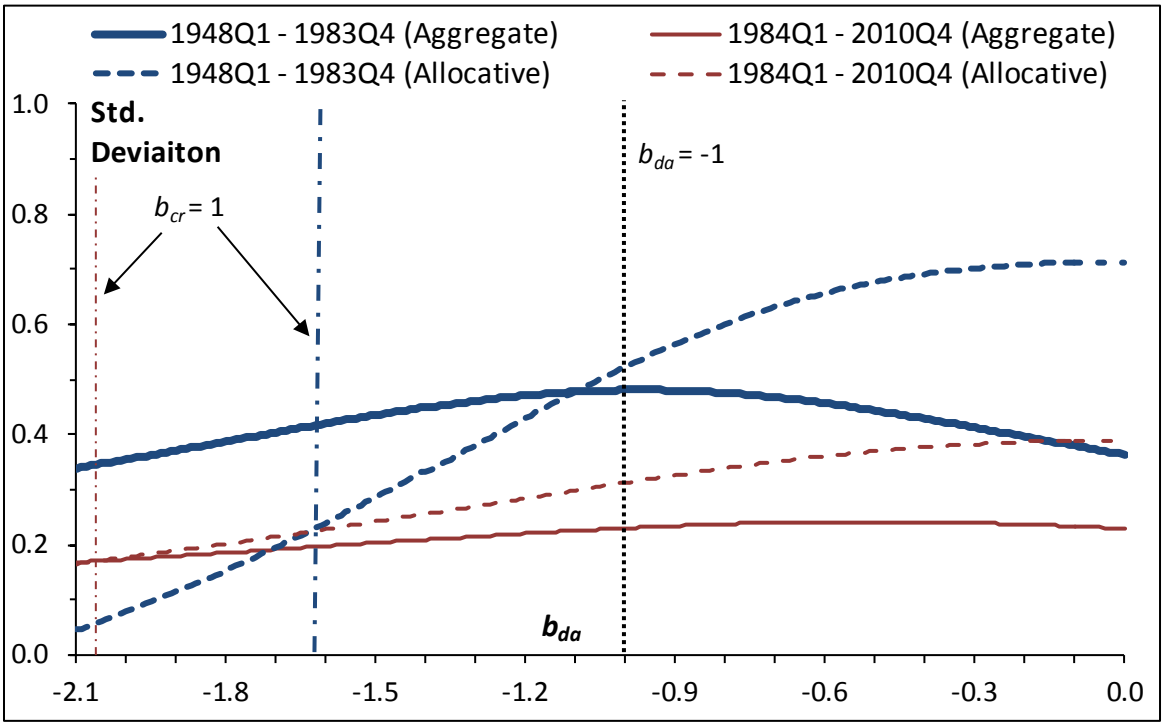
Source: Job destruction rates are from author's calculations using the spliced series of BED and LRD-LTS data (manufacturing) or the BED data alone (private sector). CPS unemployment inflows are short-term unemployment divided by employment. Inflows of UI recipients are total quarterly initial UI claims divided by employment. Rolling standard-deviations (bottom panel) use a moving window of the current and 19 preceding quarters.

Figure 7. Implications for of Structural VAR Identifying Assumptions

(a) Relationship between b_{da} and b_{cr}



(b) Standard Deviation of Structural Innovations, Based on b_{da}

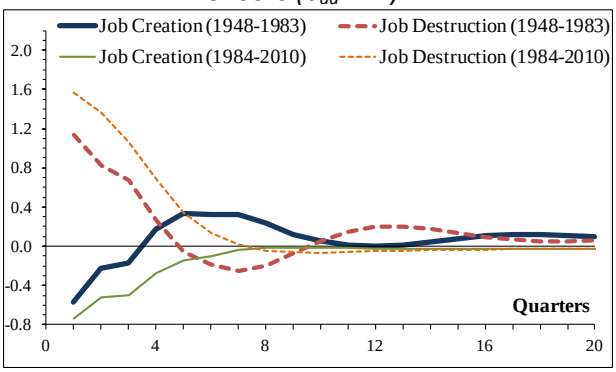


Source: Estimates come from a structural VAR of job creation and destruction rates over the 1948-1983 and 1984-2010 periods. The top panel reports the identifying relationship between the parameters of the contemporaneous response matrix based on the reduced-form innovations of each sub-period. The bottom panel reports the standard deviation of the structural innovations (allocative or aggregate shock) based on the assumption for b_{da}.

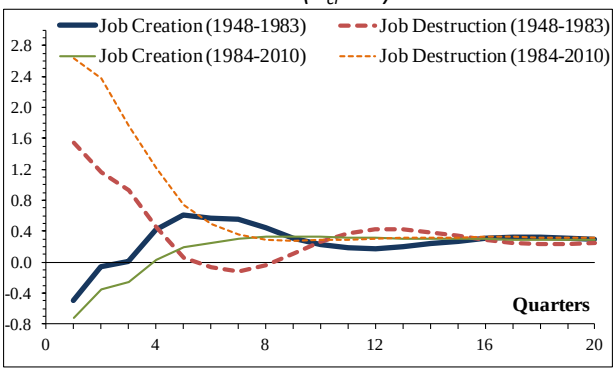
Figure 8. Impulse Responses of Job Creation and Job Destruction

Response to An Aggregate Shock

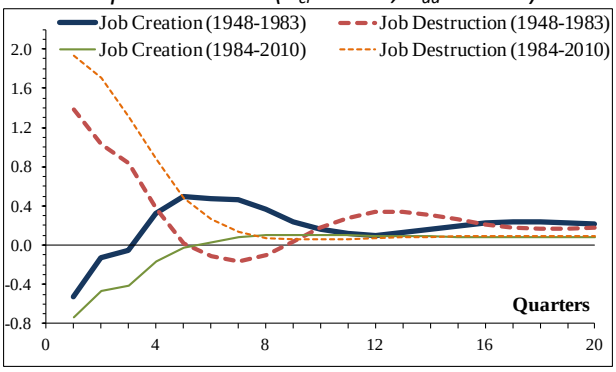
(a) Assuming Symmetric Reponses to Aggregate Shocks (b_{da} = -1)



(b) Assuming Symmetric Response to Allocative Shocks (b_{cr} = 1)

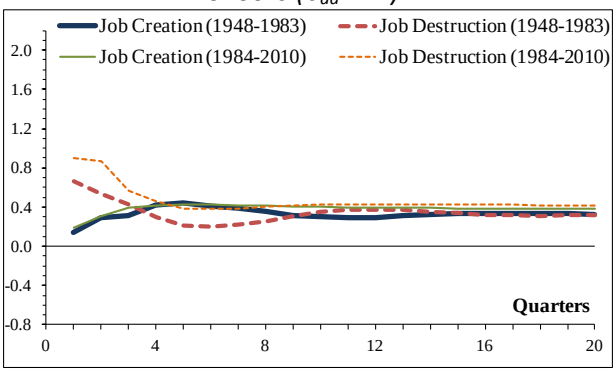


(c) Assuming Constant Contemporaneous Response Matrix (b_{cr} = 0.45, b_{da} = -1.37)

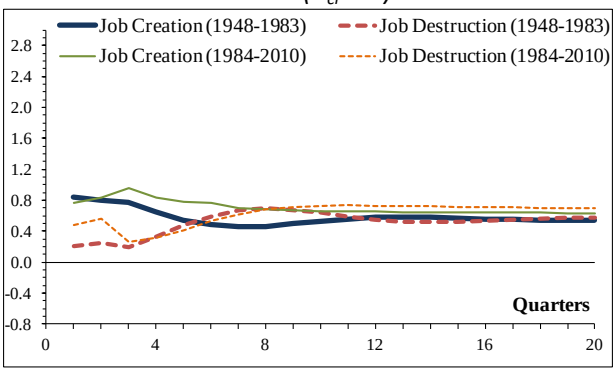


Response to an Allocative Shock

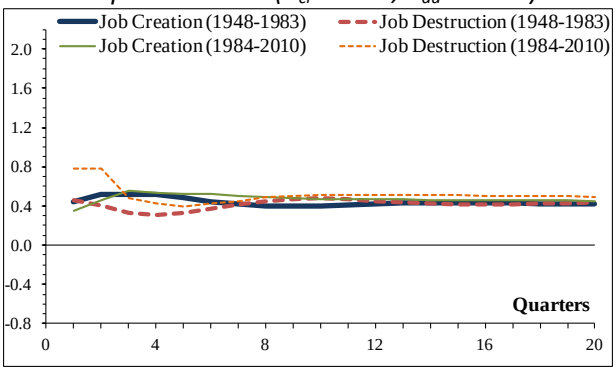
(a) Assuming Symmetric Reponses to Aggregate Shocks (b_{da} = -1)



(b) Assuming Symmetric Response to Allocative Shocks (b_{cr} = 1)

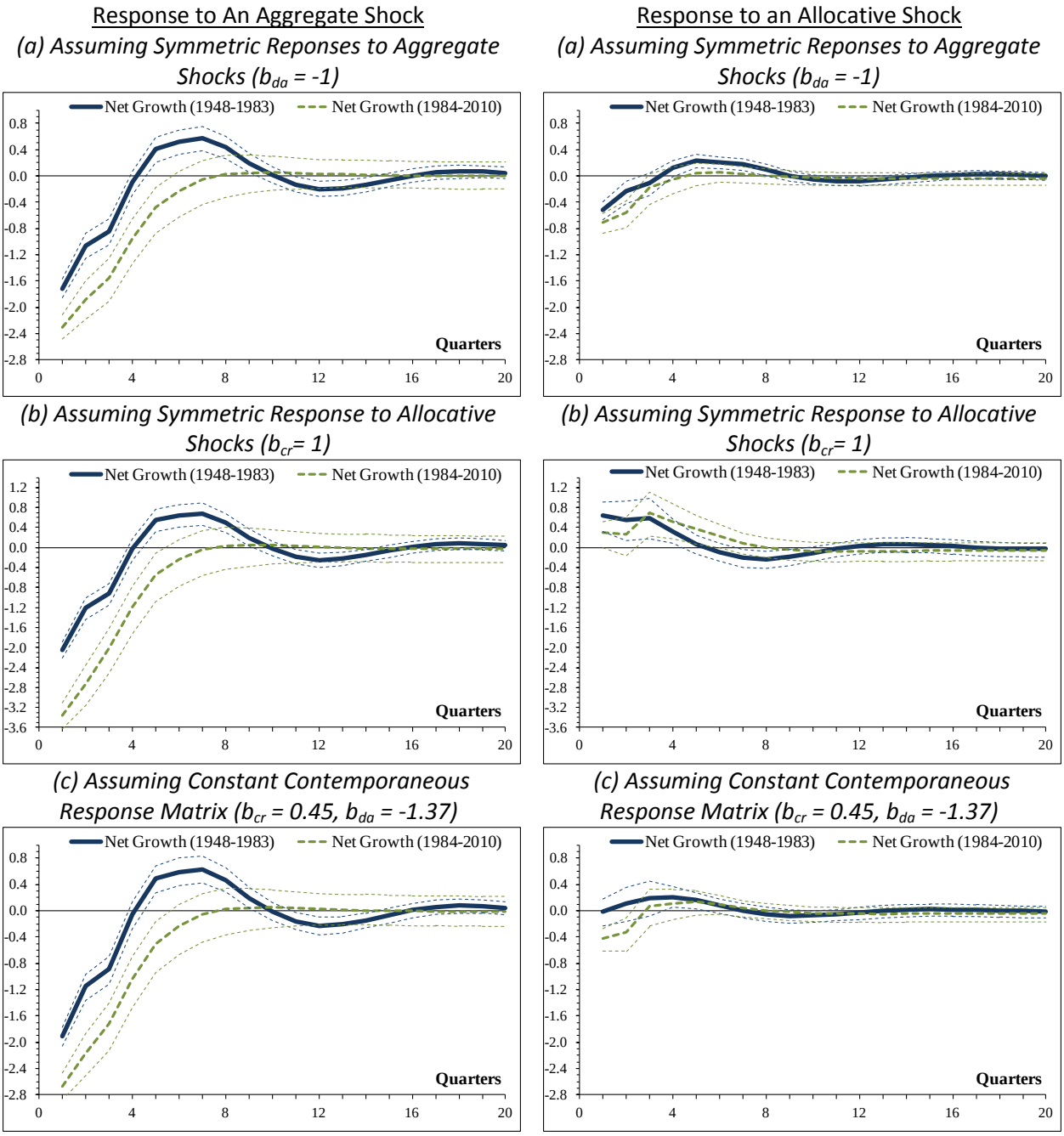


(c) Assuming Constant Contemporaneous Response Matrix (b_{cr} = 0.45, b_{da} = -1.37)



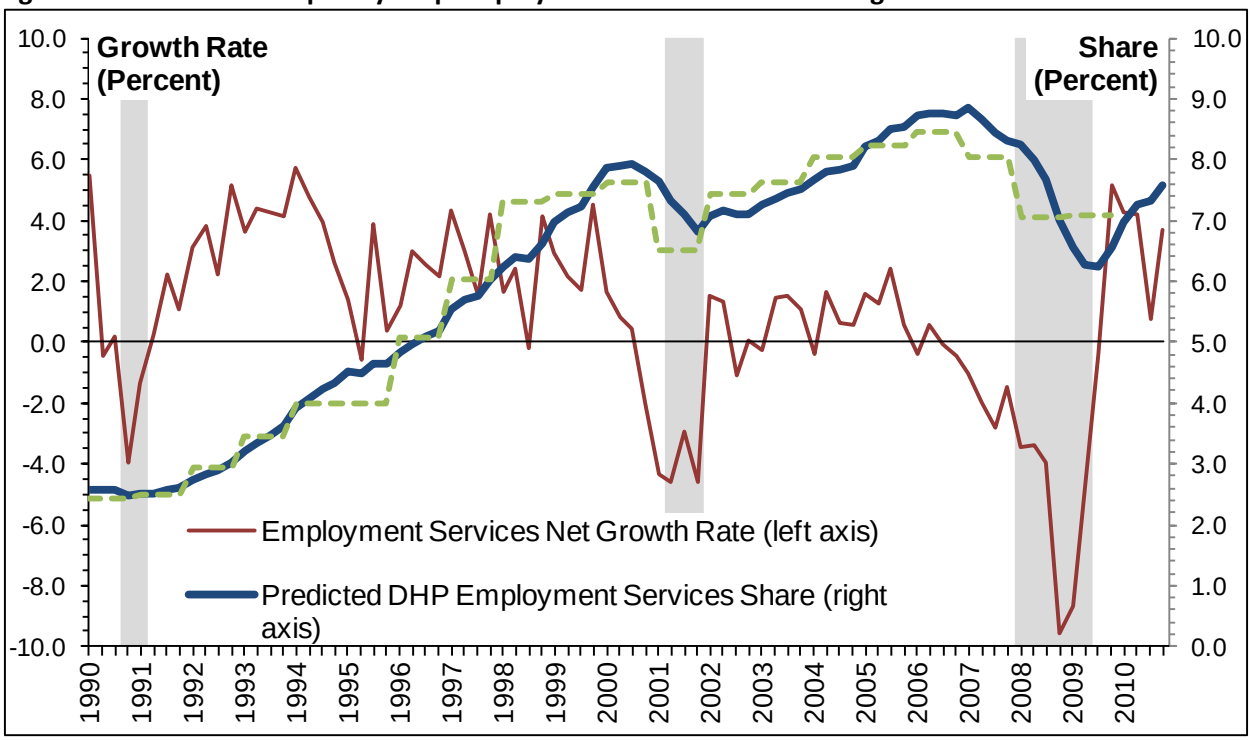
Source: Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1948-1983 and 1984-2010 sub-periods of the spliced series of LRD-LTS and BED manufacturing data. See text for details.

Figure 9. Implied Impulse Responses of Net Employment Growth



Source: Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1948-1983 and 1984-2010 sub-periods of the spliced series of LRD-LTS and BED manufacturing data. See text for details. The implied impulse response of net employment growth is the difference between the impulse response of job creation and the impulse response of job destruction. Thin dashed lines represent bootstrapped 67 percent confidence intervals.

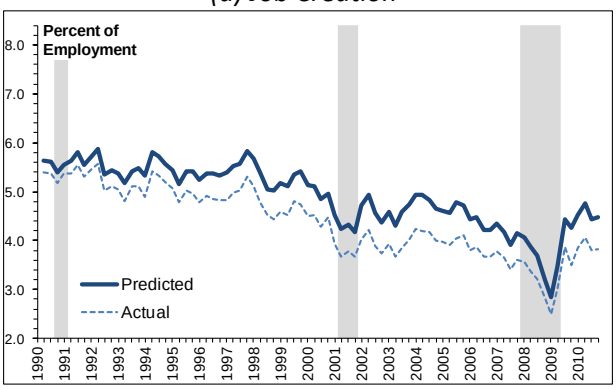
Figure 10. Estimated Temporary Help Employment within Manufacturing



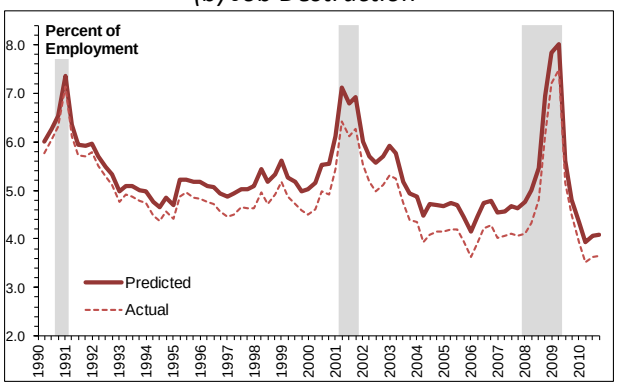
Source: Actual and predicted estimates of the employment services share of manufacturing are from Dey, Houseman, and Polivka (2012) and author's estimation based on their estimates, respectively. Net employment growth in Employment Services is the derived from the BED data.

Figure 11. Job Flows in Manufacturing: Actual and Predicted by Changes in the Manufacturing Share of Employment Services, 1990 – 2010

(a) Job Creation



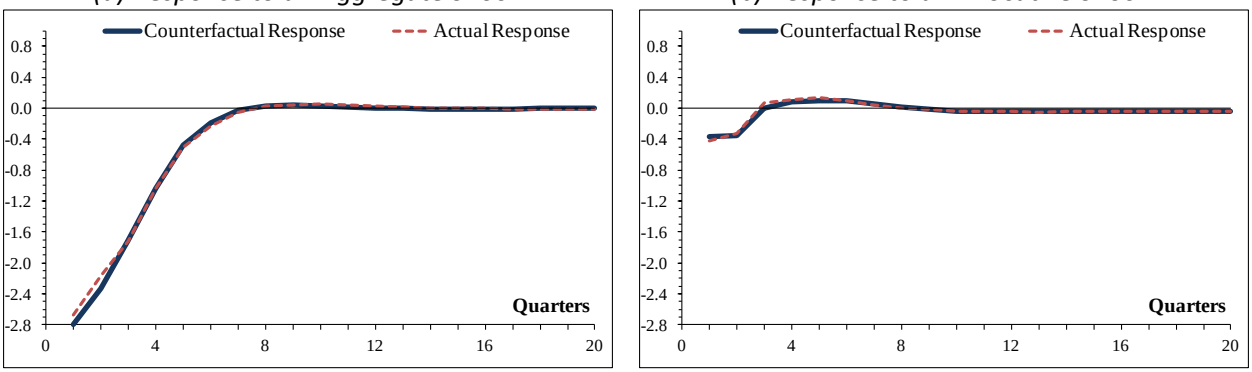
(b) Job Destruction



Source: Authors calculations using the BED data and a predicted estimate of the employment services industry share of manufacturing from Dey, Houseman, and Polivka (2012).

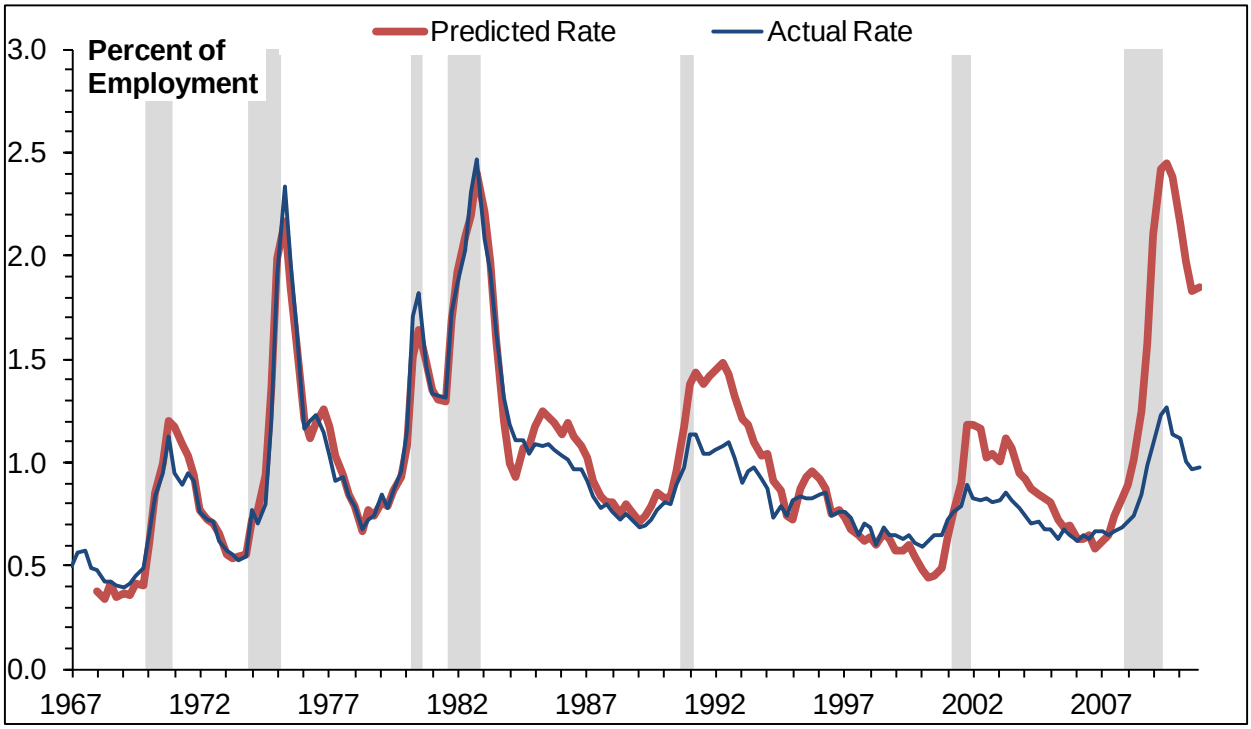
Figure 12. Implied Impulse Responses of Net Employment Growth: Actual and Predicted by Changes in the Manufacturing Share of Employment Services, 1984 – 2010

(a) Response to an Aggregate Shock *(b) Response to an Allocative Shock*



Source: Estimates are from a structural VAR of job creation and job destruction estimated on the 1984- 2010 sub-period. The implied impulse response of net employment growth is the difference between the impulse response of job creation and the impulse response of job destruction. Results using counterfactual data refer to the manufacturing series that incorporates employment changes within the employment services industry based on Dey, Houseman, and Polivka (2012). Results using actual data are from the original spliced series of BED and LRD-LTS data. Both series assume a constant contemporaneous response matrix across the full (1948-2010) sample of job flow data. See text for details.

Figure 13. Estimated Temporary Help Employment within Manufacturing



Source: Author's calculations using CPS data. Predicted estimates come from estimating the relationship between the temporary layoff rate and 4 quarter lags of net employment growth and the unemployment rate over the 1967-1983 period and extrapolating that prediction over the full sample period.

Web Appendix for Job Flows, Jobless Recoveries, and the Great Moderation

A. Linking the 1990-92 BED Data

Implementation of the "Multiple Worksite Report" (MWR) to state administrative records in the early 1990s caused serious complications for the BED linkage process. The BLS implemented the MWR so that multi-establishment firms could easily report the employment and payroll of their separate establishments. Prior to the MWR, firms in many states reported their multiple establishments as a single record. The MWR changed that, but when it did so, its restructuring of administrative records (which involved breaking out the single records into their individual establishments) was not fully recorded by every state. Consequently, the BLS did not have the necessary information to link what were in reality continuous units. This created large overstatements of opening and closing establishments in the first quarter of 1991 and the second quarter of 1992.

I correct for these overstatements by using unique characteristics of the MWR implementation process. First, since the MWR implementation occurs at the state level, I only need to focus on the affected states. Second, firm identifying codes do not change during the MWR implementation, only the codes for the individual reporting units change (this is not necessarily true of other administrative changes). Third, since these changes are theoretically only changes in paperwork, there should be no movement of employment across industries or locations, which sometimes occurs in the data during corporate mergers and other account restructurings. Finally, the administrative data have a fine level of geographic and industry detail (county level, and either 4-digit SIC or 6-digit NAICS, respectively). Large employment fluctuations at these levels of detail are relatively rare and thus easily identifiable in the

Given these characteristics, I use a three-step process. The first step calculates job flows using the standard BED methodology. From this, I take the subset of establishments identified as openings or closings. The second step uses a grid search for openings and closings with identical firm identifiers by county and detailed industry. I assume that these records are the result of the MWR implementation and match them. In the cases where there are multiple openings and multiple closings within the same cell (as opposed to one closing and one or more openings), I match probabilistically based on the employment level of each record. The final step recognizes that, in practice, some new records will have different industry codes than their predecessor. It takes the remaining unlinked records with identical firm identifiers and attempts to match within counties only. This last step produces less than 10 percent of the total matches I identify.

My approach is not without risks. First, it may produce false matches of truly opening and closing establishments. I am not too concerned with this possibility, since the false match would have to occur among opening and closing establishments within both the same firm and the same county, an occurrence that is extremely rare. Second, I may miss links that occur either within firm accounts and across counties or across entirely different firm account identifiers. Without predecessor or successor record information, I cannot identify these matches without increasing the chances of a false match among other records, so some small potential for missed links remains.

Table A.1 lists the results of my matching strategy for the quarters of interest. The matches significantly reduce employment changes at opening and closing establishments and slightly increase employment changes at continuing establishments (newly matched records often have legitimate changes in employment during these quarters).

Table A.1. Results of Early BED Match Identification

	Initial Estimate (Pct. of Employment)	Corrected Estimate (Pct. of Employment)
First Quarter, 1991		
Changes at Openings	6.0	2.8
Changes at Closings	6.1	2.4
Changes at Expansions	4.9	5.4
Changes at Contractions	8.7	9.5
Second Quarter, 1992		
Changes at Openings	3.6	2.2
Changes at Closings	2.8	1.3
Changes at Expansions	7.5	7.8
Changes at Contractions	4.9	5.1

Note: Listed job flow rates are prior to seasonal adjustment.

B. Evaluation of the GMM Splicing Exercise

The choice of moments in the GMM splicing exercise is nontrivial because many logical choices for moments that would preserve the volatility and comovement of the job flow series are linearly dependent. For example, the variance of net employment growth is equal to $\mathrm{var}(POS) + \mathrm{var}(NEG) - 2cov(POS, NEG)$, while the variance of job reallocation is $\mathrm{var}(POS) + \mathrm{var}(NEG) + 2cov(POS, NEG)$. Using nonlinear moments, such as relative volatilities or moments that include excess reallocation (which is a function of the absolute value of net growth), ensures a well-identified system. I choose the moments listed in Table B.1 because they include what I consider the "core" moments of the job flow time series (the means, variances, and covariance of job creation and job destruction, in some form or another), as well as nonlinear representations of related moments that aid in identification. Table B.1 replicates Table 1 in the text by listing the values of the moments of the BED data used in the GMM estimation. It also lists the value of the same moment in the LRD-LTS data during the overlap period.

Figure B.1 compares the fit of the spliced job flow series and original LRD-LTS data for job creation (top panel) and job destruction (bottom panel). Note that the spliced series includes the original BED data from 1990 forward. As one can see, there is a very tight relationship for between the predicted estimates and the original LRD-LTS data. The most notable difference is the reduced volatility of the predicted job flows during the earlier period. This reflects the approach's imposition of the BED time-series volatility on the earlier period data.

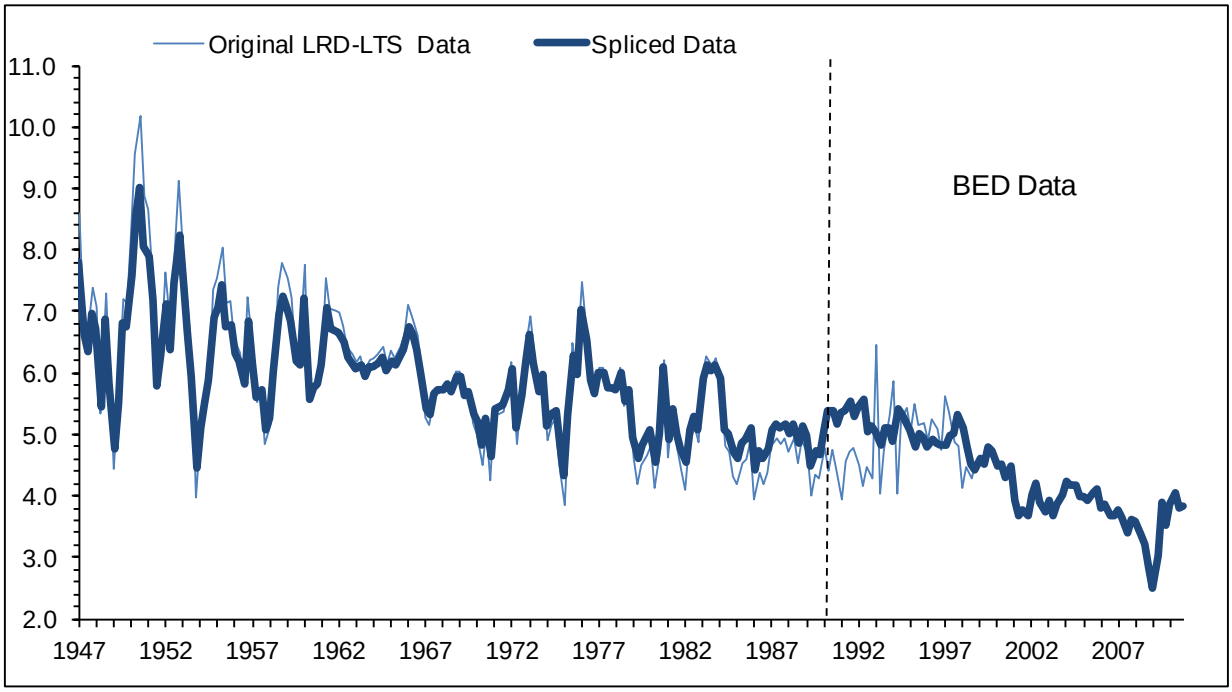
Table B.1. Moments Used in GMM Estimation of Spliced Job Flow Series and LRD-LTS Counterparts

Moment	BED Value	LRD-LTS Value
Mean Job Creation, $\boldsymbol{C_t}$	5.081	4.829
Mean Job Destruction, $\boldsymbol{D_t}$	5.068	4.786
Variance of Excess Reallocation, $\mathrm{var}(\boldsymbol{XR_t})$	0.502	0.935
Relative Volatility of Destruction to Creation, $\mathrm{var}(\boldsymbol{D_t})/\mathrm{var}(\boldsymbol{C_t})$	5.272	1.743
Correlation of Job Creation and Growth, $\mathrm{corr}(\boldsymbol{C_t}, \boldsymbol{NET_t})$	-0.070	0.593
Correlation of Job Destruction and Growth, $\mathrm{corr}(\boldsymbol{D_t}, \boldsymbol{NET_t})$	-0.901	-0.792

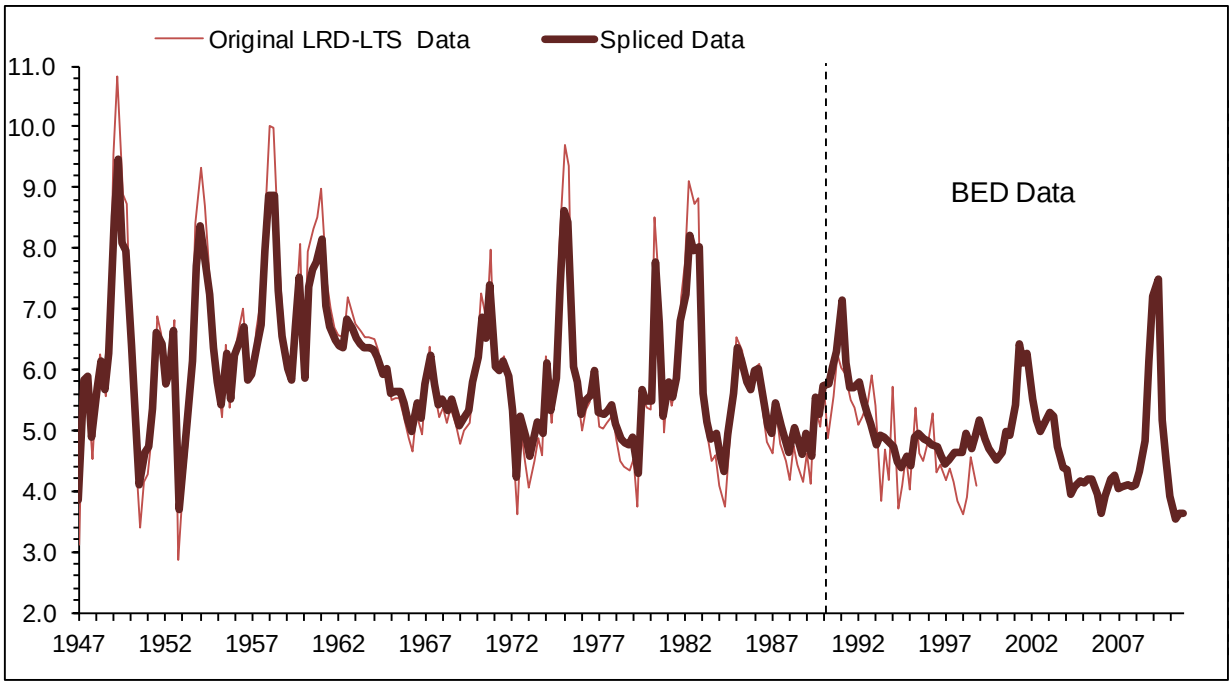
Source: Author's calculations using the BED data and the Davis-Haltiwanger (1999) spliced LRD-LTS estimates from 1990Q2 - 1998Q4.

Figure B.1. Original vs. Spliced Manufacturing Job Flow Series

Job Creation



Job Destruction



Notes: Panels compare series of spliced BED-LRD-LTS estimates derived from a GMM model to the original merged LRD-LTS series created by Davis and Haltiwanger (1999). The actual BED estimates are used to the right of the dashed vertical line in each panel.

C. QLR Statistics for Structural Breaks in Time-Series Volatility

Structural breaks in the time-series volatility of job flows, output growth, and unemployment inflows are identified using the maximum Quandt Likelihood Ratio (QLR) test statistic, as described in the text. A statistically significant QLR statistic at its maximum rejects the null of no structural break in the conditional variance of the time-series residuals. It does not reject the presence of more than one structural break. Furthermore, it can be susceptible to identifying breaks due to measurement error in cases where data series are constructed from multiple sources. Since my job flow data is constructed in such a way, it is important to keep this potential measurement error in mind. Specifically, it is important to make sure that 1990Q1-2, the point where the predicted LRD-LTS series and the BED data are spliced together, does not distort the identification of a structural break in volatility.

Figure C.1 presents the full time series of QLR statistic for each of the variables listed in Table 3 of the text. The top panel reports the QLR statistics for job creation, job destruction, job reallocation, and excess reallocation. The bottom panel reports the QLR statistics for employment growth, real GDP growth, and unemployment inflows measured through the CPS and UI initial claims, respectively. For reference, each panel identifies the critical values for 1 percent and 5 percent significance. The top panel shows that the structural breaks for job creation and job destruction identified in 1983 and 1982, respectively, do not appear to be driven by anything related to the splicing procedure. Job reallocation on the other hand appears to have only one statistically significant peak right at 1990Q2.1 attribute this peak to the splicing procedure and therefore do not reject the null of no break in the volatility of the job reallocation rate. Excess reallocation exhibits more of a plateau than a peak of QLR statistics between 1983 and 1989. All QLR statistics in this range are significant at the 1 percent level. The maximum QLR statistic identified at 1989Q2 is sufficiently close to the splicing date that it is difficult to reject the null of

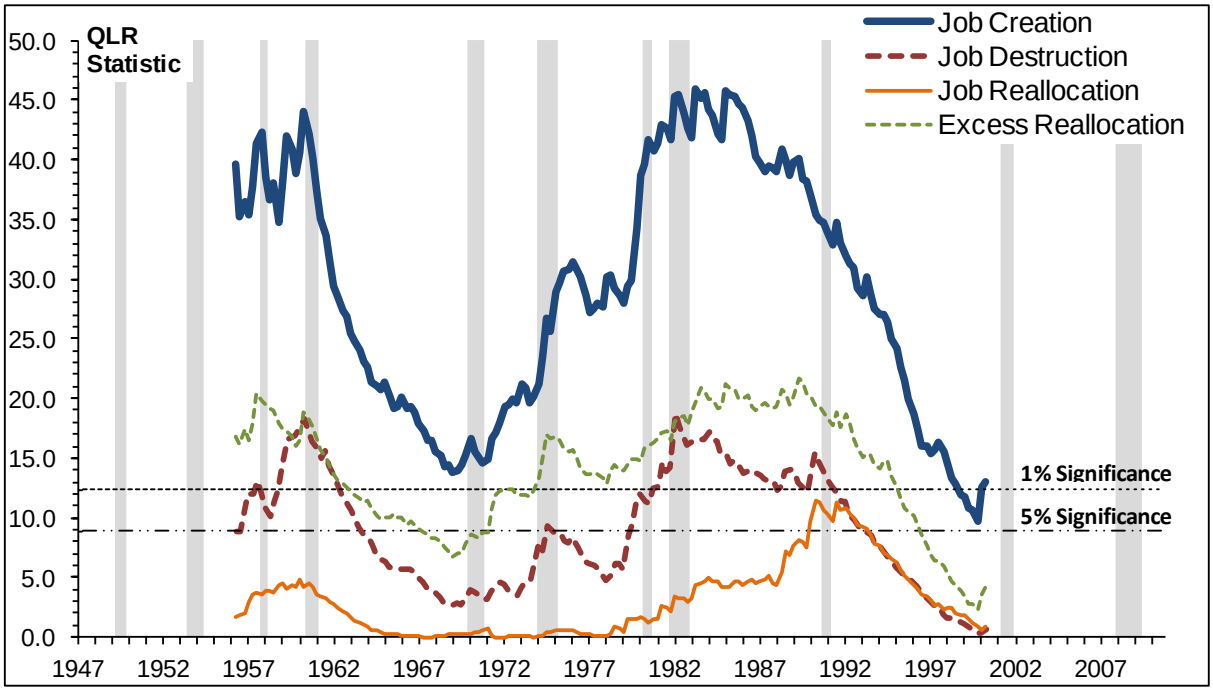
no structural break with any precision or confidence. It may be that there is a structural break in the volatility of job excess job reallocation sometime in the mid-1980s that is measured imprecisely. Alternatively, the "plateau" may represent the conflagration of two identified peaks: a true structural break in volatility around 1983 and a break due to the splicing procedure in 1989.

The bottom panel of Figure C.1 shows that the identified break dates for the QLR statistics of net employment growth, output growth, and both unemployment inflow measures exhibit clear, significant, and unquestionable structural breaks in volatility in the early to mid-1980s. While the net growth rate is derived from the spliced data, it is not surprising that the splicing date as little effect on its QLR test statistics because the splicing methodology uses the net growth rate from the CES data as an explanatory for the purpose of providing a consistent measure of net growth across the full sample period.

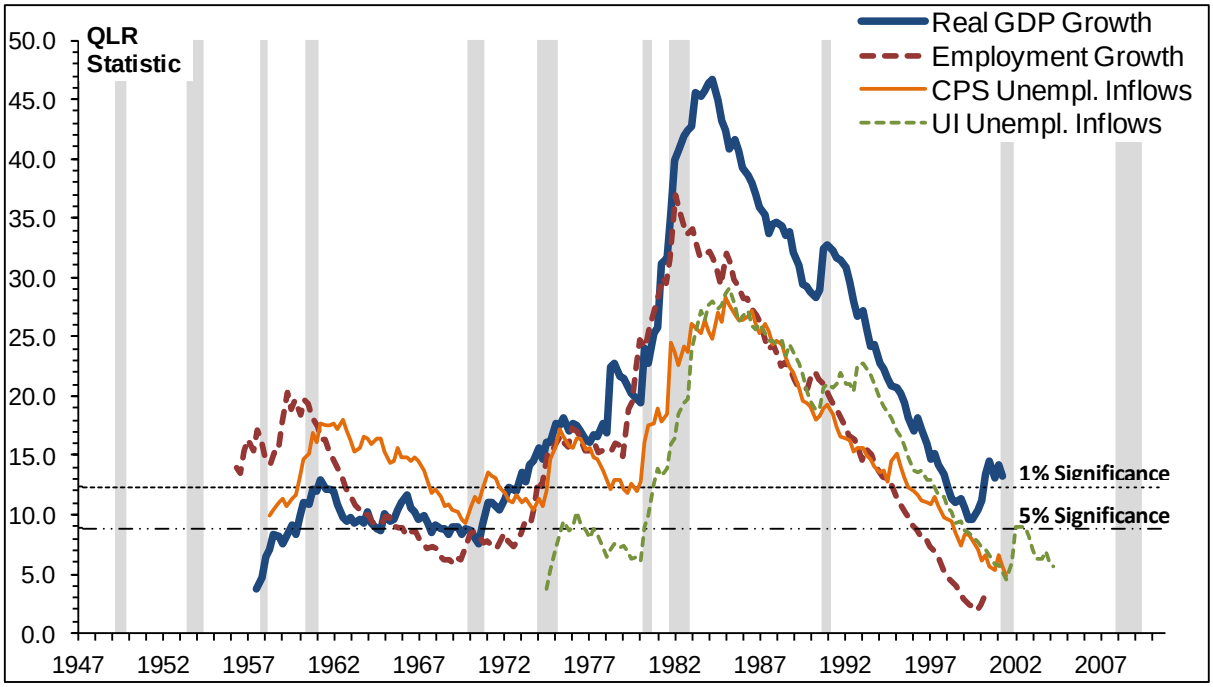
Finally, note that the job flow rates and the net employment growth rate all exhibit a local maximum between 1959 and 1960. Note that the time series do not line up because the test procedure uses the central 70 percent of observations for each time series. The CPS-based unemployment inflow measure also shows a local maximum in 1962. Output growth does not show a notable local peak around this period, indicating that there may be a second structural break in volatility in the early 1960s that is unique to the behavior of labor market dynamics. While examining this second break is outside the scope of this study, it likely warrants further research.

Figure C.1. QLR Statistics for the Tests of Structural Breaks in Volatility

Job Flow Rates



Growth and Unemployment Inflow Rates



Notes: Panels report the Quandt Likelihood Ratio (QLR) test statistic for a test of a structural break in time-series volatility for each listed variable. See main text for details of the test. Thin dashed lines represent the 1 percent and 5 percent critical values of the test, as listed.

D. Additional Results for the Structural VAR Analysis

This section provides additional results for the structural VAR analysis. Table D.1 compares the estimated standard deviations of the structural innovations for the later sub-period when including the latest recession (1984Q1-2010Q4) and when not including the last recession (1984Q1-2006Q4). Figure D.1 shows the difference in the implied impulse responses of net employment growth to either an aggregate or allocative shock using either the 2006 or 2010 end year. Table D.1 shows that excluding the most recent recession produces a small but notable reduction in the volatility of aggregate shocks, estimated to be between 15 and 23 percent. Depending on the identifying assumptions, excluding the most recent recession reduces either the volatility of allocative shocks as much as 19 percent or increases their volatility by up to 6 percent.

Figure D.1 shows that, despite its severity, including or excluding the latest recession and recovery period have almost no effect on the magnitude of the estimated impulse response of net growth to an aggregate shock, though excluding it does extend the time until steady-state growth is achieved from 8 to about 10 quarters. Depending on the identifying assumptions, excluding the latest recession either has no effect or increases the amount of initial growth due to an allocative shock.

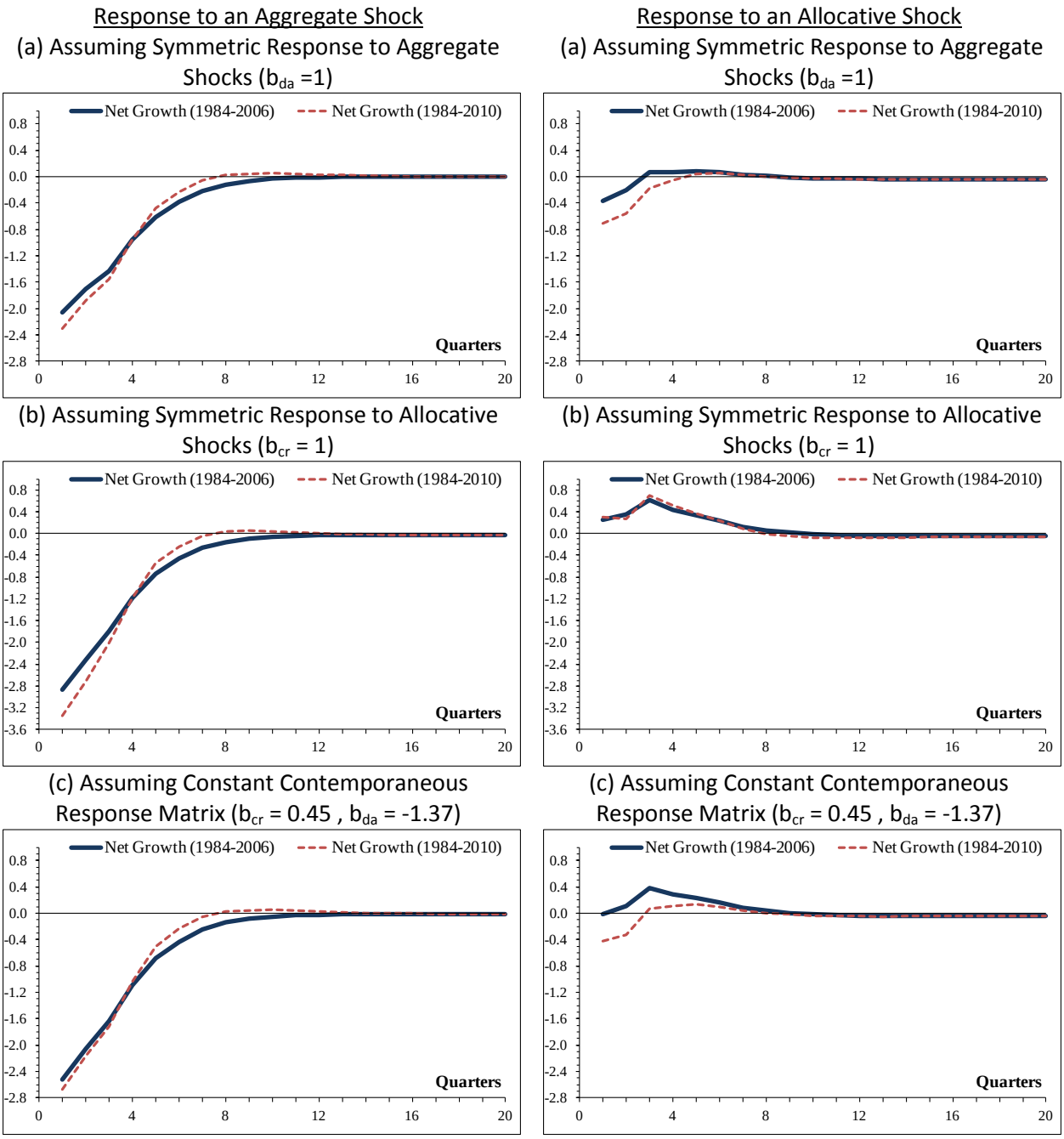
Figures D.2 and D.3 report the impulse responses of the job creation and the job destruction rate to an allocative or aggregate shock using the early sample or late sample, respectively, of manufacturing job flows. The figures include 67 percent confidence intervals that are calculated using bootstrap methods on 1,000 random draws from each sub-period's sample.

Table D.1. Structural Innovation Statistics for the Later Sub-Period

	b_{da}	b_{cr}	Std. Deviation, Aggregate Shock	Std. Deviation, Allocative Shock	Ratio of Std. Deviations
Assumption 1: Symmetric response to aggregate shocks					
1984Q1 - 2010Q4	-1.0	0.23	0.231	0.314	0.734
1984Q1 - 2006Q4	-1.0	0.47	0.196	0.262	0.747
Percent Difference in Std. Deviation			-15.1	-16.6	
Assumption 2: Symmetric response to allocative shocks					
1984Q1 - 2010Q4	-2.05	1.0	0.171	0.171	0.997
1984Q1 - 2006Q4	-1.90	1.0	0.143	0.181	0.791
Percent Difference in Std. Deviation			-16.4	5.8	
Assumption 3: Identical contemporaneous responses across periods					
1984Q1 - 2010Q4	-1.37	0.45	0.211	0.261	0.808
1984Q1 - 2006Q4	-1.37	0.45	0.164	0.212	0.772
Percent Difference in Std. Deviation			-22.7	-18.8	

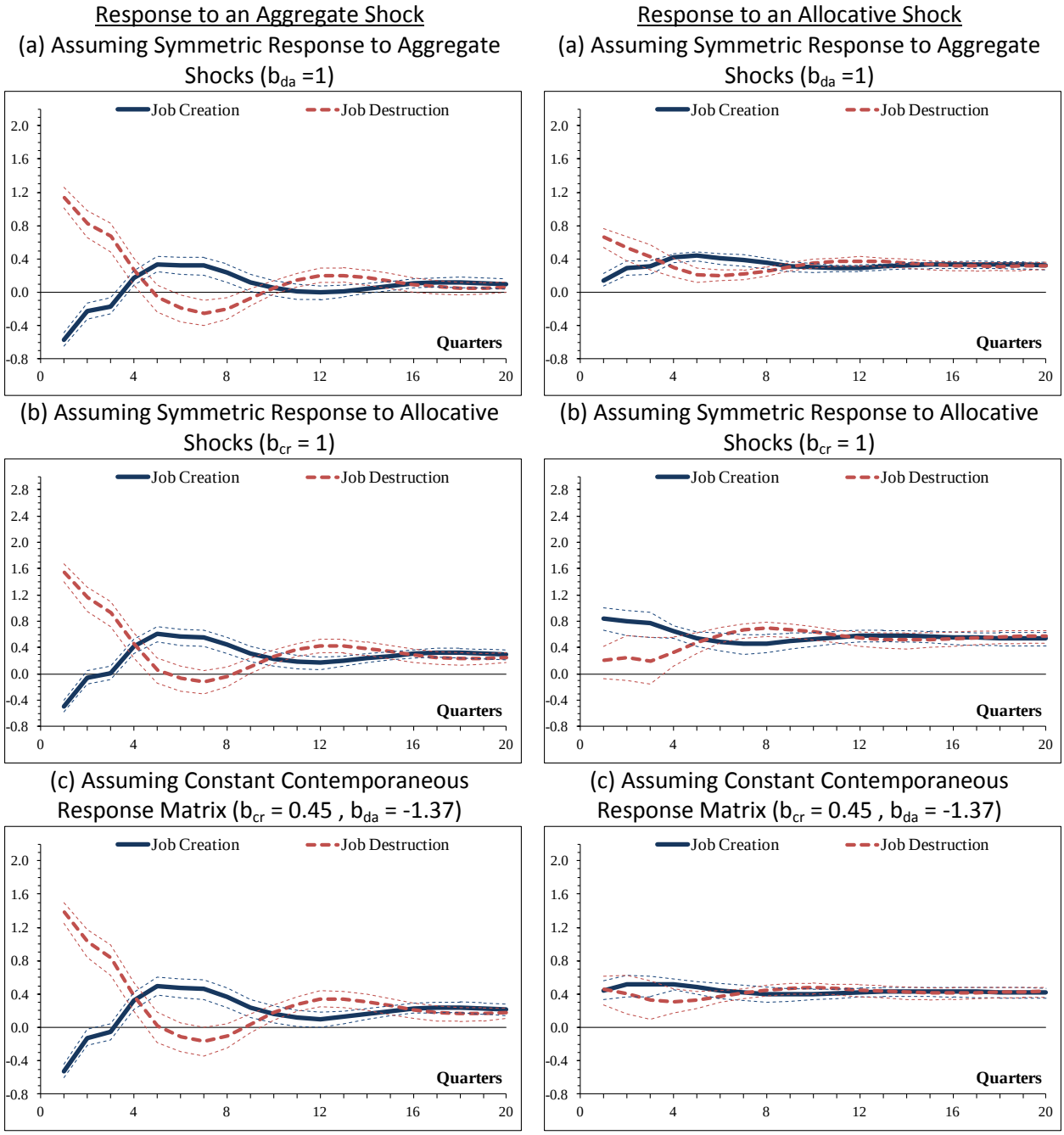
Source: Estimated job flows from LTS, LRD, and BED data. See text for details of the data construction and VAR analysis.

Figure D.1. Implied Impulse Responses of Net Employment Growth: Later Sub-Period Including (1984-2010) and Excluding (1984-2006) the Great Recession



Source: Estimates are from a structural VAR of job creation and job destruction estimated on either the 1984-2006 or the 1984-2010 sub-period. The implied impulse response of net employment growth is the difference between the impulse response of job creation and the impulse response of job destruction. Results use the spliced series of BED and LRD-LTS data. See text for details.

Figure D.2. Impulse Responses of Job Creation and Job Destruction, 1948-1983

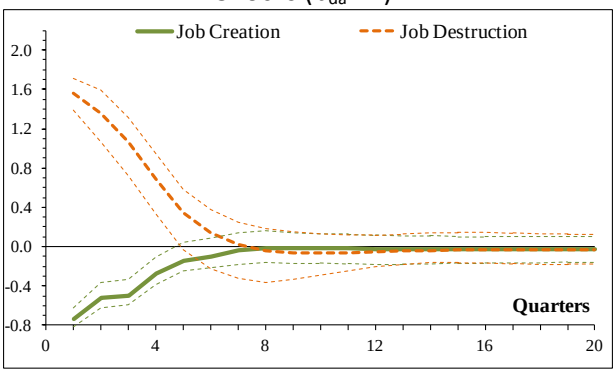


Source: Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1948-1983 subperiod. See text for details. Thin dashed lines represent bootstrapped 67 percent confidence intervals.

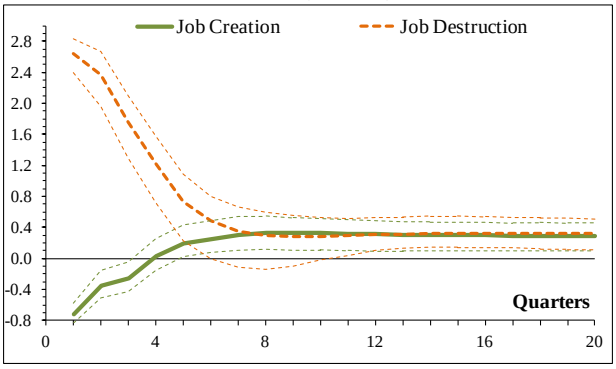
Figure D.3. Impulse Responses of Job Creation and Job Destruction, 1984-2010

Response to an Aggregate Shock

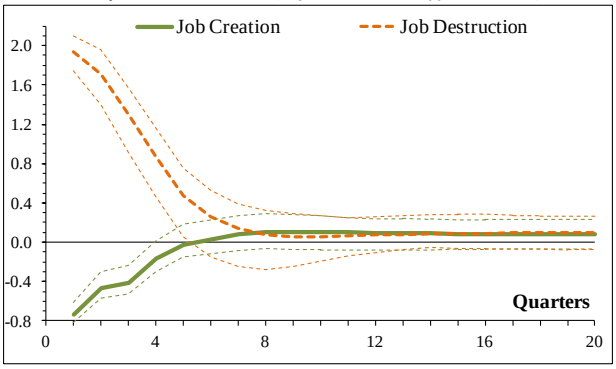
(a) Assuming Symmetric Response to Aggregate Shocks (b_{da} =1)



(b) Assuming Symmetric Response to Allocative Shocks (b_{cr} = 1)

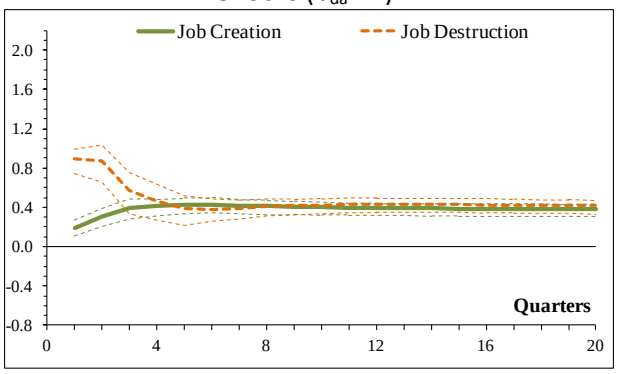


(c) Assuming Constant Contemporaneous Response Matrix (b_{cr} = 0.45 , b_{da} = -1.37)

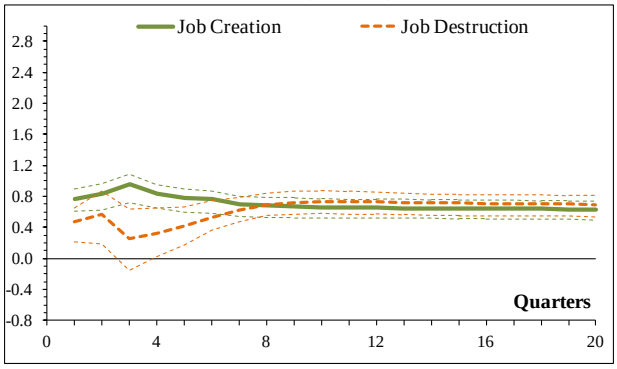


Response to an Allocative Shock

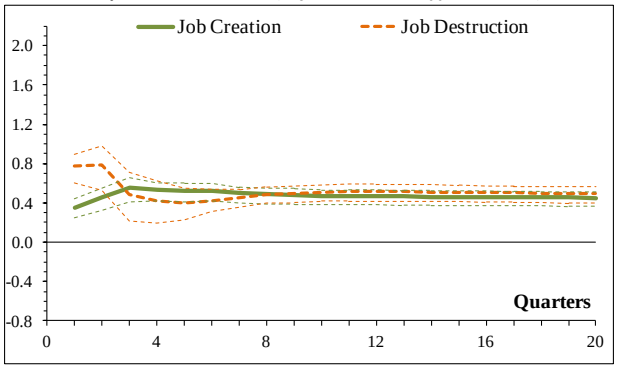
(a) Assuming Symmetric Response to Aggregate Shocks (b_{da} =1)



(b) Assuming Symmetric Response to Allocative Shocks (b_{cr} = 1)



(c) Assuming Constant Contemporaneous Response Matrix (b_{cr} = 0.45 , b_{da} = -1.37)



Source: Estimates are from a structural VAR of job creation and job destruction estimated separately on the 1984-2010 subperiod. See text for details. Thin dashed lines represent bootstrapped 67 percent confidence intervals.