Asymmetries in the Responses of Regional Job Flows to Oil Price Shocks

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Abstract

This paper studies the effect of oil price innovations on manufacturing job flows across U.S states. First, I estimate a nonlinear structural equation model and compute impulse response functions by Monte Carlo integration. I find asymmetries in the responses of job flows to positive and negative oil price innovations. Yet, these asymmetries do not pass a test of symmetry on the impulse responses, especially after accounting for data mining. Third, I use a test for the absence of job reallocation to evaluate whether an unexpected increase in the real price of oil price triggers an important change in job reallocation. I find that oil price shocks have limited regional allocative effects.

JEL Classification: E24, E32, Q43.

1 Introduction

Differences in unemployment rates across U.S. regions and states are well documented. For instance, it's well known that Texas tend to have an unemployment rate that is lower than the national average whereas other states like Michigan often experience an unemployment rate that exceeds the U.S. national unemployment rate. Yet, little is known about the fundamental labor dynamics behind these differences. Specifically, little is known on how the number of jobs created and destroyed by establishment responds to economic shocks.

In this paper, I study the effect of oil price shocks on manufacturing job creation and job destruction across U.S. states. Recently, Herrera and Karaki (2015) have examined the effect of oil price shocks on job flows in disaggregated manufacturing industries. While work by Herrera and Karaki (2015) contributes to learning about U.S. business cycles, this study contributes to the literature interested in studying regional U.S. business cycles. In particular, this paper investigates the effect of positive and negative oil price innovations on regional job flows and examines whether positive oil price shocks trigger a significant change in job reallocation.

After the 1970s stagflation, economic research on the effect of oil price shocks on economic activity has surged. Many empirical papers found that positive oil price shocks are a major source of economic fluctuations whereas negative oil price shocks only generate mild and insignificant effects on output[1]. The view that positive and negative oil price innovations have asymmetric effects on U.S. economic activity have been reinforced using slope based test of symmetry (see Mork, Olsen, and Mysen, 1994; Cuñado and Pérez de Gracia, 2003; Jiménez-Rodríguez and Sánchez, 2005).

Recently, Kilian and Vigfusson (2011a) – hereafter KV (2011a) – have questioned the consensus reached in the early 2000s literature on the asymmetry in the relationship between oil prices and output. They claim that previous empirical papers that rejected the null of symmetry in the

[1] See, e.g., Mork, 1989; Loungani, 1986; Davis, 1987a,b, Hooker, 1996.

relationship between oil prices and the macroeconomy are based on censored VAR models. In their paper, KV(2011a) explicitly demonstrate how these models can lead to biased and inconsistent estimates, which often exaggerate the impact of oil prices on economic activity. They further explain why the textbook orthogonalized impulse response functions (OIRF) – heavily used in the literature in forecasting the nonlinear impact of oil prices – are not informative about the degree of asymmetry in the response to an oil price shock, and emphasize the importance of computing impulse response functions by Monte Carlo integration that account for the history and the size of the shock (see Koop, Pesaran and Potter, 1996). In addition, KV (2011a) show that slope-based tests cannot reveal whether the responses of economic activity to positive and negative oil price shocks are symmetric. Instead, they propose a test of symmetry on the impulse response functions and find that the relationship between oil prices and GDP growth (or consumption and unemployment rate) is well captured by a linear model. While there seems to be ample evidence in the recent literature that the null of symmetry cannot be rejected using aggregate macroeconomic variables, work by Herrera, Lagalo and Wada (2011) show that the null of symmetry is rejected for some disaggregated industrial production indices.

In theory, oil price shocks affect the macroeconomy through both direct and indirect supply and demand channels (see Kilian, 2014). Direct channels imply symmetry in the response of economic activity to positive and negative oil price innovations whereas indirect channels generate amplifications and asymmetry in the responses. By direct demand side effects, I refer to the change in purchasing power upon an oil price shock, which leads to a symmetric change in aggregate demand (see Baumeister and Kilian, 2017; Baumeister, Kilian and Zhou, 2017). On the other hand, there are indirect demand side effects that generate asymmetries and amplification in the response of output to an unexpected oil price shock due to increases in precautionary saving (see Edelstein and Kilian, 2009) associated with heightened uncertainty (see Bernanke, 1983 and Pindyck, 1991) and a change in the composition of demand (see Ramey and Vine, 2012). For instance, an increase or a decrease in the price of oil will increase uncertainty and push households to increase their precautionary saving. As a result, regardless of the direction in the change of the price of oil, consumption expenditure will decrease which will increase the adverse effect associated with an oil price increase and mitigate the benefits associated with an oil price decline. By direct supply side effects, I refer to the change in the cost of production associated with oil price shocks, which leads to a symmetric change in aggregate supply (see Rotemberg and Woodford, 1996). On the other hand, I refer to the deployment of labor and capital across sectors (see Davis 1987a; Davis 1987b; Davis and Haltiwanger, 2001; Hamilton, 1988) as the indirect supply side effects that generate an asymmetric impact on output and employment. The costly sectoral reallocation channel implies that regardless of the sign of the oil price shock, resources will chose to relocate from most affected to least affected sectors creating a mismatch in the labor market. This channel of transmission will amplify the negative effects associated with higher oil prices and reduce the positive effects generated with lower oil prices.

This paper has four main contributions. First unlike previous studies (e.g. Davis and Haltiwanger, 2001, Herrera and Karaki, 2015; Herrera, Karaki and Rangaraju, 2017) that solely focused on industry level data within the manufacturing sector, this study analyzes the effect of oil price shocks on manufacturing job flows across U.S. states. Studies that use disaggregated data by industry are often based on a small sample due to the change in the industry classification from SIC to NAICS in the late 1990s. Using disaggregated data by state allow us to use a dataset that covers a variety of oil price shock episodes including the recent oil price decline in 2014.

Second, I use a nonlinear structural model building on Kilian and Vigfusson (2011a) and Herrera and Karaki (2015) methods that nest both symmetric and asymmetric effects associated with the transmission of oil prices to the economy, and compute impulse response functions by Monte Carlo integration to analyze the effect of positive and negative oil price innovations on manufacturing job creation and job destruction across U.S. states. Results show important heterogeneity in the responses of job flows. In addition, I find important asymmetries in the responses of job creation and job destruction to positive and negative oil price innovations. A closer look at the 1-year cumulative effects reveal that the responses of job creation and job destruction to a negative oil price shock are at least as large as the responses of job flows to a positive oil price shock.

Third, I evaluate whether the responses of job flows to positive and negative oil price shocks are asymmetric by using a test of symmetry following KV (2011a) and Herrera and Karaki (2015). Using conventional critical values, I find no evidence against the null of symmetry for a 1 standard deviation shock. For a 2 standard deviation shock, the null of symmetry is rejected for few states. Yet, the evidence against the null of symmetry vanishes for all states after using data mining robust critical values. This result is in line with Engemann, Owyang and Wall (2012) who find no evidence of asymmetry in the response of payroll employment across states to positive and negative oil price shocks.

Fourth, while previous work by Davis and Haltiwanger (2001) and Herrera and Karaki (2015) have studied whether oil price shocks operate through costly sectoral reallocation channels, this paper investigates whether positive oil price shocks trigger significant reallocation of jobs across U.S. states. Investigating the transmission mechanism through which oil price shocks affect regional economies directly contributes to the literature interested in studying disparities and commonality of regional U.S. business cycles (see Hamilton and Owyang, 2012; Engemann, Owyang and Wall, 2014; Karaki, 2017). To evaluate whether positive oil price shocks have a significant effect on job reallocation, I follow Herrera and Karaki (2015) and implement a test of the absence of job reallocation. I find no evidence against the null of the absence of job reallocation for a shock of 1 standard deviation. I also find that an unexpected positive oil price shock of 2 standard deviation has no effect on job reallocation across all U.S. states especially after accounting for data mining.

The rest of the paper is structured as follows. Section 2 discusses the data on regional job flows and oil prices. I present the model in section 3 and discuss the computation of the impulse response functions. Section 4 explores the empirical results. Section 5 conducts a test of symmetry à la KV (2011a) to investigate whether the responses of job flows are symmetric to positive and negative oil price innovations. Section 6 evaluates whether a positive oil price shock have significant regional allocative effects. Section 7 concludes.

2 Job Creation, Job Destruction and Oil prices

I used two databases on quarterly state job flows data in the manufacturing sector to study the effect of oil prices on job creation and job destruction across U.S. states. For the 1972:Q2 to 1998:Q4 period, I obtain data from the Gross Job Flows database (1996, 2005) by Davis and Haltiwanger and Shuh. For the 1999:Q1 to 2015:Q3, I use the Business Employment Dynamics database from the Bureau of Labor Economics.

As defined by Davis and Haltiwanger and Schuh (1996), job creation represents the sum of employment gains at expanding and entering establishments and job destruction represents the sum of employment losses at contracting and exiting establishments. These job flows measures are computed as job creation and job destruction rates, POS_t and NEG_t. Following Davis and Haltiwanger and Schuh (1996), I define the net growth rate of employment for state j at time t as:

$$NET_{j,t} = POS_{j,t} - NEG_{j,t}, \tag{1}$$

and the job reallocation rate is defined as the sum of $POS_{j,t}$ and $NEG_{j,t}$.

$$SUM_{j,t} = POS_{j,t} + NEG_{j,t}, \tag{2}$$

As an indicator for labor market flexibility I define the excess job reallocation rate as:

$$EXC_{j,t} = POS_{j,t} - |NET_{j,t}|\,. \tag{3}$$

This measure of job reallocation portrays the amount of reallocation that would have been necessary to offset the changes in net employment growth[2].

Regarding the oil price measures, I compute nominal oil prices using the imported U.S. crude oil refiners acquisition cost reported by the Energy Information Agency. Then, I obtain the real oil price by deflating the nominal price of oil with the consumer price index (CPI). In the model section, I define x_t as the percentage change in the real price of oil and $x_t^{\#}$ as a nonlinear transformation of oil prices.

I use two different nonlinear transformations of the natural logarithm of the real oil price o_t. The first measure is Mork's (1989) oil price increase. This measure was motivated by Mork's (1989) claim that oil price increases lead to significant economic downturns while decreases in oil prices have no effect on economic activity. This nonlinear transformation of oil prices sets the value of $x_t^{\#}$ equal to zero for any period where the oil price change was negative:

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

The second censored oil price measure used in our analysis is Hamilton net oil price increase measure (Hamilton, 1996). This measure set $x_t^{\#}$ equal to zero for the oil price increases that does

[2] Note that the excess job reallocation rate is measure that is known for tracking flexibility in the labor market (see Micco and Pagés, 2004; Cuñat and Melitz 2012).

not exceed the previous year's maximum:

$$x_t^4 = \max\left\{0, \ln\left(o_t\right) - \max\left\{0, \ln\left(o_{t-1}\right), ..., \ln\left(o_{t-4}\right)\right\}\right\}. \tag{5}$$

As suggested by Hamilton (1996, 2003) this nonlinear transformation of oil prices is known for successfully capturing the nonlinear relationship between the price of oil price and U.S. aggregate economic activity.

3 Model

To study the effect of oil price shocks on job creation and job destruction I estimate the following structural model using 4 quarterly lags:

$$x_t = a_{10} + \sum_{i=1}^{p} a_{11,i} x_{t-i} + \sum_{i=1}^{p} a_{12,i} NEG_{S,t-i} + \sum_{i=1}^{p} a_{13,i} POS_{S,t-i} + \varepsilon_{1,t} \tag{6a}$$

$$NEG_{S,t} = a_{20} + \sum_{i=0}^{p} a_{21,i} x_{t-i} + \sum_{i=1}^{p} a_{22,i} NEG_{S,t-i} + \sum_{i=1}^{p} a_{23,i} POS_{S,t-i} + \sum_{i=0}^{p} g_{21,i} x_{t-i}^{\#} + \varepsilon_{2,t} \tag{6b}$$

$$POS_{S,t} = a_{30} + \sum_{i=0}^{p} a_{31,i} x_{t-i} + \sum_{i=0}^{p} a_{32,i} NEG_{S,t-i} + \sum_{i=1}^{p} a_{33,i} POS_{S,t-i} + \sum_{i=0}^{p} g_{31,i} x_{t-i}^{\#} + \varepsilon_{3,t} \tag{6c}$$

where x_t stands for the percentage change in oil prices, $x_t^{\#}$ refers to any of the two nonlinear transformation of oil prices defined in section 2, $POS_{j,t}$ is the job creation rate in the state j, $NEG_{j,t}$ is the job destruction rate in state j, and $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}]$ is a vector of contemporaneously and serially uncorrelated innovations. I follow Herrera and Karaki (2015) and impose the following identification restrictions. Oil prices are assumed to be predetermined to job destruction and job creation. This assumption is consistent with work by Kilian and Vega (2011) who found that oil prices do not respond contemporaneously to employment. I also assume that job destruction does not respond contemporaneously to changes in job creation because of staggered labor contracts. The model in 6(a)-6(c) can be estimated efficiently by OLS. Given that the model is nonlinear in x_t, textbook impulse response functions will convey misleading information on the effect of oil price innovations (see Gallant, Rossi and Tauchen 1993 and Koop, Pesaran and Potter 1996, Kilian and Vigfusson 2011a). Therefore, I compute impulse response functions by Monte Carlo integration that account for the history and the size of the shock as follows:

1. I store the estimated coefficients, standard errors and residuals obtained from estimating model 6a-c by OLS.

2. I condition on a given history $\{x_{t-1}, \ldots, x_{t-p}, NEG_{t-1}, ..., NEG_{t-p}, POS_{t-1}, ..., POS_{t-p}\} = \{X_t, N_t, P_t\} \in \Omega^t$ and I generate two time paths, for oil (x_t), job destruction (NEG_t) and job creation (POS_t). The first path for x_t (x_t^1) is generated by tracing the response of x_t to an oil price innovation of size δ (1 or 2 s.d.). The other time path for x_t (x_t^2) is generated by tracing the response of x_t to a shock ε_{1t} drawn from the empirical distribution of ε_{1t}.

3. The updated information sets along with the censored variables are $\mathcal{I}_t^1 = \{1,\, x_t^1,\, X_t,\, N_t,\, P_t,\, x_t^{1\#},\, X_t^{1\#}\}$ and $\mathcal{I}_t^2 = \{1,\, x_t^2,\, X_t,\, N_t,\, P_t,\, x_t^{2\#},\, X_t^{2\#}\}$. Given these two histories, two paths for NEG_t are generated. The first time path for NEG_t (NEG_t^1) is generated by tracing the response of NEG_t to a shock ε_{2t} drawn from the empirical distribution of ε_{2t} and using the information set $\mathcal{I}_t^1$ and the other time path for NEG_t (NEG_t^2) is obtained by tracing the response of NEG_t to a shock ε_{2t} drawn from the empirical distribution of ε_{2t} and using the information set $\mathcal{I}_t^2$.

4. The new updated information sets are now defined as $\widetilde{\mathcal{I}}_t^1 = \{1,\, x_t^1,\, N_t^1,\, X_t,\, N_t,\, P_t,\, x_t^{1\#},\, X_t^{1\#}\}$ and $\widetilde{\mathcal{I}}_t^2 = \{1,\, x_t^2,\, N_t^2,\, X_t,\, N_t,\, P_t,\, x_t^{2\#},\, X_t^{2\#}\}$. Given these two histories, two paths for POS_t are generated. The first time path for POS_t (POS_t^1) is generated by tracing the response of

POS_t to a shock ε_{3t} drawn from the empirical distribution of ε_{3t} and using the information set $\widetilde{\mathcal{I}}_t^1$ and the other time path for POS_t (POS_t^2) is obtained by tracing the response of POS_t to a shock ε_{3t} drawn from the empirical distribution of ε_{3t} and using the information set $\widetilde{\mathcal{I}}_t^2$.

5. Step $2-4$ are repeated for $H+1$ times (where $H=12$).

6. After R (I set $R=10,000$) replications of steps (2)-(4), I generate the conditional $IRFs$ as

$$I_{NEG}\left(h,\delta,\Omega^t\right)=\frac{1}{R}\sum_{r=1}^{R}NEG_{t,r}^1-\frac{1}{R}\sum_{r=1}^{R}NEG_{t,r}^2 \quad \text{for } h=0,1,\ldots,H$$

and

$$I_{POS}\left(h,\delta,\Omega^t\right)=\frac{1}{R}\sum_{r=1}^{R}POS_{t,r}^1-\frac{1}{R}\sum_{r=1}^{R}POS_{t,r}^2 \quad \text{for } h=0,1,\ldots,H$$

7. The unconditional $IRFs$ are generated by repeating (2) to (6) for all possible Ω^t, and then taking the mean over all the histories.

$$I_{NEG}\left(h,\delta\right)=\int I_{NEG}\left(h,\delta,\Omega^t\right)\ d\Omega^t$$

and

$$I_{POS}\left(h,\delta\right)=\int I_{POS}\left(h,\delta,\Omega^t\right)\ d\Omega^t$$

We also follow the same approach for a negative shock $-\delta$, to obtain the unconditional response of job destruction, $I_{NEG}\left(h,-\delta\right)$, and the unconditional response for job creation, $I_{POS}\left(h,-\delta\right)$.

4 Impulse response functions and quantitative effects

In this section, I compute the effect of typical ($\delta=1$ standard deviation) and large ($\delta=2$ standard deviation) oil price innovations on job flows across U.S. states. Even though it's quite known that most oil price innovations, specifically 2 third of the oil price innovations, have a magnitude of 1 standard deviation (see Kilian and Vigfusson, 2016), Hamilton (2009) argue that researchers are often interested in the consequences of extraordinary events when they analyze the effect of oil price shocks. Therefore, despite the high uncertainty associated with estimating large oil price shocks, I discuss in this section the effect oil price shocks for two different magnitudes.

4.1 The effect of a typical shock

Figure 1 (Figure 2) reflects the responses of job creation (job destruction) to positive and negative oil price innovations of 1 standard deviation (1 s.d.) using Mork (1989) oil price increase as a nonlinear transformation for the real price of oil[3]. Results based on the net oil price increase measure (see Hamilton, 1996) are reported in the online appendix. The 95% and 90% confidence bands are reports in squares and diamonds, respectively. To get a better grasp on whether the responses of job creation (job destruction) are asymmetric to oil price shocks, I report the negative of the response of job creation (job destruction) to a negative oil price shock.

Let us focus first on the response of job creation. Figure 1 reveal that the response of job creation to positive and negative oil price innovations is asymmetric for most states except for Connecticut, Louisiana and Idaho. Table 2 reports the 1-year cumulative effects of positive and negative oil price innovations on job flows. Interestingly, I find that in absolute terms the 1-year cumulative response of job creation to a negative oil price shock is larger than the 1-year cumulative response of job creation to a positive oil price shock for total manufacturing and 29 out of 40 U.S. states. This finding indicates that job creation across states is more responsive to negative than to positive oil price innovations[4].

[3]The figures for the remaining states are available in the online appendix (see figure A.1a-c and figure A. 2a-c). Note also that the impulse responses are similar to the responses based on the 1-year net oil price increase nonlinear transformation of the real price of oil (see figure A.7a-c and figure A.8a-c of the online appendix).

[4]I report the cumulative responses of job flows for the net oil price increase measure in the online appendix (see table A.1).

The effect of oil price shocks on state job destruction rate is depicted in figure 2. These figures portray important asymmetries in the response of job destruction to positive and negative oil price innovations that greatly vary across states. For almost all states, the magnitude of this asymmetry peaks within a year following an oil price shock. The 1-year cumulative response of job destruction to a negative oil price shock is larger than the 1-year cumulative response of job destruction to a positive oil price shock for total manufacturing and 32 out of 40 U.S. states. This finding indicates that, similar to job creation, state-level job destruction responds more to negative and positive oil price innovations.

How does the net employment change across states responds to positive and negative oil price innovations of 1 standard deviation? Table 2 reveals that the 1-year cumulative effect of a positive oil price shock on net employment is negative for total manufacturing and 19 out of 40 states. The most negatively affected states with an unexpected oil price increase are Idaho and Michigan, whereas states that tend to benefit the most are Oklahoma and Texas. Interestingly, the effect of a negative oil price shock on net employment is negative for total manufacturing and 39 out of 40 states. In fact, for almost all states, a negative oil price innovation trigger a larger change in net employment compared to a positive oil price innovation. These results indicate that reductions in oil prices do not stimulate employment across states and reveal that net employment is more affected with negative than positive oil price innovations.

The response of job reallocation to oil price innovations differ greatly across states. The 1-year cumulative effect associated with a positive (negative) oil price shock on gross job reallocation is 0.47 (0.81) percentage points for Michigan and 1.79 (-1.33) percentage points for Nevada (see Table 2). Interestingly, the 1-year cumulative response of gross job reallocation and excess job reallocation to a negative oil price shock is larger in absolute terms than the cumulative effects triggered by a positive oil price shock for more than half of the states that I study. Moreover, I find that regardless of the oil price change direction, the 1-year cumulative response of the excess job reallocation rate is negative for almost all U.S. states.

4.2 The effect of a large oil price shock

How much larger is the response of job flows to oil price innovations of 2 standard deviations? Figure 3 and Figure 4 reflect the responses of job creation and job destruction to positive and negative oil price innovations of 2 standard deviations. The reported results are based on the Mork (1989) oil price increase nonlinear transformation for the real price of oil[5].

The response of job creation to positive and negative oil price innovations reveal sharp asymmetries for ($h < 4$). As in the case for a 1 s.d. shock, the 1-year cumulative response of job creation to a large shock is more responsive to a negative than a positive oil price shock for total manufacturing and 29 out of 40 U.S. The 1-year cumulative response of job creation to a positive shock is negative for 21 out of 40 states, whereas, the 1-year cumulative response of job creation to a negative shock is negative for 38 out of 40 states.

The impulse response functions reported in Figure 5 reveal sharp asymmetries in the response of job destruction rate to positive and negative oil price innovations. Table 3 reveals that the 1-year cumulative response of job destruction to a negative oil price shock exceeds the 1-year cumulative response of job destruction to a positive oil price shock for most states. More than that, for almost all states the cumulative response of job destruction is positive for both positive and negative oil price innovations. This result indicates that large oil price shocks, regardless of their sign, trigger firms to shed more jobs across states.

The 1-year cumulative response of net employment to a negative oil price shock is negative

[5] Results for remaining states are available under the online appendix (see Figure A.3a-c and figure A.4a-c). Figure A.9a-c and figure A.10a-c of the online appendix reveal that using the 1-year net oil price increase nonlinear transformation of the real price of oil generate similar results. Note also that the cumulative effects on job flows for the net oil price increase measure are reported in Table A.2.

for total manufacturing and all U.S. states. For a positive oil price shock, the 1-year cumulative response of net employment is negative for total manufacturing and 25 out of 40 U.S. states. Note that the 1-year cumulative change triggered by a negative oil price shock exceeds the 1-year cumulative response of net employment following a positive oil price shock for almost all states. These findings indicate that both positive and negative oil price innovations have a negative effect on manufacturing net employment across states.

A large positive oil price shock triggers substantial changes in job reallocation across states. Table 3 reflects that following a positive (negative) oil price shock, the 1-year cumulative change in gross job reallocation ranges between -1.82 (-2.04) and 4.27 (3.15) percentage points. For instance following a positive (negative) oil price shock, the 1-year cumulative response of gross job reallocation is 2.61 (3.15) percentage points for Michigan and 4.27 (-2.04). These effects are almost three times larger than the response of gross job reallocation to 1 standard deviation shock. Similarly, Table 3 show important heterogeneity in the 1-year cumulative response of excess job reallocation to large oil price shocks. For a positive (negative) oil price shock, the 1-year cumulative response of excess job reallocation to a large shock is more than twice as large the 1-year cumulative response of excess job reallocation for a 1 standard deviation shock for 20 (31) U.S. states.

5 Test of symmetry

Given the ample evidence in the previous section that oil price innovations trigger important asymmetries in the response of job flows to positive and negative oil price innovations, in this section I use a formal test of symmetry as in Kilian and Vigfusson (2011a) to evaluate whether the observed asymmetries in the impulse response are significant. The test of symmetry is based on the following null hypothesis for job creation:

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

and similarly for job destruction:

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

In addition I conduct the test of symmetry to evaluate whether net employment, job reallocation and excess job reallocation respond asymmetrically to positive and negative oil price innovations:

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

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

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

I set $H = 4$, to reduce the data mining problem associated with repeating the test across several horizons. Table 4 reports the p-values for this test for both 1 s.d. and 2 s.d. shocks. For a typical shock of 1 s.d, the null of symmetry in the response of job destruction to positive and negative oil price innovations is only rejected for Georgia at the 5% level. The null of symmetry cannot be rejected for job creation at the 5% level. For net employment, the null of symmetry is only rejected for Georgia at the 5% level. Moreover, the null of symmetry cannot be rejected for both gross job reallocation and excess job reallocation.

For a large shock of 2 s.d., the null of symmetry for job destruction is rejected for total manufacturing and few states (5 out of 40 states). The null of symmetry for job creation cannot be rejected neither total manufacturing nor for any U.S. states. For the net employment change, I reject the null of symmetry for total manufacturing and 6 out of 40 states. For gross job reallocation, the null of symmetry is rejected for 4 out of 40 states.

Given that I have conducted the same test of symmetry for different state-level job flows, a common concern in this approach is that there is an element of data mining. To address this concern I construct data mining robust critical values by simulating the null distribution of the supremum of the bootstrap Wald test statistic for all U.S. states and for both $x_t^1$and x_t^4 nonlinear transformations for the real price of oil as in Herrera and Karaki (2015)[6]. Yet, after accounting for data mining robust critical values, evidence against the null of symmetry vanishes[7].

6 The allocative channel of oil price shocks

One main transmission mechanism through which oil price shocks operate is the costly reallocation channel. This channel indicates that regardless of the direction of the oil price change, resources will be relocated from industries that are damaged from the oil price change to industries that benefit from the change in the real price of oil. Because, I found no evidence that positive and negative oil price innovations have asymmetric effects on job flows, I focus here on the effect of a positive oil price shock on state-level job reallocation. In fact, because different states have a different mix of industries, then one important investigation is to evaluate whether a positive oil price shock trigger important rellocative effects across U.S. states. Figure 5 and 6 report the response of job creation, job destruction, gross job reallocation and excess job reallocation to a positive oil price shock for a positive oil price shock of 1 s.d. and 2 s.d., respectively[8]. The impulse response functions reveal

[6]Work by Inoue and Kilian (2004) and Kilian and Vega (2011) explain in detail the effect of data mining and solutions for this problem.

[7]I also obtain very similar results using the net oil price increase measure (see table A.3).

[8]The results for the remaining states are reported in the online appendix (see figure A.5a-c and figure A.6a-c). Note also that the results based on the net oil price increase measure are reported in the online appendix (see figure A.11a-c and figure A.12a-c).

substantial differences in the responses of job reallocation and excess job reallocation across U.S. states and show that the largest change in the response of job reallocation occurs within a year following an unexpected positive oil price innovation.

To evaluate whether an unexpected oil price increase trigger significant changes in state-level job reallocation, I implement the test for the absence of job reallocation by Herrera and Karaki (2015) where:

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

the test is computed for $H = 4$ to reduce the data mining problem arising from repeatedly applying the test for different horizons. The focus is mainly on the 4 quarters effect given that there is ample evidence that oil price shocks have their largest effects 1-year after the shock[9].

Table 5 reports the $p - values$ for the test of the absence of job reallocation based on conventional critical values for both 1 s.d. and 2 s.d. shocks. Table 5 reveals that, for a 1 standard deviation oil price innovation, the null of the absence of job reallocation cannot be rejected for total manufacturing and all U.S. states at the 10% significance level. For a large shock, a 2.s.d. oil price innovation, the effect of oil price shocks on job reallocation is only significant at the 10% for Mississippi and Virginia. The null for the absence of job reallocation cannot be rejected for any state after using data mining robust critical values. Note that results reported in the online appendix also show that using the 1 year net oil price increase as a nonlinear transformation in the real price of oil lead to very similar results[10]. These findings indicate that oil price innovations have almost no effect on job reallocation across U.S. states, which indicates that oil price shocks mainly operate through aggregate channels.

[9] see Davis and Haltiwanger (2001), Lee and Ni (2002), Herrera and Karaki (2015).

[10] see table A.4 of the online appendix.

7 Conclusion

This paper studied the effect of oil price innovations on manufacturing job flows across U.S. states. Unlike previous studies that solely focused on industry level data and were based on a small dataset due to the change in the industry classification from SIC to NAICS, this study is based on a larger dataset on manufacturing state-level job creation and job destruction rates. The data set comprises different periods of oil price fluctuations including the recent oil price declines that started in 2014.

I used a structural equation model that nests both symmetric and asymmetric effects of oil price shocks on job creation and job destruction. I estimated the model by OLS and computed impulse response functions by Monte Carlo integration that account for the history and the size of the shock, to examine the dynamic effect of oil price shocks on job flows. The IRFs reveal important heterogeneity in the responses of job creation and job destruction across different states. For instance following a positive oil price shock, the most affected states are Idaho and Michigan, whereas some states such as Oklahoma and Texas tend to benefit from this shock. In addition, the impulse response functions show important asymmetries to positive and negative oil price innovations for both job creation and job destruction. To evaluate whether these asymmetries in the impulse responses are significant, I followed Kilian and Vigfusson (2011a) and conducted a test of symmetry. Results reveal that for a typical shock, the null of symmetry is not rejected for all state-level job creation and job destruction rates. Little evidence against the null of symmetry is found for a large shock. Furthermore, all evidence of against the null of symmetry completely vanishes after accounting for data mining.

To assess whether oil price shocks trigger important allocative effects, I studied the effect of a positive oil price shock on job reallocation. By evaluating whether oil price shocks trigger a reallocation of jobs across U.S. states, I directly contribute to the literature interested in studying regional U.S. business cycles. I implemented a test for the absence of job reallocation following

Herrera and Karaki (2015) and found no evidence that an unexpected positive oil price shock has a significant effect on job reallocation across U.S. states. These findings are in line with Herrera and Karaki (2015) who also found that oil price shocks mainly operate through aggregate channels.

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Table 1: Summary statistics for job flows

Sector	POS	NEG	NET	SUM	EXC
Total manufacturing	4.51	8.91	-4.40	13.41	8.96
Alabama	7.64	3.81	3.83	11.45	7.08
Arkansas	7.92	4.60	3.32	12.53	7.96
Arizona	6.03	6.37	-0.34	12.40	8.75
California	5.96	5.20	0.76	11.15	9.37
Colorado	5.92	4.33	1.59	10.25	8.47
Connecticut	6.86	4.20	2.66	11.06	8.05
Florida	5.33	5.58	-0.25	10.91	9.00
Georgia	5.04	7.30	-2.26	12.34	10.04
Iowa	5.41	4.97	0.43	10.38	9.07
Idaho	6.72	5.00	1.71	11.72	9.30
Illinois	4.41	9.37	-4.96	13.77	8.70
Indiana	3.72	10.98	-7.26	14.70	7.42
Kansas	5.70	8.34	-2.65	14.04	11.10
Kentucky	7.91	5.13	2.78	13.03	9.95
Louisiana	5.93	6.66	-0.73	12.59	10.33
Massachusetts	6.68	6.31	0.37	12.99	11.74
Maryland	7.19	5.11	2.07	12.30	10.15
Maine	6.65	4.92	1.74	11.57	9.35
Michigan	5.47	7.00	-1.52	12.47	10.16
Minnesota	5.74	6.30	-0.56	12.04	10.79
Missouri	6.06	5.01	1.05	11.07	9.66
Mississippi	6.37	4.65	1.72	11.03	8.91
Montana	5.46	5.56	-0.11	11.02	9.15
North Carolina	5.55	5.79	-0.23	11.34	10.16
Nebraska	6.08	3.95	2.13	10.03	7.83
New Hampshire	5.67	4.14	1.53	9.81	7.89
New Jersey	5.37	4.48	0.90	9.85	7.94
Nevada	5.14	6.00	-0.86	11.14	9.73
New York	4.45	3.62	0.84	8.07	6.99
Ohio	4.99	4.53	0.47	9.52	7.13
Oklahoma	4.45	5.23	-0.78	9.68	7.92
Oregon	4.81	6.87	-2.06	11.68	9.50
Pennsylvania	4.15	7.98	-3.82	12.13	8.17
South Carolina	5.26	6.58	-1.33	11.84	9.27
Tennessee	6.00	5.03	0.97	11.03	8.61
Texas	4.82	7.07	-2.25	11.88	9.21
Utah	4.89	5.50	-0.61	10.40	8.84
Virginia	4.95	5.14	-0.19	10.09	7.94
Washington	3.89	7.40	-3.51	11.30	7.79
Wisconsin	4.18	9.80	-5.63	13.98	8.23

Table 2: Cumulative effects of oil price innovations of 1 s.d. ($x_t^{\#} = x_t^1$)

	Positive shock					Negative shock				
sector	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Total manufacturing	0.10	0.12	-0.02	0.22	-0.16	-0.15	0.38	-0.53	0.23	-0.37
Alabama	-0.01	0.05	-0.06	0.04	-0.45	-0.12	0.44	-0.56	0.33	-0.34
Arkansas	-0.09	-0.39	0.30	-0.48	-1.11	-0.06	0.54	-0.60	0.48	-0.17
Arizona	0.18	-0.40	0.59	-0.22	-1.12	-0.41	0.83	-1.24	0.42	-0.85
California	0.43	-0.11	0.54	0.33	-0.28	-0.63	0.32	-0.95	-0.31	-1.27
Colorado	0.32	-0.22	0.54	0.09	-0.80	-0.62	0.65	-1.28	0.03	-1.28
Connecticut	0.43	-0.18	0.61	0.25	-0.47	-0.46	0.55	-1.01	0.09	-0.93
Florida	0.31	0.13	0.18	0.43	-0.11	-0.45	0.35	-0.80	-0.10	-0.95
Georgia	0.00	-0.02	0.02	-0.02	-0.51	-0.14	0.55	-0.69	0.41	-0.35
Iowa	-0.23	-0.72	0.49	-0.95	-2.04	0.11	0.92	-0.81	1.03	0.14
Idaho	-0.80	0.29	-1.09	-0.50	-1.94	0.18	0.05	0.13	0.23	-1.71
Illinois	0.09	0.14	-0.05	0.24	-0.25	-0.20	0.33	-0.54	0.13	-0.50
Indiana	-0.13	0.25	-0.38	0.12	-0.64	0.05	0.40	-0.35	0.45	-0.58
Kansas	-0.51	-0.12	-0.39	-0.63	-1.55	0.22	0.50	-0.28	0.73	0.00
Kentucky	0.00	0.12	-0.12	0.12	-0.17	-0.18	0.24	-0.42	0.06	-0.41
Louisiana	0.54	0.11	0.43	0.66	-0.17	-0.58	0.23	-0.81	-0.34	-1.20
Massachusetts	0.37	-0.18	0.55	0.18	-0.42	-0.43	0.64	-1.07	0.21	-0.87
Maryland	-0.15	-0.22	0.07	-0.37	-0.84	0.01	0.21	-0.20	0.21	-0.19
Maine	-0.07	0.10	-0.17	0.02	-0.80	-0.29	0.43	-0.72	0.14	-1.19
Michigan	-0.23	0.70	-0.92	0.47	-0.62	0.19	0.62	-0.43	0.81	-0.97
Minnesota	0.33	0.08	0.25	0.41	-0.14	-0.45	0.22	-0.67	-0.23	-1.03
Missouri	0.10	-0.01	0.11	0.09	-0.24	-0.26	0.64	-0.90	0.39	-0.53
Mississippi	-0.07	0.03	-0.10	-0.05	-0.63	0.02	0.29	-0.26	0.31	-0.21
Montana	-0.25	0.36	-0.61	0.12	-2.21	-0.01	-0.20	0.20	-0.21	-1.28
North Carolina	-0.18	-0.14	-0.03	-0.32	-0.77	0.02	0.53	-0.52	0.55	-0.08
Nebraska	0.44	0.22	0.22	0.65	-0.07	-0.76	-0.06	-0.70	-0.82	-1.58
New Hampshire	0.36	-0.25	0.62	0.11	-0.51	-0.63	0.62	-1.24	-0.01	-1.26
New Jersey	0.13	-0.16	0.29	-0.03	-0.49	-0.30	0.38	-0.68	0.09	-0.60
Nevada	0.79	1.00	-0.21	1.79	0.78	-0.99	-0.34	-0.66	-1.33	-2.60
New York	0.48	0.04	0.44	0.52	-0.06	-0.56	0.31	-0.87	-0.25	-1.13
Ohio	0.02	0.11	-0.09	0.13	-0.40	-0.09	0.59	-0.67	0.50	-0.59
Oklahoma	0.55	-0.60	1.15	-0.04	-1.36	-0.71	1.33	-2.03	0.62	-1.44
Oregon	0.21	0.27	-0.06	0.48	-0.75	-0.29	0.21	-0.50	-0.08	-1.18
Pennsylvania	0.14	-0.15	0.29	0.00	-0.51	-0.19	0.49	-0.68	0.31	-0.43
South Carolina	0.06	-0.45	0.50	-0.39	-1.04	-0.22	0.75	-0.97	0.54	-0.45
Tennessee	0.07	0.18	-0.12	0.25	-0.26	-0.20	0.35	-0.55	0.15	-0.51
Texas	0.38	-0.54	0.92	-0.17	-1.09	-0.52	0.85	-1.37	0.33	-1.04
Utah	0.07	0.37	-0.30	0.44	-0.99	-0.40	-0.04	-0.36	-0.44	-1.51
Virginia	-0.13	-0.07	-0.06	-0.20	-0.71	0.05	0.39	-0.34	0.44	-0.08
Washington	0.32	0.07	0.25	0.39	-0.57	-0.65	0.28	-0.93	-0.36	-1.43
Wisconsin	-0.01	0.17	-0.19	0.16	-0.50	-0.06	0.26	-0.32	0.20	-0.44

Table 3: Cumulative effects of oil price innovations of 2 s.d. ($x_t^{\#} = x_t^1$)

	Positive shock					Negative shock				
sector	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Total manufacturing	0.14	0.88	-0.75	1.02	0.15	-0.36	1.34	-1.71	0.98	-0.73
Alabama	-0.18	0.72	-0.91	0.54	-0.54	-0.39	1.47	-1.86	1.08	-0.79
Arkansas	-0.38	-0.58	0.20	-0.95	-2.31	-0.30	1.26	-1.55	0.96	-0.59
Arizona	0.04	-0.22	0.26	-0.17	-2.22	-1.12	2.22	-3.34	1.09	-2.25
California	0.57	0.08	0.49	0.66	-0.41	-1.54	0.91	-2.45	-0.62	-3.07
Colorado	0.21	0.11	0.09	0.32	-1.76	-1.65	1.82	-3.47	0.17	-3.30
Connecticut	0.81	0.12	0.70	0.93	-0.41	-0.96	1.54	-2.50	0.58	-1.92
Florida	0.41	0.90	-0.49	1.32	0.34	-1.08	1.30	-2.38	0.21	-2.17
Georgia	-0.21	0.73	-0.93	0.52	-0.86	-0.47	1.81	-2.28	1.34	-0.94
Iowa	-0.62	-1.20	0.58	-1.82	-4.53	0.07	2.08	-2.01	2.15	0.14
Idaho	-2.44	1.05	-3.49	-1.38	-4.90	-0.41	0.53	-0.94	0.12	-4.65
Illinois	0.04	0.93	-0.89	0.96	-0.33	-0.54	1.27	-1.81	0.72	-1.09
Indiana	-0.37	1.35	-1.72	0.98	-0.83	-0.01	1.57	-1.58	1.56	-1.05
Kansas	-1.39	0.26	-1.64	-1.13	-3.84	0.11	1.46	-1.36	1.57	-0.29
Kentucky	-0.24	0.71	-0.95	0.46	-0.51	-0.59	0.91	-1.50	0.32	-1.18
Louisiana	1.04	0.68	0.36	1.72	-0.43	-1.20	0.88	-2.08	-0.32	-2.40
Massachusetts	0.64	0.24	0.40	0.88	0.03	-0.95	1.83	-2.78	0.88	-1.90
Maryland	-0.49	-0.46	-0.03	-0.95	-2.06	-0.16	0.39	-0.56	0.23	-0.64
Maine	-0.58	0.82	-1.40	0.24	-2.22	-0.98	1.45	-2.43	0.46	-3.50
Michigan	-0.51	3.12	-3.64	2.61	-1.07	0.32	2.83	-2.51	3.15	-2.43
Minnesota	0.50	0.57	-0.07	1.06	0.32	-1.05	0.83	-1.88	-0.23	-2.16
Missouri	-0.01	0.81	-0.82	0.80	-0.19	-0.71	2.05	-2.76	1.34	-1.42
Mississippi	-0.21	0.47	-0.68	0.27	-1.21	-0.01	0.96	-0.98	0.95	-0.39
Montana	-0.87	0.94	-1.80	0.07	-6.74	-0.37	-0.21	-0.15	-0.58	-2.14
North Carolina	-0.59	0.27	-0.85	-0.32	-1.30	-0.18	1.58	-1.76	1.39	-0.37
Nebraska	0.45	0.63	-0.18	1.08	-1.08	-1.92	0.07	-1.99	-1.84	-3.85
New Hampshire	0.39	-0.04	0.43	0.34	-0.28	-1.57	1.66	-3.22	0.09	-3.13
New Jersey	0.06	-0.06	0.12	0.00	-1.00	-0.78	1.01	-1.79	0.22	-1.57
Nevada	1.29	2.98	-1.69	4.27	2.00	-2.26	0.22	-2.48	-2.04	-5.25
New York	0.86	0.56	0.30	1.42	0.22	-1.22	1.07	-2.28	-0.15	-2.44
Ohio	-0.06	1.13	-1.19	1.07	-0.28	-0.26	2.01	-2.27	1.75	-1.44
Oklahoma	0.89	-0.17	1.06	0.72	-1.62	-1.61	3.59	-5.20	1.98	-3.22
Oregon	0.30	1.26	-0.95	1.56	-1.62	-0.69	1.07	-1.76	0.38	-1.89
Pennsylvania	0.22	0.17	0.05	0.38	-0.46	-0.43	1.41	-1.85	0.98	-0.87
South Carolina	-0.13	-0.44	0.31	-0.57	-1.68	-0.65	1.92	-2.57	1.27	-1.31
Tennessee	-0.04	1.06	-1.11	1.02	-0.29	-0.57	1.35	-1.91	0.78	-1.14
Texas	0.55	-0.65	1.21	-0.10	-1.40	-1.22	2.10	-3.33	0.88	-2.45
Utah	-0.30	1.19	-1.50	0.89	-2.47	-1.22	0.34	-1.56	-0.88	-2.84
Virginia	-0.37	0.28	-0.66	-0.09	-1.19	0.00	1.17	-1.18	1.17	-0.06
Washington	0.18	0.66	-0.48	0.83	-1.65	-1.73	1.06	-2.79	-0.66	-3.46
Wisconsin	-0.13	0.92	-1.05	0.79	-1.10	-0.22	1.06	-1.28	0.84	-0.78

Table 4: Test of symmetry for positive and negative oil price innovations ($x_t^{\#} = x_t^1$)

	typical shock 1 s.d.					large shock 2 s.d.				
Sector	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Total manufacturing	0.58	*0.07*	*0.06*	0.25	0.31	0.55	**0.05**	**0.03**	0.25	0.65
Alabama	0.73	0.18	0.22	0.26	0.50	0.70	0.11	0.14	0.15	0.66
Arkansas	0.89	0.66	0.68	0.82	0.43	0.88	0.63	0.66	0.81	0.69
Arizona	0.34	0.23	0.46	0.16	*0.08*	0.21	0.17	0.41	*0.08*	*0.09*
California	0.54	0.86	0.57	0.97	0.18	0.41	0.86	0.54	0.97	0.39
Colorado	0.25	*0.08*	0.11	*0.10*	**0.02**	*0.09*	**0.03**	**0.04**	**0.04**	**0.01**
Connecticut	0.90	0.30	0.37	0.57	0.19	0.90	0.22	0.30	0.51	0.63
Florida	0.89	0.25	0.39	0.45	0.41	0.87	0.21	0.33	0.42	0.80
Georgia	0.84	**0.04**	**0.03**	0.22	0.39	0.81	**0.01**	**0.00**	0.14	0.57
Iowa	0.68	0.60	0.49	0.85	*0.10*	0.65	0.53	0.42	0.84	0.18
Idaho	0.18	0.91	0.25	0.49	**0.04**	**0.05**	0.91	0.12	0.36	0.05
Illinois	0.46	0.16	0.18	0.42	0.61	0.38	*0.10*	*0.08*	0.41	0.48
Indiana	0.54	0.31	0.21	0.53	0.31	0.43	0.26	0.12	0.52	0.71
Kansas	0.48	0.38	0.37	0.58	0.33	0.38	0.33	0.30	0.53	0.36
Kentucky	0.84	0.38	0.51	0.50	0.89	0.82	0.39	0.52	0.50	0.85
Louisiana	0.99	0.23	0.23	0.44	0.12	0.99	0.16	0.15	0.40	0.26
Massachusetts	0.35	0.59	0.31	0.71	0.32	0.23	0.54	0.20	0.69	0.50
Maryland	0.56	0.68	0.94	0.27	0.47	0.51	0.66	0.95	0.18	0.33
Maine	0.27	0.28	*0.09*	0.98	0.18	0.19	0.21	**0.03**	0.98	0.32
Michigan	0.24	0.16	0.11	0.51	0.44	*0.09*	**0.05**	**0.02**	0.41	0.41
Minnesota	0.96	0.89	0.78	0.98	0.51	0.95	0.88	0.76	0.98	0.84
Missouri	0.41	0.16	0.11	0.27	0.43	0.31	*0.06*	**0.04**	0.13	0.39
Mississippi	0.41	0.15	0.42	*0.06*	0.56	0.24	*0.09*	0.36	**0.01**	0.19
Montana	0.68	0.27	0.25	0.75	0.15	0.58	*0.10*	*0.09*	0.70	0.23
North Carolina	0.54	0.40	0.40	0.55	0.44	0.45	0.34	0.35	0.50	0.54
Nebraska	0.88	0.26	0.33	0.56	0.35	0.88	0.20	0.29	0.50	0.41
New Hampshire	0.65	0.84	0.62	0.91	0.19	0.59	0.84	0.60	0.91	0.36
New Jersey	0.43	0.71	0.59	0.50	0.11	0.35	0.72	0.58	0.44	0.10
Nevada	0.39	0.80	0.79	0.44	0.43	0.25	0.77	0.77	0.30	0.28
New York	0.69	0.50	0.43	0.66	0.28	0.64	0.42	0.32	0.63	0.46
Ohio	0.27	*0.10*	*0.07*	0.26	0.51	0.12	**0.03**	**0.01**	0.20	0.76
Oklahoma	0.76	0.11	0.24	0.20	**0.00**	0.73	**0.02**	0.11	*0.08*	0.07
Oregon	0.92	0.39	0.55	0.39	0.34	0.91	0.28	0.46	0.26	0.38
Pennsylvania	0.33	0.62	0.68	0.47	0.51	0.22	0.60	0.66	0.42	0.44
South Carolina	0.62	0.70	0.57	0.88	*0.07*	0.49	0.66	0.48	0.88	0.45
Tennessee	0.85	0.17	0.27	0.44	0.72	0.84	0.13	0.18	0.43	0.77
Texas	0.47	0.68	0.77	0.68	*0.10*	0.39	0.66	0.75	0.67	0.13
Utah	0.37	0.29	0.77	*0.10*	0.11	0.30	0.24	0.76	**0.04**	0.17
Virginia	0.42	0.21	0.44	0.15	0.45	0.21	0.14	0.40	**0.04**	0.30
Washington	0.54	0.38	0.27	0.91	0.18	0.45	0.32	0.17	0.89	0.41
Wisconsin	0.42	0.72	0.52	0.83	0.70	0.37	0.72	0.51	0.81	0.68

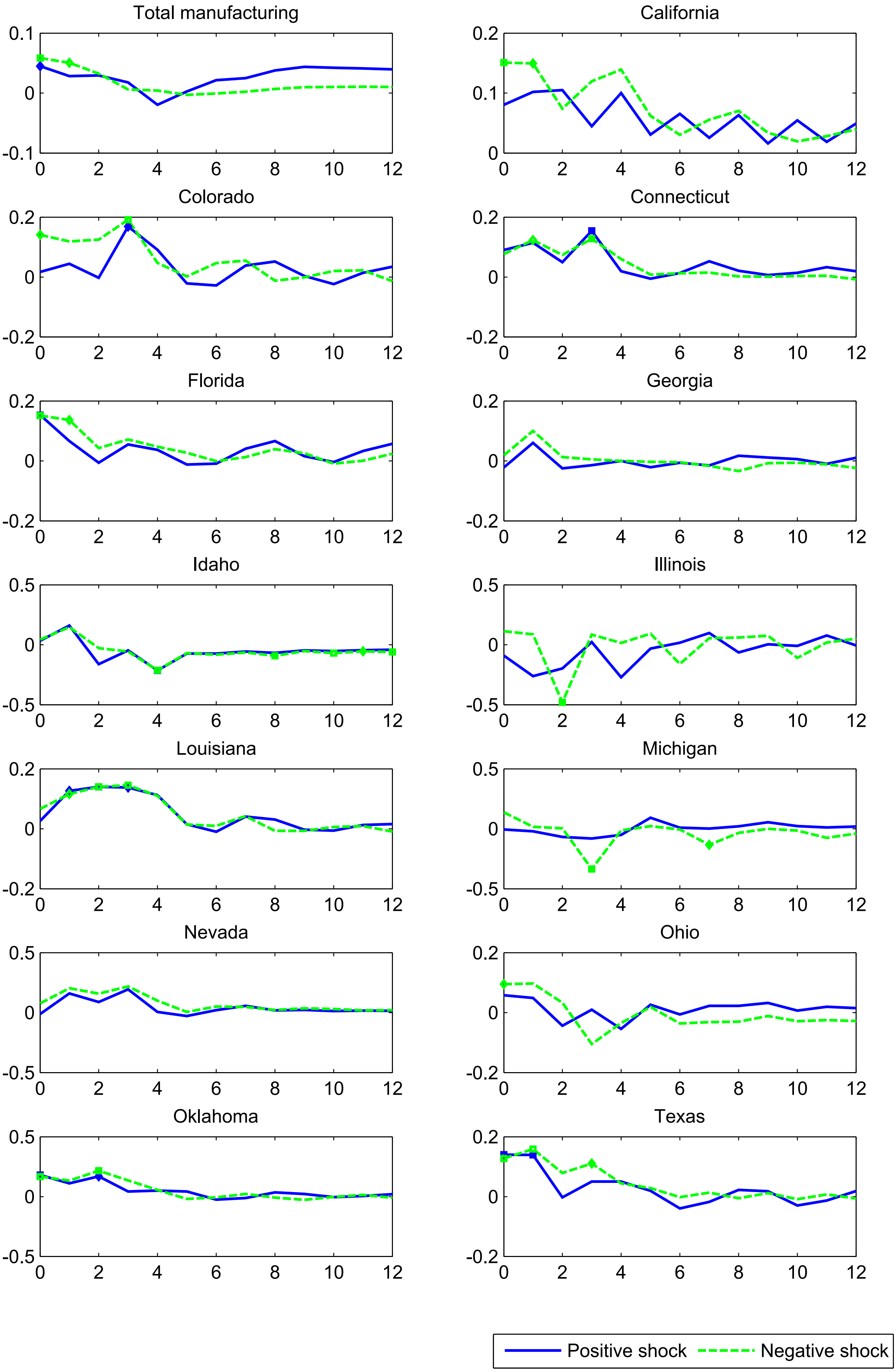
Notes: Computations are based on 10,000 simulations of model (6a-c). p-values are based on the χ^2_{H+1}. Bold and italics refer to significance at the 5% and 10% significance level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

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

sector	typical shock 1 s.d.	large shock 2 s.d.
Total manufacturing	0.81	0.76
Alabama	0.69	0.42
Arkansas	0.89	0.88
Arizona	0.56	0.24
California	0.91	0.93
Colorado	0.52	0.18
Connecticut	0.97	0.92
Florida	0.83	0.71
Georgia	0.93	0.79
Iowa	0.42	0.70
Idaho	0.42	0.44
Illinois	0.70	0.50
Indiana	0.66	0.75
Kansas	0.50	0.54
Kentucky	0.91	0.79
Louisiana	0.48	0.47
Massachusetts	0.93	0.93
Maryland	0.50	0.44
Maine	0.80	0.86
Michigan	0.90	0.76
Minnesota	0.97	0.98
Missouri	0.27	0.37
Mississippi	0.42	*0.10*
Montana	0.75	0.67
North Carolina	0.63	0.70
Nebraska	0.77	0.74
New Hampshire	0.48	0.74
New Jersey	0.58	0.52
Nevada	0.40	0.50
New York	0.38	0.44
Ohio	0.54	0.61
Oklahoma	0.24	0.12
Oregon	0.41	0.24
Pennsylvania	0.94	0.81
South Carolina	0.81	0.96
Tennessee	0.77	0.76
Texas	0.45	0.45
Utah	0.71	0.40
Virginia	0.15	*0.07*
Washington	0.79	0.80
Wisconsin	0.57	0.62

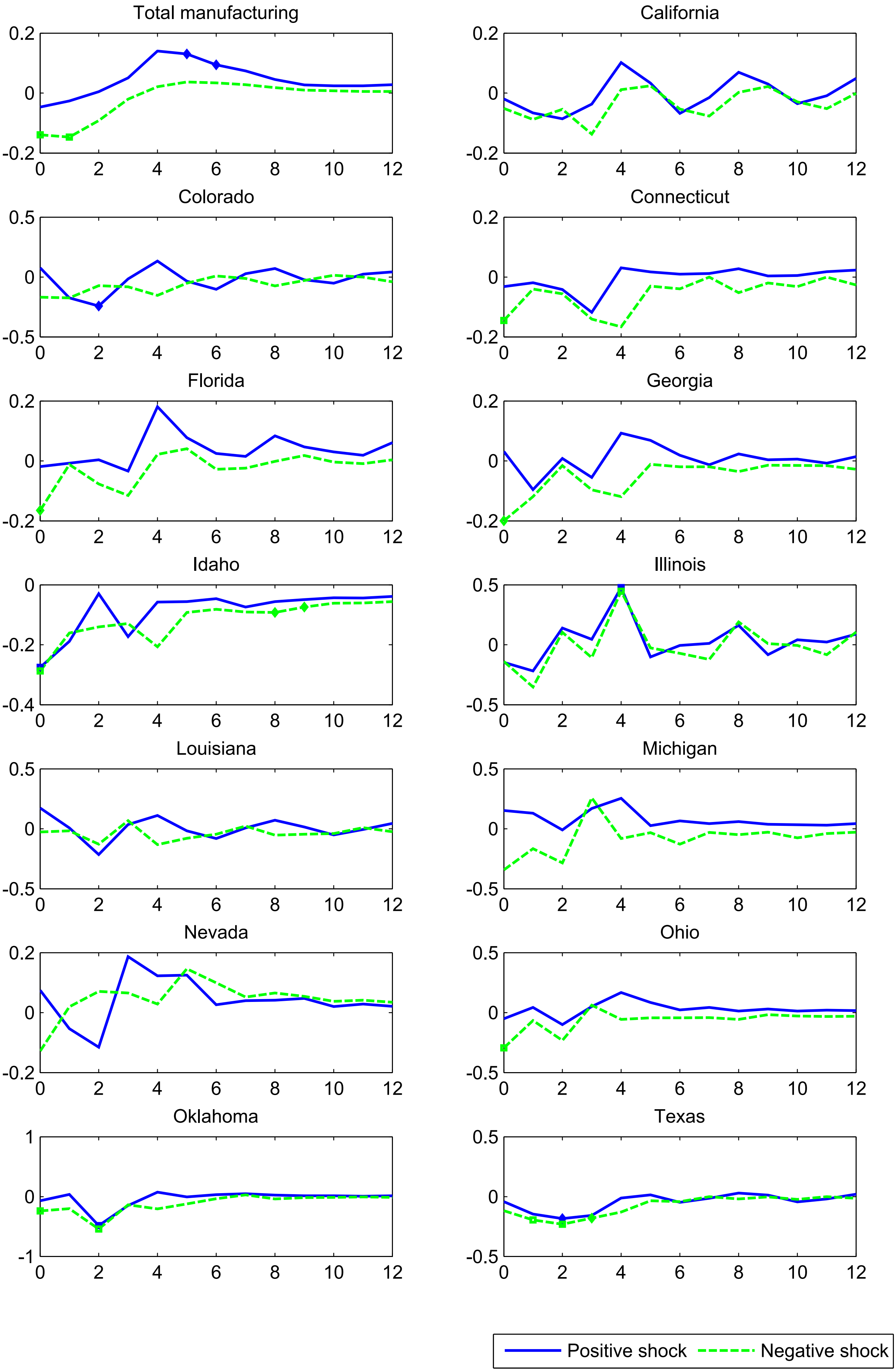
Notes: Computations are based on 10,000 simulations of model (6a-c). p-values are based on the χ^2_{H+1}. Bold and italics refer to significance at the 5% and 10% significance level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Figure 1: The responses of job creation to positive and negative oil price shocks of 1 s.d. ($x_t^{\#} = x_t^1$)



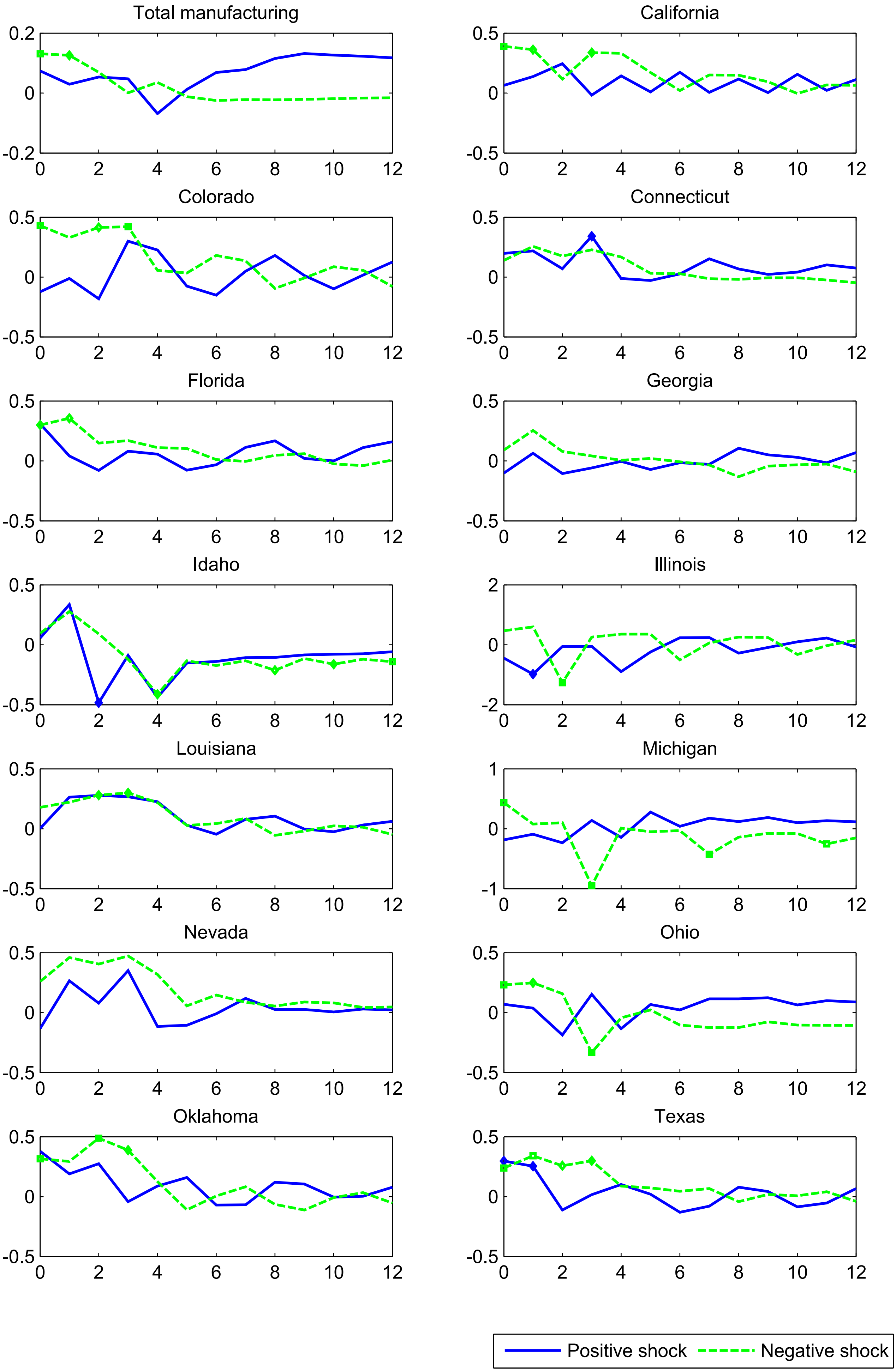
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations.

Figure 2: The responses of job destruction to positive and negative oil price shocks of 1 s.d. ($x_t^{\#} = x_t^1$)



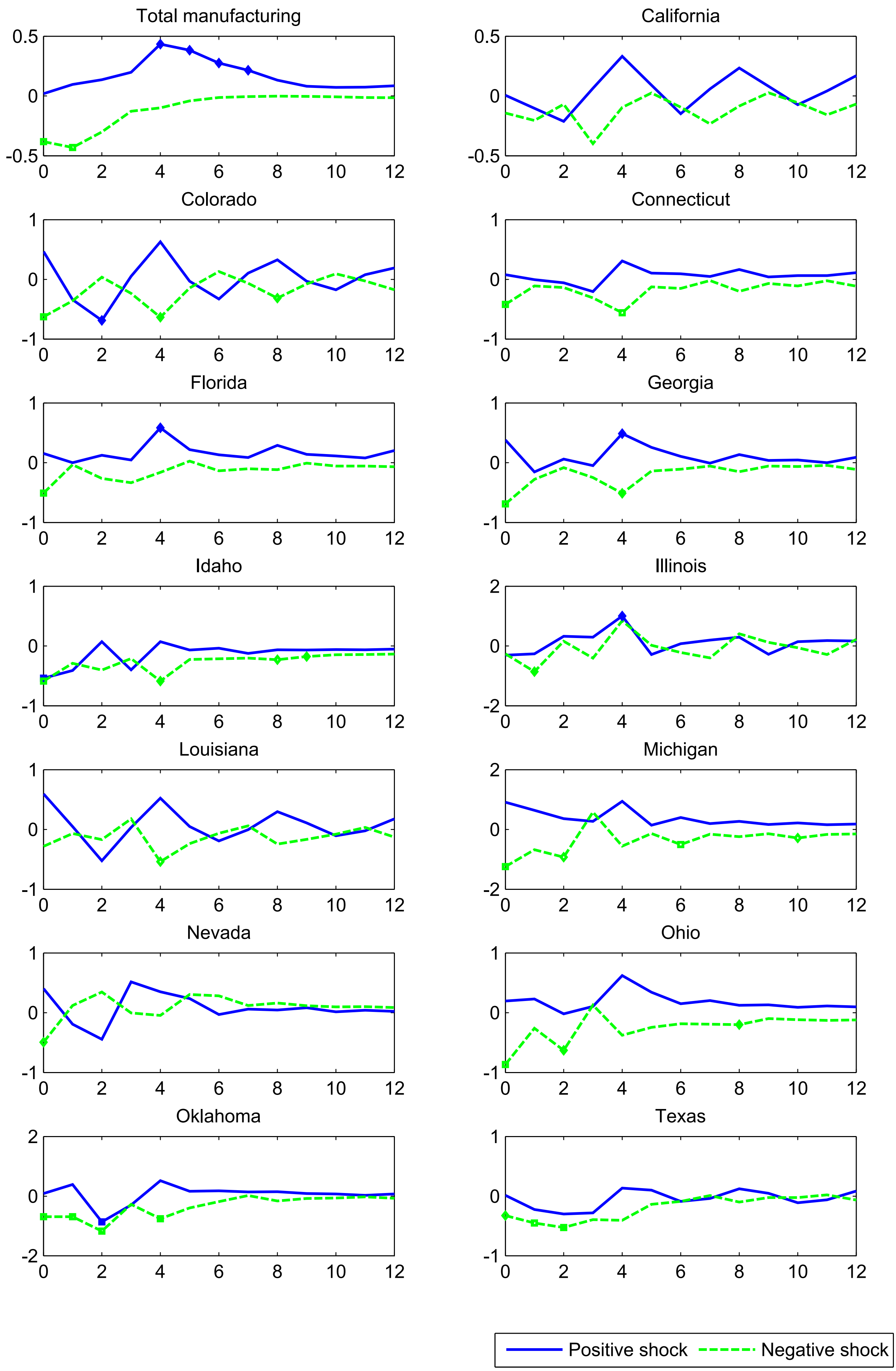
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations.

Figure 3: The responses of job creation to positive and negative oil price shocks of 2 s.d. ($x^{\#}_t = x^1_t$)



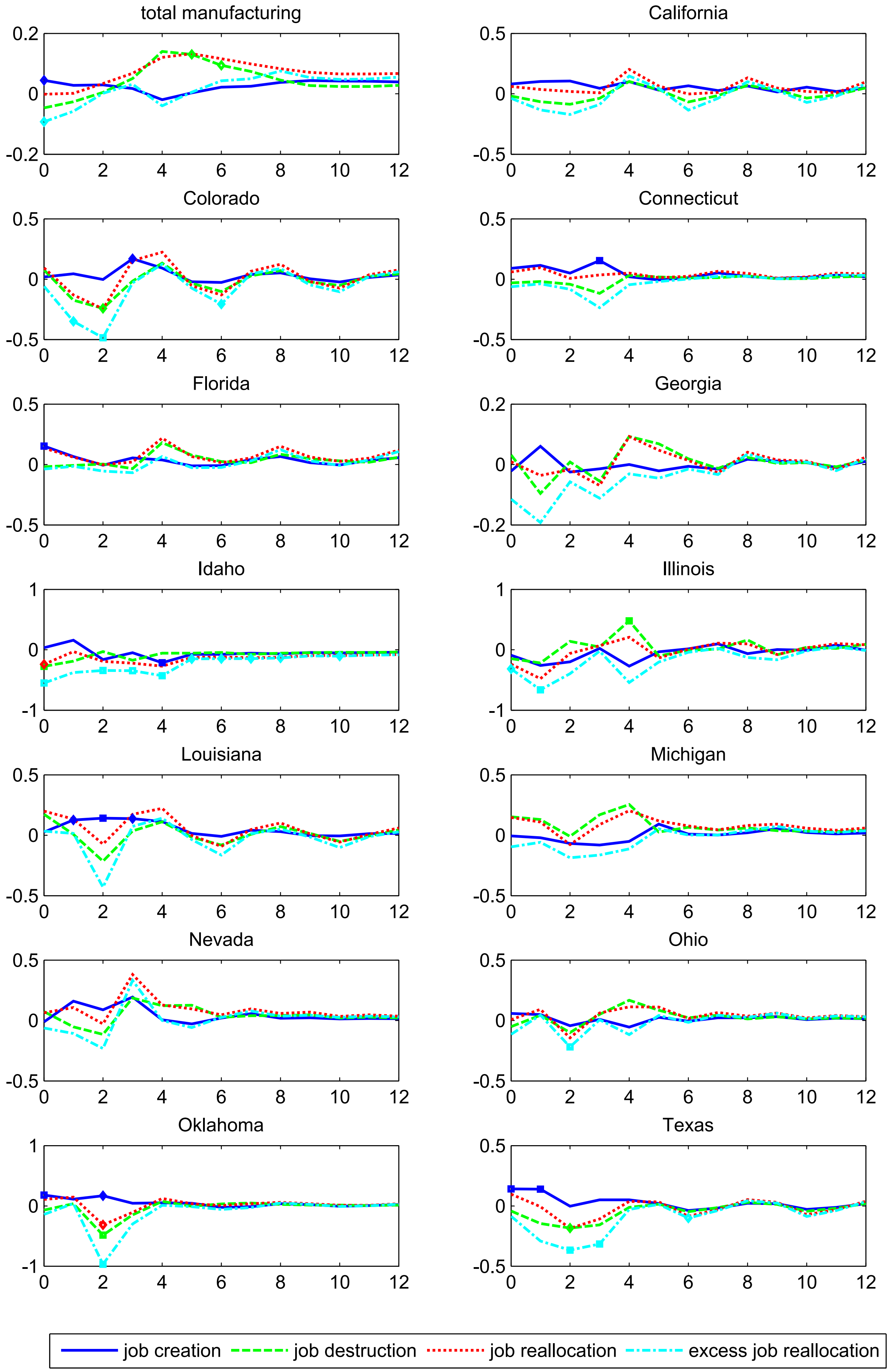
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations.

Figure 4: The responses of job destruction to positive and negative oil price shocks of 2 s.d. ($x_t^{\#} = x_t^1$)



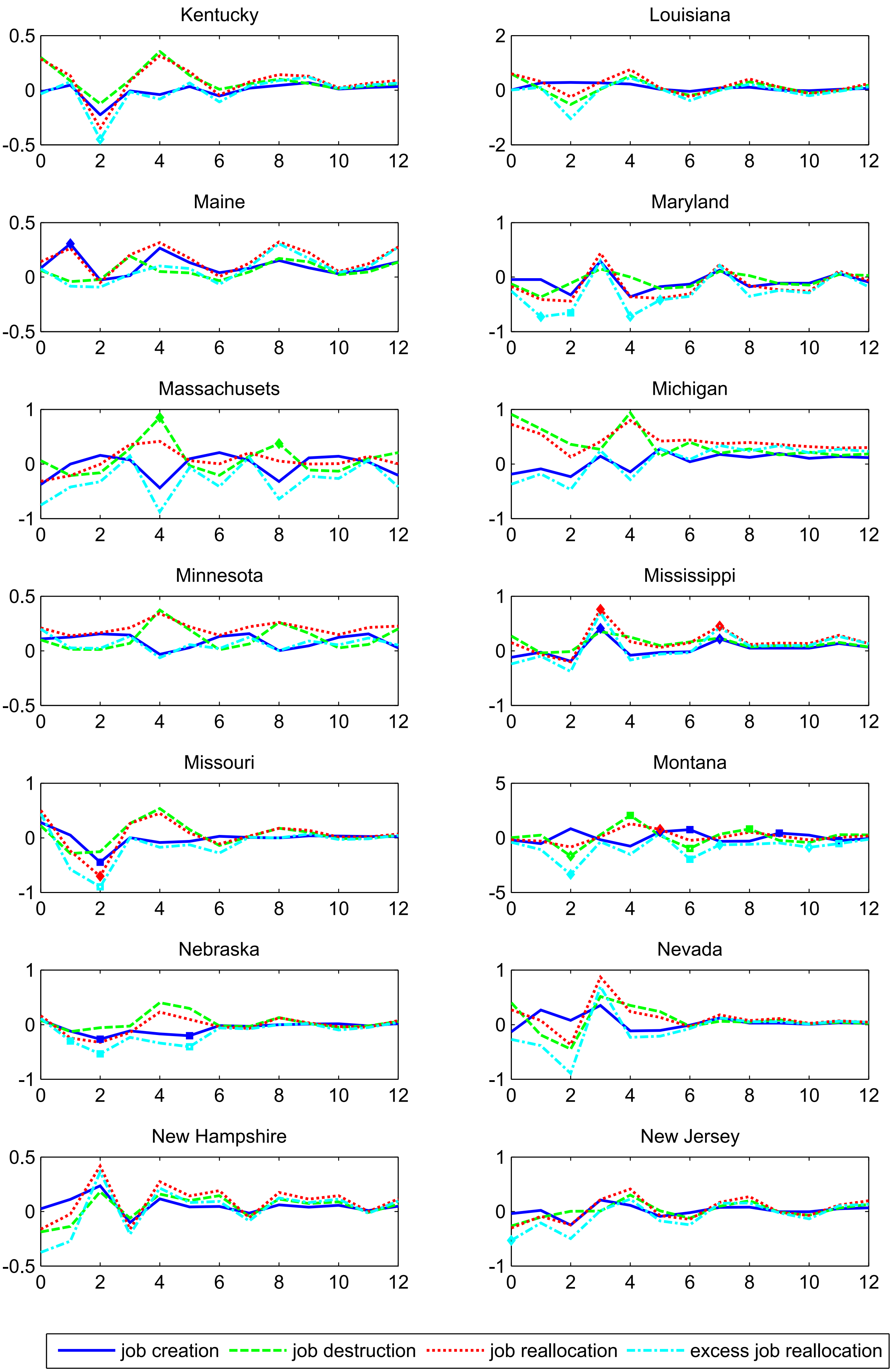
Notes: Squares and diamonds represent significance at the 5% and 10%, respectively.
Computations are based on 10,000 simulations.

Figure 5: The responses of job flows 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 6: The responses of job flows to a positive oil price shock of 2 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.