The Effects of Oil Price Shocks on Job Reallocation

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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 to oil price shocks. 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 show 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 job reallocation, especially excess job reallocation. These variations were caused by a change in the transmission channel and not by smaller oil price shocks.

Keywords: oil price shocks, business cycles, job flows.

JEL codes: C32, E24, E32

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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, 2012). Kilian and Vigfusson (2011a) prove that the estimators commonly used in the empirical literature to 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 find no evidence of asymmetry in the responses of U.S. GDP and the unemployment rate. Herrera, Lagalo and Wada (2011) find similar results for aggregate industrial production; nevertheless, they find some evidence against the null of symmetric responses at the industry level. 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.

One of the channels through which oil price innovations are purported to have an asymmetric impact on aggregate output and employment is costly sectoral reallocation in the presence of labor market frictions.[1] This transmission channel implies that both positive and negative oil price innovations affect the closeness of the match between the actual and the desired characteristics of workers across firms, thus generating a process of labor reallocation from declining to expanding sectors. In the presence of search costs and matching issues, this process of reallocation is costly, resulting in prolonged unemployment spells and curtailed production. On the one hand, costly sectoral reallocation exacerbates the negative

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

effect that positive oil price innovations have on employment and output via the usual aggregate channels (such as the transfer of resources to oil exporting economies, the negative effect on discretionary income, and the increase in production costs). On the other hand, costly sectoral reallocation, due to frictions in the labor market, dampens the positive effect of negative oil price innovations on aggregate output and employment, as it affects the match between the actual and the desired job characteristics.

The aim of this paper is to dig deeper into the nature of the response of U.S. manufacturing job flows to oil price shocks. Specifically, we inquire whether the response of sectoral job creation and job destruction, one year after the shock, is equal for positive and negative oil price innovations of typical (one standard deviation) and large (two standard deviations) magnitude. We also investigate whether oil price innovations entail significant job reallocation, and whether that reallocation process helps explain why the output responses exhibit asymmetries for some industries but not for others.

Our analysis complements earlier studies in that it focuses on highly disaggregated data for employment, similar to Davis and Haltiwanger (2001, hereafter DH), while taking full advantage of recent methodological advances in estimating and testing for symmetric responses, as discussed in Kilian and Vigfusson (2011a). We estimate a structural model that nests symmetric and asymmetric responses to oil price shocks of sectoral job creation and job destruction using data for total manufacturing, twenty 2-digit SIC sectors and four 4-digit SIC industries. We then compute the responses of job creation and job destruction by Monte Carlo integration, taking into account the size of the shock (one or two standard deviations) and the history of real oil prices, job creation and job destruction.

Our contribution to the literature 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. 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.[2]

Once we control for the possible effect of data mining that results from repeatedly applying the symmetry test to alternative sectors, we find almost no statistical evidence in support of the hypothesis that sectoral job creation and job destruction respond asymmet-

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

rically to positive and negative oil price innovations of one standard deviation.[3] Similarly, using robust critical values, we find no evidence of asymmetry in the response to large (two standard deviations) innovations. Our results for sectoral job creation and job destruction are consistent with Herrera, Lagalo and Wada's (2011) who find very little evidence of asymmetry in the response of industrial production when the effect of data mining has been taken into account.

Having found that the response of job creation and job destruction to positive and negative oil price shocks is mostly symmetric, we then inquire whether oil price shocks might have an asymmetric effect on employment via an asymmetric response of job creation and job destruction to oil price innovations. That is, we turn our attention to assessing whether oil price shocks operate mainly through aggregate or allocative channels. To do this we first estimate the response of net employment, job reallocation and excess reallocation to positive innovations in the real oil price.[4] Then, 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 and lower job creation. Consequently, unless the increase in the rate of job destruction exceeds the decline in the rate of job creation, the job reallocation

[3] Conventional critical values do not account for repeated applications of the IRF based test to different sectors. Thus, as in Herrera, Lagalo and Wada (2011), we compute critical values that are robust to data mining by simulating the null distribution of the supremum of the bootstrap test statistic across all sectors for each of the analyzed oil price measures (see section 4 for a detailed description).

[4] Recall that Davis, Haltiwanger and Schuh (1990) define job reallocation as the sum of job creation and job destruction, and the net employment change as job creation minus job destruction. Excess job reallocation is defined as the difference between job reallocation and the absolute value of net employment change. (See section 2 for a precise definition).

rate will contract or stay unchanged. 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 inputs–, then a positive oil price innovation results in higher job destruction and higher job creation. Consequently, the job reallocation rate will increase. Therefore, testing whether positive innovations lead to job reallocation is equivalent to directly evaluating the relevance of the allocative channel. Moreover, in a world with heterogeneous firms and reallocation frictions, the amount of job turnover generated by a shock, will exceed the amount required to accommodate the change in net employment as reallocation will be costly and possibly slow. Hence, in face of contraction in net employment, such a test is informative regarding the importance of a channel that could lead to asymmetries in the transmission of oil price shocks to sectoral unemployment and output.

When analyzed from a sector-by-sector perspective, our results would appear to indicate that oil price shocks have an impact on gross 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., transportation equipment). Whereas these results are consistent with DH findings based on visually comparing the impulse response functions of job creation and job destruction, using critical values that are robust to data mining reveals a different picture: we are unable to reject the null of absence of job reallocation. This result suggests that oil price shocks operated mainly through aggregate channels.

Third, motivated by the observation that the effect of oil price shocks on economic activity declined in the 2000s relative to the 1970s,[5] we inquire whether our finding of a statistically

[5] See Edelstein and Kilian (2009), Herrera and Pesavento (2009), and Blanchard and Galí (2010).

insignificant reallocation effect is driven by the fact that we are estimating the average response over two periods with different patterns of job flows and oil prices. Figure 1 illustrates the evolution of job flows in U.S. manufacturing as well as that of real oil prices. A decline in job reallocation (SUM) and excess job reallocation (EXC) for aggregate manufacturing appears to have taken place during the Great Moderation, a period with higher oil price volatility. Although, job flows in U.S. manufacturing varied importantly across 2-digit SIC manufacturing industries (see Table 1), a decline in average sectoral job reallocation is also apparent when we compare pre and post-1984 data (see Table 2). Interestingly, no such pattern is evident when we consider excess reallocation, which represents the amount of job turnover that occurs above and beyond what would be required to attain an observed net change in employment. 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 results suggest that the sectoral responses of job creation and job destruction to a positive oil price innovation (of the same size) were smaller during the Great Moderation. Yet, such innovations lead to greater gross and excess reallocation in total manufacturing a year after the shock. In fact, unexpected oil price increases resulted in a decline in excess reallocation for all sectors but motor vehicles and parts before the Great Moderation and a slight increase during the Great Moderation. These two findings, in conjunction with the fact that the volatility of oil price shocks –measured by the standard deviation of the oil price innovations– was twice as large during the Great Moderation suggests that the smaller response of job flows was due to a change in the transmission mechanism of oil price shocks and not to a reduction in the volatility of these shocks. Whether this change in the transmission process 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 Galí 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 before and during the Great Moderation. Section 7 concludes.

2 Job Flows and Oil Prices

In order to explore the effect of oil price shocks on sectoral reallocation we use the gross job flows data collected by Davis, Haltiwanger and Schuh (1996) in the 1990s and updated online in 2009. This database contains quarterly data on total manufacturing and sectoral job flows. Data on total manufacturing span the period between 1972:Q2 and 2005:Q1, whereas data at the 2-digit and 4-digit SIC level cover the period between 1972:Q2 and 1998:Q4.[6] In this paper we use data for twenty 2-digit sectors and four 4-digit industries in the transportation

[6] Given the change in the industry classification system from SIC to NAICS in the late 1990s, industry-level data after 1998 are not available. We use the X-11 Census method to seasonally adjust the data.

equipment sector. 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.[7]

2.1 Job Flows

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:

$$POS_{S,t} = \sum_{e \epsilon S^+} \frac{Z_{est}}{Z_{St}} g_{est} \tag{1}$$

[7] We 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.

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

$$NEG_{S,t} = \sum_{e \epsilon S^-} \frac{Z_{est}}{Z_{St}} |g_{est}| \tag{2}$$

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

$$SUM_{S,t} = POS_{S,t} + NEG_{S,t}, \tag{3}$$

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

$$NET_{S,t} = POS_{S,t} - NEG_{S,t}, \tag{4}$$

and

$$EXC_{S,t} = SUM_{S,t} - |NET_{S,t}| \,. \tag{5}$$

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:Q2-2005:Q1 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:Q2-1983:Q4 and the 1984:Q1-1998:Q4 periods.[8] 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).

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

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, we use two nonlinear transformations of the natural logarithm of the real oil price. The first measure is the oil price increase (Mork 1989), which sets all quarterly oil price decreases to zero so that

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

The second measure is the net oil price increase over the previous 4-quarter maximum (Hamilton, 1996):

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

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:Q2-2005:Q1 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.

3 Empirical Strategy

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

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

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

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

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 to any of the two nonlinear transformations of oil prices (x_t^1, x_t^4) 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.[9] 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.

Note that our model specification differs from that in DH in a number of aspects. First, DH use an oil price index defined as the real oil price at time t divided by a "weighted average of the real prices in the prior 20 quarters, with weights that sum to one and decline linearly to zero" (DH, pg. 481). We follow the bulk of the literature and use instead the quarter-to-quarter percent change in the price of crude oil. Second, whereas DH include both the oil index and the absolute value of 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 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

[9] Kilian 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.

$IRFs$– 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).[10]

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 to oil price increases and decreases, where:

$$H_o : I_{POS}\left(H, \delta\right) = -I_{POS}\left(h, -\delta\right) \text{ for } h = 0, 1, 2, ..., H.$$

[10] Section 1 of the on-line appendix available at http://gatton.uky.edu/faculty/herrera/documents/HKappendix.pdf provides a detailed description of the computation. See Inoue and Kilian(2004) for the effect of data mining and solutions to the problem of data mining in the related context of tests of predictability.

Similarly, for job destruction we test the null

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

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 (left and right panels, respectively) to a one standard deviation oil price innovation (hereafter a 1 s.d. shock). Table 3 shows that, for an innovation of this magnitude, we are unable to reject the null of symmetry at a 5% significance level for both job creation and job destruction. This result holds true for all sectors, regardless of the nonlinear transformation of oil prices.[11]

Test results reported in Table 4 reveal some evidence of asymmetry for a two standard deviation oil price innovation (hereafter a 2 s.d. shock). Note that we are able to reject the null of symmetry in job creation for tobacco when we use x_t^1, and for total manufacturing (1972:Q2-2005:Q1) and lumber when we use x_t^4. Similarly, for job destruction the number or rejections is higher for a 2 s.d. shock than for a 1 s.d. shock. Using x_t^1, we reject the null of

[11] For 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.

symmetry in the response to positive and negative oil price shocks for food, and petroleum and coal. Using x_t^4, we reject the null for textiles, furniture and fixtures, petroleum and coal, rubber and plastics, fabricated metals, electronic and electric equipment, and truck trailers.

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 for each of the two oil price measures. As it is well known, the usual 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).[12] The data mining robust critical values are based on 1000 pseudo series generated using the estimated coefficients for all sector and maintaining the observed correlation of the residuals. As it can be seen in the tables, we find no evidence of asymmetry in the response of job creation once we have accounted for the effect of data mining. Evidence of asymmetry is only found in the response of job destruction to a 1 s.d. innovation for petroleum and coal products.[13]

Comparing these results with those obtained for industrial production by Herrera, Lagalo

[12] See Inoue and Kilian (2004) and Kilian and Vega (2011) for the effect of data mining and solutions to the problem of data mining in the related context of tests of predictability.

[13] Estimation 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.

and Wada (2011) at a 12-month horizon for the post-1972 period reveals two similarities. First, output and job flows in total manufacturing exhibit no asymmetry in the response to positive and negative oil price innovations, both for the oil price increase (x_t^1) and the net oil price increase with respect to the previous year maximum (x_t^4 here and x_t^{12} in Herrera, Lagalo and Wada 2011). Second, 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 significant for industrial production. However, evidence of asymmetry using the oil price increase and the net oil price increase with respect to the previous year maximum vanishes when controlling for data mining across sectors.

To conclude this section, we compare our results with those obtained using a model à la DH. As part of their investigation on the effect of oil price shocks on 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 estimated 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.[14] We found no asymmetry in the response of job creation and job destruction to positive and negative oil price innovations.[15]

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 presence (or absence) of asymmetry in the response of job creation and job destruction to positive oil price innovations. That is, when faced with an unexpected 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. The latter effect stems from search and matching issues faced by heterogeneous firms and workers. Hence, in this section we explore whether asymmetry in the response of employment to oil price shock stems not from an asymmetric response in job flows to oil price increases and decreases but from an asymmetric response of job creation

[14] Our 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.

[15] See Table A.2 of the online appendix.

and destruction to positive innovations in the price of crude oil.

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. Figures 3a and 3b plot the responses of job creation and job destruction to a 1 s.d. positive innovation in the real oil price. For ease of comparison, we plot the negative of the response of job destruction. The responses generated using the oil price increase, x_t^1, and the net oil price increase, x_t^4, are plotted in the left and right panels, respectively. To conserve space, the $IRFs$ for the remaining nine 2-digit SIC industries are reported in the online appendix (see Figure A.5.)

As the top panel of Figure 3a illustrates, job destruction in total manufacturing experiences a larger increase than the decline observed in job creation. For instance, regardless of the non-linear transformation of oil prices used (i.e., x_t^1 or x_t^4), the response of job destruction is about 34% larger than the response of job creation four quarters after the shock. The one-year cumulative response of job destruction is 0.320 (0.384) percentage points whereas the cumulative response of job creation is only 0.004 (-0.027) percentage points using x_t^1 (x_t^4). 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.[16]

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 5 reports the cumulative effect four and eight quarters after the shock. Based on the model with x_t^1 and the 1973-2005 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 (0.51) percentage points in net employment (NET) for total manufacturing. The corresponding one-year (two-year) cumulative increase in job reallocation (SUM) equaled 0.33 (0.67) percentage points. These numbers suggest that unexpected oil price increases generate a decline in net job flows, an increase in gross job reallocation, and only a moderate change in excess reallocation. Interestingly, a comparison of the cumulative effects computed using the 1973-1998 and the 1973-2005 samples for total manufacturing, suggest a smaller effect of oil price shocks during the 1999-2005 period.[17] Note that the magnitude of the impact on net employment, job reallocation and excess reallocation (EXC) is greater for the shorter sample. We will explore the possibility of a break in the response of job flows to oil price shocks in section 6.

As for the 2-digit SIC industry-level data, the magnitude of the cumulative effect on

[16] The $IRFs$ are qualitatively similar across different nonlinear transformations of oil prices, although the magnitude of the effect on job reallocation tends to be somewhat larger for x_t^4.

[17] Recall that sectoral level data is only available for the 1973-1998 period.

job flows diverges greatly across sectors. For instance, the two-year cumulative effect on job reallocation ranges between 0.12 (0.03) percentage points for tobacco and 3.93 (4.67) percentage points for transportation equipment using x_t^1 (x_t^4), respectively. Other industries that exhibit two-year cumulative declines in net employment exceeding one percentage point are textiles, lumber, furniture and fixtures, rubber and plastics, stone, clay and glass, and fabricated metals. These industries, as well as petroleum and coal, display substantial job reallocation. Clearly, the fact that transportation equipment 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 Figures A.6a and A.6b). For total manufacturing, regardless of the sample specification (1973-1998 or 1973-2005) and the non-linear transformation of oil prices (x_t^1 or x_t^4), 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 (compare Table 5 and Table 6). 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, using x_t^1, 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 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.7 of the online appendix). For instance, the responses for rubber and plastics, and transportation equipment reported at $h = 4$ by DH are about 50% larger than 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 panels of Figure 3b 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 using x_t^1, a 1 s.d. oil price innovation leads to a 0.02 percentage point 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 5 suggest that a 1 s.d. oil price innovation leads to considerable reallocation activity within of the automobile sector. The one-year cumulative change in the job reallocation rate equals 10.59 (12.42) percentage points for motor vehicles and passenger car bodies, 0.41 (0.28) for truck and bus bodies, 2.61 (3.55) for motor vehicle parts and accessories, and 4.66 (5.50) for truck trailers using x_t^1 (x_t^4). 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 (compare Tables 5 and 6). For instance, using x_t^1, 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 5.84 and 12.7 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 $IRFs$ 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, $IRFs$ 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 the rate of job destruction exceeds the decline in the rate of job creation, the job reallocation rate will contract or stay unchanged. 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 more jobs will be destroyed. Consequently, the job reallocation rate will increase. Hence, to test the null of absence of job reallocation is equivalent to evaluating whether the allocative channel plays a statistically significant role in transmitting oil price innovations.

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:

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

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

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

where

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

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 (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 $h = 0, 1, 2, ..., H$.) 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 the null distribution of the supremum of the bootstrap test statistic across all sectors for each of the oil price measures.[18]

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 7. Statistical significance at the 5% level using the conventional and the data mining robust critical values is denoted in bold and **, respectively. Regardless of the oil price measure, x_t^1 or x_t^4, we fail to reject the null of no job reallocation for total manufacturing when we consider a 1 s.d. shock (see left panel of Table 7). In contrast, using the conventional critical values, we reject the null for furniture and fixtures, rubber and plastics, and truck trailers, using either x_t^1 or x_t^4, and for lumber and stone, clay and glass when we use x_t^4.

Somewhat more widespread evidence of job reallocation is found when we consider a 2 s.d. innovation using x_t^4. Using the conventional critical values, we reject the null of absence of job reallocation for 10 sectors: textiles, lumber, furniture and fixtures, petroleum and coal, rubber and plastics, stone, clay and glass, electronic and electric equipment, motor vehicles and passenger car bodies, motor vehicle parts and accessories, and truck trailers. Less evidence of asymmetry is found for x_t^1 (see right panel of Table 7), where we reject the

[18]The data mining robust critical values are computed using 1000 pseudo series.

null of no job reallocation only for furniture and fixtures.

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 7, which indicates that none of the results are statistically significant once we account for data mining.

It is worth comparing the results obtained here with results obtained when we test for the absence of job reallocation in a model à la DH. To implement this test we re-estimate our model including a macro block before the sectoral block and using only the 1972-1988 sample. We then compute the unconditional $IRFs$ and construct the test for absence of job reallocation. In that case we are unable to reject the null hypothesis for all sectors, regardless of the nonlinear transformation of oil prices 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 $IRFs$ plotted in Figures 3a and 3b 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.

[19] See Table A.3 of the online appendix.

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 $IRFs$ based test for two subsamples: 1972:Q2-1983:Q4 and 1984:Q1-2005:Q1 for total manufacturing, and 1972:Q2-1983:Q4 and 1984: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 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. To facilitate the comparison and to conserve space, we plot the negative of the job destruction rate and we depict the $IRFs$ only for fourteen 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, when we use x_t^1.

This muted response of job creation and job destruction resulted in a smaller effect on net employment for more than 75% of the 2-digit SIC industries (see Table 8). 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 -3.55 percentage points before the Great Moderation to -1.57 in the subsequent period. As a result, the impact of a positive oil price innovation was less detrimental for net employment in total manufacturing during the Great Moderation. The one-year cumulative effect on net employment for total manufacturing equaled -1.37 percentage points in the first sub-sample and -0.69 in the second sub-sample. Similar results are obtained when we use x_t^4 (see Figures A.8a and A.8b, and Table A.4 of the online appendix).

Even though positive oil price innovations have lead to smaller changes in the net employment growth, they appear to have led to a slight increase in job turnover for total manufacturing during the Great Moderation. Note that the one-year cumulative effect on job reallocation equals 0.21 and 0.95 for the 1972-1983 and 1974-1998 periods, respectively. Given that the respective average of SUM was 11.5 and 10.4, the effect on gross reallocation appears to be of larger economic significance during the Great Moderation (i.e., a 2% versus a 9% increase). A slight increase in the one-year cumulative response of job reallocation (SUM) to a 16% innovation is also apparent for more than half of the 2-digit SIC industries and two of the 4-digit industries.

In addition, a change in the intensity of reallocation brought about by an oil price shock is evident in Table 8. During the 1972-1983 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 (1.1 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 (11.51), but decreased for the other 4-digit sectors (-15.21 for truck and bus bodies, -6.33 for motor vehicle parts and accessories, and -14.81 for truck trailers).

In contrast, during the Great Moderation oil price innovations of the same magnitude lead to 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. In brief, a 16% increase in oil prices would have led to an 11% decline (-1.16 percentage points) in excess reallocation four quarters after the shock but only a 3% increase (0.27 percentage points) during the Great Moderation.

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, which is not publicly available.

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 $\delta_{1973-1983} = 8\%$ to $\delta_{1984-1998} = 2 * \delta_{1973-1983} = 16\%$. 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 9 reports $p-values$ computed using the usual critical values for the test of absence of job reallocation in response to a 16% shock before (1973-1983) and during the Great Moderation (1984-1998). Test statistics that are significant at a 5% significance level using the robust critical values are denoted in the tables by **. Note that, regardless of the oil price measure, we are unable to reject the null for any of the industries or for the aggregate. 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 1973-1983 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.

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. We first estimated a simultaneous equation model that nests both a symmetric and an asymmetric model of the transmission of oil price shocks to job creation and job destruction. We then tested for symmetry in the response of job creation and job destruction to positive and negative innovations to the real oil price. We found no evidence of asymmetry in the responses of job creation and job destruction to oil price innovations of 1 s.d. These results are consistent with Kilian and Vigfusson's (2011a) finding of symmetry in the response of the U.S. unemployment rate to shocks of the typical magnitude. Some evidence of asymmetry in the responses of job creation and job destruction to a 2 s.d. innovation was found 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.

Having found no evidence of asymmetry in the response of job creation and job destruction to positive and negative oil price innovations, we then proceeded to explore another possible source of asymmetry in the response of employment. That is, we explored whether U.S. manufacturing firms shed jobs at a higher rate than they create jobs when faced with an unexpected oil price increase. The $IRFs$ 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. Therefore, oil price shocks appear to have acted through the aggregate channels (e.g., income transfers from oil importing to oil producing economies, declines in potential output).

Motivated by the finding that oil price shocks had a muted effect during the Great Moderation we then inquired whether our result of a statistically insignificant effect on job reallocation could be driven by the fact that we compute the average effect over the periods before and during the Great Moderation. Splitting the sample in these two periods suggested that the magnitude of the response of job creation and job destruction to a 16% innovation (this is equivalent to a 2 s.d. and a 1 s.d. innovation in the first and second subsamples, respectively) has declined over time. This result is consistent with previous literature, which concludes that oil prices did not shock in the 2000s as they shocked in the 1970s (see for instance, Edelstein and Kilian 2009, Herrera and Pesavento 2009, and Blanchard and Galí 2010). Yet, our results suggest that looking only at the variation in the response of the unemployment rate or aggregate output, hides the fact that, a year after the shock, oil price shocks entailed a larger decline in the intensity of job reallocation process before the Great Moderation for all sectors but motor vehicles and parts. Our results point towards a change in the oil price transmission mechanism during the Great Moderation, which could have stemmed from a change in the composition of oil price shocks (Kilian 2009), and increase in labor market flexibility (Blanchard and Galí 2010), or an increase in the adjustments needed -at the firm level- to close the wedge created by an oil price shock between the desired and the actual characteristics of the labor input.

It is useful to put our results in perspective relative to earlier studies of the effect of aggregate shocks on job flows. Using data for the 1972:Q2–1988:Q4 period, Davis and Haltiwanger (2001) concluded that the allocative channel played an important role in the transmission of oil price shocks. Their conclusion appears to have been based on comparing the plots for the impulse response functions of job creation and job destruction. Their VAR was estimated using a nonlinear measure of oil prices but the impulse response functions were computed in the usual manner. Based on a longer same sample period and a more parsimonious model that is more likely to reject the null, we found the reallocation effect to be statistically insignificant. We showed that this finding is robust to including a macro block and using the same sample period as Davis and Haltiwanger (2001). Differences in the results are driven mainly by the specification of the oil price shock measure. Censored VARs such as that used by Davis and Haltiwanger (2001) have been shown to yield inconsistent estimates of the impulse response functions (Kilian and Vigfusson, 2011a). Actually, they tend to result in larger estimates of the effect of oil price shocks on output and employment. Our analysis relies on impulse response functions computed via Monte Carlo integration, which take into account possible nonlinearities in the response to oil price shocks. Furthermore, because impulse response estimates are subject to a large degree of uncertainty, even though the eyeball metric could suggest the presence of reallocation, a formal test revealed no statistical evidence in favor of the allocative channel.

A potential concern with any structural model of job flows and oil prices is the possibility of breaks in the response functions associated with structural changes in the labor market that appear to have taken place during the Great Moderation. Our subsample analysis of the periods before and during the Great Moderation addressed this issue within the constraints imposed by the data. Ours is not the first study to find important changes in the response of job flows to aggregate shocks. Faberman (2008) concluded that changes job flow movements where 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. His conclusion appears to have been based on a bivariate VAR on job creation and job destruction for total manufacturing covering two subsamples: 1947:Q1-1983Q4 and 1984:Q1-2006:Q3. In fact, in spite of important differences in the sample period, data and model specification, our empirical analysis supports his conclusion regarding the shift in the impulse response functions. Yet, our analysis differs in the type of aggregate shock and in the volatility of the shock of interest. Whereas Faberman (2008) is concerned with the role of general aggregate and allocative shocks, we are interested in a specific shock: an unexpected increase in the real price of crude oil. We showed that oil price innovations where more volatile during the Great Moderation, hence the change in the response of job flows to oil price shocks is due to a shift in the transmission mechanism and not to a reduction in the volatility of the innovation of interest.

An important question in the recent literature has been whether the response of economic activity to oil price shocks is asymmetric. We have found no evidence of asymmetry in the response of job creation and destruction to positive and negative oil price innovations. Moreover, we showed that the finding of symmetry was not a result of aggregating flows to compute net employment growth nor of aggregating across sectors to compute the change in total manufacturing creation and destruction. These points are crucial because, to the extent that the response of U.S. manufacturing job flows is symmetric, one can then proceed to study the importance of reallocation effects by focusing only on unexpected oil price increases.

Much of the discussion in this paper has been about the economic and statistical significance of the reallocation effect generated by oil price shocks and about whether the effect on job flows was muted during the Great Moderation. These questions are not only key for the construction of theoretical models of the transmission of oil price shocks, but also for the design of policy aimed at assisting sectors that might be more affected by such shocks. Moreover, the question of how large are the effects of higher oil prices on the labor market is likely to take a central stage during this jobless recovery. Understanding the oil price transmission channels, how they affect different sectors, and the degree of reallocation they might entail, is key for policy makers as the world economies struggle to recover from the Great Recession.

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Table 1. Magnitude of gross job flows by sectors

Sector	POS	NEG	SUM	NET	EXC
Total manufacturing (1972:Q2-2005:Q1)	5.14	5.47	10.61	-0.34	9.79
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 table are in percent.

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

	1972:Q2-1983:Q4					1984:Q1-1998:Q4				
Sector	*POS*	*NEG*	*SUM*	*NET*	*EXC*	*POS*	*NEG*	*SUM*	*NET*	*EXC*
Total manufacturing (1973-2005)						4.86	5.25	10.11	-0.39	9.72
Total manufacturing (1973-1998)	5.63	5.88	11.51	-0.24	10.34	5.09	5.30	10.39	-0.21	10.19
Food	9.41	9.53	18.94	-0.11	18.06	7.38	7.16	14.53	0.22	14.31
Tobacco	6.32	6.84	13.16	-0.52	10.75	5.83	6.38	12.21	-0.55	11.66
Textiles	3.60	4.24	7.84	-0.63	6.46	3.18	3.84	7.02	-0.66	6.37
Apparel	5.62	6.36	11.99	-0.74	10.41	5.46	6.45	11.91	-0.99	10.92
Lumber	7.06	7.45	14.51	-0.39	11.91	5.57	5.51	10.98	0.16	10.82
Furniture and fixtures	5.34	5.51	10.84	-0.17	8.76	4.91	4.83	9.74	0.07	9.67
Paper	3.72	3.95	7.67	-0.23	6.54	3.29	3.27	6.56	0.02	6.54
Printing	4.64	4.57	9.21	0.07	8.19	4.62	4.48	9.10	0.14	8.96
Chemicals	3.80	4.14	7.94	-0.34	6.92	3.33	3.50	6.83	-0.16	6.66
Petroleum and coal	3.96	4.46	8.41	-0.50	6.94	3.71	4.06	7.77	-0.36	7.42
Rubber and plastics	5.66	5.60	11.26	0.06	8.90	4.87	4.52	9.39	0.35	9.04
Leather	4.88	5.89	10.77	-1.01	9.15	4.70	5.97	10.67	-1.27	9.40
Stone, clay, and glass	5.48	5.89	11.36	-0.41	9.53	4.95	4.98	9.92	-0.03	9.89
Primary metals	3.74	4.68	8.42	-0.94	5.67	3.26	3.62	6.88	-0.36	6.53
Fabricated metals	5.60	5.97	11.57	-0.36	9.45	4.75	4.80	9.55	-0.05	9.50
Industrial machinery	5.07	5.34	10.41	-0.27	8.23	4.68	4.76	9.44	-0.08	9.36
Electronic and electric equipment	4.98	4.97	9.95	0.00	7.81	4.41	4.67	9.09	-0.26	8.82
Transportation equipment	5.94	6.31	12.25	-0.38	9.32	4.49	4.63	9.12	-0.14	8.99
Instruments and related products	4.48	4.23	8.71	0.25	7.13	3.71	4.23	7.94	-0.53	7.41
Miscellaneous manufacturing	6.92	7.32	14.24	-0.40	12.17	6.44	6.48	12.92	-0.04	12.88
Motor vehicles and passenger car bodies	9.63	10.39	20.03	-0.76	11.79	5.74	5.92	11.66	-0.18	11.48
Truck and bus bodies	8.47	8.52	16.99	-0.50	12.54	6.05	5.76	11.81	0.29	11.52
Motor vehicle parts and accessories	5.30	5.68	10.98	-0.38	6.64	4.01	4.02	8.04	-0.01	8.02
Truck trailers	8.25	8.25	16.50	-0.01	10.28	6.75	6.42	13.17	0.34	12.84

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 table are in percent.

Table 3. IRF based test of symmetry in the response to a 1 s.d. oil price shock

	Job creation		Job destruction	
Sector / Oil price measure	$x_t^{\#}= x_t^1$	$x_t^{\#}= x_t^4$	$x_t^{\#}= x_t^1$	$x_t^{\#}= x_t^4$
Total manufacturing (1972:Q2-2005:Q1)	0.71	0.46	0.66	0.61
Total manufacturing (1972:Q2-1998:Q4)	0.67	0.74	0.73	0.73
Food	1.00	0.93	0.27	0.83
Tobacco	0.27	0.89	0.77	0.82
Textiles	0.96	0.95	0.77	0.48
Apparel	0.95	0.79	0.81	0.59
Lumber	0.35	0.54	0.40	0.42
Furniture and fixtures	0.83	0.67	0.30	0.38
Paper	0.78	0.76	0.78	0.72
Printing	0.68	0.75	0.84	0.74
Chemicals	0.64	0.50	0.70	0.46
Petroleum and coal	0.31	0.56	*0.10*	0.23**
Rubber and plastics	0.54	0.80	0.69	0.44
Leather	0.44	0.67	0.64	0.97
Stone, clay and glass	0.60	0.72	0.76	0.71
Primary metals	0.77	0.76	0.73	0.71
Fabricated metals	0.75	0.73	0.87	0.54
Industrial machinery	0.94	0.73	0.93	0.81
Electronic and electric equipment	0.81	0.91	0.81	0.41
Transportation equipment	0.36	0.94	0.91	0.88
Instruments and related products	0.53	0.82	0.74	0.58
Miscellaneous manufacturing	0.67	0.72	0.99	0.79
Motor vehicles and passenger car bodies	0.28	0.79	0.66	0.78
Truck and bus bodies	0.89	0.88	0.95	0.72
Motor vehicle parts and accessories	0.43	0.79	0.93	0.78
Truck trailers	0.49	0.86	0.34	0.51

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% significance level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 4. IRF based test of symmetry in the response to a 2 s.d. oil price shock

	Job creation		Job destruction	
Sector / Oil price measure	$x_t^{\#}= x_t^1$	$x_t^{\#}= x_t^4$	$x_t^{\#}= x_t^1$	$x_t^{\#}= x_t^4$
Total manufacturing (1972:Q2-2005:Q1)	0.60	**0.01**	0.52	*0.06*
Total manufacturing (1972:Q2-1998:Q4)	0.42	0.16	0.55	*0.06*
Food	1.00	0.92	**0.04**	0.73
Tobacco	**0.04**	0.80	0.63	0.64
Textiles	0.93	0.78	0.61	**0.00**
Apparel	0.92	0.44	0.69	0.13
Lumber	0.14	**0.05**	0.17	*0.07*
Furniture and fixtures	0.68	*0.09*	*0.07*	**0.00**
Paper	0.54	0.32	0.56	0.17
Printing	0.53	0.38	0.80	0.29
Chemicals	0.45	0.18	0.57	*0.10*
Petroleum and coal	*0.07*	*0.10*	**0.00**	**0.00**
Rubber and plastics	0.23	0.30	0.57	**0.02**
Leather	0.25	0.33	0.40	0.93
Stone, clay and glass	0.34	0.12	0.65	0.24
Primary metals	0.62	0.36	0.60	0.22
Fabricated metals	0.44	0.19	0.79	**0.02**
Industrial machinery	0.90	0.31	0.89	0.60
Electronic and electric equipment	0.72	0.77	0.75	**0.02**
Transportation equipment	*0.10*	0.87	0.88	0.55
Instruments and related products	0.38	0.55	0.64	0.12
Miscellaneous manufacturing	0.54	0.25	0.98	0.59
Motor vehicles and passenger car bodies	*0.07*	0.37	0.47	0.25
Truck and bus bodies	0.78	0.29	0.92	0.27
Motor vehicle parts and accessories	0.23	0.57	0.88	0.33
Truck trailers	0.41	0.72	0.20	**0.03**

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% significance level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 5. Cumulative change in job flows due to a 1 s.d. oil price shock

	$x_t^{\#} = x_t^1$						$x_t^{\#} = x_t^4$					
	NET		SUM		EXC		NET		SUM		EXC	
Sector / Quarters since the shock	4	8	4	8	4	8	4	8	4	8	4	8
Total manufacturing (1972:Q2-2005:Q1)	-0.32	-0.51	0.33	0.67	0.01	0.12	-0.41	-0.89	0.36	0.92	-0.05	0.03
Total manufacturing (1972:Q2-1998:Q4)	-0.71	-0.83	0.85	1.44	0.14	0.51	-0.78	-1.10	0.90	1.72	0.12	0.51
Food	-0.25	-0.38	0.83	1.61	0.18	0.80	-0.33	-0.55	1.00	2.04	0.40	1.21
Tobacco	0.73	0.69	0.14	0.12	-1.27	-1.50	1.16	1.31	-0.03	0.03	-1.84	-2.01
Textiles	-1.08	-0.81	0.73	1.20	-0.35	-0.41	-1.23	-1.07	0.88	1.62	-0.34	-0.19
Apparel	0.06	-0.01	0.47	0.75	-0.22	-0.31	0.04	-0.36	0.52	0.91	-0.25	-0.47
Lumber	-3.28	-3.05	2.05	3.53	-1.23	-0.19	-3.22	-3.11	2.09	3.79	-1.13	0.05
Furniture and fixtures	-1.67	-1.66	1.08	2.01	-0.60	-0.33	-1.78	-2.31	1.09	2.35	-0.70	-0.34
Paper	-0.79	-0.77	0.35	0.74	-0.45	-0.41	-0.89	-1.14	0.48	1.18	-0.40	-0.19
Printing	-0.46	-0.47	0.63	0.75	0.06	0.11	-0.45	-0.62	0.48	0.53	-0.05	-0.19
Chemicals	-0.04	-0.05	0.40	0.68	-0.09	0.05	-0.25	-0.60	0.59	1.22	0.02	0.30
Petroleum and coal	-0.32	-0.44	1.02	1.15	-0.81	-0.83	-0.59	-0.84	1.54	1.86	-0.11	-0.04
Rubber and plastics	-1.75	-1.54	1.39	2.36	-0.36	0.04	-1.97	-1.99	1.60	3.08	-0.37	0.43
Leather	-0.12	-0.42	-0.23	0.12	-1.27	-1.29	0.07	-0.32	-0.29	0.06	-1.68	-1.81
Stone, clay, and glass	-1.85	-2.32	1.15	2.00	-0.70	-0.36	-1.91	-2.53	1.26	2.31	-0.66	-0.29
Primary metals	-0.72	-1.40	0.27	1.17	-0.62	-0.49	-1.00	-2.26	0.63	2.24	-0.37	-0.02
Fabricated metals	-1.38	-1.50	1.17	1.85	-0.22	0.23	-1.47	-1.89	1.28	2.33	-0.19	0.39
Industrial machinery	0.02	-0.48	-0.04	0.10	-0.52	-0.88	-0.23	-1.29	0.17	0.61	-0.46	-1.07
Electronic and electric equipment	-0.92	-1.02	0.65	1.07	-0.27	-0.23	-1.01	-1.47	0.88	1.70	-0.14	-0.04
Transportation equipment	-2.15	-2.37	2.62	3.93	0.47	1.43	-2.19	-2.36	3.01	4.67	0.81	2.22
Instruments and related products	0.19	-0.02	0.17	0.32	-0.50	-0.60	0.31	-0.07	0.38	0.78	-0.33	-0.34
Miscellaneous manufacturing	-0.93	-0.78	1.07	1.34	0.01	0.00	-1.31	-1.53	1.02	1.31	-0.31	-0.60
Motor vehicles and passenger car bodies	-4.75	-4.67	10.59	13.81	5.84	8.68	-4.73	-4.47	12.42	16.10	7.69	10.76
Truck and bus bodies	-2.43	-2.92	0.41	1.28	-2.02	-1.83	-2.96	-3.74	0.28	1.30	-2.68	-2.64
Motor vehicle parts and accessories	-3.18	-2.41	2.61	3.65	-0.56	-0.29	-3.73	-2.74	3.55	5.20	-0.18	0.48
Truck trailers	-5.22	-4.42	4.66	8.85	-0.56	1.38	-5.10	-4.99	5.50	10.80	0.40	2.78

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 6. Cumulative change in job flows due to a 2 s.d. oil price shock

	$x_t^{\#} = x_t^1$						$x_t^{\#} = x_t^4$					
	NET		*SUM*		*EXC*		*NET*		*SUM*		*EXC*	
Sector / Quarters since the shock	4	8	4	8	4	8	4	8	4	8	4	8
Total manufacturing (1972:Q2-2005:Q1)	-0.83	-1.28	0.73	1.43	-0.10	0.09	-1.40	-2.41	1.04	2.41	-0.36	-0.03
Total manufacturing (1972:Q2-1998:Q4)	-1.81	-2.14	1.94	3.28	0.14	0.92	-2.46	-3.06	2.38	4.40	-0.08	0.95
Food	-0.67	-0.99	1.47	3.21	-0.37	1.01	-0.95	-1.37	1.91	4.14	0.32	2.08
Tobacco	1.18	1.26	0.48	0.52	-3.84	-4.42	2.38	2.71	-0.09	0.00	-3.48	-3.79
Textiles	-2.33	-1.76	1.30	2.24	-1.03	-1.18	-3.20	-2.53	2.04	3.65	-1.16	-1.13
Apparel	-0.09	-0.47	0.55	1.26	-1.09	-1.39	-0.42	-1.37	0.51	1.41	-2.12	-2.82
Lumber	-7.57	-6.49	3.78	6.22	-3.79	-2.48	-8.69	-7.90	4.36	8.05	-4.33	-1.96
Furniture and fixtures	-4.05	-4.12	2.21	4.38	-1.83	-1.2	-5.17	-6.30	2.22	5.26	-2.94	-2.23
Paper	-1.87	-1.93	0.49	1.32	-1.38	-1.40	-2.38	-2.79	1.11	2.83	-1.27	-0.93
Printing	-1.42	-1.62	1.44	1.80	-0.01	0.10	-1.77	-2.27	0.86	0.97	-0.90	-1.30
Chemicals	0.00	-0.03	0.79	1.56	-0.47	-0.05	-0.94	-1.70	1.42	2.98	-0.41	0.32
Petroleum and coal	-0.70	-0.87	1.90	2.12	-3.59	-3.71	-1.61	-2.14	4.05	4.75	-1.02	-0.96
Rubber and plastics	-4.12	-3.63	2.77	4.90	-1.35	-0.54	-5.75	-5.35	3.77	7.19	-1.98	-0.32
Leather	0.04	-0.47	-1.02	-0.52	-2.94	-3.03	0.53	-0.57	-1.55	-0.78	-4.54	-4.93
Stone, clay and glass	-4.95	-5.84	2.42	4.07	-2.54	-1.97	-5.96	-7.03	3.06	5.44	-2.90	-2.04
Primary metals	-2.32	-3.71	0.74	3.01	-1.73	-0.99	-4.13	-6.70	2.41	6.63	-1.72	-0.21
Fabricated metals	-3.39	-3.61	2.22	3.60	-1.17	-0.31	-4.58	-5.37	3.00	5.54	-1.59	-0.02
Industrial machinery	0.09	-1.31	-0.78	-0.48	-1.97	-3.05	-1.20	-4.02	-0.01	1.28	-2.04	-3.58
Electronic and electric equipment	-2.51	-2.89	1.35	2.47	-1.16	-1.13	-3.23	-4.12	2.27	4.35	-1.12	-0.86
Transportation equipment	-5.43	-6.06	5.46	8.24	0.04	1.81	-6.25	-6.37	7.64	11.62	1.39	4.74
Instruments and related products	-0.21	-1.14	-0.05	0.29	-1.64	-2.24	0.06	-1.16	0.62	1.55	-1.58	-1.97
Miscellaneous manufacturing	-2.13	-1.92	1.62	2.01	-0.57	-0.69	-4.11	-4.69	1.37	2.14	-2.73	-3.39
Motor vehicles and passenger car bodies	-11.63	-11.92	24.32	30.79	12.7	17.9	-14.20	-12.74	35.19	44.05	21.00	28.40
Truck and bus bodies	-5.75	-6.45	-1.50	-0.33	-7.25	-7.38	-8.42	-9.43	-1.48	0.54	-9.91	-9.85
Motor vehicle parts and accessories	-7.13	-5.63	5.28	7.52	-1.84	-1.35	-10.25	-7.14	9.26	13.20	-0.99	-0.16
Truck trailers	-12.60	-11.04	10.55	20.86	-2.05	3.59	-14.22	-12.92	14.99	28.46	0.77	6.06

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 two 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

Sector / Oil price measure	1 s.d. oil price shock $x_t^{\#}= x_t^1$	1 s.d. oil price shock $x_t^{\#}= x_t^4$	2 s.d. oil price shock $x_t^{\#}= x_t^1$	2 s.d. oil price shock $x_t^{\#}= x_t^4$
Total Manufacturing (1972:Q2-2005:Q1)	0.27	0.40	0.49	0.38
Total Manufacturing (1972:Q2-1998:Q4)	0.34	0.14	0.42	*0.06*
Food	0.81	0.21	0.87	0.35
Tobacco	0.84	0.98	0.71	0.99
Textiles	*0.08*	*0.07*	0.14	**0.01**
Apparel	0.71	0.65	0.83	0.70
Lumber	*0.08*	**0.05**	0.13	**0.02**
Furniture and fixtures	**0.05**	**0.05**	**0.04**	**0.00**
Paper	0.42	0.32	0.36	0.13
Printing	0.72	0.88	0.65	0.81
Chemicals	0.55	0.22	0.50	0.13
Petroleum and coal	0.40	0.11	*0.09*	**0.01**
Rubber and plastics	**0.04**	**0.01**	*0.07*	**0.00**
Leather	0.49	0.78	0.26	0.85
Stone, clay, and glass	*0.10*	**0.04**	0.17	**0.02**
Primary metals	0.61	0.37	0.53	0.16
Fabricated metals	0.41	0.26	0.60	*0.10*
Industrial machinery	0.80	0.89	0.76	0.73
Electronic and electric equipment	0.53	0.26	0.57	**0.03**
Transportation equipment	0.22	0.12	0.47	*0.09*
Instruments and related products	0.62	0.30	0.68	0.20
Miscellaneous manufacturing	0.32	0.32	0.55	0.34
Motor vehicles and passenger car bodies	0.18	0.13	0.17	**0.02**
Truck and bus bodies	0.66	0.37	0.79	0.32
Motor vehicle parts and accessories	0.11	*0.07*	*0.07*	**0.02**
Truck trailers	**0.05**	**0.01**	*0.06*	**0.00**

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% significance level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 8. Cumulative change in job flows after a 16% positive oil price shock ($x_t^{\#} = x_t^1$)

	1973-1983						1984-1998					
	NET		SUM		EXC		NET		SUM		EXC	
Sector / Quarters since the shock	4	8	4	8	4	8	4	8	4	8	4	8
Total manufacturing (1972:Q2-2005:Q1)							-0.44	-0.71	0.40	0.58	-0.04	-0.13
Total manufacturing (1972:Q2-1998:Q4)	-1.37	-2.10	0.21	0.95	-1.16	-1.27	-0.69	-0.94	0.95	1.27	0.27	0.33
Food	-0.49	-1.02	-0.69	0.67	-2.74	-1.91	0.08	-0.10	0.77	1.25	0.02	0.29
Tobacco	0.43	-0.25	-1.33	-0.86	-2.74	-3.64	1.30	1.14	0.36	0.51	-2.43	-2.89
Textiles	-1.64	-1.37	0.66	2.38	-2.08	-1.60	-0.88	-0.80	0.87	1.01	0.00	0.05
Apparel	-1.22	-2.02	0.35	2.14	-2.08	-2.27	0.44	0.67	1.05	1.07	0.53	0.32
Lumber	-7.21	-6.95	-0.22	1.60	-7.43	-7.17	-1.77	-2.01	1.44	1.61	-0.39	-0.48
Furniture and fixtures	-4.46	-4.41	1.41	3.10	-3.42	-3.80	-0.99	-1.03	1.35	1.55	0.36	0.37
Paper	-3.30	-3.62	0.17	2.18	-3.13	-3.33	-0.14	-0.08	0.05	0.03	-0.38	-0.51
Printing	-0.63	-1.34	-0.26	0.44	-1.63	-1.85	-0.28	-0.18	1.02	0.91	0.39	0.15
Chemicals	-0.13	-0.79	0.50	1.89	-2.13	-2.65	-0.01	0.06	0.19	0.13	-0.47	-0.69
Petroleum and coal	-1.78	-1.88	3.08	4.13	-2.59	-1.96	0.33	0.38	0.06	-0.06	-1.29	-1.56
Rubber and plastics	-3.43	-2.37	1.51	3.45	-1.92	-1.89	-1.45	-1.58	1.24	1.34	-0.21	-0.34
Leather	0.22	-1.36	-0.06	1.77	-2.73	-2.62	-0.81	-0.73	0.48	0.84	-0.75	-0.60
Stone, clay and glass	-4.64	-6.11	0.81	3.24	-3.82	-3.41	-1.16	-1.63	0.91	0.99	-0.28	-0.68
Primary metals	1.06	-3.84	-0.72	2.51	-3.94	-5.61	-0.43	-0.72	-0.12	0.04	-0.91	-1.04
Fabricated metals	-4.23	-5.61	-0.36	1.84	-4.59	-4.81	-0.21	0.13	0.66	0.51	-0.13	-0.61
Industrial machinery	2.48	-2.19	-3.50	-2.82	-6.25	-10.24	-0.14	-0.13	0.37	0.35	0.19	0.07
Electronic and electric equipment	-3.65	-3.92	1.58	2.72	-2.24	-2.24	-0.72	-0.87	0.62	0.78	-0.18	-0.30
Transportation equipment	-3.55	-6.22	4.65	6.09	1.10	-0.13	-1.57	-2.15	1.90	2.98	0.33	0.83
Instruments and related products	1.09	-1.05	0.41	1.53	-2.09	-3.12	0.17	0.22	0.18	0.22	-0.07	-0.10
Miscellaneous manufacturing	-2.14	-2.52	1.49	3.47	-0.82	-0.43	-0.53	-0.24	1.74	1.34	0.60	-0.09
Motor vehicles and passenger car bodies	-16.83	-14.49	32.08	30.68	15.25	11.51	-1.91	-2.19	3.67	6.37	1.77	3.76
Truck and bus bodies	-11.78	-10.57	-2.46	-1.39	-14.52	-15.21	-0.74	-2.01	1.06	1.90	-1.40	-1.84
Motor vehicle parts and accessories	-11.48	-8.92	7.85	10.18	-3.63	-6.33	-1.43	-1.08	0.90	1.25	-0.53	-0.58
Truck trailers	-0.41	-8.67	3.34	14.57	-11.9	-14.81	-5.70	-4.26	4.63	7.49	-1.07	0.34

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

	$x_t^{\#} = x_t^1$		$x_t^{\#} = x_t^4$	
Sector / Sub-sample	1973-1983	1984-1998	1973-1983	1984-1998
Total manufacturing (1972:Q2-2005:Q1)		0.27		0.40
Total manufacturing (1972:Q2-1998:Q4)	0.75	**0.02**	0.76	**0.02**
Food	0.54	0.73	0.31	0.24
Tobacco	0.94	0.69	0.85	0.50
Textiles	1.00	0.16	0.73	0.60
Apparel	0.99	0.71	0.64	0.66
Lumber	1.00	0.30	0.81	0.43
Furniture and fixtures	0.31	0.13	1.00	0.15
Paper	0.32	0.95	0.58	0.97
Printing	0.87	0.34	0.87	0.42
Chemicals	0.72	0.85	0.74	0.71
Petroleum and coal	1.00	0.31	*0.10*	0.39
Rubber and plastics	0.31	**0.05**	0.19	*0.09*
Leather	0.91	0.47	0.85	0.70
Stone, clay and glass	0.82	0.39	0.56	0.45
Primary metals	1.00	0.69	0.76	0.64
Fabricated metals	1.00	0.44	0.64	0.61
Industrial machinery	1.00	0.78	1.00	0.81
Electronic and electric equipment	0.82	0.73	0.50	0.49
Transportation equipment	0.81	0.13	0.84	0.12
Instruments and related products	1.00	0.91	0.56	0.88
Miscellaneous manufacturing	0.91	0.15	0.77	0.36
Motor vehicles and passenger car bodies	0.38	0.33	0.26	0.57
Truck and bus bodies	0.96	0.63	0.77	0.44
Motor vehicle parts and accessories	0.48	0.40	0.62	0.20
Truck trailers	0.19	**0.00**	*0.07*	**0.05**

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% significance level. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Figure 1: Job flows and quarterly change of the real price of oil

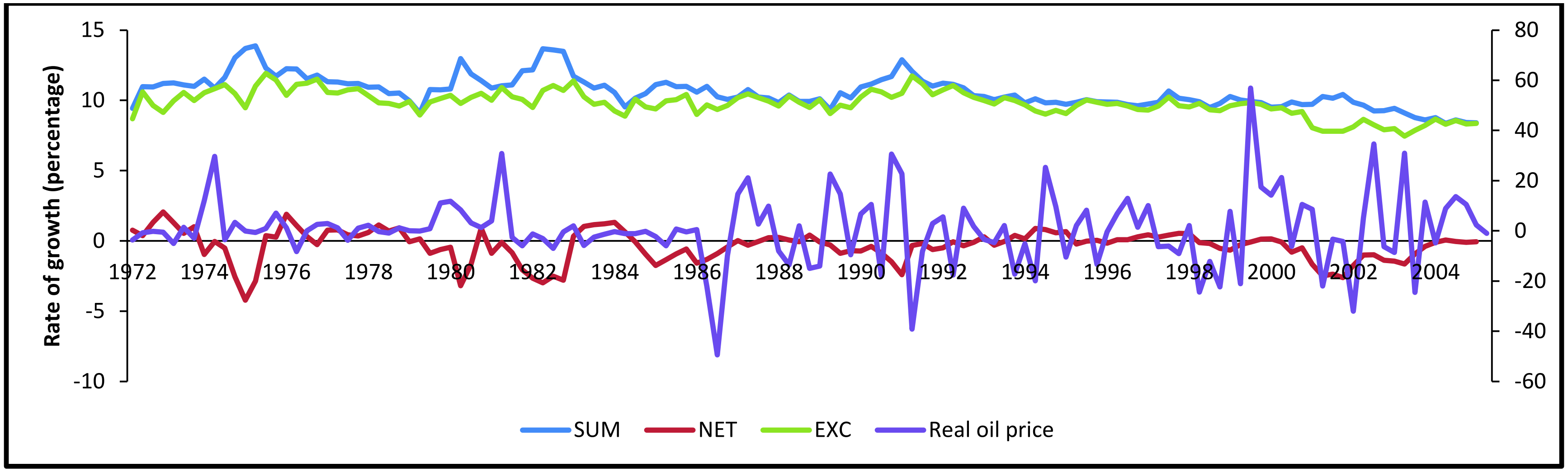


Figure 2: Oil prices and censored oil price measures

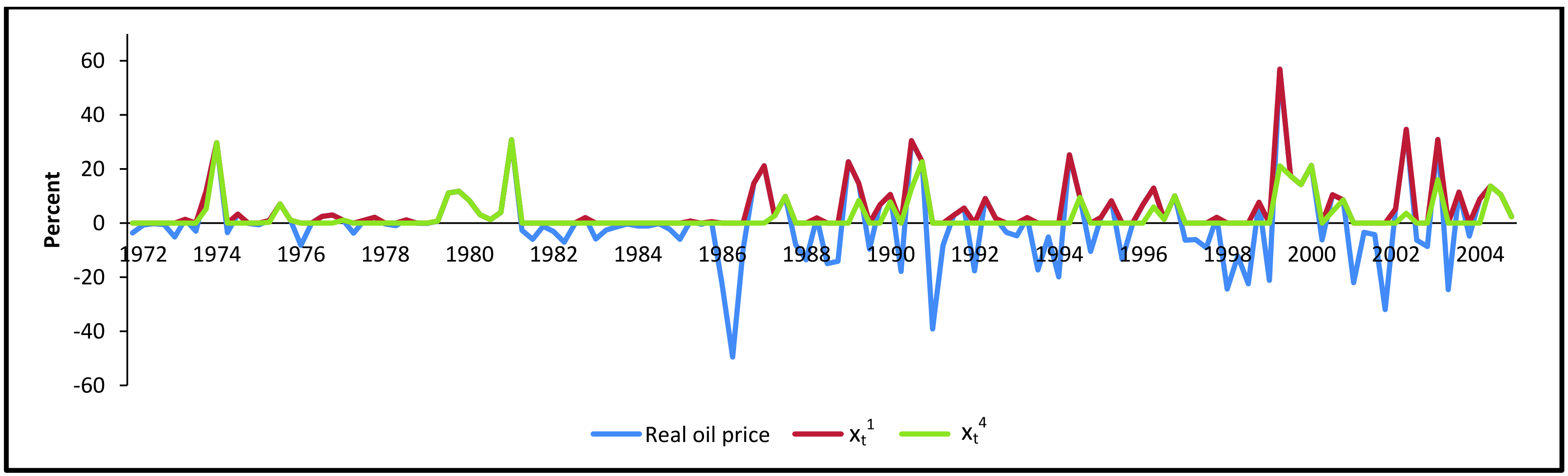
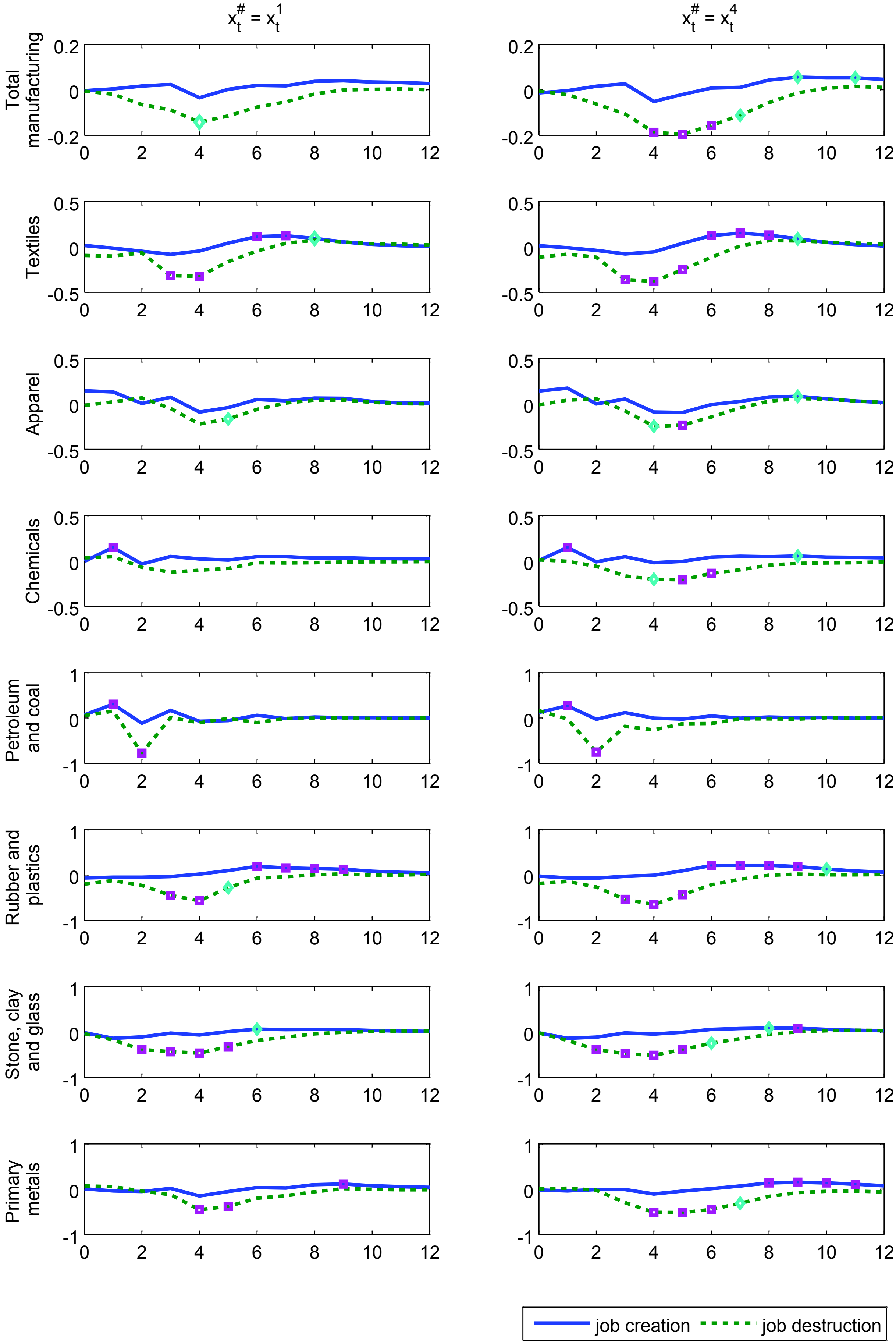
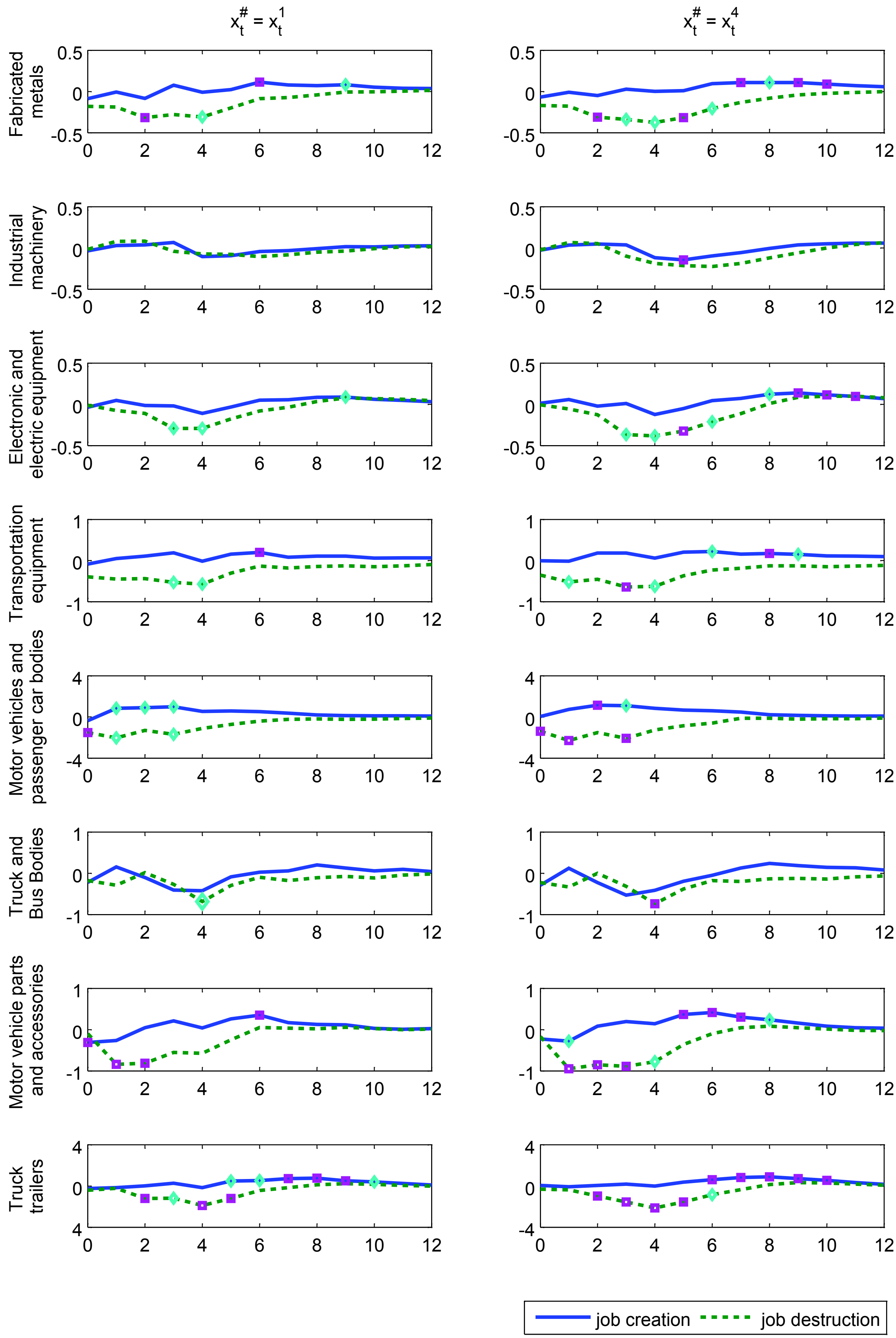


Figure 3a: Job creation and job destruction responses to a positive oil price shock of 1 s.d.



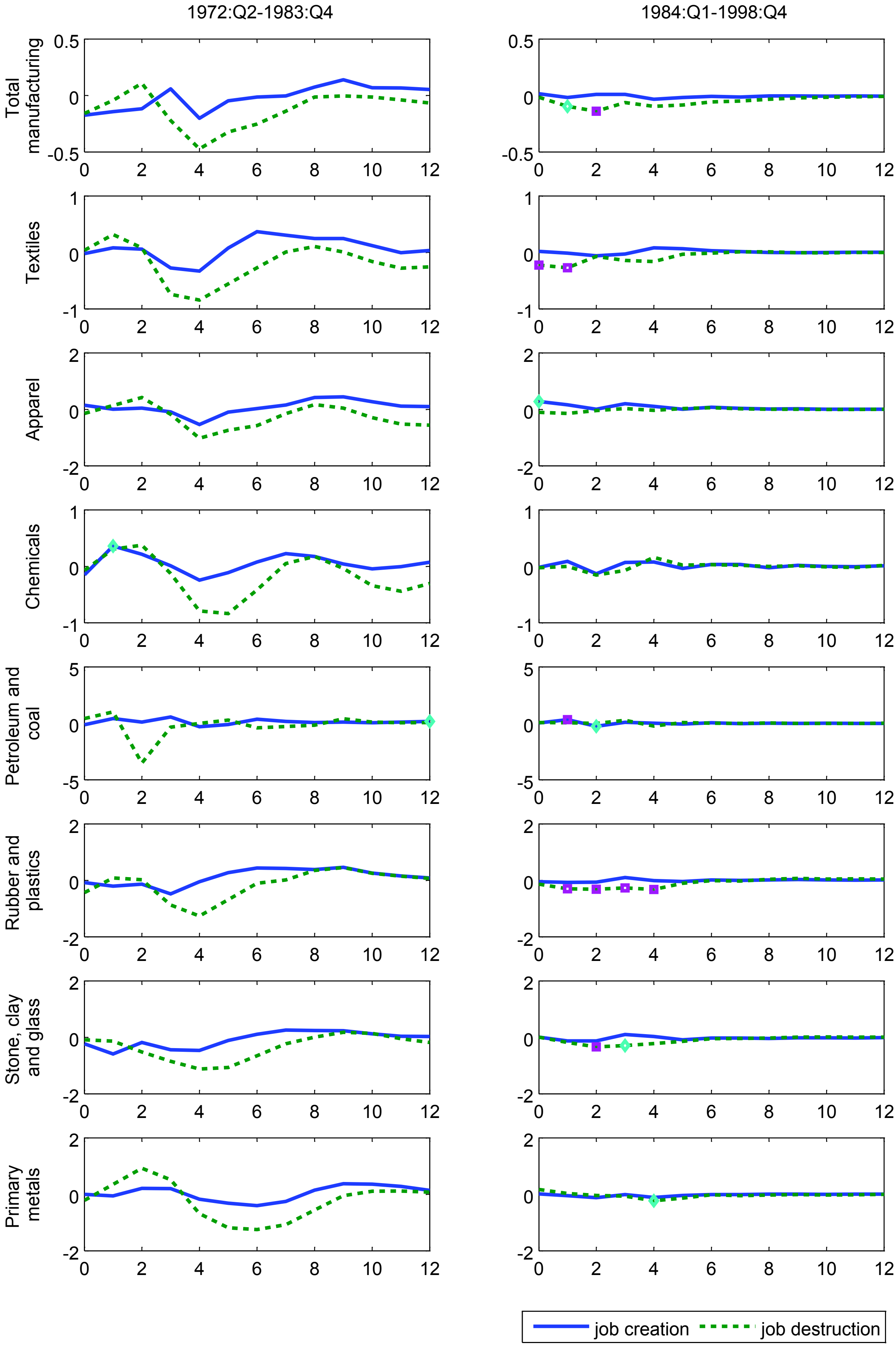
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations of model (8).

Figure 3b: Job creation and job destruction responses to a positive oil price shock of 1 s.d.



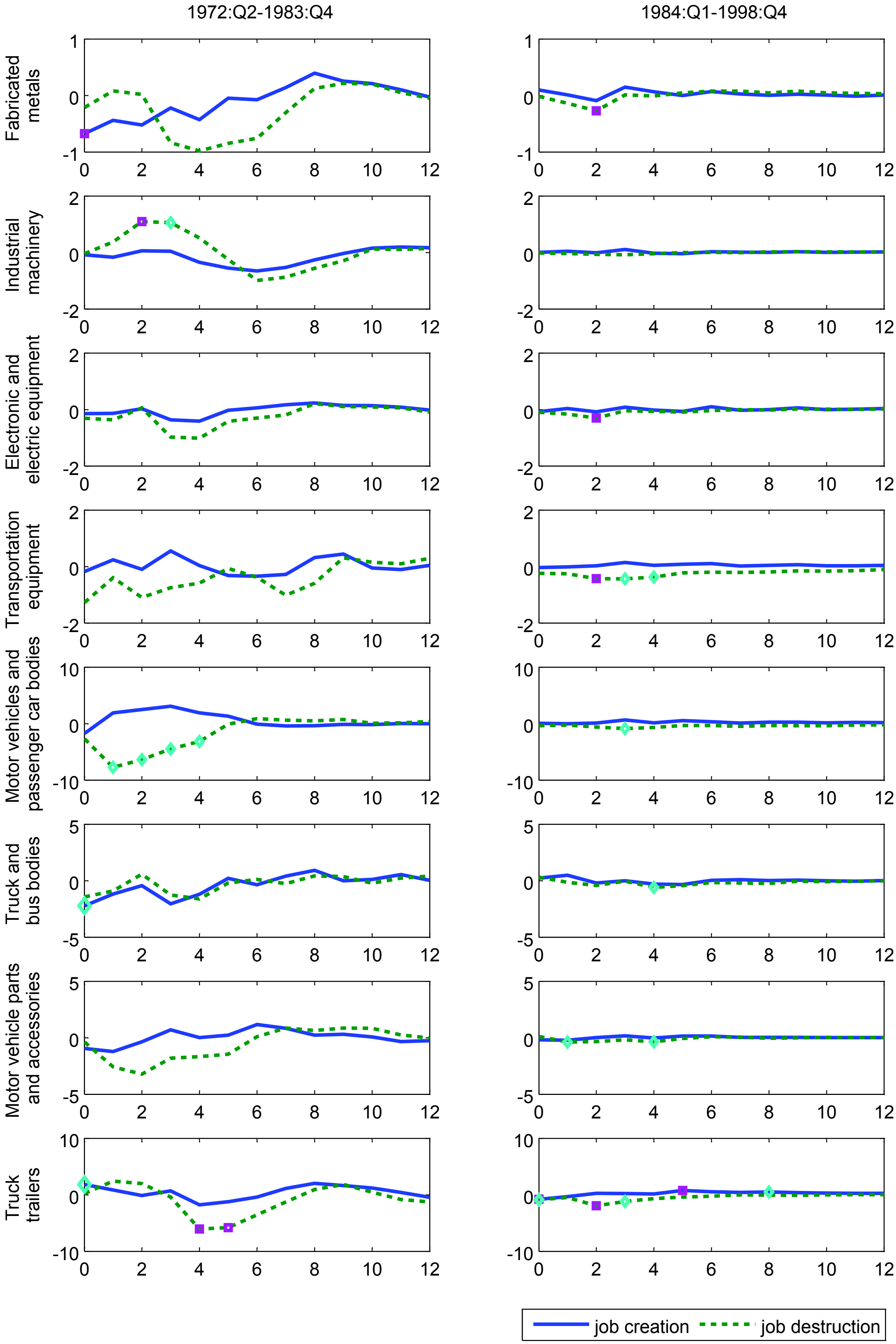
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations of model (8).

Figure 4a: Job creation and job destruction responses to a positive oil price shock before and during the Great Moderation ($x_t^{\#} = x_t^{1}$)



Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations of model (8).

Figure 4b: Job creation and job destruction responses to a positive oil price shock before and during the Great Moderation ($x_t^{\#} = x_t^{1}$)



Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations of model (8).