

The Effects of Oil Price Shocks on Job Reallocation

Ana María Herrera*

Mohamad B. Karaki†

Abstract

We investigate the effect of oil price innovations on U.S. manufacturing job flows using a simultaneous equation model that nests symmetric and asymmetric responses. We find no evidence of asymmetry in the response of job flows to positive and negative oil price innovations. We then inquire whether firms, when facing positive shocks, shed jobs faster than they create jobs. We show that positive innovations lead to a decline in net employment and an increase in job reallocation, possibly due to search and matching issues. Yet, the latter effect becomes statistically insignificant when we control for data mining. We demonstrate that the cumulative one-year effect of oil price shocks on job creation and destruction was smaller during the Great Moderation, but it was larger for gross job reallocation. These variations were caused by a change in the transmission channel and not by smaller oil price shocks.

Keywords: oil prices, job flows, job reallocation, asymmetric responses.

JEL Classification: E24, E32, Q43.

*Corresponding author: Department of Economics, Gatton College of Business and Economics, University of Kentucky, Lexington, KY, 40506-0034; e-mail: amherrera@uky.edu

†Department of Economics, School of Business Administration, Lebanese American University, 1515 Business Building, Beirut, Lebanon; e-mail: mkaraki@lau.edu.lb. We are thankful to Lutz Kilian, Tatsuma Wada, James Ziliak, an anonymous referee, the associate editor, as well as participants at the 2012 Midwest Macroeconomics Meetings, the 2012 Midwest Economics Association Meetings, and the 3rd Annual Cleveland Federal Reserve-University of Kentucky Workshop for helpful comments and suggestions.

1 Introduction

In the last five years, there has been renewed interest in studying whether the response of macroeconomic activity to positive and negative oil price shocks is asymmetric (see, e.g., Kilian and Vigfusson 2011a, b; Hamilton 2011; Herrera, Lagalo and Wada 2011, 2015). Kilian and Vigfusson (2011a) prove that the estimators commonly used to empirically assess the presence of asymmetry in the response of economic activity to positive and negative oil price innovations are inconsistent, and show that –by construction– they tend to overestimate the magnitude of the response. Moreover, they discover no evidence of asymmetry in the responses of U.S. real GDP and unemployment. Herrera, Lagalo and Wada (2011) find similar results for aggregate industrial production; nevertheless, they uncover evidence against the null of symmetry for few industries. This literature highlights the importance of re-examining the question of asymmetry at a more disaggregate level and the need to re-evaluate the mechanisms at play in the transmission of oil price shocks. Our analysis complements earlier studies by focusing on highly disaggregated data for job flows, similar to Davis and Haltiwanger (2001, hereafter DH), while taking full advantage of recent methodological advances in estimating and testing for symmetric responses.

The aim of this paper is threefold. First, we use updated time series data on U.S. manufacturing job creation and job destruction, as well as state-of-the-art methods to study the question of asymmetry in the response of U.S. manufacturing job flows to oil price shocks. In particular, whereas Kilian and Vigfusson’s (2011a) finding of symmetry in the response of the U.S. unemployment rate could be interpreted an indication of symmetry in the response of the labor market, it is well known that focusing on the aggregate unemployment rate gives a very limited view of movements in job flows (see Table 1). In fact, a lot can be learned about the manner in which an economy adjusts to shocks by looking at the response of job creation and job destruction. For instance,

are asymmetries in the responses of job creation and job destruction masked by aggregating these flows when computing the net employment change? Are asymmetries in the responses of sectoral job flows attenuated by the aggregation across sectors? To answer these questions we directly test for symmetry in the responses of sectoral job creation and destruction to positive and negative innovations in the real oil price. Furthermore, we look into the response of more disaggregated data in the automobile sector, as previous work suggests that it was in this sector where issues of mismatch between the desired and the actual characteristics of the labor force (and the capital stock) played an important role in the transmission of oil price shocks to aggregate employment and production.¹

Second, we evaluate whether oil price shocks operate mainly through aggregate or allocative channels. To do this we propose and implement a novel test for the absence of job reallocation. As DH point out, if oil price shocks operate mainly through aggregate channels –such as income transfers from oil importing to oil exporting countries, declines in potential output, or sticky prices and wages–, then positive oil price innovations result in higher job destruction, lower job creation, and lower job reallocation. On the other hand, if oil price shocks operate mainly through allocative channels –that is, by causing changes in the closeness of the match between the desired and the actual factor inputs²–, then a positive oil price innovation results in higher job destruction, job creation, and job reallocation. Therefore, testing whether positive innovations lead to higher job reallocation is equivalent to directly evaluating the relevance of the allocative channel.

Third, motivated by the observation that the effect of oil price shocks on economic activity declined in the 2000s relative to the 1970s,³ we inquire whether the response of job flows to oil

¹See, for instance, Hamilton (1988), Bresnahan and Ramey (1993), Edelstein and Kilian (2007, 2009), Herrera (2012) and Ramey and Vine (2010).

²See, e.g., Davis 1987a, b; Hamilton 1988; Bresnahan and Ramey 1993; Davis and Haltiwanger 2001.

³See Edelstein and Kilian (2009), Herrera and Pesavento (2009), and Blanchard and Galí (2010).

price shocks changed during the Great Moderation. In particular, a decline in gross (SUM) and excess (EXC) job reallocation for aggregate manufacturing appears to have taken place during the Great Moderation, a period with higher oil price volatility (see Figure 1). Although, a decline in average sectoral job reallocation is also apparent when we compare pre and post-1984 data, no such pattern is evident for excess job reallocation (see Table 2). Thus, the question arises whether U.S. manufacturing experienced a decline in the intensity of job reallocation generated by oil price innovations during the Great Moderation.

Our findings can be summarized as follows:

- *Asymmetric effects of oil price shocks:* Using data-mining robust critical values we find no statistical evidence of an asymmetric response of U.S. manufacturing job flows to positive and negative oil price innovations. These results are robust to the use of different oil price transformations and the size of the innovation. Furthermore, it holds both at the aggregate and the sectoral level.
- *Allocative effects of oil price shocks:* When analyzed from a sector-by-sector perspective, we find that oil price shocks have an impact on job reallocation, especially for sectors that are energy intensive in production (e.g., textiles, petroleum and coal, rubber and plastics) or in consumption (e.g., truck trailers). However, using data-mining robust inference we are unable to reject the null of absence of job reallocation. This result suggests that oil price shocks operated mainly through aggregate channels.
- *Oil price shocks before and during the Great Moderation:* Oil price shocks were roughly twice as volatile during the Great Moderation, yet they induced smaller job creation/destruction and excess job reallocation responses. These results suggest that the transmission mechanism of oil price shocks has changed. Whether this change is due to variation in the composition

of the oil price shocks faced by the U.S. economy (i.e., demand versus supply driven oil price shocks as in Kilian, 2009), changes in the flexibility of the labor market (Blanchard and Gali 2010), or any other changes in the adjustments needed to eliminate the wedge (driven by the shock) between the desired and the actual characteristics of the work force, is an issue that is open for further investigation.

The remainder of the paper is organized as follows. Section 2 briefly reviews the data on job flows and oil prices. Section 3 describes the empirical strategy. Section 4 presents the results for the test of symmetry in the response of job creation and job destruction to positive and negative oil price shocks. Section 5 investigates the importance of the allocative channel. Section 6 inquires into the changes in the response of job creation and destruction during the Great Moderation. Section 7 concludes.

2 Job Flows and Oil Prices

2.1 Job Flows

In order to explore the effect of oil price shocks on sectoral reallocation we use the job flows data collected by Davis, Haltiwanger and Schuh (1996) in the 1990s and updated online in 2009. This database contains quarterly data on job flows spanning the period between 1972:Q2 and 2005:Q1 for total manufacturing, and between 1972:Q2 and 1998:Q4 for 2-digit and 4-digit SIC industries.⁴ We are able to extend the series for total manufacturing to 2014:Q2 using the Business Employment Dynamics (BED) data provided by the Bureau of Labor Statistics. Unfortunately, due to the change in industry classification from SIC to NAICS in the late 1990s, there is no concordance between the

⁴We use the X-11 Census method to seasonally adjust the data.

older 2-digit SIC data and the newer NAICS data available from the BED. Thus, for the sectoral job flows we use data for twenty 2-digit sectors and four 4-digit industries in the transportation equipment sector covering the 1972:Q2-1998:Q4 period. We include the latter industries because we believe additional insight into the effect of oil price shocks on job reallocation can be gained by focusing on a number of sectors in the automobile industry, an industry that has been shown to be very responsive to oil price shocks.⁵

As in Davis, Haltiwanger and Schuh (1996), let Z_{est} be the average employment at establishment e in industry s between time t and $t - 1$ (i.e., $0.5(EMP_{es,t} + EMP_{es,t-1})$ where $EMP_{es,t}$ is the number of workers at establishment e in industry s in period t). Similarly define Z_{St} as the average employment in industry S . Define the employment growth rate g_{est} in establishment e of industry S at time t as the change in employment between t and $t - 1$ periods divided by Z_{est} ($\Delta EMP_{es,t}/Z_{est}$). The job creation rate, $POS_{S,t}$, in industry S at time t is given by the sum of employment growth at expanding and entering establishments within industry S , where this sum is divided by the size of the industry in order to express the flow in terms of a rate:

$$POS_{S,t} = \sum_{e \in S^+} \frac{Z_{est}}{Z_{St}} g_{est}. \quad (1)$$

Similarly, job destruction is given by the sum of employment losses at contracting and exiting establishments, and expressed as a rate:

$$NEG_{S,t} = \sum_{e \in S^-} \frac{Z_{est}}{Z_{St}} |g_{est}|. \quad (2)$$

⁵We leave the investigation of the effect of job reallocation on other 4-digit SIC industries for future research due to the large computational time. Replicating the impulse response based test in section 5 for the 244 four-digit industries available in the data set, would take about 5,612 hours using a high performance Grid enabled computing system, which allows us to run 10 or more parallel codes. If we add to this time, the computation time required to replicate the subsample results in section 6, we would end up with nearly 2 years of continuous computation.

Job creation and job destruction rates are used to compute other measures of job flows. In particular, total job reallocation ($SUM_{S,t}$) inside industry S between quarter $t - 1$ and t represents an upper bound on the rate of job reallocation and is defined as

$$SUM_{S,t} = POS_{S,t} + NEG_{S,t}, \quad (3)$$

whereas excess job reallocation ($EXC_{S,t}$) represents job reallocation in excess of the net change in jobs ($NET_{S,t}$) where

$$NET_{S,t} = POS_{S,t} - NEG_{S,t}, \quad (4)$$

and

$$EXC_{S,t} = SUM_{S,t} - |NET_{S,t}|. \quad (5)$$

Note that $EXC_{S,t}$, which is the amount of job turnover that goes on above and beyond what would be required to attain the observed net change in employment in industry S at time t , constitutes an indicator of the flexibility of the labor market in a particular industry (see, e.g., Bauer and Lee, 2007, Cuñat and Melitz 2012, Micco and Pagés, 2004).

Table 1 summarizes the average quarterly job flows by industry between 1972:Q2 and 1998:Q4; we also include the average flows for total manufacturing over the 1972:Q2-2014:Q2 sample. The variation in job reallocation and excess reallocation rates across industries is driven by differences in both job creation and destruction. In particular, industries with higher job creation also have higher job destruction, which results in higher job reallocation and excess reallocation rates. Furthermore, the fact that excess reallocation tends to be quite large suggests that a considerable proportion of job reallocation is not driven by aggregate shocks. (Recall that in the absence of heterogeneous job creation and destruction patterns across establishments within sectors, excess job reallocation

would be zero.) Note that reallocation at the interior of the transportation equipment sector, tends to be larger for industries in the automobile sector than for total manufacturing.

With respect to the evolution of job flows over time, Figure 1 suggests a slight decline in the rate of job reallocation (*SUM*) and excess reallocation (*EXC*) for total manufacturing, which coincides with a period of increased volatility in real oil prices and the dampening effect of oil price shocks during the Great Moderation (Blanchard and Galí, 2010; Edelstein and Kilian, 2009; Herrera and Pesavento, 2009). Nevertheless, comparing the two *EXC* columns in Table 2, does not reveal a clear pattern of decline in excess reallocation by industry between the 1972:Q2-1984:Q4 and the 1985:Q1-1998:Q4 periods.⁶ Thus, a more in depth analysis is required to inquire into the changes in the response of job flows to oil price shocks before and during the Great Moderation (see section 6).

2.2 Oil Prices

We follow Hamilton (1996, 2003) and DH by measuring nominal oil prices using the producer price index of crude petroleum and, as the latter, we compute real oil prices (o_t) by deflating the nominal price of oil by the total producer price index (PPI). The choice of the deflator (CPI vs. PPI) makes little difference for the empirical results, however, by computing real oil prices in this manner our results are easier to compare to DH. The growth rate of the real oil price is then defined as $x_t = \ln(o_t) - \ln(o_{t-1})$.

Because we are interested in estimating a model that nests both symmetric and asymmetric responses of job flows to oil price increases and decreases, our baseline results are obtained using a nonlinear transformation of the log growth in the real oil price: the oil price increase (Mork 1989).

⁶See Davis, Faberman and Haltiwanger (2012) for an in-depth analysis of changes in labor flows over time.

This measure sets all quarterly oil price decreases to zero so that

$$x_t^1 = \max \{0, \ln(o_t) - \ln(o_{t-1})\}. \quad (6)$$

To ensure that our results are robust to other nonlinear transformations we repeat our estimation using two alternative oil price specifications. The first specification is the net oil price increase over the previous 4-quarter maximum (Hamilton, 1996),

$$x_t^4 = \max \{0, \ln(o_t) - \max \{\ln(o_{t-1}), \dots, \ln(o_{t-4})\}\}. \quad (7)$$

This nonlinear transformation filters out increases in real oil prices that correct for previous declines, and has been purported to be successful in capturing the nonlinear relationship between oil prices and economic activity (Hamilton 1996, 2003). Figure 2 illustrates the evolution of the real oil price change (x_t), the oil price increase (x_t^1), and the net oil price increase (x_t^4) over the 1972:Q2-2014:Q2 period. Notice that, as implied by equations (6) and (7), the degree of censoring is higher for the net oil price increase than for the oil price increase.

In addition, to provide a more direct comparison with DH, we also estimate a model in which the growth rate in the real price of oil, x_t , is replaced with DH's oil price index and the absolute change in the index corresponds to the nonlinear transformation, \tilde{x}_t^{abs} . DH's index is defined as the log of the ratio between the real oil price in quarter t and a weighted average of the real oil price in the previous 20 quarters with weights that linearly decline to zero and sum up to 1.

3 Empirical Strategy

To study the effect of oil price shocks on job flows we estimate the following simultaneous equation model

$$x_t = a_{10} + \sum_{i=1}^p a_{11,i}x_{t-i} + \sum_{i=1}^p a_{12,i}NEG_{S,t-i} + \sum_{i=1}^p a_{13,i}POS_{S,t-i} + \varepsilon_{1,t} \quad (8a)$$

$$NEG_{S,t} = a_{20} + \sum_{i=0}^p a_{21,i}x_{t-i} + \sum_{i=1}^p a_{22,i}NEG_{S,t-i} + \sum_{i=1}^p a_{23,i}POS_{S,t-i} + \sum_{i=0}^p g_{21,i}x_{t-i}^{\#} + \varepsilon_{2,t} \quad (8b)$$

$$POS_{S,t} = a_{30} + \sum_{i=0}^p a_{31,i}x_{t-i} + \sum_{i=0}^p a_{32,i}NEG_{S,t-i} + \sum_{i=1}^p a_{33,i}POS_{S,t-i} + \sum_{i=0}^p g_{31,i}x_{t-i}^{\#} + \varepsilon_{3,t} \quad (8c)$$

where $POS_{S,t}$ and $NEG_{S,t}$ are job creation and job destruction in sector S as time t , respectively,

as defined in equations (1) and (2) of section 2.1; $x_t^{\#}$ refers the nonlinear transformations of oil prices defined in section 2.2; ε_t is a vector of contemporaneously and serially uncorrelated innovations; and $p = 4$. Note that for identification purposes we assume that oil prices do not respond contemporaneously to changes in job destruction or job creation, and that job destruction does not respond contemporaneously to changes in job creation.⁷ Furthermore, given that we do not impose any exclusion restrictions on the lags of the endogenous variables and given that the innovations are orthogonal by construction, the system in (8) can be estimated via OLS equation by equation.

The impulse response functions (hereafter *IRFs*) derived from this model are nonlinear functions of the parameter estimates. Moreover, they depend on the history and the size of the shock. Therefore we compute the *IRFs* by Monte Carlo integration in the following manner. First, we estimate the model by OLS and keep the estimated coefficients, the standard errors, and the

⁷Kilian and Vega's (2011) work supports the assumption that aggregate output and employment does not affect oil prices contemporaneously. Thus, sectoral job creation and job destruction should not affect oil prices contemporaneously. The assumption that *NEG* is Wold-causally prior to *POS* is plausible given the staggering of labor contracts.

residuals. Then, conditional on a given history $\{x_{t-1}, \dots, x_{t-p}, NEG_{t-1}, \dots, NEG_{t-p}, POS_{t-1}, \dots, POS_{t-p}\} = \{X_t, N_t, P_t\} \in \Omega^t$, we generate two time paths for job destruction, NEG_t (job creation, POS_t). The first path traces the response of job destruction (creation) to an oil price innovation of size δ (1 or 2 s.d.). The second path traces the response to a shock ε_{1t} drawn from the empirical distribution of ε_{1t} (i.e., resampled with replacement from the residual $\widehat{\varepsilon}_1$ in (8a)). These new updated information sets together with the censored variable are used to generate an updated information set. These steps are repeated to generate a response path up to horizon H . This procedure is replicated 10,000 times to generate the unconditional impulse responses $I_y(h, \delta, \Omega^t)$ as the difference between the average of the simulated paths for a shock δ and the average of the paths for a shock ε_{1t} . We repeat this computation for all possible histories and average over all the conditional *IRFs*, $I_y(h, \delta, \Omega^t)$, to compute the unconditional *IRF*, $I_y(h, \delta)$. Similarly for a negative shock of size $-\delta$, we first compute the conditional *IRFs*, $I_y(h, -\delta, \Omega^t)$, and then average over all the histories to obtain the unconditional *IRF*, $I_y(h, -\delta)$.⁸

Note that our baseline model specification differs from that in DH in a number of aspects. First, DH use the oil price index described in the previous section. Instead, we follow the bulk of the literature and use the quarter-to-quarter percent change in the price of crude oil. Second, whereas DH include both the oil index and the absolute change in the oil index as left-hand-side variables in their near-VAR, we include only x_t as a left-hand-side variable in (8a) and both x_t and $x_t^\#$ as explanatory variables in (8b) and (8c). Third, DH include a macro block before the sectoral job creation and job destruction rates. This macro block contains the oil price index, the absolute change of the oil index, total job creation in the manufacturing sector, total job destruction in the manufacturing sector, and the quality spread (i.e., the difference between the 6-month commercial

⁸Section 1 of the on-line appendix available at <http://gatton.uky.edu/faculty/herrera/documents/HKappendix.pdf> provides a detailed description of the computation procedure.

paper rate and the 6-month Treasury bill rate). We opt for a more parsimonious model that is better suited for our purpose of explicitly testing for symmetry in the response of job creation and job destruction. Adding the macro block would lower the power of the test, making it less likely to reject the null of symmetry and stacking the odds against finding any statistical evidence of job reallocation. Finally, because our simultaneous equation model, (8), is nonlinear in x_t , computing the impulse response functions –hereafter *IRFs*– in the usual textbook manner is erroneous (see Gallant, Rossi and Tauchen 1993 and Koop, Pesaran and Potter 1996, Kilian and Vigfusson 2011a). Ignoring this nonlinearity causes an overestimate of the effect of an oil price shock. Hence, we compute the *IRFs* by Monte Carlo integration, conditional on the history and the size of the shock (i.e., one standard and two standard deviations).

4 Are the Responses of Job Creation and Job Destruction to Positive and Negative Oil Price Innovations Symmetric?

One key question about the relationship between oil prices and the macroeconomy is whether the response of job destruction (and creation) to positive and negative oil price innovations is symmetric. In other words, do positive innovations lead to the same response (with opposite sign) in the rate of job destruction (creation) than the response brought about by negative innovations of the same magnitude? To investigate this issue, we adapt Kilian and Vigfusson’s (2011a) *IRF* based test to examine the null of symmetry in the response of job creation/destruction to oil price increases and decreases, where:

$$H_o : I_y(h, \delta) = -I_y(h, -\delta) \text{ for } h = 0, 1, 2, \dots, H; y = POS, NEG.$$

We compute the test for a one-year horizon (4 quarters) in order to avoid the data mining problem related with repeating the test over a number of different horizons. Note that the symmetry test for $H = 4$ is a joint test that the response of job creation (or job destruction) to positive and negative innovations is symmetric for horizons $h = 1, 2, 3, 4$. Therefore, by reporting the test for $H = 4$ we include the period where the effect of oil price shocks tends to be largest, $h = 4$ (see e.g., DH, and Lee and Ni, 2002).

Table 3 reports p -values –based on the conventional asymptotics– for the *IRF* based test of symmetry in the response of job creation and job destruction to one and two standard deviations oil price innovations (hereafter 1 s.d. and 2 s.d. shocks). The left panel of Table 3 shows that, for a 1 s.d. shock, we are unable to reject the null of symmetry at a 5% significance level for both job creation and job destruction.⁹ The right panel of Table 3 reveals some evidence of asymmetry for a 2 s.d. shock. Note that we are able to reject the null of symmetry in job creation for tobacco and in job destruction for total manufacturing, food, and petroleum and coal.

One concern with interpreting the sectoral results as evidence of asymmetry in the aggregate job creation and job destruction rates is that there is an element of data mining involved. Specifically, so far we have ignored the fact that we have repeated the same Wald test over twenty 2-digit SIC sectors and four 4-digit SIC industries. As it is well known, the conventional critical values do not account for repeated applications of the *IRF* based test to alternative job creation (destruction) rates, and we would expect the number of rejections to increase as the number of series tested increases. To address this concern we simulate the null distribution of the supremum of the bootstrap test statistic across all sectors for each of the oil price measures and each job flow as in Herrera, Lagalo and Wada (2011).¹⁰ The data mining robust critical values are based on 1000 pseudo series generated using

⁹For the sake of brevity, we report the *IRFs* to positive and negative innovations of 1 s.d. and 2 s.d. in Figures A.1-A.4 of the online appendix available at <http://gatton.uky.edu/faculty/herrera/documents/HKappendix.pdf>.

¹⁰See Inoue and Kilian (2004) and Kilian and Vega (2011) for the effect of data mining and solutions to the problem

the estimated coefficients for all sector and maintaining the observed correlation of the residuals. As it can be seen in Table 3, we find no evidence of asymmetry in the response of job creation or job destruction once we have accounted for the effect of data mining.¹¹

It is interesting to compare our results with those obtained by Kilian and Vigfusson (2011a) and Herrera, Lagalo and Wada (2011). The former evaluate the question of symmetry using aggregate data on U.S. GDP and unemployment, whereas the latter employ industry-level data on industrial production. Both of these studies estimate simultaneous equation models that nest symmetric and asymmetric responses to oil price increases and decreases and base their inference on impulse response based tests. Yet, only the latter accounts for data mining as the test is repeated over a large number of industrial production indexes. Comparing our results with these studies reveals two similarities. First, real GDP, national unemployment, as well as output and job flows in total manufacturing exhibit no asymmetry in the response to positive and negative oil price innovations. Second, at a sectoral level and without accounting for data mining, evidence of asymmetry is more widespread for a 2 s.d. shock than for a 1 s.d. shock, with evidence of asymmetry being more prevalent for industrial production. However, evidence of asymmetry vanishes when data mining robust inference is utilized.

To conclude this section, we evaluate the robustness of our findings by comparing our baseline results with those obtained using alternative model specifications. First, we repeat our estimation using the net oil price increase and then using DH's oil price index. Estimation results reported in Table A.2 of the on-line appendix reveal that, regardless of the specification, we cannot reject the null of symmetry using data mining robust inference,

Second, we use a model à la DH. As part of their investigation on the effect of oil price shocks on

of data mining in the related context of tests of predictability.

¹¹Estimation results reported in Table A.1 of the on-line appendix reveal no evidence of asymmetry in the response of the net change in jobs, job reallocation and excess reallocation to positive and negative oil price shocks.

the creation and destruction of U.S. manufacturing jobs, DH compute impulse response functions based on their estimated near-VAR for six 2-digit SIC industries (apparel, rubber and plastics, primary metals, industrial machinery, electronic and electric equipment and transportation equipment). As discussed in section 3, their model included a macro block comprised by the percentage change in the price of oil, a nonlinear transformation of the oil price, total job destruction, TD_t , and total job creation, TC_t , in manufacturing, and the quality spread, SPR_t . Thus, we re-estimated our simultaneous equations model (8) including the variables TD_t , TC_t , and SPR_t (in that order) after the oil price change, x_t , and before the industry level job destruction and creation. We estimate this augmented model using DH’s sample: 1972-1988. In addition to the identification assumption used in model (8) –oil prices changes, x_t , are predetermined and sectoral job destruction does not respond to changes in sectoral job destruction contemporaneously– we assume that TD_t responds to changes in all variables, but x_t , with a lag; TC_t respond to changes in SPR_t and the sectoral job flows with a lag; and the industry level job flows affect the macro variables with a lag.¹² We find no asymmetry in the response of job creation and job destruction to positive and negative oil price innovations.¹³

5 Assessing the Effect of Oil Price Shocks on Job Reallocation

One could argue, however, that the issue addressed by DH is not whether positive and negative oil price innovations lead to asymmetric responses in job creation and job destruction. Instead, the question tackled by DH might be better described as an investigation on the direction of the job reallocation response to positive oil price innovations. That is, when faced with an unexpected

¹²Our identification assumptions differ from DH in that we assume recursive ordering of the system. Given the methodology we use to compute the *IRFs* we need a model that is fully identified.

¹³See Table A.8 of the online appendix.

increase in oil prices, do firms shed jobs at a faster rate than the rate at which they create jobs? If this is the case, then positive innovations in oil prices should lead to a decline in net employment and an increase in job reallocation. Hence, in this section we explore whether oil price shocks have an effect on the economy through the allocative channel.

5.1 The Responses of Sectoral Job Flows to Oil Price Shocks

Having found no evidence of asymmetry in the response of job creation and job destruction to positive and negative oil price innovations, we restrict our analysis here to the response of job flows to positive innovations. Figure 3 plots the responses of job creation, job destruction, job reallocation and excess job reallocation to a 1 s.d. positive innovation in the real oil price. To conserve space, we only depict the responses of eleven 2-digit SIC industries; the *IRF*s for the remaining nine 2-digit SIC industries are reported in the online appendix (see Figure A.5).

As the top panel of Figure 3 illustrates, job destruction in total manufacturing experiences a larger increase than the decline observed in job creation. For instance, the response of job destruction is an order of magnitude larger than the response of job creation four quarters after the shock. The one-year cumulative response of job destruction is 0.348 percentage points whereas the cumulative response of job creation is only 0.026 percentage points. Moreover, note that the difference appears to increase for the first year after the shock and it declines afterwards. These responses are suggestive of an allocative effect of oil price innovations, as job reallocation increases while net employment declines.

Regarding the industry level data, Figure 3 illustrates a greater response of job destruction relative to job creation, especially for sectors that are energy intensive in production (e.g., textiles, petroleum and coal, rubber and plastics) or in consumption (e.g., transportation equipment). For

most sectors, the *IRFs* indicate that a considerable increase in job destruction takes place during the first year, while there is a muted response or no change in job creation.¹⁴

To illustrate the magnitude of the effects on job flows, we use the computed *IRFs* for job creation and job destruction plus the job flows definitions in equations (3)-(5) to calculate the cumulative effect on net employment, job reallocation, and excess job reallocation. Table 4 reports the cumulative effect four and eight quarters after the shock. Based on the 1972-2014 sample, our calculations indicate that a 1 s.d. innovation in the real oil price leads to a one-year (two-year) cumulative decline of 0.32 (0.59) percentage points in net employment (*NET*) for total manufacturing. The corresponding one-year (two-year) cumulative increase in job reallocation (*SUM*) equaled 0.37 (0.87) percentage points. These numbers suggest that unexpected oil price increases generate a decline in net job flows and an increase in gross job reallocation. Interestingly, a comparison of the cumulative effects computed using the 1973-1998 and the 1972-2014 samples for total manufacturing, suggest a smaller effect of oil price shocks during the 1999-2014 period.¹⁵ Note that the magnitude of the impact on net employment, job reallocation and excess reallocation (*EXC*) is greater for the shorter sample.

As for the 2-digit SIC industry-level data, the magnitude of the cumulative effect on job flows diverges greatly across sectors. For instance, the two-year cumulative effect on job reallocation ranges between 0.12 percentage points for tobacco/leather and 3.93 percentage points for transportation equipment. Other industries that exhibit two-year cumulative declines in net employment exceeding one percentage point are lumber, furniture and fixtures, rubber and plastics, stone, clay and glass, primary metals, fabricated metals, and electronic and electric equipment. These industries also display substantial job reallocation. Clearly, the fact that transportation equipment

¹⁴The *IRFs* are qualitatively similar across different nonlinear transformations of oil prices (see Figures A.1-A.4 of the on-line appendix).

¹⁵Recall that sectoral level data is only available for the 1973-1998 period.

exhibited the largest increase in excess reallocation one or two years after the shock suggests that the intensity of reallocation was higher in this industry.

Consider now the effect of a 2 s.d. positive innovation in the real price of oil (see Figure A.7a in the on-line appendix). For total manufacturing, the one-year and two-year cumulative change in job reallocation and net employment brought about by a 2 s.d. shock is slightly more than twice of that generated by a 1 s.d. shock (see Table 4). Similarly, the magnitude of the job reallocation generated by a 2 s.d. innovation at the industry level is significantly larger than that caused by a 1 s.d. innovation. For instance, the one-year (two-year) cumulative change in job reallocation after a 2 s.d. innovation is 5.46 (8.24) percentage points for transportation equipment, 3.78 (6.22) for lumber, and 2.77 (4.90) for rubber and plastics. The corresponding change for a 1 s.d. innovation is 2.62 (3.93) percentage points for transportation equipment, 2.05 (3.53) percentage points for lumber, and 1.39 (2.36) for rubber and plastics. Note that both innovations lead to considerable reallocation activity in transportation equipment. This is also the case for the models where we do not include the macro block but consider alternative nonlinear transformations of the oil price (x_t^4 , \tilde{x}_t^{abs}).¹⁶ This result is consistent with Bresnahan and Ramey's (1993) finding that the 1973 oil price shock generated labor and capital mismatch in the automobile industry; as well as with Ramey and Vine's (2010) finding of a disruptive effect of oil price shocks on the motor vehicle industry both before and during the Great Moderation.

Here again, as in section 4, it is interesting to compare our findings with the results obtained using a model à la DH. Our model estimates a smaller effect of oil price shocks on the creation and destruction of manufacturing jobs than DH (see Figure A.8 of the online appendix). For instance, the responses for transportation equipment reported at $h = 4$ by DH are about 50% larger than

¹⁶See Table A.4 of the on-line appendix.

our estimated responses. This smaller impact is consistent with Kilian and Vigfusson's (2011a) conclusion that the inclusion of a censored oil price variable in the VAR will cause the impact of an oil price shock to be overestimated. Yet, as discussed above, both models point towards a considerable reallocation effect at the interior of the transportation equipment sector. Whether this economically significant effect on sectoral reallocation translates in a statistically significant reallocation effect on total manufacturing, or even in transportation equipment, is a question we will address in section 5.3.

5.2 A Closer Look at Motor Vehicles and Trucks

Research into the effects of energy shocks has found ample evidence that oil price innovations have a larger impact on the automobile sector than on any other manufacturing industry (see, for instance, Hamilton 1988; Bresnahan and Ramey 1993; Edelstein and Kilian 2007, 2009; Herrera 2012; Ramey and Vine 2010). In particular, issues of mismatch between the desired and the actual characteristics of the labor force (and the capital stock) in the automobile sector appear to have played an important role in the transmission of oil price shocks to aggregate employment and production. Bolstered by this literature, and in the light of our finding of sizeable job reallocation in transportation equipment, we now estimate our simultaneous equation model and compute the *IRFs* for four 4-digit SIC industries in the automobile sector. These industries are: motor vehicles and passenger car bodies, truck and bus bodies, motor vehicle parts and accessories, and truck trailers.

The four bottom-right panels of Figure 3 depict the *IRFs* to a 1 s.d. shock for these 4-digit SIC industries. As can be seen by comparing these panels with the *IRFs* for total manufacturing and transportation equipment, the magnitude of the job flows in and out of employment tends to be

larger for these 4-digit industries than for the aggregates. For instance, a 1 s.d. oil price innovation leads to a 0.02 percentage points reduction of job creation and a 0.57 percentage points increase in job destruction for transportation equipment at a four quarter horizon, the horizon at which oil price shocks tend to have the largest effect. The corresponding changes in job creation (job destruction) are 0.54 (1.11) for motor vehicles and passenger car bodies, -0.43 (0.69) for truck and bus bodies, 0.04 (0.58) for motor vehicle parts and accessories, and -0.16 (1.90) for truck trailers.

The last four rows of Table 4 suggest that an oil price shock leads to considerable reallocation activity within of the automobile sector. The one-year cumulative change in the job reallocation rate due to a 1 s.d. innovation equals 10.59 percentage points for motor vehicles and passenger car bodies, 0.41 for truck and bus bodies, 2.61 for motor vehicle parts and accessories, and 4.66 for truck trailers. Note that the effect on excess reallocation is larger for motor vehicles and passenger car bodies than it is for any of the other 4-digit industries.

How much larger is the process of job reallocation generated by a 2 s.d. oil price innovation? Comparing the one-year cumulative change for the two 4-digit sectors with the largest job reallocation –motor vehicles and passenger car bodies, and truck trailers– suggests that a doubling in the size of the innovation leads to slightly more than double the amount of job reallocation (see Table 4). For instance, the one-year cumulative change in job reallocation for motor vehicles and passenger car bodies equals 10.59 and 24.32 percentage points for a 1 s.d. and a 2 s.d. shock, respectively. The corresponding changes in net employment are -4.75 percentage points for a 1 s.d. shock and -11.63 percentage points for a 2 s.d. shock, whereas the corresponding impact on excess reallocation equals 5.78 and 12.69 percentage points.

These results suggest that oil price innovations lead to a substantial job reallocation process at the interior of the transportation equipment sector, especially for motor vehicles and passenger car

bodies and truck trailers. Both industries experience a considerable decline in net employment and an increase in job reallocation; yet, the fact that excess reallocation is greater for motor vehicles is indicative of higher reallocation intensity in this industry as it reflects a larger simultaneous increase in job creation and job destruction.

5.3 A Test for Absence of Job Reallocation

Although the *IRF*s described in sections 5.1 and 5.2 are indicative of a substantial effect of oil price shocks on job reallocation, and largely agree with Davis and Haltiwanger's (2001) results for a smaller sample, *IRF* estimates are subject to considerable sampling uncertainty. Thus, to evaluate whether the allocative effect is statistically significant, we construct a formal test for the absence of job reallocation. Before we proceed to describe the statistical test, let us first build up some intuition as to why implementing such test is useful in evaluating the importance of the allocative channel vis a vis the aggregate channel of oil price transmission.

Consider the effect of an unexpected increase in oil prices on job reallocation, which as equation (3) states equals the sum of job creation and job destruction. If oil price shocks are transmitted to U.S. job flows mainly through aggregate channels (e.g., income transfer from oil importing to oil producing economies or a decline in potential output), then fewer jobs will be created and more jobs will be destroyed in response to a positive innovation in oil prices. Consequently, unless the increase in job destruction exceeds the decline in job creation, job reallocation will contract. On the contrary, if oil price shocks are transmitted mainly through the allocative channel (i.e., via the effect on the closeness of the match between jobs and workers' characteristics), then more jobs will be created and destroyed. Consequently, job reallocation will increase. Hence, testing the null of absence of job reallocation is equivalent to evaluating whether the allocative channel plays a

statistically significant role in transmitting oil price shocks.

Now, because job reallocation is defined as the sum of job creation and job destruction, we can implement a test for the absence of job reallocation by directly testing the null hypothesis:

$$H_o : I_{POS}(h, \delta) + I_{NEG}(h, \delta) = 0 \text{ for } h = 0, 1, 2, \dots, H,$$

where we consider the effect of a positive oil price innovation of size δ on the response of job reallocation up to horizon $H = 4$. That is, after computing the unconditional *IRF*s for job creation, $I_{POS}(h, \delta)$, and job destruction, $I_{NEG}(h, \delta)$, we construct the Wald test:

$$W = \left(R\hat{\beta} \right)' \left(R\hat{\Xi}R' \right)^{-1} \left(R\hat{\beta} \right) \sim \chi_{H+1}^2$$

where

$$\begin{aligned} \hat{\beta}_{2(H+1) \times 1} &= \begin{bmatrix} I_{NEG}(0, \delta) \\ \vdots \\ I_{NEG}(H, \delta) \\ I_{POS}(0, \delta) \\ \vdots \\ I_{POS}(H, \delta) \end{bmatrix}; \quad R_{(H+1) \times 2(H+1)} = \begin{bmatrix} 1 & \dots & 0 & 1 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 1 & 0 & \dots & 1 \end{bmatrix}; \\ \hat{\Xi}_{2(H+1) \times 2(H+1)} &= E \left[\left(\hat{\beta} - \beta \right) \left(\hat{\beta} - \beta \right)' \right]. \end{aligned}$$

Note that the null hypothesis evaluated in this section differs from that in Kilian and Vigfusson (2011a) –which we explored in section 4– where the null is that the response of a variable $y = POS$, *NEG* (i.e., job creation or job destruction) to a positive oil price shock of size δ and the negative

of the response of the same variable y to a negative oil price shock of size $-\delta$, up to horizon H , is symmetric (i.e., $H_o : I_y(h, \delta) + I_y(h, -\delta) = 0$ for $h = 0, 1, 2, \dots, H$.) As in the previous section, we compute the test for the absence of job reallocation for a one-year horizon ($H = 4$) in order to avoid data mining issues related to repetitions of the same test over different horizons, and simulate the null distribution of the supremum of the bootstrap test statistic across all sectors.¹⁷

To underscore the importance of robust inference, let us first evaluate the test results using the conventional critical values and then analyze how our conclusions change when we control for data mining. Results regarding the test for the absence of job reallocation for a 1 s.d. and a 2 s.d. shock are reported in Table 5. Statistical significance at the 5% level using the conventional and the data-mining robust critical values is denoted by bold and **, respectively. Regardless of the size of the shock, we fail to reject the null of no job reallocation for total manufacturing. In contrast, using the conventional critical values, we reject the null for furniture and fixtures, rubber and plastics, and truck trailers for 1 s.d. shock and for furniture and fixtures when we consider a 2 s.d. shock.

Although some statistical evidence of job reallocation is found when we use the conventional critical values, our results change dramatically when we use robust inference. The reader will note that no asterisks appear in Table 5, which indicates that none of the results are statistically significant at the conventional levels once we account for data mining.

It is worth comparing the results reported here with results obtained using alternative model specifications. First, when we use the net oil price increase or DH's oil price index, we reject the null of absence of job reallocation at the conventional critical values for a few sectors. Nevertheless, we are unable to reject the null using data-mining robust critical values.¹⁸ Second, when we use a

¹⁷The data mining robust critical values are computed using 1000 pseudo series.

¹⁸See Table A.5 of the on-line the appendix

model à la DH estimated on their sample, we are unable to reject the null hypothesis for all sectors, even without controlling for data mining. This is consistent with the argument that adding these variables undermines the power of the test.¹⁹

In brief, the *IRF*s plotted in Figure 3 suggest that, in the face of an unexpected oil price increase, the rate at which exiting and contracting establishments shed jobs increases more than the rate at which entering and expanding establishments create jobs. As a result a process of job reallocation appears to take place as net employment drops, especially for a 2 s.d. innovation. Yet, once we control for data mining, we fail to find statistical evidence in support of the hypothesis that oil price shocks generated gross job reallocation. Contrary to Davis and Haltiwanger (2001), our test results indicate that oil price shocks affected employment mainly through aggregate, and not allocative, channels.

6 Did the Responses of Job Flows Change During the Great Moderation?

Work by Edelstein and Kilian (2009), Herrera and Pesavento (2009) and Blanchard and Galí (2010) has found a muted effect of oil price shocks on real GDP growth. In contrast, Ramey and Vine (2012) find that U.S. motor vehicle production has been as sensitive to oil price shocks since the Great Moderation as before the onset of the decline in output volatility. One might thus wonder whether the response of job flows to positive oil price innovations has changed since the Great Moderation and, therefore, whether our finding of a statistically insignificant effect on gross reallocation is driven by a smaller response of job flows during the Great Moderation. In order to answer these questions, we re-estimate our model and compute the *IRF*s based test for two subsamples: 1972:Q2-1984:Q4

¹⁹See Table A.6 of the on-line the appendix

and 1985:Q1-2014:Q2 for total manufacturing, and 1972:Q2-1984:Q4 and 1985:Q1-1998:Q4 for the sectoral data.

6.1 The Response of Sectoral Job Flows to Oil Price Shocks Before and During the Great Moderation

Before we proceed to discuss our results it is important to note that the volatility of the oil price innovations increased during the Great Moderation. The estimated standard deviation of $\varepsilon_{1,t}$ in (8a) equaled 8% before the Great Moderation and 16% during the Great Moderation. To inquire into the changes in the response of sectoral job flows we estimate the response to a 16% innovation in real oil prices. Note that, even though this shock is equivalent to a 1 s.d. shock during the Great Moderation and a 2 s.d. shock before the Great Moderation, using a shock of the same magnitude allows us to disentangle shifts in the response due to changes in the transmission channel versus shifts due to changes in the volatility of the shock.

Figures 4a and 4b plot the responses of job creation and job destruction to a 16% positive oil price innovation, as well as the responses for job reallocation (*SUM*) and excess job reallocation (*EXC*). To conserve space we depict the *IRF*s only for eleven of the twenty 2-digit SIC industries and four 4-digit SIC industries in the automobile sector. A quick glance at the figures suggests that the responses of sectoral job creation and job destruction to oil price shocks have been milder since the onset of the Great Moderation. This appears to be the case for total manufacturing, as well as for the sectoral job creation and job destruction rates.

This muted response of job creation and job destruction resulted in a smaller effect on net employment for approximately 75% of the 2-digit SIC industries (see Table 6). For instance, for transportation equipment –an industry that accounts for 10% of employment in manufacturing–

the one-year cumulative effect on net employment went from -3.47 percentage points before the Great Moderation to -1.63 in the subsequent period. As a result, the impact of a positive oil price innovation was less detrimental for net employment in total manufacturing. In particular, the one-year cumulative effect went from -0.94 percentage points in 1972-1984 to -0.64 (-0.25) in 1985-1998 (1985-2014). These results reflect an even smaller response of net manufacturing employment in the 2000s than in the late 1980s and 1990s.

Even though oil price innovations resulted in smaller net employment responses during the Great Moderation, they appear to have led to a slight increase in job turnover for total manufacturing. Note that the one-year (two-year) cumulative effect on job reallocation increased from 0.22 (0.79) in 1972-1984 to 0.92 (1.24) in 1985-1998. Yet, once we extend the total manufacturing data up to 2014:Q2, the raise in the one-year (two-year) cumulative response of job reallocation is not as striking. This result is consistent with the decline in job flows that has been observed since the 2000s (Davis and Haltiwanger, 2014).

In addition, a change in the intensity of reallocation –measured by excess reallocation– brought about by an oil price shock is evident in Table 6. During the 1972-1984 period an unexpected increase in oil prices resulted in a reduction of *EXC* for total manufacturing, and all the 2-digit industries but transportation equipment. The slight increase in *EXC* for transportation equipment (0.07 percentage points a year after the shock) hides a more intensive process of reallocation at the interior of the motor vehicles industry. In fact, *EXC* increased for motor vehicles and passenger car bodies (13.66), but decreased for the other 4-digit sectors (-11.83 for truck and bus bodies, -3.63 for motor vehicle parts and accessories, and -13.70 for truck trailers). In contrast, during the Great Moderation oil price innovations generated considerably smaller reductions in *EXC* for most 2-digit sectors, suggesting that the intensity of job reallocation in U.S. manufacturing suffered

considerably less in this period. In fact, this pattern was also observed for the 4-digit industries in transportation equipment.

This change in the effect on excess reallocation could reflect changes in the nature of the oil price shock (Kilian, 2009; Kilian and Murphy, 2013), increased flexibility in the labor market, for instance via more flexible wages (Blanchard and Galí 2010), or any other changes in the adjustments needed –at the firm-level– to eliminate mismatches between the desired and actual characteristics of the labor force created by the oil price shocks. A careful answer to this question would require a more in-depth look into the firm-level responses. Pinning down the source of this change is a question that we leave for future research as it would require access to the establishment level data on job flows.

To evaluate the robustness of our results, we estimated the *IRF*s using two alternative model specifications: (a) a model with the percentage change in oil prices and the net oil price increase, and (b) a model with DH’s oil index and the absolute change in the index (see Figures A.9a-A.10b, and Tables A.7 and A.8 of the online appendix). Regardless of the specification, we uncover a decline in the responsiveness of job creation/destruction and excess job reallocation to oil price shocks during the Great Moderation.

6.2 Oil Prices, Job Reallocation, and the Importance of the Allocative Channel During the Great Moderation

Our estimation results suggest that the decline in the response of job creation and job destruction to oil price shocks stemmed from a change in the transmission channel and not from a decline in the volatility of oil price shocks. Recall that the standard deviation of the oil price innovations considered in this paper went from approximately $\delta_{1973-1984} = 8\%$ to $\delta_{1985-1998} = 2 * \delta_{1973-1984} =$

16%. That is, the variance of the structural shock of interest increased.

Can this smaller response of job creation and job destruction account for our finding of a statistically insignificant reallocation effect? To answer this question we implement our test for the absence of job reallocation on both sub-samples. Table 7 reports p -values computed using the conventional critical values for the test of absence of job reallocation in response to a 16% shock before (1972-1984) and during the Great Moderation (1985-1998). Significance at the 5% and 10% level using data-mining robust inference is denoted by ** and *, respectively. When we use the conventional critical values we find no significant evidence of job reallocation before the Great Moderation; yet, we reject the null for total manufacturing, rubber and plastics, transportation equipment and truck trailers during the Great Moderation. However, once we use data-mining robust inference, we are unable to reject the null for any of the industries or the aggregate.

These results are robust to using the net oil price increase, x_t^4 , and the absolute change in DH's oil price index, \tilde{x}_t^{abs} , instead of the oil price increase (see Table A.9 in the appendix). Specifically, using the conventional critical values we are unable to reject the null in the 1972-1984 period but obtain some rejections during the Great Moderation (total manufacturing, transportation equipment and truck trailers for both x_t^4 and \tilde{x}_t^{abs} , rubber and plastics for x_t^4 , and petroleum and coal products for \tilde{x}_t^{abs}). One may conjecture that the inability to reject the null could be due to the low power of the test when applied to the smaller 1972-1984 sub-sample. Nevertheless, the fact that we were also unable to reject the null in the full sample suggests that the reallocation effect was statistically insignificant both before and during the Great Moderation.

We close this section by noting that ours is not the first study to uncover important changes in the response of job flows to aggregate shocks. Faberman (2008) finds that changes in job flows were attributable to a decline in the volatility of aggregate and allocative shocks, as well as to

a shift in the response of job flows to aggregate disturbances during the Great Moderation. Our findings are consistent with a shift in the response of job flows to oil price shocks. However, since oil price shocks were about twice as volatile during the Great Moderation, we conclude that the change in the response of job flows to oil price shocks were due to a shift in the transmission mechanism.

7 Conclusions

We built on the work by Davis and Haltiwanger (2001) and Kilian and Vigfusson (2011a) to explore the nature of the response of job flows to oil price innovations. Using a simultaneous equation model that nests symmetric and asymmetric transmission channels of oil price shocks to job creation and job destruction, we found no evidence of asymmetry in the response of the latter to positive and negative oil price innovations of 1 s.d. Some evidence of asymmetry was found in the responses to a 2 s.d. shock for total manufacturing, as well as for sectors that are intensive in the use of energy. Nevertheless, evidence of asymmetry vanished when we controlled for data mining.

Then, we investigated whether oil price shocks lead to job reallocation in U.S. manufacturing. The estimated *IRFs* for sectoral job creation and job destruction, as well as the implied cumulative changes on net employment, job reallocation and excess reallocation, suggested that oil price innovations lead to a process of job reallocation. This pattern was more evident for sectors that use energy intensively in production or consumption. Nevertheless, the effect of oil price shocks on job reallocation was found to be statistically insignificant both at the aggregate and the sectoral level. Thus we concluded that oil price shocks acted **mainly** through aggregate channels (e.g., income transfers from oil importing to oil producing economies, declines in potential output).

Finally, we inquired whether the effect of oil price shocks on job flows changed during the Great Moderation. Splitting the sample in two subperiods (1972-1984 and 1985-1998) pointed to a

smaller response of job creation, destruction, net job changes and excess job reallocation but a slight increase in job reallocation. Our results thus implied that a change in the oil price transmission mechanism occurred during the Great Moderation. Whether this change stemmed from a different composition of oil price shocks (Kilian 2009), an increase in labor market flexibility (Blanchard and Galí 2010), or a modification in the adjustment needed to close the wedge between the desired and actual characteristics of the labor input, is a question that we leave for future research.

To conclude, it is useful to put our results in perspective relative to earlier studies on the effect of oil price shocks on job flows. Using data for the 1972:Q2–1988:Q4 period, Davis and Haltiwanger (2001) found that the allocative channel played an important role in the transmission of oil price shocks. Based on a longer sample period and a more parsimonious model –that is more likely to reject the null– we found the reallocation effect to be statistically insignificant. Contrary to Davis and Haltiwanger (2001), our test results suggested that oil price shocks affected employment mainly through aggregate, and not allocative, channels.

References

- [1] Bauer, P.W., Lee, Y. (2007). "Regional Variation in Job Creation and Destruction," *Economic Commentary*, Federal Reserve Bank of Cleveland. <http://www.clevelandfed.org/research/Commentary/2007/0915.pdf>
- [2] Blanchard, O. J. and J. Galí (2010). The Macroeconomic Effects of Oil Price Shocks: Why are the 2000s so Different from the 1970s?" in J. Galí and M. Gertler (eds). *International Dimensions of Monetary Policy*, University of Chicago Press (Chicago, IL), 373-428.
- [3] Bresnahan, Timothy F., and Valerie A. Ramey (1993), "Segment Shifts and Capacity Utilization in the U.S. Automobile Industry," *American Economic Review Papers and Proceedings*, 83(2), 213-218.
- [4] Cuñat, Alejandro and Marc Melitz (2012), "Volatility, Labor Market Flexibility, and the Pattern of Comparative Advantage", *Journal of the European Economic Association*, 10(2), 225-254.
- [5] Davis, Steven J. (1987a), "Fluctuations in the pace of labor reallocation," *Carnegie-Rochester Conference Series on Public Policy*, 27(1), 335-402.
- [6] Davis, Steven J. (1987b), "Allocative Disturbances and Specific Capital in Real Business Cycle Theories," *The American Economic Review*, 77(2), 326-332.
- [7] Davis, Steven J., J. Faberman, and J. Haltiwanger (2012). "Labor Market Flows in the Cross Section and Over Time," *Journal of Monetary Economics* 59(1), 1-18
- [8] Davis, Steven S. J. and J. Haltiwanger (1996). "Driving forces and employment fluctuations," *NBER Working Paper* No. 5775, National Bureau of Economic Research.

- [9] Davis, S. J. and J. Haltiwanger (2001). "Sectoral job creation and destruction responses to oil price changes," *Journal of Monetary Economics* 48(3), 465-512.
- [10] Davis, S. J. and J. Haltiwanger (2014). "Labor Market Fluidity and Economic Performance," NBER Working Paper No. 20479, National Bureau of Economic Research.
- [11] Davis, S. J., Haltiwanger, J., Schuh, S. (1996). *Job Creation and Destruction*. MIT Press, Cambridge, MA.
- [12] Edelstein, P. and L. Kilian (2007). "The Response of Business Fixed Investment to Changes in Energy Prices: A Test of Some Hypotheses About the Transmission of Energy Price Shocks," *The B.E. Journal of Macroeconomics* 7(1).
- [13] Edelstein, P. and L. Kilian (2009). "How Sensitive are Consumer Expenditures to Retail Energy Prices?," *Journal of Monetary Economics* 56(6), 766-779.
- [14] Faberman, R. J. (2008), "Job Flows, Jobless Recoveries, and the Great Moderation." Federal Reserve Bank of Philadelphia Working Paper 08-11.
- [15] Gallant, A. Ronald, Peter E. Rossi, and George Tauchen (1993). "Nonlinear dynamic structures," *Econometrica*, 61, 871-907.
- [16] Hamilton, J.D. (1988), "A Neoclassical Model of Unemployment and the Business Cycle", *Journal of Political Economy*, 96, 593-617.
- [17] Hamilton, J. D. (1996). "This is What Happened to the Oil Price-Macroeconomy Relationship," *Journal of Monetary Economics* 38(2), 215-220.
- [18] Hamilton, J. D. (2003). "What Is an Oil Shock?," *Journal of Econometrics*, 113(2), 363-398.

- [19] Hamilton, J. D. (2011). "Nonlinearities and the Macroeconomic Effects of Oil Prices," *Macroeconomics Dynamics*, 15(S3), 364-378.
- [20] Herrera, A. M. (2012), 'Oil Price Shocks, Inventories and Macroeconomic Dynamics,' working paper, University of Kentucky.
- [21] Herrera, A. M., L. G. Lagalo, and T. Wada (2011). "Oil Price Shocks and Industrial Production: Is the Relationship Linear?," *Macroeconomic Dynamics*, 15(S3), 472-497.
- [22] Herrera, A. M., L. G. Lagalo, and T. Wada (2015). "Asymmetries in the response of economic activity to oil price increases and decreases?," *Journal of International Money and Finance*, 50, 108-133.
- [23] Herrera, A. M. and E. Pesavento (2009). "Oil Price Shocks, Systematic Monetary Policy and the 'Great Moderation'," *Macroeconomic Dynamics* 13(1), 107-137.
- [24] Inoue, A. and L. Kilian (2004) "In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?," *Econometric Reviews*, 23(4), 371-402.
- [25] Kilian, L. (2009), "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market", *American Economic Review*, 99(3), 1053-1069.
- [26] Kilian, L. and C. Vega (2011), "Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices," *The Review of Economics and Statistics*, MIT Press, 93(2), 660-671.
- [27] Kilian, L. and D. P. Murphy (2013), "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil," *Journal of Applied Econometrics*, 29(3), 454-478.

- [28] Kilian, L. and R. J. Vigfusson (2011a). "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?" *Quantitative Economics*, 2(3), 419-453.
- [29] Kilian, L. and R. J. Vigfusson (2011b). "Nonlinearities in the Oil Price-Output Relationship," *Macroeconomics Dynamics*, 15(S3), 337-363.
- [30] Koop, G., M. H. Pesaran and S. Potter (1996), "Impulse Response Analysis in Nonlinear Multivariate Models", *Journal of Econometrics*, 74(1), 119-147.
- [31] Lee, K. and S. Ni (2002), "On the dynamic effects of oil price shocks: a study using industry level data," *Journal of Monetary Economics*, 49(4), 823-852.
- [32] Lee, K., S. Ni, and R. Ratti (1995). "Oil Shocks and the Macroeconomy: The Role of Price Variability," *The Energy Journal*, 16(4), 39-56.
- [33] Micco, A., Pagés, C. (2004). "Employment Protection and Gross Job Flows: A Differences-in-Differences Approach," *RES Working papers 4365*, Inter-American Development Bank, Research Department.
- [34] Mork, K. A. (1989). "Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results." *Journal of Political Economy* 97(3), 740-744.
- [35] Ramey, V. A. and Vine, D.J. (2010). "Oil, Automobiles, and the U.S. Economy: How much things have really changed?" *NBER Macroeconomics Annual 2011*.

Table 1. Magnitude of gross job flows by sector

Sector	<i>POS</i>	<i>NEG</i>	<i>SUM</i>	<i>NET</i>	<i>EXC</i>
Total manufacturing (1972:Q2-2014:Q2)	4.80	5.16	9.96	-0.37	9.15
Total manufacturing (1972:Q2-1998:Q4)	5.33	5.55	10.88	-0.22	10.08
Food	8.27	8.20	16.47	0.07	15.64
Tobacco	6.04	6.58	12.63	-0.54	9.58
Textiles	3.37	4.01	7.38	-0.65	6.29
Apparel	5.53	6.41	11.95	-0.88	10.44
Lumber	6.22	6.31	12.53	-0.08	10.66
Furniture and fixtures	5.09	5.13	10.22	-0.03	8.70
Paper	3.48	3.57	7.05	-0.09	6.20
Printing	4.63	4.52	9.15	0.11	8.17
Chemicals	3.54	3.78	7.31	-0.24	6.43
Petroleum and coal	3.82	4.24	8.05	-0.42	6.80
Rubber and plastics	5.22	4.99	10.21	0.22	8.72
Leather	4.78	5.93	10.71	-1.15	8.88
Stone, clay and glass	5.18	5.38	10.56	-0.20	9.16
Primary metals	3.47	4.08	7.56	-0.61	5.70
Fabricated metals	5.12	5.31	10.44	-0.19	8.92
Industrial machinery	4.85	5.02	9.87	-0.16	8.15
Electronic and electric equipment	4.66	4.81	9.47	-0.15	7.92
Transportation equipment	5.13	5.37	10.50	-0.24	8.46
Instruments and related products	4.05	4.23	8.28	-0.19	7.02
Miscellaneous manufacturing	6.65	6.85	13.50	-0.19	11.82
Motor vehicles and passenger car bodies	7.45	7.89	15.34	-0.44	9.69
Truck and bus bodies	7.11	6.97	14.08	0.14	10.61
Motor vehicle parts and accessories	4.58	4.75	9.33	-0.17	6.57
Truck trailers	7.47	7.22	14.63	0.19	9.58

Notes: This table reports the average job creation (*POS*), job destruction (*NEG*), net employment change (*NET*), job reallocation (*SUM*), and excess job reallocation (*EXC*). Values in the table are in percent.

Table 2. Magnitude of gross job flows before and during the Great Moderation

Sector	1972:Q2-1984:Q4				1985:Q1-1998:Q4				
	POS	NEG	SUM	NET	POS	NEG	SUM	NET	EXC
Total manufacturing (1972-2014)	5.60	5.80	11.41	-0.20	4.45	4.89	9.34	-0.44	8.67
Total manufacturing (1972-1998)	5.60	5.80	11.41	-0.20	5.09	5.32	10.41	-0.24	9.91
Food	9.36	9.35	18.72	0.01	7.28	7.14	14.42	0.13	13.71
Tobacco	6.19	6.76	12.95	-0.57	5.91	6.42	12.33	-0.51	8.69
Textiles	3.58	4.22	7.80	-0.63	3.17	3.83	7.00	-0.66	6.16
Apparel	5.63	6.32	11.94	-0.69	5.44	6.50	11.95	-1.06	10.61
Lumber	6.96	7.31	14.27	-0.35	5.56	5.39	10.94	0.17	9.66
Furniture and fixtures	5.31	5.41	10.72	-0.10	4.90	4.88	9.78	0.02	8.69
Paper	3.71	3.89	7.60	-0.18	3.27	3.27	6.54	-0.01	5.97
Printing	4.61	4.46	9.07	0.14	4.66	4.57	9.23	0.08	8.29
Chemicals	3.74	4.08	7.82	-0.33	3.35	3.51	6.85	-0.16	6.04
Petroleum and coal	3.93	4.42	8.35	-0.49	3.72	4.07	7.79	-0.35	6.72
Rubber and plastics	5.58	5.47	11.05	0.11	4.88	4.56	9.45	0.32	8.65
Leather	4.88	6.03	10.91	-1.15	4.69	5.85	10.54	-1.16	8.60
Stone, clay, and glass	5.47	5.79	11.27	-0.32	4.91	5.00	9.91	-0.09	8.88
Primary metals	3.81	4.66	8.47	-0.86	3.17	3.56	6.73	-0.39	5.65
Fabricated metals	5.53	5.82	11.35	-0.28	4.75	4.85	9.61	-0.10	8.56
Industrial machinery	5.08	5.25	10.33	-0.18	4.65	4.80	9.45	-0.15	8.11
Electronic and electric equipment	4.97	4.90	9.87	0.08	4.37	4.72	9.10	-0.35	8.06
Transportation equipment	5.88	6.11	11.99	-0.23	4.44	4.70	9.14	-0.26	7.84
Instruments and related products	4.45	4.18	8.63	0.27	3.67	4.28	7.96	-0.61	6.93
Miscellaneous manufacturing	6.85	7.29	14.14	-0.45	6.47	6.44	12.91	0.04	11.55
Motor vehicles and passenger car bodies	9.33	9.90	19.23	-0.57	5.74	6.06	11.79	-0.32	8.11
Truck and bus bodies	8.43	8.23	16.66	0.21	5.91	5.83	11.74	0.08	9.05
Motor vehicle parts and accessories	5.22	5.48	10.70	-0.26	3.99	4.09	8.08	-0.09	6.61
Truck trailers	8.21	8.01	16.22	0.20	6.68	6.51	13.19	0.17	9.30

Notes: This table reports the average job creation (POS), job destruction (NEG), net employment change (NET), job reallocation (SUM), and excess job reallocation (EXC). Values in the table are in percent.

Table 3. IRF based test of symmetry in the response to a real oil price ($x_t^\# = x_t^1$)

Sector / Job flow	1 s.d. oil price shock		2 s.d. oil price shock	
	Job creation	Job destruction.	Job creation	Job destruction
Total manufacturing (1972:Q2-2014:Q2)	0.69	0.13	0.65	0.04
Total manufacturing (1972:Q2-1998:Q4)	0.67	0.73	0.42	0.55
Food	1.00	0.27	1.00	0.04
Tobacco	0.27	0.77	0.04	0.63
Textiles	0.96	0.77	0.93	0.61
Apparel	0.95	0.81	0.92	0.69
Lumber	0.35	0.40	0.14	0.17
Furniture and fixtures	0.83	0.30	0.68	<i>0.07</i>
Paper	0.78	0.78	0.54	0.56
Printing	0.68	0.84	0.53	0.80
Chemicals	0.64	0.70	0.45	0.57
Petroleum and coal	0.31	<i>0.10</i>	<i>0.07</i>	0.00
Rubber and plastics	0.54	0.69	0.23	0.57
Leather	0.44	0.64	0.25	0.40
Stone, clay and glass	0.60	0.76	0.34	0.65
Primary metals	0.77	0.73	0.62	0.60
Fabricated metals	0.75	0.87	0.44	0.79
Industrial machinery	0.94	0.93	0.90	0.89
Electronic and electric equipment	0.81	0.81	0.72	0.75
Transportation equipment	0.36	0.91	<i>0.10</i>	0.88
Instruments and related products	0.53	0.74	0.38	0.64
Miscellaneous manufacturing	0.67	0.99	0.54	0.98
Motor vehicles and passenger car bodies	0.28	0.66	<i>0.07</i>	0.47
Truck and bus bodies	0.89	0.95	0.78	0.92
Motor vehicle parts and accessories	0.43	0.93	0.23	0.88
Truck trailers	0.49	0.34	0.41	0.20

Notes: Computations are based on 10,000 simulations of model (8). p-values are based on the χ^2_{H+1} . Bold and italics refer to significance at the 5% and 10% level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 4. Cumulative change in job flows due to a real oil price shock ($x_t^\# = x_t^1$)

Sector / Quarters since the shock	1 s.d. oil price shock						2 s.d. oil price shock					
	NET		SUM		EXC		NET		SUM		EXC	
	4	8	4	8	4	8	4	8	4	8	4	8
Total manufacturing (1972:Q2-2014:Q2)	-0.32	-0.59	0.37	0.87	-0.15	0.05	-1.23	-1.85	1.20	2.42	-0.06	0.46
Total manufacturing (1972:Q2-1998:Q4)	-0.71	-0.83	0.85	1.44	0.13	0.49	-1.81	-2.14	1.94	3.28	0.14	0.91
Food	-0.25	-0.38	0.83	1.61	0.12	0.73	-0.67	-0.99	1.47	3.21	-0.37	0.99
Tobacco	0.73	0.69	0.14	0.12	-2.01	-2.34	1.18	1.26	0.48	0.52	-4.07	-4.71
Textiles	-1.08	-0.81	0.73	1.20	-0.35	-0.41	-2.33	-1.76	1.30	2.24	-1.03	-1.18
Apparel	0.06	-0.01	0.47	0.75	-0.26	-0.38	-0.09	-0.47	0.55	1.26	-1.11	-1.41
Lumber	-3.28	-3.05	2.05	3.53	-1.24	-0.24	-7.57	-6.49	3.78	6.22	-3.79	-2.53
Furniture and fixtures	-1.67	-1.66	1.08	2.01	-0.65	-0.39	-4.05	-4.12	2.21	4.38	-1.84	-1.20
Paper	-0.79	-0.77	0.35	0.74	-0.46	-0.42	-1.87	-1.93	0.49	1.32	-1.38	-1.42
Printing	-0.46	-0.47	0.63	0.75	0.04	0.07	-1.42	-1.62	1.44	1.80	-0.05	0.05
Chemicals	-0.04	-0.05	0.40	0.68	-0.11	0.03	0.00	-0.03	0.79	1.56	-0.47	-0.06
Petroleum and coal	-0.32	-0.44	1.02	1.15	-0.87	-0.91	-0.70	-0.87	1.90	2.12	-3.59	-3.73
Rubber and plastics	-1.75	-1.54	1.39	2.36	-0.36	0.03	-4.12	-3.63	2.77	4.90	-1.35	-0.54
Leather	-0.12	-0.42	-0.23	0.12	-1.39	-1.42	0.04	-0.47	-1.02	-0.52	-2.96	-3.08
Stone, clay, and glass	-1.85	-2.32	1.15	2.00	-0.76	-0.44	-4.95	-5.84	2.42	4.07	-2.54	-1.97
Primary metals	-0.72	-1.40	0.27	1.17	-0.79	-0.66	-2.32	-3.71	0.74	3.01	-1.74	-1.00
Fabricated metals	-1.38	-1.50	1.17	1.85	-0.23	0.22	-3.39	-3.61	2.22	3.60	-1.17	-0.31
Industrial machinery	0.02	-0.48	-0.04	0.10	-0.52	-0.89	0.09	-1.31	-0.78	-0.48	-1.97	-3.05
Electronic and electric equipment	-0.92	-1.02	0.65	1.07	-0.29	-0.27	-2.51	-2.89	1.35	2.47	-1.16	-1.13
Transportation equipment	-2.15	-2.37	2.62	3.93	0.45	1.40	-5.43	-6.06	5.46	8.24	0.04	1.81
Instruments and related products	0.19	-0.02	0.17	0.32	-0.54	-0.67	-0.21	-1.14	-0.05	0.29	-1.64	-2.26
Miscellaneous manufacturing	-0.93	-0.78	1.07	1.34	0.01	0.00	-2.13	-1.92	1.62	2.01	-0.57	-0.70
Motor vehicles and passenger car bodies	-4.75	-4.67	10.59	13.81	5.78	8.54	-11.63	-11.92	24.32	30.79	12.69	17.93
Truck and bus bodies	-2.43	-2.92	0.41	1.28	-2.04	-1.85	-5.75	-6.45	-1.50	-0.33	-7.25	-7.38
Motor vehicle parts and accessories	-3.18	-2.41	2.61	3.65	-0.56	-0.33	-7.13	-5.63	5.28	7.52	-1.84	-1.36
Truck trailers	-5.22	-4.42	4.66	8.85	-0.56	1.38	-12.60	-11.04	10.55	20.86	-2.05	3.55

Notes: This table reports the cumulative change (measured in percentage points) in net employment (NET), job reallocation (SUM), and excess reallocation (EXC) due to a positive one standard deviation innovation in the real oil price. Computations are based on 10,000 simulations of model (8).

Table 5. Test for the absence of job reallocation ($x_t^\# = x_t^1$)

Sector / Innovation	1 s.d. oil price shock	2 s.d. oil price shock
Total Manufacturing (1972:Q2-2014:Q2)	0.30	0.27
Total Manufacturing (1972:Q2-1998:Q4)	0.34	0.42
Food	0.81	0.87
Tobacco	0.84	0.71
Textiles	<i>0.08</i>	0.14
Apparel	0.71	0.83
Lumber	<i>0.08</i>	0.13
Furniture and fixtures	0.05	0.04
Paper	0.42	0.36
Printing	0.72	0.65
Chemicals	0.55	0.50
Petroleum and coal	0.40	<i>0.09</i>
Rubber and plastics	0.04	<i>0.07</i>
Leather	0.49	0.26
Stone, clay, and glass	<i>0.10</i>	0.17
Primary metals	0.61	0.53
Fabricated metals	0.41	0.60
Industrial machinery	0.80	0.76
Electronic and electric equipment	0.53	0.57
Transportation equipment	0.22	0.47
Instruments and related products	0.62	0.68
Miscellaneous manufacturing	0.32	0.55
Motor vehicles and passenger car bodies	0.18	0.17
Truck and bus bodies	0.66	0.79
Motor vehicle parts and accessories	0.11	<i>0.07</i>
Truck trailers	0.05	<i>0.06</i>

Notes: Computations are based on 10,000 simulations of model (8). p - values are based on the χ_{H+1}^2 . Bold and italics refer to significance at the 5% and 10% level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 6. Cumulative change in job flows after a 16% positive oil price shock ($x_t^\# = x_t^+$)

Sector / Quarters since the shock	1972-1984						1985-1998					
	NET		SUM		EXC		NET		SUM		EXC	
	4	8	4	8	4	8	4	8	4	8	4	8
Total manufacturing (1972:Q2-2014:Q2)	-0.94	-1.32	0.22	0.79	-1.49	-1.75	-0.25	-0.47	0.33	0.66	-0.17	-0.07
Total manufacturing (1972:Q2-1998:Q4)	-0.94	-1.32	0.22	0.79	-1.49	-1.75	-0.64	-0.89	0.92	1.24	0.21	0.27
Food	-0.54	-1.00	0.07	1.94	-2.23	-0.90	-0.05	-0.14	0.97	1.42	-0.17	0.13
Tobacco	0.84	0.42	1.53	2.37	-0.74	-0.99	1.26	1.03	0.08	0.23	-4.41	-5.26
Textiles	-1.07	-0.71	0.51	1.53	-2.63	-3.19	-0.98	-0.94	0.91	1.05	-0.08	-0.03
Apparel	-1.04	-1.88	0.26	1.60	-2.96	-4.28	0.47	0.74	1.05	1.01	0.40	0.08
Lumber	-6.62	-6.37	0.01	1.48	-6.89	-7.07	-1.66	-1.71	1.37	1.39	-0.58	-0.84
Furniture and fixtures	-4.18	-4.26	1.42	3.23	-3.29	-3.80	-1.23	-1.49	1.63	1.98	0.21	0.23
Paper	-2.83	-3.48	0.02	1.95	-2.88	-3.25	-0.12	-0.08	0.01	0.02	-0.47	-0.55
Printing	-1.13	-1.59	0.55	1.48	-0.94	-0.74	-0.52	-0.57	1.14	0.99	0.24	-0.13
Chemicals	0.38	-0.15	0.32	2.02	-2.50	-2.72	-0.20	-0.22	0.28	0.28	-0.64	-0.84
Petroleum and coal	-1.21	-0.50	2.83	3.76	-2.97	-3.42	-0.04	0.01	0.40	0.34	-1.40	-1.73
Rubber and plastics	-3.24	-1.90	1.67	3.90	-2.14	-2.30	-1.50	-1.74	1.31	1.41	-0.30	-0.46
Leather	1.45	-0.55	-1.63	-0.71	-4.97	-6.16	-0.86	-0.80	0.48	0.96	-1.29	-1.19
Stone, clay and glass	-3.73	-4.91	0.41	2.18	-3.53	-3.66	-1.24	-1.72	0.96	0.96	-0.60	-1.21
Primary metals	1.07	-3.74	-0.70	2.06	-5.45	-7.71	-0.32	-0.60	-0.17	-0.01	-1.39	-1.61
Fabricated metals	-3.91	-4.42	-0.03	1.84	-4.45	-4.71	-0.29	-0.08	0.70	0.62	-0.29	-0.60
Industrial machinery	4.43	1.62	-4.50	-5.34	-9.68	-14.85	-0.13	-0.11	0.38	0.36	-0.36	-0.57
Electronic and electric equipment	-2.55	-3.20	0.92	1.93	-2.79	-3.42	-0.75	-0.99	0.71	0.91	-0.12	-0.25
Transportation equipment	-3.47	-5.37	4.80	5.63	0.07	-1.08	-1.63	-2.22	1.97	3.14	-0.15	0.29
Instruments and related products	2.12	1.10	0.19	0.77	-2.98	-3.93	0.10	0.11	0.37	0.43	-0.36	-0.59
Miscellaneous manufacturing	-1.80	-1.82	0.94	2.08	-1.64	-1.63	-0.90	-0.64	2.02	1.56	0.49	-0.25
Motor vehicles and passenger car bodies	-16.56	-15.03	30.32	30.88	13.66	12.38	-1.97	-2.42	4.36	7.37	0.05	1.69
Truck and bus bodies	-11.26	-11.78	-0.46	0.93	-11.83	-12.55	0.36	-0.87	0.88	1.46	-2.30	-3.33
Motor vehicle parts and accessories	-10.42	-8.29	7.07	9.05	-3.63	-6.00	-1.66	-1.34	0.96	1.44	-1.09	-1.17
Truck trailers	-3.66	-8.82	3.56	13.89	-13.70	-20.19	-6.30	-4.44	4.70	7.40	-1.88	-1.21

Notes: This table reports the cumulative change (measured in percentage points) in net employment (NET), job reallocation (SUM), and excess reallocation (EXC) due to a positive one standard deviation innovation in the real oil price. Computations are based on 10,000 simulations of model (8).

Table 7: Test for the absence of job reallocation in response to a 16% oil price shock

Sector / Sub-sample	$x_t^\# = x_t^1$	
	1972-1984	1985-1998
Total manufacturing (1972:Q2-2014:Q2)	0.77	0.57
Total manufacturing (1972:Q2-1998:Q4)	0.77	0.02
Food	0.96	0.51
Tobacco	0.84	0.63
Textiles	1.00	0.12
Apparel	0.84	0.61
Lumber	0.95	0.23
Furniture and fixtures	0.35	<i>0.08</i>
Paper	0.29	0.94
Printing	0.90	0.41
Chemicals	0.45	0.82
Petroleum and coal	1.00	0.32
Rubber and plastics	0.19	0.04
Leather	0.86	0.45
Stone, clay and glass	0.91	0.32
Primary metals	1.00	0.60
Fabricated metals	0.70	0.51
Industrial machinery	1.00	0.78
Electronic and electric equipment	0.90	0.73
Transportation equipment	0.71	0.03
Instruments and related products	1.00	0.87
Miscellaneous manufacturing	0.91	<i>0.09</i>
Motor vehicles and passenger car bodies	0.41	<i>0.08</i>
Truck and bus bodies	0.99	0.40
Motor vehicle parts and accessories	0.52	0.32
Truck trailers	0.14	0.01

Notes: Computations are based on 10,000 simulations of model (8). p-values are based on the χ^2_{H+1} . Bold and italics refer to significance at the 5% and 10% level. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Figure 1. Job flows and real oil price

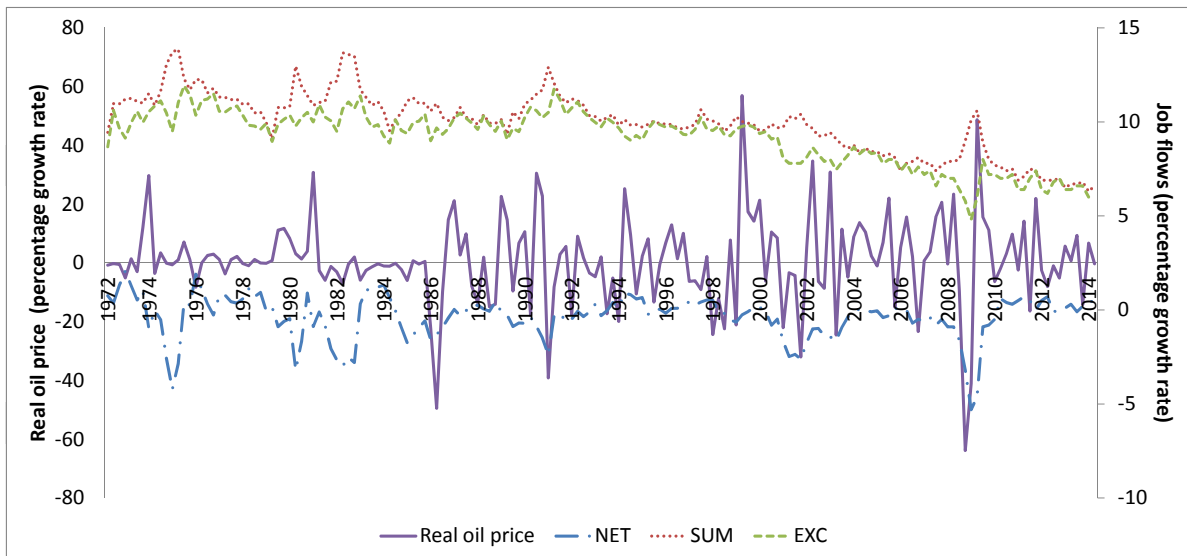


Figure 2. Real oil price and nonlinear transformations

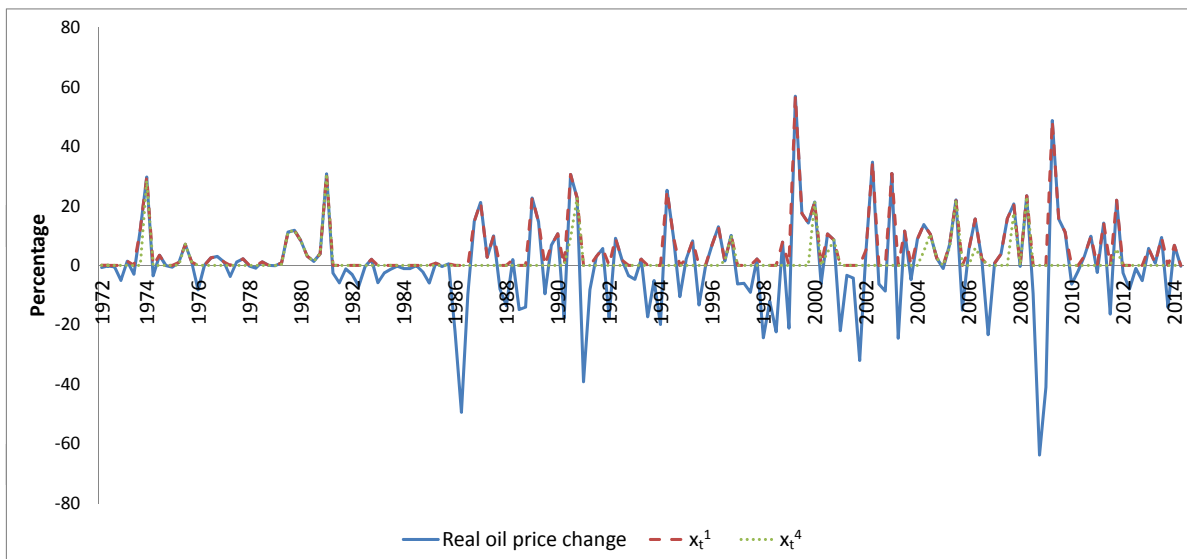
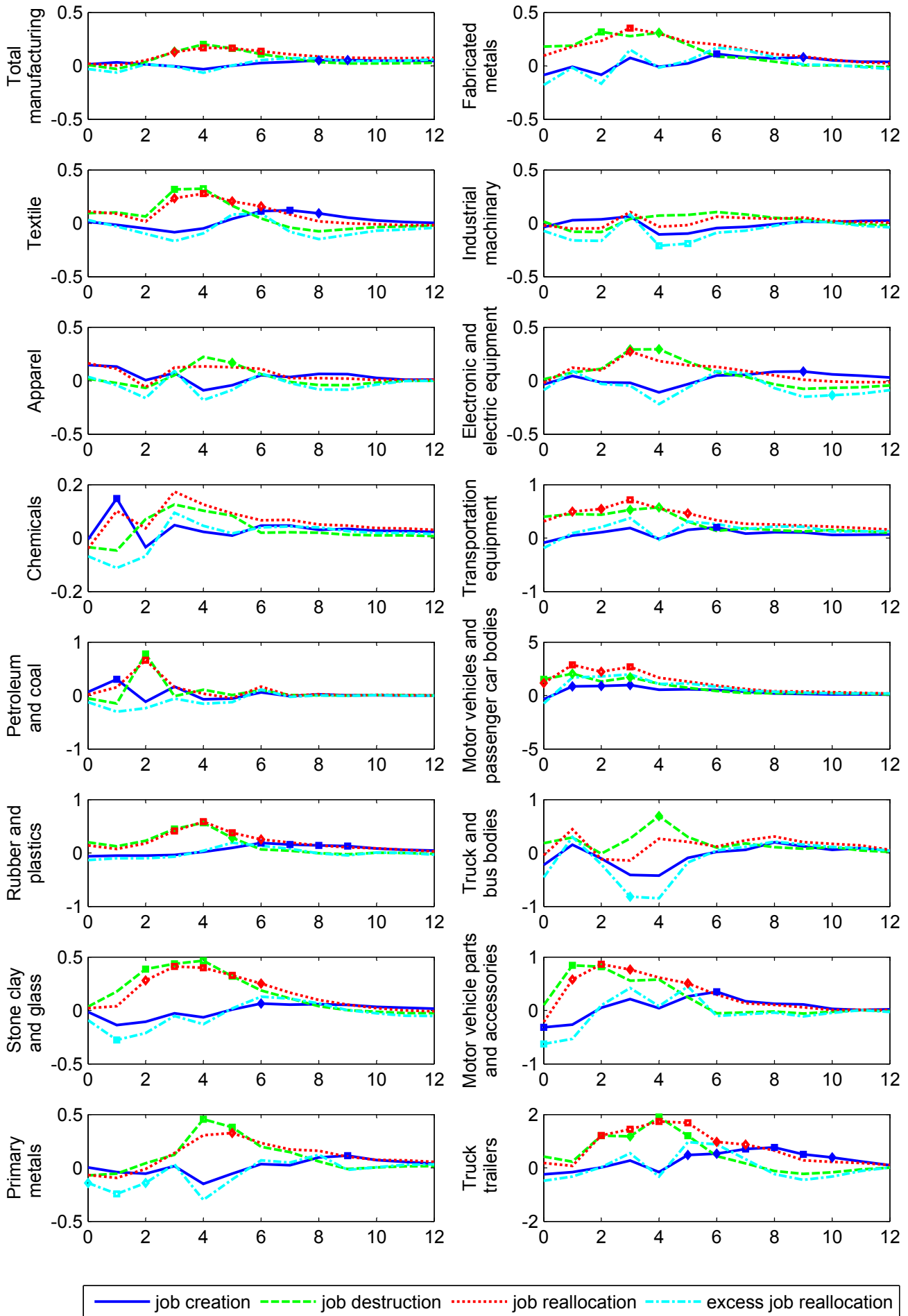
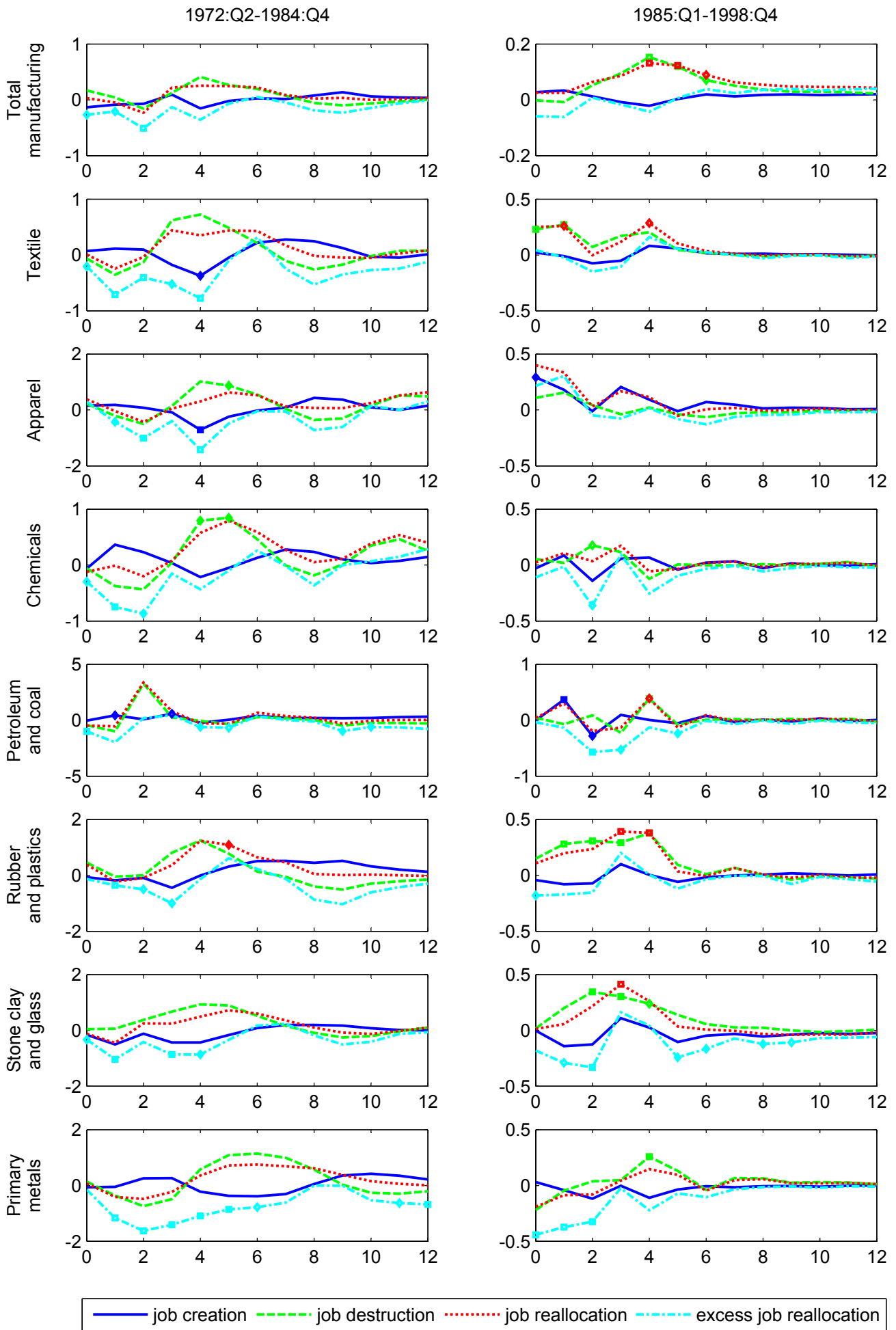


Figure 3: Job creation and job destruction responses to a positive oil price shock of 1 s.d. ($x_t^\# = x_t^1$)



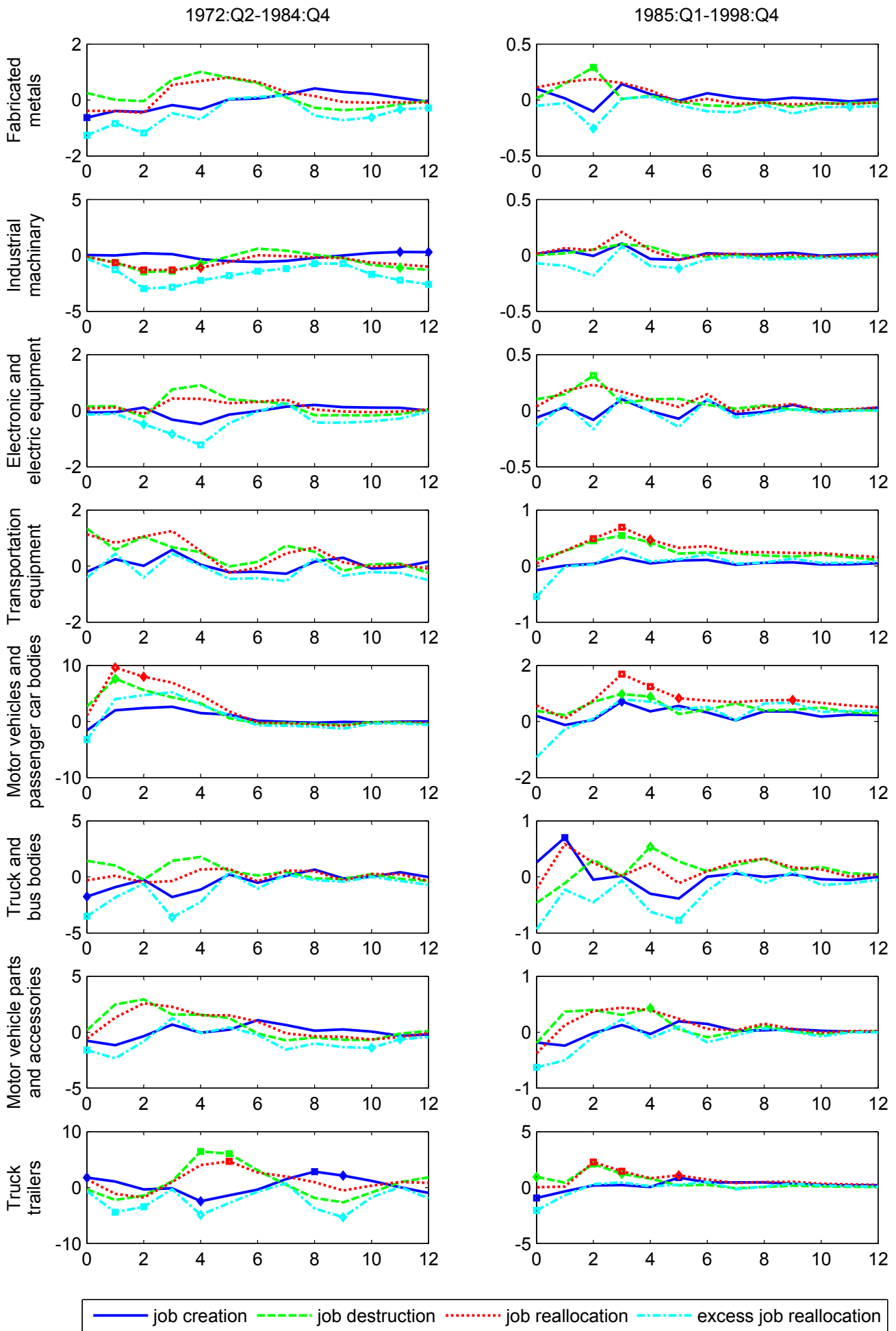
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively. Computations are based on 10,000 simulations.

Figure 4a: Job creation and job destruction responses to a positive oil price shock of 1 s.d. ($x_t^\# = x_t^1$)



Notes: Squares and diamonds represent significance at the 5% and 10%, respectively. Computations are based on 10,000 simulations.

Figure 4b: Job creation and job destruction responses to a positive oil price shock of 1 s.d. ($x_t^\# = x_t^1$)



Notes: Squares and diamonds represent significance at the 5% and 10%, respectively. Computations are based on 10,000 simulations.