The Effect of Oil News Shocks on Job Creation and Destruction*

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Abstract

Using data from the Annual Survey of Manufactures and Census of Manufactures we address three questions regarding the effect of oil news shocks. How do sectoral labor flows respond to these shocks? What establishment characteristics explain cross-industry heterogeneity? Have the responses changed over time? Oil news shocks moderately affect aggregate manufacturing employment growth, but significantly increase job reallocation. Heterogeneity in responses across industries is related to differences in energy costs, the rate of energy to capital expenditure, and the share of mature firms. We document a decline in the dynamic responses of sectoral job creation and destruction since the mid-2000s.

Keywords: Job flows, oil news shocks, high frequency identification, OPEC announcements.

JEL: E24, E32, Q43.

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1 Introduction

Interest in understanding the effect of expectations about future oil prices on aggregate economic activity has been bolstered in recent years by geopolitical events and the plunge in global demand experienced during the COVID-19 pandemic. For instance, on 24 February 2022, Russia invaded Ukraine and significantly escalated the Russian-Ukranian War. As part of unified sanctions, the United States and many nations banned the import of Russian crude oil; this ban, if effective, would have stopped the approximately 700,000 barrels of Russian petroleum products imported into the US each day, a significant shock in national supply. Within two weeks, the price of the West Texas Intermediate (WTI) increased by more than 30%. Meanwhile, after falling by more than 16 million barrels per day in 2020, the Organization of the Petroleum Exporting Countries (OPEC) announced on 31 March 2022 that global oil demand was expected to grow to 100.9 million barrels per day in 2022, surpassing the pre-pandemic levels, and the monthly overall production level would increase by 0.432 mb/d in May 2022. How did the news about this future increase in production affect US job reallocation? More generally, how do oil price news affect the dynamic process of inter-firm job reallocation? Understanding how changes in expectations about future oil prices affect job gains and job losses is key to understanding business cycles and central to thinking about the effect of policies aimed at reducing the use of oil.

To assess the impact of oil news on sectoral job creation and destruction, we start by constructing time series of manufacturing job flows from confidential establishment-level data collected by the Census Bureau spanning the period between 1980:Q3 and 2016:Q4. More precisely, following Davis et al. (1998), we use quarterly data on the number of production workers reported in the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CMF) to compute industry-level measures of job creation and destruction. The use of these confidential data enables us to construct longer and more disaggregated times series of manufacturing job gains and losses than publicly available from the Business Employment Dynamics. We then use a Proxy-VAR á la Känzig (2021) to estimate the response of sectoral job creation and destruction to oil news shocks. That is, we measure oil surprises from changes in the West Texas Intermediate oil price futures around OPEC announcements and estimate the effect of oil news shocks on job reallocation using surprises to identify shocks to oil prices. Throughout this article, we refer to these shocks as oil news shocks instead of oil supply news shocks, as changes in crude oil futures prices may reflect OPEC's decision to modify production targets to counteract the effect of a steep decline in demand for oil, as was the case during the COVID-19 pandemic.[1]

We find that oil news shocks have a small negative and short-lived impact on manufacturing net employment growth, but a larger and longer-lasting impact on job reallocation. The news of a future increase in oil prices leads to a higher rate of job reallocation among sectors that are intensive in the use of energy (petroleum & coal products, wood products, and nonmetallic mineral products); in these sectors, the larger increase in job losses compared to gains results in lower employment

[1] See Degasperi (2023) and Kilian (2024).

growth. Perhaps not surprisingly, the largest declines in net employment growth and changes in job reallocation are experienced by the transportation equipment sector. In particular, expectations of higher crude oil prices result in a deeper and longer reduction in employment growth, as well as a more dynamic process of job reallocation for motor vehicle manufacturing than for any other industry. However, for other sectors that comprise a large share of manufacturing employment, such as food, we do not find a statistically significant response to news of higher oil prices. All in all, we find a considerable degree of cross-industry heterogeneity in the response to oil news shocks but, on average, we estimate responses that are smaller in magnitude than reported by earlier studies (e.g., Davis and Haltiwanger (2001), Herrera and Karaki (2015)).

We then turn to exploring what firm-level characteristics explain the differences in the magnitude of the response of job gains and losses and, in turn, net employment growth and excess job reallocation across industries. To do so, we exploit establishment-level data to compute job flows at a finer level of aggregation, 4-digit North American Industrial Classifcation System (NAICS). We then construct measures of energy expenditures, capital expenditures, age, establishment growth, and other characteristics that may be correlated with the responsiveness of establishments' job flows to oil news shocks. We document that the sensitivity of job reallocation to oil news shocks is greater in industries that face higher energy costs, a higher ratio of capital to energy expenditures, and have a larger proportion of mature establishments.

At first glance, the estimation results for aggregate manufacturing would seem to imply that oil news shocks cause rather small fluctuations in manufacturing jobs, despite their impact being statistically and economically significant for real GDP (Känzig (2021)). Yet, a careful look at the sectoral results reveals that focusing on aggregate data conceals the nature of the job reallocation dynamics triggered by an oil news shock. In particular, news of future oil price increases alter the closeness of the match between actual and desired distribution of capital and labor inputs. Indeed, we find evidence that the shock triggers a more dynamic reallocation process in industries with higher energy costs and capital-to-energy expenditure ratios, such as wood, nonmetallic minerals, and paper. Moreover, our findings are consistent with the view that oil news shocks create anxiety among consumers, and, in turn, such concerns about higher future crude oil prices disrupt the demand for motor vehicles and related products (i.e., motor vehicle parts) leading to heightened job reshuffling in the transportation equipment sector. Given the importance of this sector in generating manufacturing employment (it accounted for 13.5% of manufacturing employment in the sample), it is crucial to understand the sensitivity of manufacturing job gains and losses to oil news shocks.

Finally, we show that the response of sectoral job creation and destruction to an oil news shock is smaller in our sample than estimates obtained by previous studies using earlier samples. This discrepancy in the magnitude of the response could stem from three sources. First, a broad body of literature documents a decline in job market fluidity since the 1980s (see, e.g. Davis and Haltiwanger (2014)) linked to a decline in responsiveness to productivity shocks (Decker et al., 2018). This decline in the responsiveness of business-level employment to oil shocks could explain the smaller magnitude of our estimates. Second, important technological changes occurred in the oil extraction process during our sample period. The shale revolution enabled the U.S. to significantly increase crude oil production since the mid-2000s and become a net oil exporter in September 2019. Finally, contrary to other studies into the effects of oil price shocks on job reallocation, we focus on the expectational component of oil shocks. To explore whether the responsiveness of business-level employment has changed in recent years, we reestimate our Proxy-VAR on expanding sample windows that start from a subsample spanning 1980Q3-2000Q1, shortly after the US became a net oil exporter, and end with the full sample. We find striking evidence of a decline in the responsiveness of manufacturing job creation and destruction since the mid-2000s, which points to a change in the transmission of oil news shocks from the time of the shale boom.

This article is closely related to several investigations into the effect of oil price shocks on labor markets. First, our work contributes to a large body of literature that investigates the relationship between oil price shocks and the macroeconomy. In particular, we build on the work of Känzig (2021) who proposed the use of changes in oil futures prices around OPEC announcements to identify oil supply shocks. His work provides empirical evidence for a transmission channel of oil news shocks that operates through expectations of oil market conditions. We depart from Känzig (2021) in that we consider the identified shocks to be driven not only by the news of future changes in oil supply, but may also be driven by changes in demand (see Degasperi (2023)). More importantly, we leverage the confidential CMF-ASM data to document the response of job flows to oil news shocks and investigate whether cross-industry variation in the response to oil news shocks is systematically related to establishment characteristics.

Second, our work is related to investigations about the effects of oil price shocks on the destruction and creation of jobs in the U.S. Starting from the work of Davis and Haltiwanger (2001), several studies have shown that unexpected increases in oil prices lead to declines in employment growth and increased job reallocation (see, e.g. Davis and Haltiwanger (2001), Herrera and Karaki (2015), Karaki (2018)). This literature has underscored the importance of understanding how sectoral job gains and losses act as a mechanism whereby oil shocks result in economic recessions. However, these studies employ samples that end before the fracking revolution and identify oil price shocks through short-term restrictions in SVAR models. Hence, their estimates could understate the role that the shale oil boom has played in how the labor market adjusts to oil news and impose more restrictive identification assumptions.

Finally, this study complements the work of Bjørnland and Skretting (2024) who, using a time-varying parameter factor vector autoregressive model (TVP-FAVAR), found evidence of a change in the transmission mechanism of oil shocks since the shale boom. More specifically, unexpected oil price increases –stemming from contractions in world oil supply– now give rise to employment growth in sectors that are connected to the oil industry. Their study is the first to provide evidence on how the dynamic response of investment, income, industrial production, and (non-oil) employment to oil supply shocks has evolved over a period of crucial technological change in the oil industry. However, because Bjørnland and Skretting (2024) examine employment rates at the industry and state level, their work is silent on the process of reallocation and restructuring of jobs among establishments that results from an oil news shock. Our study complements their work as we provide a richer characterization of the sectoral job creation and destruction dynamics and we focus on the expectations channel. To investigate time-variation in the transmission of oil news shocks, we opt for a different estimation strategy than the TVP-FAVAR used by Bjørnland and Skretting (2024) for two reasons. Our framework allows us to avoid the assumption of common factors across all sectors, does not rely on short-run identification but on an IV strategy, and by using expanding windows we allow the relationship between the IV and the oil shock to vary over time. A drawback is that we do not exploit the richer data taken into account in the FAVAR setup.

The remainder of this article is organized as follows. Section 2 describes the data used in the empirical analysis, paying particular attention to the measures of sectoral job creation and destruction. Section 3 describes the empirical strategy. Section 4 discusses the dynamic response to oil news shocks, whereas Section 5 investigates the factors that account for the cross-industry heterogeneity in the responses. Section 6 investigates whether job flows have become less responsive to oil news shocks, and Section 7 concludes.

2 Data

In this paper, we explore the effect of oil news shocks on job reallocation using confidential data from the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CMF) spanning from 1980 to 2016. In this section, we start by detailing the computation of job flows, compare these flows with publicly available measures of job gains and losses, and end with a description of the oil market data.[2]

2.1 Job Flows Data

Data on job flows for US manufacturing are calculated using establishment-level data collected by the Census Bureau. Specifically, we employ the quarterly number of production workers as reported at the establishment level in the ASM and the CMF. We supplement these data with total employment, openings/closings of establishments, and firm age from the Longitudinal Business Database (LBD). The LBD allows us to better evaluate whether an establishment that appears for the first/last time in the ASM is a true entry/exit in the market or whether it is the first/last time it appears in the surveys spanning our sample.[3]

We follow the methodology proposed by Davis and Haltiwanger (1998) to calculate job flows for total manufacturing, 20 three-digit sectors of the North American Industrial Classification System

[2]Because we compute job flows using quarterly establishment-level data, we aggregate the oil market variables to the same frequency.

[3]Following Foster, Haltiwanger, and Kim (2006), we identify establishment births and deaths using the LBD age and initial year. Firms are only considered new births if the year of observation matches the initial year and the LBD age is one. This minimizes the risk of mislabeling a firm as a new birth if, in reality, it does not appear in the last sample but was sampled in the past.

(NAICS), and 4 four-digit NAICS sub-industries in the transportation equipment sector. Letting EMP_{it} denote the employment in quarter t for establishment i, we define the growth of employment at the establishment level as:

$$g_{it} = \frac{(EMP_{it} - EMP_{it-1})}{Z_{it}}. \quad (1)$$

where

$$Z_{it} = 0.5 * (EMP_{it} + EMP_{it-1}). \quad (2)$$

This measure of employment growth has become standard in the literature on establishment dynamics because it accommodates entry and exit (see, e.g. Davis et al. (1998)). Then, we calculate the job creation and job destruction in group j (e.g., a three- or four-digit NAICS industry) as: $C_{jt} = \sum_{i \in j^+} \Delta EMP_{it}$ and $D_{jt} = \sum_{i \in j^-} |\Delta EMP_{it}|$ where Δ denotes the first difference operator. Thus, C_{jt} corresponds to the sum of employment gains in establishments that started or expanded in group j ($i \in j^+$) between quarters $t-1$ and t and D_{jt} corresponds to the sum of employment losses in establishments that contracted or closed in group j ($i \in j^-$) between quarters $t-1$ and t. The growth rates of job creation, POS_{jt}, and job destruction, NEG_{jt}, in industry j are then calculated as weighted sums of the growth rates at the establishment level as follows:

$$POS_{jt} = C_{jt}/Z_{jt} = \sum_{i \in j^+} (Z_{ijt}/Z_{jt})\, g_{ijt}$$
$$NEG_{jt} = D_{jt}/Z_{jt} = \sum_{i \in j^-} (Z_{ijt}/Z_{jt})|g_{ijt}|.$$

Using these rates, we calculate the net change in employment growth, $NET_{jt} = POS_{jt} - NEG_{jt}$, gross reallocation, $SUM_{jt} = POS_{jt} + NEG_{jt}$, and excess reallocation, $EXC_{jt} = SUM_{jt} - |NET_{jt}|$. The latter measures the amount of job movements in industry j above what is required to accommodate the observed net change in employment. All data series are seasonally adjusted using the Census Bureau's X-12-ARIMA seasonal adjustment program.

The first panel of Figure 1 shows the evolution of seasonally adjusted job creation and job destruction rates for total manufacturing along with the NBER recessions represented by gray-shaded areas. Note that these rates represent movements in the employment of production workers, because only data on these workers are reported on a quarterly basis. Job creation and destruction rates in US manufacturing were more volatile in the early 1980s than in any other period in the sample. This increased volatility in the 1980s relative to later years is also evident in the job creation and destruction rates constructed by Foster et al. (2006) using a sample of the Longitudinal Research Database (LRD) that spans from 1972:2 to 1998:4.[4] As expected, job destruction rates largely exceeded job creation rates during recessions; pronounced and persistent spikes during economic downturns are evident for all recessions, but for the 1990-1991 recession. The figure also

[4] The LRD includes data on US manufacturing establishments collected in the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CMF). The latter is a quinquennial census collected on years ending in '2' and '7' comprising the universe of manufacturing establishments. See Foster et al. (2006) for a detailed description of the sampling procedure of the ASM.

shows that US manufacturing experienced a slow decline in job creation before and during the 2001 recession and the Great Recession. In addition, as noted in the literature (see, e.g. Davis and Haltiwanger (2014)), a decline in labor market fluidity is evident in the decreasing trend of job creation and destruction rates since the late 1980s.

Figures 1 and 2 plot job creation and destruction for the three-digit NAICS industries and the 4 four-digit transportation sub-industries of interest. As the figures illustrate, two of the patterns observed at the aggregate level are also evident in the disaggregated data: the 1980s comprised a period of higher volatility than the later years, and job flows exhibit a decreasing trend since the 1990s. This secular decline in the rates of job creation and destruction is consistent with evidence found in many empirical studies regarding the decline of labor market fluidity since the late 1980s (see, e.g., Davis and Haltiwanger (2014)).

Table 1 reports summary statistics for job creation and destruction rates throughout the sample period (1980Q3-2016Q4). The mean is computed as the simple average in all quarters. The average quarterly job creation and destruction rates for manufacturing were 4.20 and 4.38 percent, respectively. Significant heterogeneity is evident across NAICS industries. For example, food manufacturing had the highest average creation and destruction rates, 6.10 and 5.90, while paper manufacturing had the lowest average job creation and destruction, 2.68 and 2.94. The table shows that, on average, the job destruction rate exceeded the job creation rate, leading to a slightly negative (-0.18) net employment growth in US manufacturing during the period. Several industries, such as food manufacturing, printing, wood products, and miscellaneous manufacturing, exhibited higher creation than destruction.

Table 1 also reports summary statistics for three additional job flow measures: NET, SUM, and EXC. As mentioned above, on average, net employment growth in manufacturing was slightly negative during the sample period. The rates of gross reallocation (SUM) and excess reallocation (EXC) in manufacturing –8.58 and 7.61, respectively– suggest a fluid labor market. In fact, while most sectors experienced a slightly negative net employment change, the gross (excess) reallocation rate ranged from 5.62 (4.87) in paper to 12.00 (11.17) in food manufacturing. The fact that excess reallocation rates are sizable suggests that most reallocation occurred within establishments in the same industry. This fact, along with the reduction in net employment growth for most industries, suggests that few jobs shifted from one industry to another.

2.2 Comparison of Job Creation and Job Destruction Rates

Our use of the ASM and CMF data to study the dynamic effect of oil price shocks has two advantages relative to the use of publicly available data from the Business Employment Dynamics (BED). First, the BED, generated from the Quarterly Census of Employment and Wages, covers all establishments subject to state unemployment insurance and comprises a broader set of establishments than the ASM/CMF. However, the BED data are not available prior to 1992 and hence would force us to exclude the 1980s from our study. Second, because the ASM contains establishment-level data on the use of inputs such as energy and capital, we are able to track which establishment-level characteristics matter for the transmission of oil news shocks.

However, the reader may wonder how the job creation and destruction rates computed from the ASM/CMF data compare with their BED counterparts. Thus, Figure 3 plots the job creation and destruction rates for the ASM/CMF and BED data. In general, the series tend to move together; the correlation between the two sources is 0.47 for job creation, 0.75 for job destruction, and 0.91 for net employment growth. The ASM/CMF rates exhibit slightly lower variation and lower mean. The standard deviation of job creation (job destruction) in the BED is 0.68 (0.92) compared to 0.42 (0.84) in the ASM/CMF. The average job creation and destruction rates are 4.10 and 4.43 in the BED data versus 3.92 and 4.02 in the ASM/CMF.[5] On average, measures computed from the BED are about 0.2 percentage points higher than their ASM/CMF counterparts.

Earlier work by Davis and Haltiwanger (2001) used data from the Longitudinal Research Database (LRD) spanning 1972:2 to 1988:4 to study the response of sectoral job creation and destruction to oil price changes. Because the data sources are the same (ASM/CMF) and the object of study is closely related, we also compare our job creation and destruction rates with those reported by Davis and Haltiwanger (2001). Table 2 documents the job creation and destruction rates for our 1980Q3-2016Q4 sample, the BED sample spanning 1992Q2 to 2016Q4, and Davis and Haltiwanger (2001) LRD rates covering the period between 1972Q2 and 1988Q4. As the table shows, the average rates for 1972-1988 exceed the rates we computed for the later sample by about one percentage point. Smaller rates of job creation, and especially job destruction, in the 1990s compared to earlier years are also documented by Foster et al. (2006) who report an average job creation (destruction) rate of 4.98 (4.41) for 1994Q1-1998Q4 versus a 5.07 (5.47) for 1972Q2-1993Q4. Lastly, a key similarity between most samples and sources is that job destruction exceeds creation, which reflects the large spikes in job losses during employment downturns. The only exception is the 1994Q1-1998Q4 period reported by Foster et al. (2006) when the US economy expanded.

2.3 Oil Market Data

The oil market variables considered in this paper follow the baseline specification of Känzig (2021). Unless otherwise specified, oil market variables are measured in logarithms.

As a measure of real oil prices, we employ the spot price of the West Texas Intermediate (WTI) deflated by the Consumer Price Index (CPI). Data for both variables are obtained from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.

Data on world oil production (including lease condensate production) are obtained from the Energy Information Administration (EIA) and measured in thousands of barrels per day. To construct a measure of crude oil inventories, we obtain data on total crude oil inventories and petroleum stocks for the U.S. and on OECD petroleum stocks from the Energy Information Agency (EIA). Then, following Hamilton (2009) and Kilian and Vigfusson (2014), we calculate world inventories by scaling the total US crude oil inventories by the ratio of OECD petroleum stocks to US petroleum

[5] Similarly, Foster et al. (2006) find the BED job creation and destruction rates to be more volatile than their LRD counterparts over 1972-1998.

stocks.

Our baseline specification follows Känzig (2021), thus to measure global economic activity we aggregate industrial production from the OECD, Brazil, China, India, Indonesia, the Russian Federation, and South Africa.[6] However, our estimation results are robust to replacing the world industrial production index with Kilian (2009)'s real economic activity index (Section A.1).[7]

Oil surprises are calculated as follows. Let $F^h_{m,d}$ denote the futures price for the West Texas Intermediate (WTI) h-month contract on day d of month m, then the oil surprise $OS^h_{m,d}$ is calculated as the logarithmic difference between the price of the WTI oil futures on the day of the announcement and the day before the announcement as:

$$OS^h_{m,d} = log(F^h_{m,d}) - log(F^h_{m,d-1}). \tag{3}$$

The first principal component of the surprises in contracts ranging from one to twelve months is then used as a measure of oil supply news; the value is set to zero in absence of an announcement. Figure 4 shows the evolution of the quarterly oil news series over time. Larger spikes, such as in August 1986 or after September 11, 2001, represent instances where the announcement led to a large revision of oil price expectations. As mentioned above, while Känzig refers to this variable as a measure of oil supply news, we refer to these shocks as *oil news shocks* given that OPEC decisions to alter production quotas could stem from agents' beliefs about the path of future demand (see, e.g., Kilian and Zhou (2023) and Alsalman et al. (2023)).

3 Empirical Strategy

To study the effect of oil news shocks, we first estimate a Proxy-VAR model (Stock and Watson (2012) and Mertens and Ravn (2013)) à la Känzig (2021) where oil surprises are employed as an instrument.[8] That is, we start by estimating a reduced-form VAR(p) given by

$$\boldsymbol{y_t} = \boldsymbol{c} + \boldsymbol{B_0} + \boldsymbol{B_1} y_{t-1} + ... + \boldsymbol{B_k} y_{t-p} + \boldsymbol{u_t} \tag{4}$$

where $\boldsymbol{y_t}$ is a 6×1 vector that contains the oil market variables followed by the job creation and destruction rates for the industry of interest (e.g., total manufacturing, a 3-digit, or a 4-digit NAICS industry); $\boldsymbol{c}$ is a 6×1 vector of intercepts; $\boldsymbol{B_i}$ are 6×5 matrices of autoregressive coefficients; and $\boldsymbol{u_t}$ denotes a 6×1 vector of Gaussian innovations with mean $\mathbf{0}$ and variance $\boldsymbol{\Sigma}$. The oil market variables include the real price of oil, world oil production, world oil inventories, and a measure of real economic activity, in that order. We rotate each pair of job creation and job destruction rates

[6] This index of world industrial production comprises real production in the manufacturing, mining, electric and gas industries and is available at: https://sites.google.com/site/cjsbaumeister/datasets.

[7] This index is available from the St. Louis Federal Reserve Bank Economic Data (FRED) at https://fred.stlouisfed.org/series/IGREA.

[8] Proxy-VARs (SVAR-IV) have also been commonly used in the literature to estimate the effect of monetary policy and uncertainty shocks. See, among others, Carriero et al. (2015), Gertler and Karadi (2015), Caldara and Kamps (2017), and Stock and Watson (2018)).

(one pair for the aggregate or each industry of interest), after the oil variables. We set the lag order p to 4 and estimate the model in log levels.

As is common in the literature, we assume that the reduced-form innovations, $\boldsymbol{u_t}$, are related with the structural shocks, $\boldsymbol{\epsilon_t}$ through a linear mapping $\boldsymbol{u_t} = \boldsymbol{S\epsilon_t}$ where $\boldsymbol{S}$ is a non-singular 6×6 matrix that captures the impact effect of the structural shocks. The structural shocks are assumed to be i.i.d. and mutually uncorrelated with mean $\mathbf{0}$ and variance Ω. Note that, because we are only interested in identifying the structural effect of a shock to the real oil price, we only need to identify the first column of $\boldsymbol{S}$, which we denote by $\boldsymbol{s_1}$. Then, using the oil news series as an instrument,z_t, and assuming the instrument is relevant, $\mathbb{E}[z_t\boldsymbol{\epsilon_t}] = \alpha \neq 0$, and exogenous with respect to the other structural shocks, $\epsilon_{2:n,t}$, (i.e., $\mathbb{E}[z_t\boldsymbol{\epsilon_{2:6,t}}] = 0$)we can identify the vector s_1 (up to sign and scale) as

$$\bar{s}_{2:6,1} \equiv s_{2:6,1}/s_{1,1} = \mathbb{E}[z_t u_{2:n,t}]/\mathbb{E}[z_t u_{1,t}] \tag{5}$$

as long as $\mathbb{E}[z_t u_{1,t}] \neq 0$. This yields the structural impact vector $s_1 = (s_{1,1}, \bar{s}_{2,1}s'_{1,1})'$ where the scale of $s_{1,1}$ is normalized so that $\Sigma = S\Omega S'$. For ease of interpretation, we normalize the oil news shock such that it corresponds to a 10 percent increase in the price of oil.[9]

4 The Effect of Oil News on Job Reallocation

This section first describes the estimated responses for the oil market and aggregate manufacturing. It then discusses the estimates for the three-digit NAICS industries and follows by exploring the responses of 4 four-digit sub-industries in the transportation sector.

4.1 Oil market and aggregate manufacturing responses

We begin this section by describing the estimation results for the oil market block. Before we discuss our results, it is important to note that because the job creation and destruction data start in 1980, our sample excludes most of the years when the oil futures market did not exist or transaction volumes were low. In contrast, Känzig (2021) uses monthly data starting in 1975. The exclusion of the 1970s might be seen as a drawback, since the great variability of oil prices during this period could help to better identify the effect of an oil price shock. However, excluding this part of the sample has some advantages when identifying oil news shocks using a proxy variable constructed from daily futures data. In particular, as Kilian (2024) notes, oil futures only started trading in 1983, longer maturities were introduced later, and some periods saw no or low trading. Hence, the extracted principal component may be affected by data censoring.

As Figure 5 illustrates, an oil news shock leads to an immediate increase in the oil price which continues to be above the historical average for about five years. World oil inventories exhibit a slight decrease on impact, but an increase in the long run. Oil production responds positively

[9]For more detailed analysis of the assumptions, theory, and proof, see Mertens and Ravn (2013) and the appendix of Känzig (2021).

in the first quarters, although not in a statistically significant manner, which is consistent with oil producers responding to expectations of higher future oil prices. Furthermore, the transitory increase in world oil production suggests that oil news shocks convey beliefs of heightened aggregate demand (Kilian and Zhou (2023) and Herrera et al. (2023)) and do not only represent expectations of oil supply cuts (Känzig (2021)).

We now turn our attention to the response of US manufacturing job flows to oil news shocks. The top left panel of Figure 6 depicts the response of US manufacturing job creation (solid red line) and job destruction (blue dashed line) to an oil news shock that results in a 10% increase in the real price of oil. The 68% confidence bands, denoted by shaded areas, are computed using a moving block bootstrap (see Jentsch and Lunsford (2019)) with 10,000 bootstrap replications. In addition, the figure plots the response of the net employment (NET) growth (black dotted line).

The estimated impulse responses reveal a small increase in job creation on impact that becomes statistically significant two quarters after the shock. With no initial increase in job destruction, net employment growth increases moderately. However, job destruction rises significantly three to four quarters after the shock, leading to a reduction in net employment growth. This decline in employment growth is rather short-lived, as evidenced by the close to zero (0.02 percentage points) fourth-quarter cumulative change (see the second column of Table 3). Now, while the fourth-quarter cumulative increase in net employment growth is negligible, news of an increase in oil prices leads to a statistically significant increase in job reallocation of 0.54 percentage points (about 6% of the average quarterly rate). Two years after the shock, both job creation and destruction have largely returned to their pre-shock levels.

In brief, our estimation results indicate that oil news shocks have a small negative and short-lived impact on net employment growth. This contrasts with the findings of previous studies such as Davis and Haltiwanger (2001) and Herrera and Karaki (2015) where oil price shocks are estimated to result in a significant reduction in employment growth that lasts over a year. There are several potential causes for these differences. First, while the above-mentioned studies used SVARs where the oil price shock was identified via short-run restrictions, we use a Proxy-VAR that identifies unexpected changes in oil prices related to OPEC news. Hence, while the first identification scheme captures movements in oil prices that may be due to supply, demand, or precautionary demand motives, the latter measures the effect of the surprise component of OPEC policy decisions. Second, due to data availability, our sample excludes the years prior to 1980 which are included in previous studies but includes data for the 1990s and 2000s. As we will discuss in detail in Section 6, had we used a shorter sample we would have estimated a larger impact of oil news shocks on the reallocation of US manufacturing jobs.

4.2 Sectoral Job Flows

Figure 6 reports the estimated responses for the nondurable manufacturing industries. A considerable degree of heterogeneity is evident in the response to the news of an oil price increase. First, industries such as food manufacturing, textiles & fabrics, textile mill products, apparel, petroleum

& coal, and paper experience significant variation in job creation and destruction during the first year after the shock. For all these industries, the increase in job destruction exceeds the increase in job creation, leading to declines in net employment change around the second quarter after the shock. However, as Table 3 reveals, four quarters after the shock, the cumulative changes in net employment growth are statistically insignificant, indicating that the response is short-lived. However, as is the case for total manufacturing, the insignificant response of net employment growth masks significant changes in reallocation at the establishment level. As Table 3 illustrates, excess job reallocation (the amount of job movement above what is required to accommodate the change in employment) decreases on impact for leather products, printing, and rubber & plastics, whereas the fourth-quarter cumulative change in excess reallocation is positive for paper and petroleum & coal. The 0.67 percentage point cumulative increase in excess reallocation in petroleum and coal is particularly notable as, given the historical average excess reallocation rate of 5.85%, this represents approximately an 11% increase in job movements needed beyond what is required to accommodate the 0.08 percentage point drop in net employment growth. This increase constitutes the largest change in EXC among nondurable industries.

The responses for durable industries are reported in Figure 7. As was the case for nondurable industries, we observe considerable heterogeneity in the impulse responses. Significant increases in job creation and destruction are estimated for wood products, nonmetallic mineral products, furniture, and transportation equipment in the first year after the shock. For some of these industries, the initial increase in job destruction exceeds the rise in job creation (e.g., nonmetallic mineral products, transportation equipment), thus net employment growth falls on impact; only a couple of three-digit industries (e.g. wood products, furniture) experience increases in net employment growth on impact (see Table 3). The effect of the oil news shock on net employment growth is rather short-lived. A year after the shock, the cumulative effect is positive for six out of the 10 three-digit industries; economically significant declines in net employment growth are observed for nonmetallic mineral products (-0.34) and transportation equipment (-0.38), although they are estimated with a low degree of precision.

As Table 3 illustrates, a year after the oil news shock the process of firm entry, exit, growth, and contraction has intensified for about half of industries. Statistically significant increases in job reallocation are estimated for nonmetallic mineral products (1.03 percentage points), transportation equipment (1.05), and furniture (0.51). More than half of the job reallocation in these industries is needed to accommodate the drop in net employment growth. This is evidenced by the magnitude of the cumulative change in excess reallocation four quarters after the shock, which ranges between 0.39 for furniture and 0.69 percentage points for nonmetallic mineral products. That industries such as wood and nonmetallic mineral products exhibit large changes in job reallocation is perhaps not surprising. After all, wood production (i.e., the forest product subsector) is the second largest consumer of fuels and power in US manufacturing, with approximately 75% of fuel needs being satisfied with distillate fuel and oil (Department of Energy (2013)). Similarly, the industry of nonmetallic mineral products relies heavily on heat to refine minerals, which is an energy intensive and costly process.

Three takeaways are derived from the estimation results presented in this section. First, there is a great degree of heterogeneity in the response of sectoral job flows to oil news shocks. Sectors that have traditionally been considered to be intensive in the use of oil (petroleum & coal products, wood, and nonmetallic mineral products) experience contractions in employment and increased labor reallocation. Second, the effect of an oil news shock that results in a 10% increase in the price of crude oil on sectoral job creation and destruction is shorter-lived, yet it leads to substantial job reallocation in several nondurable and durable industries. These findings are consistent with empirical and theoretical literature that suggest that oil price shocks lead to reallocation of workers from industries that heavily rely on oil as an input for manufacturing or consumption (such as transportation equipment) to less energy-intensive industries. Finally, our results indicate that the transportation sector continues to play an important role in the transmission of oil price shocks. In the following section, we further inquire into the effect of oil news shocks on this sector.

4.3 Digging deeper into the response of the transportation sector

The results presented in the previous section suggest that the transportation equipment sector plays a key role in the dynamic adjustment of manufacturing jobs after an oil news shock. To further investigate the labor reallocation responses in this sector, we re-estimate our model for 4 four-digit sub-industries: motor vehicles, motor vehicle bodies and trailers, motor vehicle parts manufacturing, and other transportation equipment. The motivation for such a decomposition is threefold. First, as Table 1 illustrates, transportation equipment represented 13.46% of manufacturing employment between 1980Q3 and 2016Q4, the largest share among all three-digit industries. In addition, among the sub-industries in this sector, motor vehicles and motor vehicle bodies exhibited higher average job creation and destruction rates than most manufacturing industries. Second, the transportation equipment industry includes all forms of transportation equipment, such as boats and airplanes, which may respond differently to expectations of higher oil prices than motor vehicles. Finally, work by Ramey and Vine (2011) suggests that despite the reduced impact of oil price changes on the US economy since the 2000s, motor vehicle consumption continued to be quite sensitive to fluctuations in oil prices. We stress the importance of analyzing the transportation sector's responses to better understand how oil news shocks impact overall manufacturing labor dynamics.

Figure 8 reports the impulse response functions for the four-digit NAICS sub-industries of interest. We estimate that an oil news shock leads to an immediate, large, and statistically significant increase in job destruction for motor vehicle manufacturing and other transportation equipment. Statistically significant increases in job destruction are also observed for motor vehicle parts and for motor vehicle bodies and trailers two quarters after the shock. The rise in job destruction for motor vehicles and related industries is greater and more persistent than for any other industry. As for job creation, while no significant response is evident for motor vehicle parts and other transportation in the first year following the shock, a delayed increase is observed for motor vehicles and motor vehicle bodies and trailers; however, this increase is not enough to offset the rise in job destruction. As a result, net employment growth declines.

The cumulative responses of net employment (NET), gross reallocation (SUM), and excess reallocation (EXC) reported in Table 3 provide a summary of the impact of oil news shocks on the labor dynamics for the sub-industries in transportation equipment. Of note is the significant fourth-quarter cumulative response of job reallocation in motor vehicles (3.14 percentage points), motor vehicle parts (0.34), and other transportation equipment (1.22). These changes are economically significant, as they represent increases of 28.1, 4.0, and 12.3% relative to the historical average reallocation rates for these sub-industries.

5 What Factors Explain the Heterogeneous Response of Sectoral Job Creation and Destruction to Oil News Shocks?

Estimation results presented in the previous section reveal a significant degree of heterogeneity in the response of job creation and destruction to oil news shocks. What characteristics drive this variation in industry-level responses? Davis and Haltiwanger (2001) find that the sensitivity of job creation and destruction to oil price shocks is related to the degree of energy intensity, capital intensity, and size of the establishment. Similarly, the work by Kehrig and Ziebarth (2017) suggests that the effect of oil supply shocks is greater in firms with higher capital-energy complementarities. How important are these factors in accounting for the different industry responses to oil news shocks? To answer this question, we exploit the variation in the cumulative job flow responses and inquire whether cross-industry differences in the size of the responses are systematically related to the above-mentioned factors.

5.1 Estimation Strategy and Industry-level Characteristics

As mentioned above, one advantage of using the ASM/CMF data is that we can compute measures of job creation and destruction at a more disaggregated level (four-digit NAICS) than publicly available. This allows us to leverage the variation in responses across sub-industries to explore what sectoral characteristics matter for the transmission of oil news shocks. Another advantage of these data is that they allow us to construct industry-level measures of energy intensity, capital intensity, size, age, and other industry-level characteristics over the period under analysis and then investigate the role of these characteristics in explaining cross-industry variation in impulse responses. To investigate what industry-level characteristics play a role in the transmission of oil news shocks, we proceed in the following manner. First, we compute job creation and destruction rates that span 1980Q3-2016Q4 for 86 four-digit sub-industries. We then reestimate the Proxy-VAR model in equation (4) rotating in the job creation and destruction rates for each of these sub-industries and compute the cumulative response at different horizons of interest.[10] Similarly,

[10]Due to limits on the disclosure of estimates obtained from the confidential data, we do not report the impulse response estimates at the 4-digit level.

we estimate the cumulative impulse responses of net employment growth, gross reallocation, and excess reallocation. The four-quarter and twelve-quarter cumulative responses, respectively, are employed as a measure of the short- and medium-run responses to an oil news shock.

Second, we construct measures of industry-level characteristics over the 1980Q3-2016Q4 period. Given that cumulative impulse response functions represent the average medium- or long-run responses during the estimation period, all industry-level characteristics are computed by averaging the variables over the sample. We consider the following variables (or their transformation) as possible determinants of the variation in cross-industry responses to oil news shocks.

Energy-intensity is a likely determinant of the industry-level sensitivity and its importance is apparent from the estimation results reported in section 4. Hence, as in Davis and Haltiwanger (2001), we compute a measure of energy-intensity at the establishment level dividing the cost of energy by the total value of shipments. To gain some insight into the differences in job flows across firms with different levels of energy-intensity, we report summary statistics for job creation and destruction by energy deciles in Table 4. The mean and standard deviation of job creation are higher for firms that are less energy-intensive. As for job destruction, firms in the top three deciles exhibit a slightly lower mean and volatility than in the bottom three deciles.

Capital-intensity is measured as the cost of capital expenditure per production worker. It is worth noting that this variable differs from other measures of capital intensity used in the literature in that we do not calculate the stock of physical capital. Instead, we directly use the expenditure reported by the establishment in acquiring and maintaining fixed assets. Thus, our measure captures variation in investment per worker across industries. Two interesting patterns can be observed in Table 4 where we summarize the mean and standard deviation of job creation and destruction by capital-intensity deciles. First, average job flows decrease systematically with capital intensity. Second, establishments in the top deciles of capital intensity exhibit less variation in job flows over time. These statistics suggest that capital deepening is correlated with decreased labor market fluidity.

Capital-energy ratio is defined as the ratio of capital expenditures to energy expenditures. Recall that we measure job flows based on the changes in production workers, thus this ratio could be thought of as a proxy for the ratio of capital expenditures to expenditures in unskilled workers. If there are capital-skill and capital-energy complementarities, an increase in the price of energy could result in the substitution of capital for unskilled workers.[11]

Size and age of the establishments in an industry are also characteristics that could influence the dynamic response of businesses and jobs to shocks. For instance, drops in job creation and destruction over the sample have contributed to a decline in employment dynamism, however, this decline in fluidity has not been homogeneous across age and size. Differences in these characteristics may affect the sensitivity of employment to oil news shocks. We define the size of an establishment as the number of production workers reported in a quarter and then take the average size in the industry and over time. To measure an establishment's age we match the ASM/CMF data with

[11] See, e.g. Polgreen and Silos (2009).

the LBD and measure age as the difference between the current year and the first year when the establishment reports positive employment in the LBD.[12] We also consider the percentage of *mature* establishments in the four-digit sub-industry. We define mature as establishments aged nine and above. Table 5 reports the mean and standard deviation of job creation and destruction for establishments in different size brackets split between mature and young firms. As the table illustrates, mature firms account for almost 80% of the employment in manufacturing and, with the exception of the smallest and largest firms, they exhibit larger mean job creation and destruction rates than their young counterparts.

Establishment growth is defined as the first difference in the log of the number of establishments in the four-digit NAICS sub-industry. The motivation for considering this variable as a possible source of variation in cross-industry responses is twofold. First, differential rates of establishment growth are likely to be linked to differences in market fluidity across industries. In turn, industries with lower labor market fluidity are likely to be less responsive to shocks.[13] Second, the interplay of establishment births and deaths enhances job churn and may lead to productivity gains via creative destruction (see e.g., Aghion and Howitt (1990)). In turn, cross-industry variation in job churning could lead to differences in the dynamic response of job flows to shocks.

5.2 Estimation Results

Table 6 summarizes the key characteristics that explain cross-industry variation in the fourth- and twelfth-quarter cumulative response of job creation, job destruction, net employment growth, and excess job reallocation.[14] Because excess job reallocation is a better measure of the intensity of reallocation activity, we focus on this index instead of the gross job reallocation rate (see e.g., Davis (1998) and Liu (2013)).

We find that variation in energy cost is the main driver of the cross-industry variation. The higher the energy cost, the more likely an industry is to experience job losses in the short- (fourth-quarter) and medium-run (twelve-quarter) and job gains in the medium-run. As a result, employment growth in industries characterized by higher energy costs is more sensitive to oil news shocks. News shocks prompt a more intense process of job reallocation in these industries, as illustrated by the positive and statistically significant coefficients on energy cost in the excess reallocation regressions.

The ratio of capital to energy and the share of mature plants account for statistically significant variation in the cumulative responses of job destruction and excess reallocation, and marginally explain the variation in the response of net employment growth. The magnitude of the cumulative response of job destruction decreases with the capital-energy ratio and is larger in industries with a

[12] Regression results not reported in the paper reveal no statistically significant effect of age^2.

[13] See Davis and Haltiwanger (2014) for evidence on the link between labor market fluidity and responsiveness to shocks.

[14] Due to disclosure restrictions, we do not report results for alternatives regression specifications with nonlinear transformations of the regressors or additional explanatory variables when the characteristics are insignificant for all horizons.

higher percentage of mature firms. In addition, the response of excess reallocation is considerably higher in industries with more mature establishments.

Our finding that energy-intensive industries experience more intense job reallocation is in line with previous theoretical and empirical studies that point to energy costs as a key transmission channel of oil price increases to employment and output. However, the finding that the response of job destruction and excess reallocation is greater for industries with a higher percentage of mature firms stands in contrast with Davis and Haltiwanger (2001) who estimate that industries with younger firms are more sensitive to oil price shocks. Differences in the estimation results could stem from two sources: differences in identification strategy and sample period. First, as noted earlier, we identify the effect of oil news shocks using OPEC announcements, whereas Davis and Haltiwanger (2001) rely on short-run restrictions to identify the effect of oil price fluctuations. Hence, our empirical strategy captures an expectations effect that is likely missed by the earlier literature. Second, our sample starts in 1980 and spans until 2016 whereas Davis and Haltiwanger (2001) uses an earlier sample. Thus, changes in the age profile of industries and in the transmission mechanism might explain why we find mature industries to be more responsive to oil news shocks.

Interestingly, we do not find any evidence that the response of excess reallocation is greater for industries where capital intensity is higher. To further investigate this issue, we separate industries by capital intensity quintiles, compute job flows, and estimate the impulse response functions (IRFs) for job creation and destruction for the top and bottom capital expenditure quintiles. Figure 9 reveals an important difference in responses; while job destruction for industries in the lowest capital quintile does not change significantly, a significant increase is observed a quarter after the shock for the highest quintile. For both quintiles, job creation increases significantly one year after the shock. As a result, net employment growth increases in the very short-run (two quarters after the shock) for the less capital intensive firms, whereas it decreases for the more capital intensive firms. In summary, while differences in the response by capital quintiles are evident in these impulse response functions, the reshuffling of jobs among firms with different capital-intensity levels takes place in the very short-run. This rapid adjustment to oil news shocks, as well as aggregation by industries, explains why the coefficient of capital intensity is not significant in the cross-industry regressions that use the cumulative responses four quarters after the shock.

6 The Changing Impact of Oil News Shocks

This section investigates whether the responses of job creation and destruction have changed over time. Two changes in the US economy prompt this investigation. First, a decline in the fluidity of the US labor market has been widely documented in the literature. In turn, this decline could be related to establishments that became less responsive to shocks over time (Bloom (2009) and Decker et al. (2018)). Second, the transmission of oil price shocks to the labor market may have changed as a result of the shale oil boom in the mid-2000s (see Bjørnland and Skretting (2024)).

To investigate whether job flows have become less responsive to oil news shocks, we re-estimate our Proxy-VARs on expanding subsamples that start from 1980Q3-2000Q1 and end with the full sample. We opt to investigate time-variation using this expanding window method on the more aggregated data for several reasons. First, we want to allow for the possibility that the relationship between the oil price and the oil surprises IV varies over time, which current Proxy-TVP-VAR models are not well equipped to do. Second, estimating Proxy-TVP-VARs using the particle Gibbs algorithm proposed by Mumtaz and Petrova (2023) with more than a few variables is computationally intensive and can face convergence issues. Last but not least, due to limits on research output placed by the Census Bureau on projects using confidential ASM/CMF data, we are only able to use expanding samples of the more aggregated (3-digit NAICS) data.

Figures 10 and 11 plot the cumulative impulse response functions estimated over the expanding subsamples. For the sake of brevity, we focus on the responses for total manufacturing and the industries that consume the most energy from fuel or petroleum.[15] The top row provides striking evidence of a reduction in the responsiveness of job creation and, especially, destruction to oil news shocks in US manufacturing. The cumulative change in job destruction went from a peak of 5.8% in the earlier samples to less than 1% in the full sample, whereas that of job creation decreased from a peak of 3.4% to 0.4%. [16]

The top fuel and petroleum consumers in nondurable industries, such as paper, chemicals, petroleum & coal products, and plastics & rubber, also experienced a decline in the responsiveness of job creation and destruction to oil news shocks. For all of these industries, at peak, the estimated cumulative increase in job destruction declined by an order of magnitude. The response declined from 1.3% to 0.2% for chemicals, 2.6% to 0.6% for petroleum & coal products, 1.4% to 0.3% for paper, and 2.3% to 0.3% for plastics & rubber. Similar decreases were observed for job creation.

We observe a similar pattern for the top fuel consumers in the durable industries. In the early subsamples, the top fuel consumers, transportation equipment and primary metal products, were estimated to immediately reduce job creation by 2.1% and 0.4%, respectively; in contrast, no significant decline is estimated in the later subsamples. In addition, at peak the cumulative change in job creation decreases by about half for these industries. Regarding job destruction, we estimate maximum cumulative increases of 8.1%, 5.5%, and 4.4% for transportation equipment, primary metal products, and nonmetallic mineral products in the earlier subsamples. In contrast, at the peak, the change triggered by the oil news shock is about 75% smaller in the later subsamples.

We conclude this section by noting that, despite the change in the responsiveness of business-level employment to oil news shocks, the characteristics that explain the cross-industry variability remained roughly unchanged over time. Estimation results, not reported herein due to disclosure limits, indicate that energy intensity and establishment age (or maturity) were key drivers of the heterogeneous response to oil news shocks in the earlier sub-samples. Over time, the ratio of capital to energy expenditures gained importance in accounting for this variation. This evidence suggests that technological change plays a role in the responsiveness of job reallocation to oil news shocks.

[15] See `https://eia.gov/energyexplained/use-of-energy/industry.php` and `https://www.eia.gov/todayinenergy/detail.php?id=40752`

[16] Figures for the remaining industries can be found in the Online Appendix.

7 Conclusions

To investigate the effect of oil news shocks on the creation and destruction of jobs in US manufacturing, we computed job flow rates from confidential establishment-level data covering the period between 1980Q3 and 2016Q4. Thus, we first provided a rich characterization of the dynamics of job creation and destruction in US manufacturing. We documented a decline in gross job flows since the late 1980s. Job destruction exhibited greater variation than job creation for almost all the sectors, with the only exception of plastics & rubber. Transportation equipment and food manufacturing averaged the highest employment shares during the sample period.

We then estimated a Proxy-VAR using movements in oil futures prices around OPEC announcements as an instrument. We found a small negative and short-lived decline in net employment growth and an increase in job reallocation for aggregate manufacturing. We demonstrated that this muted aggregate response masks a great degree of heterogeneity across industries. In addition, we showed that the sensitivity of employment growth and job reallocation rose significantly with the degree of energy intensity, the ratio of capital-to-energy spending, the share of mature establishments, and the rate of growth of establishments in the industry.

While our results revealed important reallocative consequences of oil news shocks, we noted a muted response compared to the larger GDP contraction estimated by Känzig (2021) and the more intense increase in job reallocation estimated by previous studies. We offered two plausible explanations for this muted response: the decrease in the responsiveness of business-level employment and the role of the shale boom in altering the transmission of oil price shocks. Our finding of a decline in the responsiveness of sectoral job creation and destruction to oil news shocks since the mid-2000s supports the relevance of the second explanation.

We close by highlighting three key aspects of the response of sectoral job creation and destruction to oil news shocks. First, there is a great degree of heterogeneity in responsiveness across industries, both for the full sample and the subsamples. Secondly, we find that no other sector bears the same degree of reshuffling as the motor vehicle industry. Finally, cross-industry variation is systematically correlated with observable establishment-level characteristics, such as the cost of energy and the percentage of mature firms within the industry. These findings have implications for the implementation of policies aimed at mitigating the economic consequences of oil price shocks and the design of theoretical models. On the one hand, evidence of heterogeneity in the industry-level response to these shocks underscores the need for policy makers to understand how policies may have radically different effects on employment growth in different sectors. On the other hand, the use of models with representative firms in macroeconomics runs the risk of overlooking the role played by firm heterogeneity in the transmission of oil shocks.

Table 1: Summary Statistics for Job Creation and Job Destruction, 1980:Q3-2016:Q4

			POS		**NEG**		**NET**	**SUM**	**EXC**
Sector	NAICS	Emp. Share	Mean	S.D.	Mean	S.D.			
Total Manufacturing	300-399	100	4.20	(1.05)	4.38	(1.53)	-0.18	8.58	7.61
Nondurables									
Food Manufacturing	311	11.05	6.10	(1.83)	5.90	(2.52)	0.21	12.00	11.17
Beverages & Tobacco	312	1.06	4.80	(1.38)	5.01	(1.47)	-0.21	9.81	8.52
Textiles & Fabrics	313	2.99	3.00	(1.19)	4.03	(1.97)	-1.03	7.03	5.51
Textile Mills	314	1.16	4.36	(1.29)	4.33	(1.68)	0.03	8.69	7.27
Apparel & Accessories	315	4.07	5.39	(2.49)	5.21	(2.72)	0.17	10.60	8.96
Leather & Allied	316	0.72	4.39	(1.87)	5.27	(3.04)	-0.88	9.67	7.80
Paper	322	3.98	2.68	(0.85)	2.94	(1.17)	-0.26	5.62	4.87
Printing Matter	323	3.59	3.85	(1.72)	3.74	(1.84)	0.11	7.58	6.56
Petroleum & Coal	324	0.90	3.32	(1.06)	3.54	(1.30)	-0.22	6.86	5.85
Chemicals	325	5.22	2.98	(0.64)	3.32	(1.09)	-0.34	6.30	5.56
Plastics & Rubber	326	5.84	3.94	(1.30)	3.84	(1.10)	0.10	7.78	6.80
Durables									
Wood Products	321	3.31	4.78	(1.66)	4.50	(2.40)	0.28	9.28	7.52
Nonmetallic Minerals	327	3.14	4.35	(1.11)	4.42	(1.71)	-0.07	8.77	7.58
Primary Metals	331	4.72	2.98	(1.12)	3.65	(1.92)	-0.66	6.63	5.07
Fabricated Metals	332	9.19	4.27	(1.36)	4.33	(1.88)	-0.06	8.60	7.31
Machinery, Non-Electrical	333	7.57	4.24	(1.17)	4.60	(1.69)	-0.36	8.84	7.48
Computer & Electronics	334	7.26	3.94	(1.30)	4.66	(1.94)	-0.72	8.60	7.11
Electrical Equipment	335	3.92	3.59	(1.03)	4.10	(1.52)	-0.50	7.69	6.43
Transportation Equipment	336	13.46	4.42	(1.62)	4.62	(1.92)	-0.20	9.04	7.27
Motor Vehicles	3361	-	5.63	(4.41)	5.55	(4.69)	0.08	11.18	11.10
Motor Vehicle Bodies	3362	-	5.67	(2.11)	5.31	(2.83)	0.36	10.99	8.11
Motor Vehicle Parts	3363	-	4.19	(2.09)	4.44	(2.20)	-0.24	8.63	6.41
Other Transportation Equipment	3369	-	4.81	(2.21)	5.11	2.55)	-0.30	9.93	7.53
Furniture & Fixtures	337	3.46	4.27	(1.39)	4.19	(1.83)	0.08	8.45	7.02
Miscellaneous Other	339	3.40	4.49	(1.05)	4.31	(1.38)	0.18	8.81	7.90

Notes: This table reports the average quarterly rates of job creation (POS, destruction (NEG), net employment (NET), gross reallocation (SUM) and excess reallocation(EXC) for total manufacturing, 3-digit NAICS industries, and key 4-digit NAICS sub-industries. Employment shares are average annual percent of total manufacturing workers within each 3-digit NAICS industry. Standard deviations are reported in parentheses where applicable.

Table 2: Comparison of Average Labor Flows by Industry

	ASM/CMF (1980Q3:2016Q4)		BED (1992Q2:2016Q4)		DH2001 (1972Q2:1988Q4))	
NAICS Description	POS	NEG	POS	NEG	POS	NEG
Total Manufacturing	4.20	4.38	4.1	4.4	5.2	5.5
Nondurables						
Food Manufacturing	6.10	5.90	5.4	5.4	9.0	9.0
Beverages & Tobacco	4.80	5.01	5.6	5.3	-	-
Textiles & Fabrics	3.00	4.03	3.4	4.8	-	-
Textile Mills	4.36	4.33	5.3	6.0	3.5	4.1
Apparel & Accessories	5.39	5.21	6.7	8.6	5.4	6.3
Leather & Allied	4.39	5.27	4.6	5.7	4.8	6.1
Paper	2.68	2.94	2.8	3.3	3.6	3.8
Printing Matter	3.85	3.74	4.4	5.0	4.5	4.5
Petroleum & Coal 3.32	3.54	3.9	4.2	4.9	5.3	
Chemicals	2.98	3.32	2.9	3.1	3.6	4.0
Plastics & Rubber	3.94	3.84	3.9	4.0	5.4	5.3
Durables						
Wood Products	4.78	4.50	5.2	5.5	6.6	6.9
Nonmetallic Minerals	4.35	4.42	5.1	5.3	5.3	5.7
Primary Metals	2.98	3.65	2.9	3.5	3.7	4.6
Fabricated Metals	4.27	4.33	4.5	4.6	5.3	5.6
Machinery, Non-Electrical	4.24	4.60	3.8	4.0	4.9	5.3
Computer & Electronics	3.94	4.66	3.2	3.7	-	-
Electrical Equipment	3.59	4.10	3.2	3.7	4.7	4.9
Transportation Equipment	4.42	4.62	3.4	-3.6	5.5	5.7
Furniture & Fixtures	4.27	4.19	4.9	5.4	5.1	5.3
Miscellaneous Other	4.49	4.31	4.6	4.8	6.7	7.1

Notes: Average job creation (POS) and destruction (NEG) rates from the ASM/CMF private data, BED public access data, and Davis and Haltiwanger (2001) reported estimates. - denotes that the industry was not reported for the sample.

Table 3: Cumulative Changes in Labor Flows by Sector

	NET		SUM		EXC	
Quarters after shock	0	4	0	4	0	4
Total Manufacturing	0.02	0.03	0.10	**0.54**	0.08	0.51
Nondurables						
Food Manufacturing	0.13	-0.17	-0.03	0.50	-0.15	0.33
Beverages & Tobacco	**0.46**	0.31	-0.04	-0.28	-0.51	-0.60
Textiles & Fabrics	0.06	-0.31	-0.19	0.25	-0.25	-0.06
Textile Mills	0.22	-0.17	-0.16	0.42	-0.38	0.25
Apparel & Accessories	-0.07	-0.02	-0.17	0.69	-0.24	0.67
Leather & Allied	0.18	0.15	**-0.48**	-0.30	**-0.66**	-0.45
Paper	0.00	-0.02	0.13	**0.54**	0.13	**0.52**
Printing Matter	0.17	0.06	**-0.29**	0.22	**-0.46**	-0.49
Petroleum & Coal	0.05	-0.08	**0.34**	**0.76**	0.29	**0.67**
Chemicals	0.15	0.08	0.02	0.06	-0.13	-0.03
Plastics & Rubber	0.15	0.19	-0.14	-0.05	**-0.29**	-0.23
Durables						
Wood Products	**0.49**	0.38	-0.02	0.70	**-0.51**	0.32
Nonmetallic Minerals	-0.12	-0.34	**0.25**	**1.03**	0.13	**0.69**
Primary Metals	-0.23	-0.07	0.12	0.22	-0.11	0.15
Fabricated Metals	-0.11	0.11	-0.02	0.53	-0.13	0.42
Machinery, Non-Electrical	-0.12	0.12	-0.18	-0.14	**-0.29**	-0.26
Computer & Electronics	-0.01	0.11	-0.07	-0.05	-0.08	-0.11
Electrical Equipment	0.05	0.11	-0.18	0.00	-0.24	-0.11
Transportation Equipment	-0.18	-0.38	**0.32**	**1.05**	0.14	0.67
Motor Vehicles	**-1.61**	**-1.61**	**0.75**	**3.14**	**-0.85**	1.53
Motor Vehicle Bodies	-0.34	-1.47	0.21	2.02	-0.13	0.56
Motor Vehicle Parts	0.18	-0.42	0.04	**0.34**	-0.14	-0.08
Other Transportation Equipment	-0.75	-1.23	**0.88**	**1.22**	0.13	-0.01
Furniture & Fixtures	0.12	-0.19	-0.09	**0.51**	-0.21	0.33
Miscellaneous Other	-0.13	0.03	-0.26	0.21	-0.38	**0.18**

Notes: This table reports the cumulative change (measured in percentage points) 0 and 4 quarters after the shock for net employment growth (NET), gross job reallocation (SUM), and excess reallocation (EXC) to a positive innovation in the real oil price. We normalize the oil news shock to 10% increase in oil price. 68% confidence bands are computed via 10,000 bootstrap and significance is denoted in bold.

Table 4: Summary Statistics for Job Creation and Job Destruction by Energy and Capital Decile, 1980:Q3-2016:Q4

		Job Creation		**Job Destruction**	
	Emp. Share (%)	Mean	S.D.	Mean	S.D.
Energy Decile					
0 - 9	10	4.669	(1.269)	4.617	(1.671)
10 - 19	10	4.679	(1.168)	4.759	(1.659)
20 - 29	10	4.459	(1.235)	4.606	(1.996)
30 - 39	10	4.274	(1.350)	4.406	(1.878)
40 - 49	10	4.175	(1.080)	4.389	(1.676)
50 - 59	10	4.040	(1.029)	4.275	(1.488)
60 - 69	10	3.980	(1.093)	4.402	(1.542)
70 - 79	10	3.946	(1.069)	4.404	(1.451)
80 - 89	10	3.760	(0.925)	4.376	(1.374)
90 - 100	10	3.798	(0.956)	4.553	(1.513)
Capital Decile					
0 - 9	10	4.663	(1.833)	5.433	(2.634)
10 - 19	10	4.523	(1.468)	5.047	(2.341)
20 - 29	10	4.406	(1.340)	4.767	(1.953)
30 - 39	10	4.351	(1.248)	4.582	(1.726)
40 - 49	10	4.238	(1.061)	4.511	(1.666)
50 - 59	10	4.136	(1.095)	4.393	(1.630)
60 - 69	10	4.035	(0.955)	4.230	(1.369)
70 - 79	10	3.846	(0.861)	4.123	(1.180)
80 - 89	10	3.820	(0.849)	4.137	(1.221)
90 - 100	10	3.853	(0.921)	4.092	(1.384)

Notes: This table reports the average quarterly job creation and destruction rates for each energy and capital decile. Standard deviations are reported in parentheses.

Table 5: Summary Statistics for Job Creation and Job Destruction by Firm Age-Size Category, 1980:Q3-2016:Q4

		Job Creation		**Job Destruction**	
	Emp. Share (%)	Mean	S.D.	Mean	S.D.
Mature Firms (≥9 Years)					
0 - 19 Workers	2.57	0.872	(0.996)	5.437	(6.851)
20 - 99 Workers	13.87	3.718	(2.162)	4.685	(3.050)
100 - 199 Workers	18.56	4.232	(2.432)	4.196	(2.773)
200 - 399 Workers	16.26	3.188	(1.827)	2.65	(1.790)
400 - 749 Workers	21.57	3.049	(1.834)	2.138	(1.516)
750+ Workers	6.14	0.393	(0.329)	0.248	(0.228)
Young Firms (<9 Years)					
0 - 19 Workers	1.83	1.988	(4.678)	2.681	(6.601)
20 - 99 Workers	4.25	2.394	(2.640)	1.335	(2.268)
100 - 199 Workers	3.00	1.077	(2.148)	0.770	(1.624)
200 - 399 Workers	3.72	1.053	(2.577)	0.679	(1.609)
400 - 749 Workers	2.93	0.648	(1.528)	0.403	(1.013)
750+ Workers	5.31	0.726	(1.826)	0.330	(0.944)

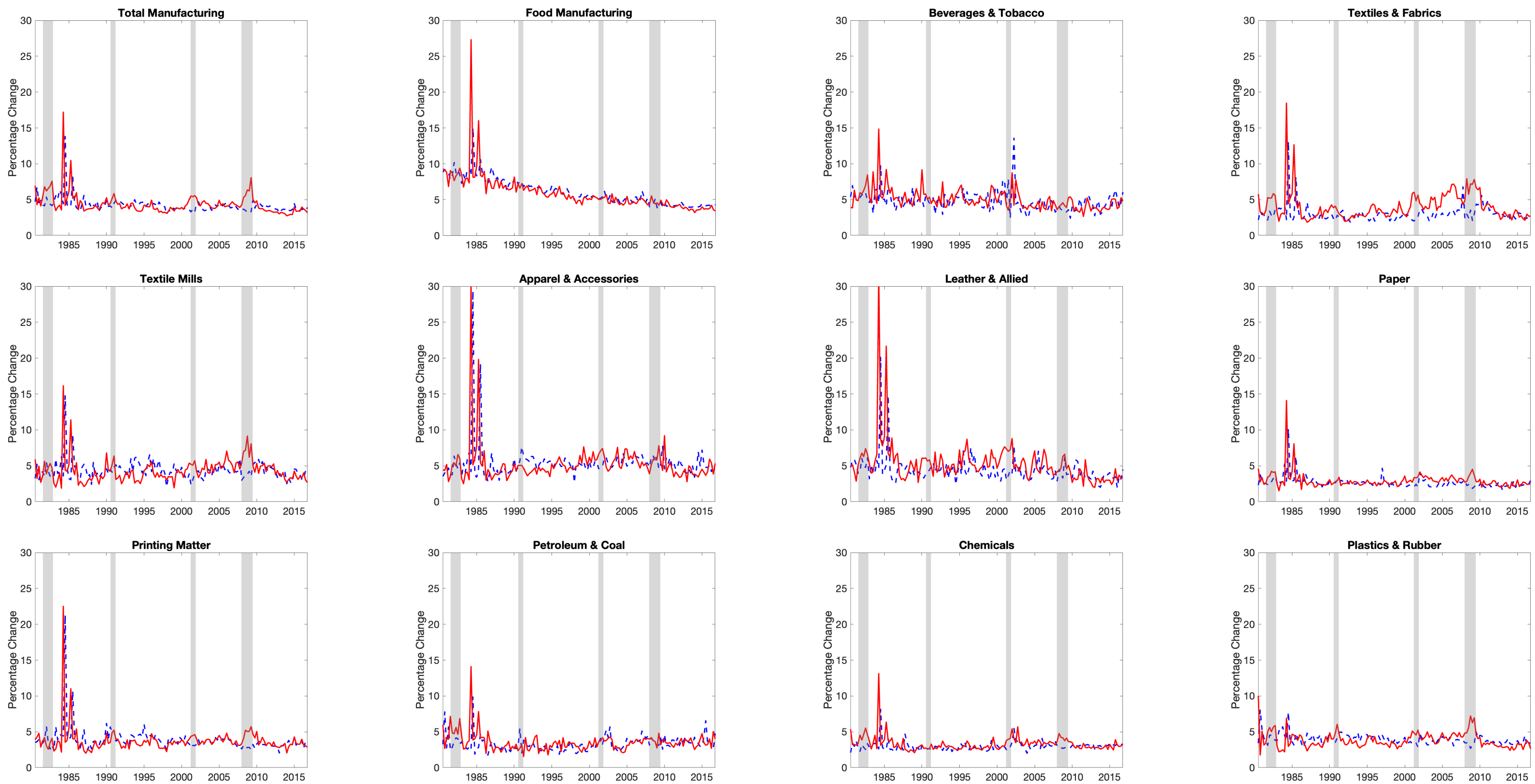
Notes: This table reports the average quarterly job creation and destruction rates for each age-size category. Firms nine years or older are classified as Mature Firms; the remaining firms are classified as young. Employment shares are average annual percent of total manufacturing workers within each age-size category. Standard deviations are reported in parentheses.

Table 6: Relation between Firm-Level Characteristics and the Cumulative Response of Job Creation and Destruction to Oil News Shocks

	Job Creation		**Job Destruction**	
Quarters after the shock	4	12	4	12
Energy-Cost	0.0144	0.0566***	0.0546***	0.0845***
	(0.0087)	(0.0126))	(0.0137)	(0.0174)
Energy-Capital Ratio	-0.000198	-0.000115	-0.000649*	-0.000891**
	(0.000222)	(0.000322)	(0.00035)	(0.000445)
Mature Share	0.0080	0.0158	-0.0033	0.0108
	(0.0067)	(0.0097)	(0.0106)	(0.0134)
Establishment Growth	-0.0021	0.0194	0.0388	0.0737**
	(0.0154)	(0.0223)	(0.0243)	(0.0309)
	Net Employment Growth		**Excess Reallocation**	
Quarters after the shock	4	12	4	12
Energy-Cost	-0.0402**	-0.0280	0.0340**	0.1270***
	(0.0159)	(0.0175)	(0.0168)	(0.0243)
Energy-Capital Ratio	0.000451	0.000775*	-0.000520	-0.000726
	(0.000408)	(0.000448)	(0.000429)	(0.000622)
Mature Share	0.0113	0.0050	0.0235*	0.0570***
	(0.0123)	(0.0135)	(0.0130)	(0.0188)
Establishment Growth	-0.0409	-0.0542*	0.0298	0.0431
	(0.0283)	(0.0310	(0.0298)	(0.0431)

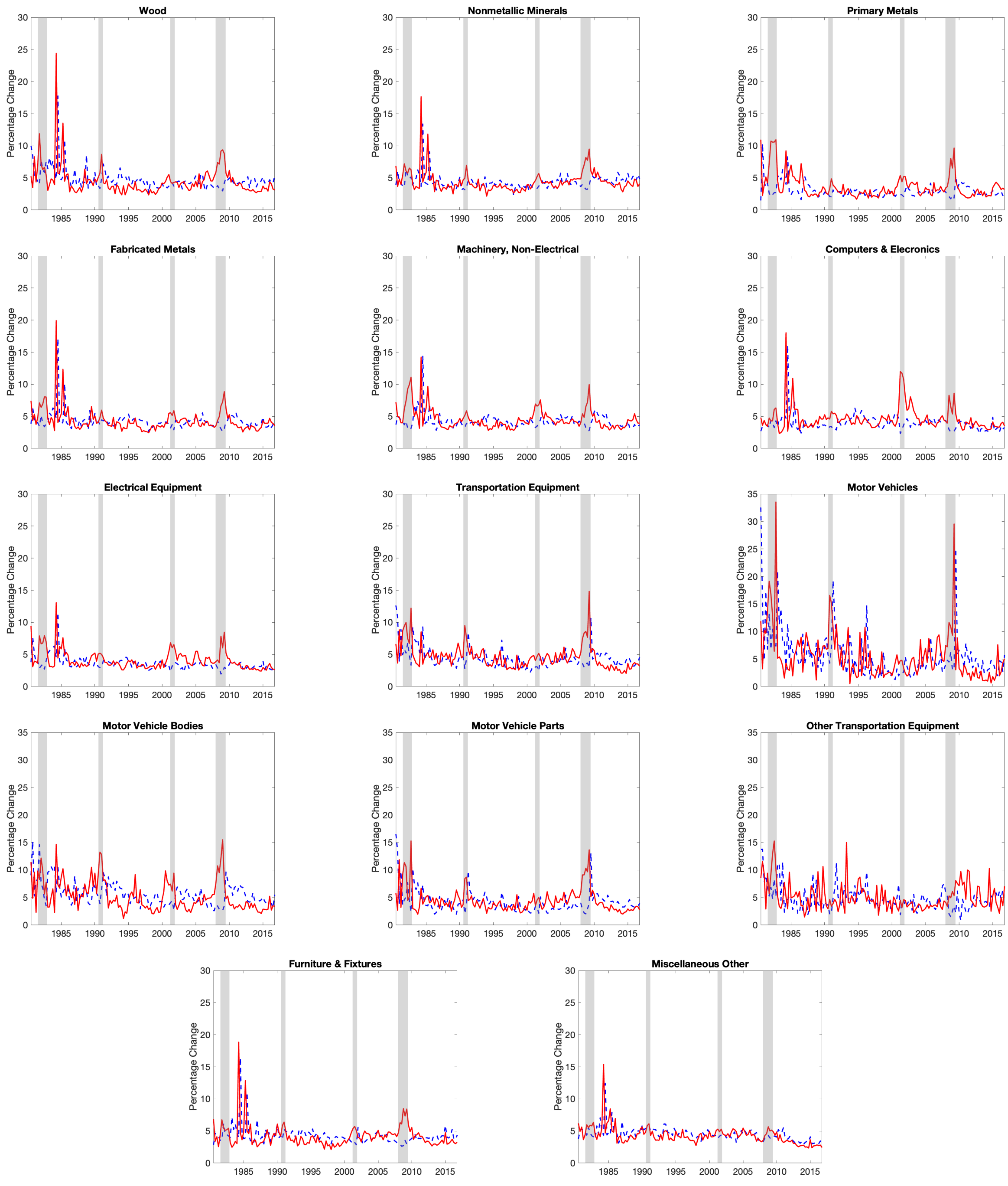
Notes: This table reports results from regressing industry-level cumulative responses to an oil news shock on the indicated industry characteristics. See text for full description of the variables. Robust standard errors are reported in parenthesis. *, **, and *** denote significance level at the 10%, 5% and 1%, respectively.

Figure 1: US Manufacturing Job Creation and Destruction Rates, 1980Q3-2016Q4



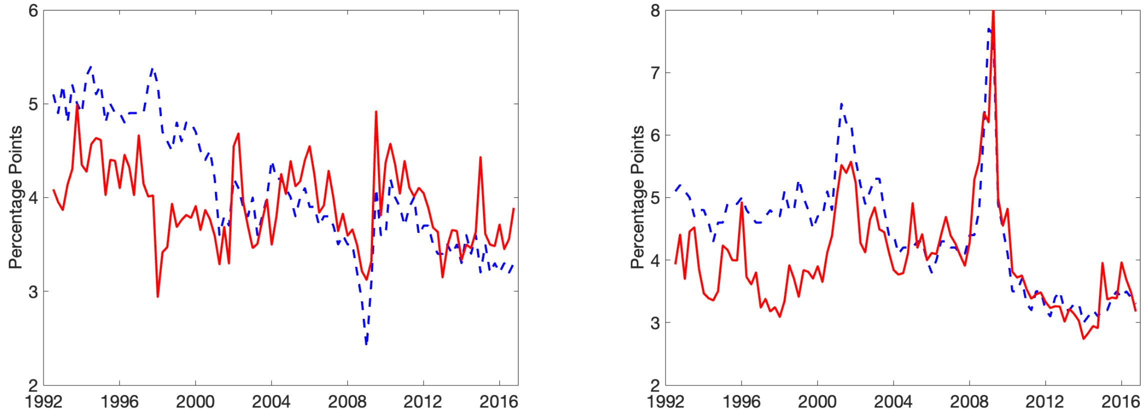
Notes: This figure reports quarterly rates of US manufacturing job creation (POS) and destruction (NEG). Recessionary periods shaded in gray.

Figure 2: US Manufacturing Job Creation and Destruction Rates, 1980Q3-2016Q4 (continued)



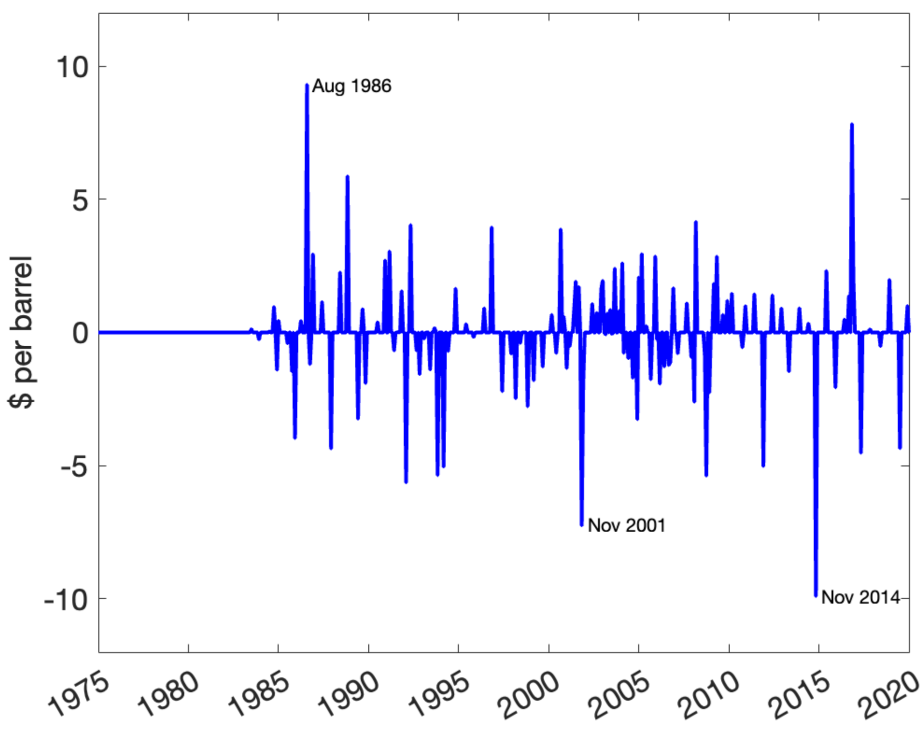
Notes: This figure reports quarterly rates of US manufacturing job creation (POS) and destruction (NEG). Recessionary periods shaded in gray.

Figure 3: Comparison of US Manufacturing Job Creation and Destruction



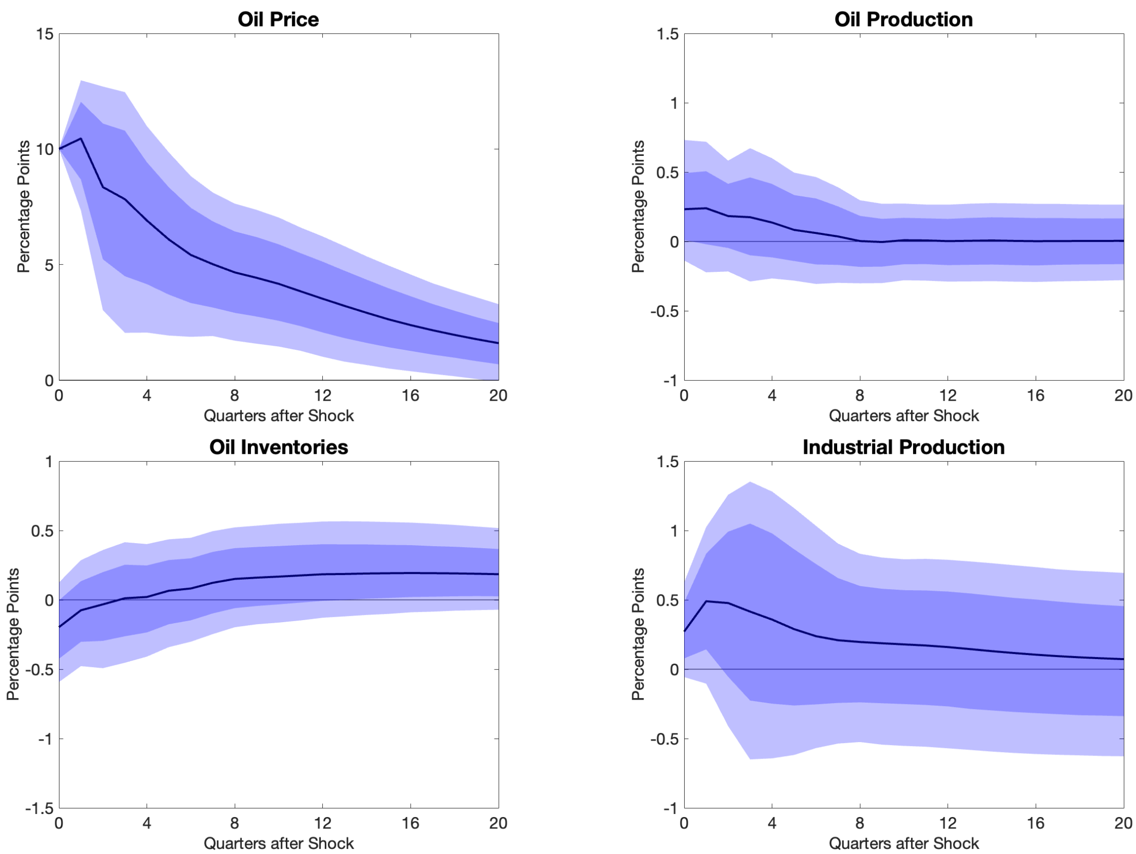
Notes: This figure compares the job creation (left) and destruction (right) rates between the BED (dashed) and ASM/CMF (solid) for the common samples spanning from 1993Q2 to 2016Q4.

Figure 4: Quarterly Oil Price Surprises



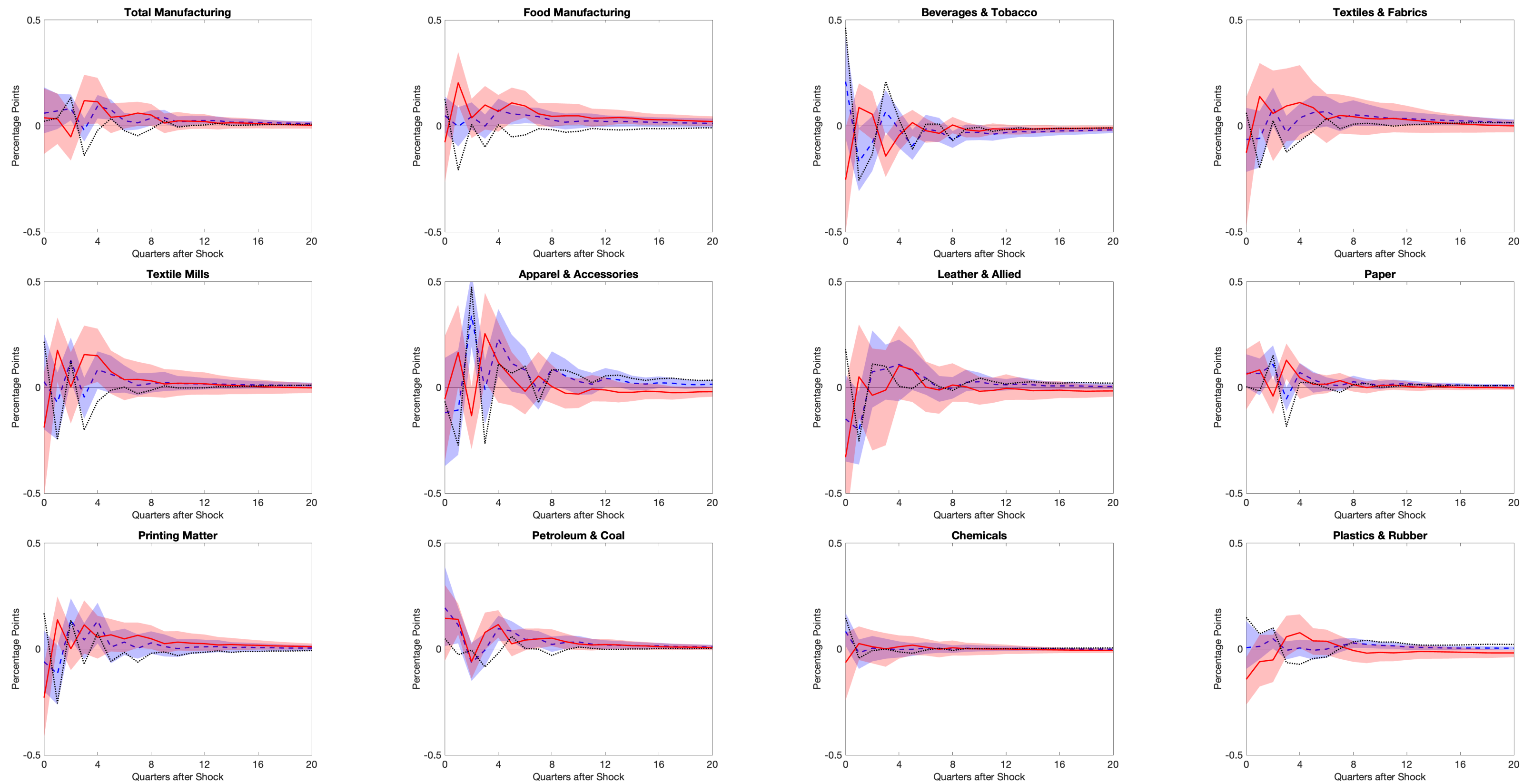
Notes: The figure illustrates the oil news surprise series as the first principle component from changes in oil future prices around OPEC announcements, scaled to match average volatility of underlying price changes.

Figure 5: The Effect of Oil News Shocks on the Oil Market



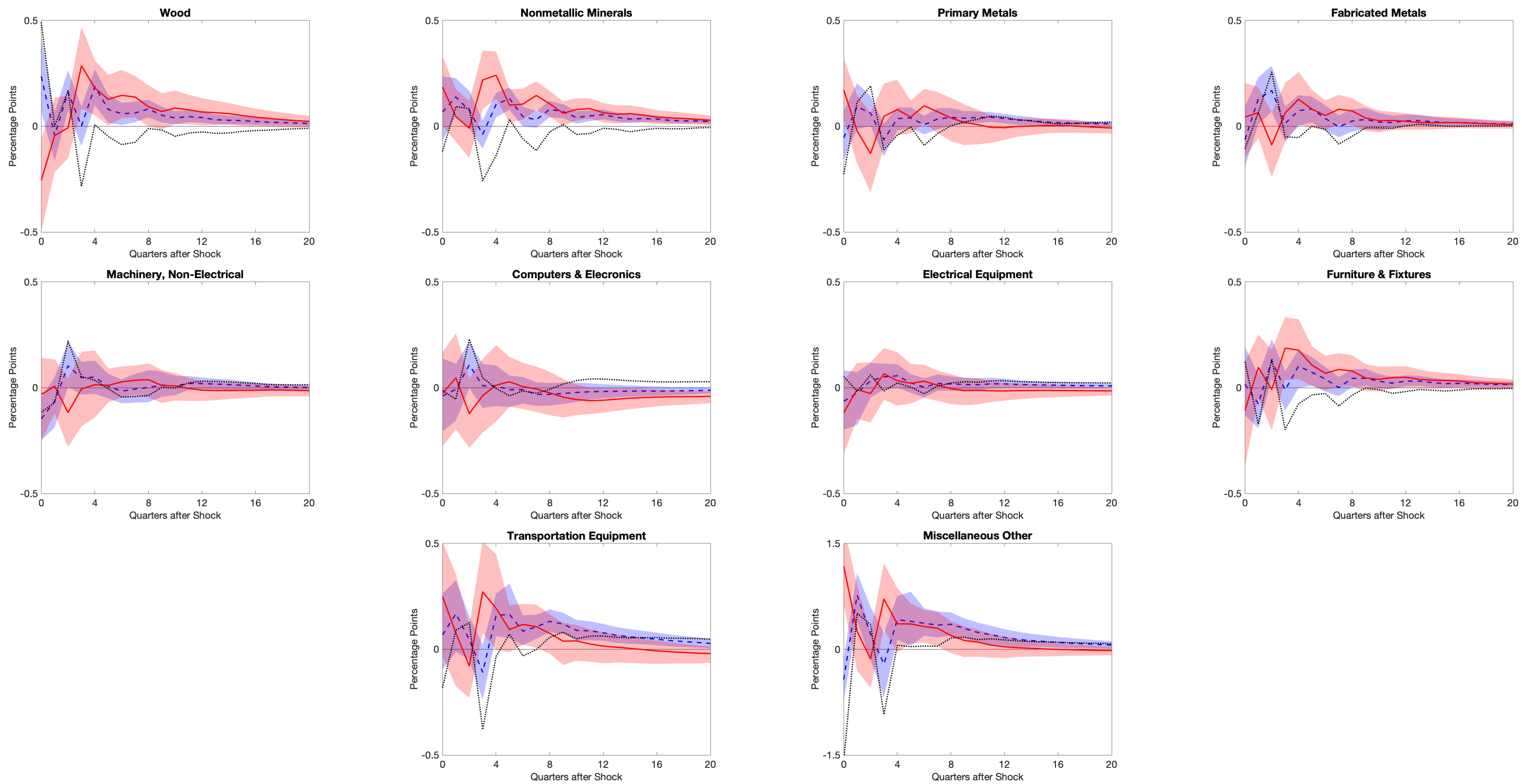
Notes: This figure reports the response of the oil market block to the oil news shock. The shock has been normalized to increase the real oil price by 10 percent on impact. Dark and light shaded areas are 68 and 90 percent confidence bands, respectively, obtained using a moving-block bootstrap with 10,000 repetitions.

Figure 6: The Effect of Oil News Shocks on Job Creation and Destruction



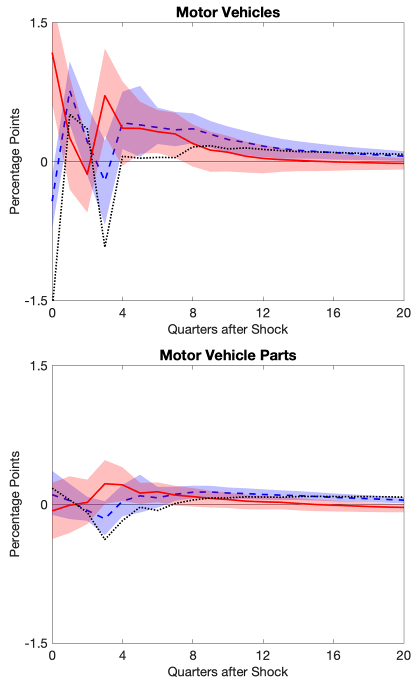
Notes: This figure reports the responses of job creation (dashed blue line) and destruction (solid red line) to an oil news shock. The shock is normalized to increase the real oil price by 10 percent on impact. Shaded areas represent 68 percent confidence bands obtained using a moving-block bootstrap with 10,000 repetitions.

Figure 7: The Effect of Oil News Shocks on Job Creation and Destruction (continued)



Notes: This figure reports the responses of job creation (dashed blue line) and destruction (solid red line) to an oil news shock. The shock is normalized to increase the real oil price by 10 percent on impact. Shaded areas represent 68 percent confidence bands obtained using a moving-block bootstrap with 10,000 repetitions.

Figure 8: The Effect of Oil News Shocks on Job Creation and Destruction - Transportation Equipment Industries

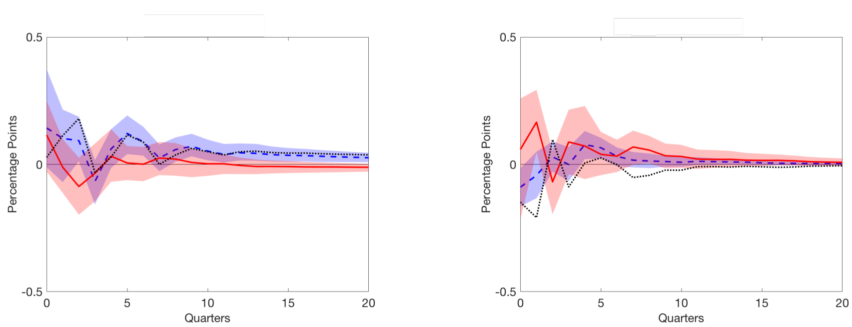


Notes: This figure reports the responses of job creation (dashed blue line) and destruction (solid red line) to an oil news shock. The shock is normalized to increase the real oil price by 10 percent on impact. Shaded areas represent 68 percent confidence bands obtained using a moving-block bootstrap with 10,000 repetitions.

Figure 9: The Effect of Oil News Shocks on Job Creation and Job Destruction - Capital Intensity Quintiles

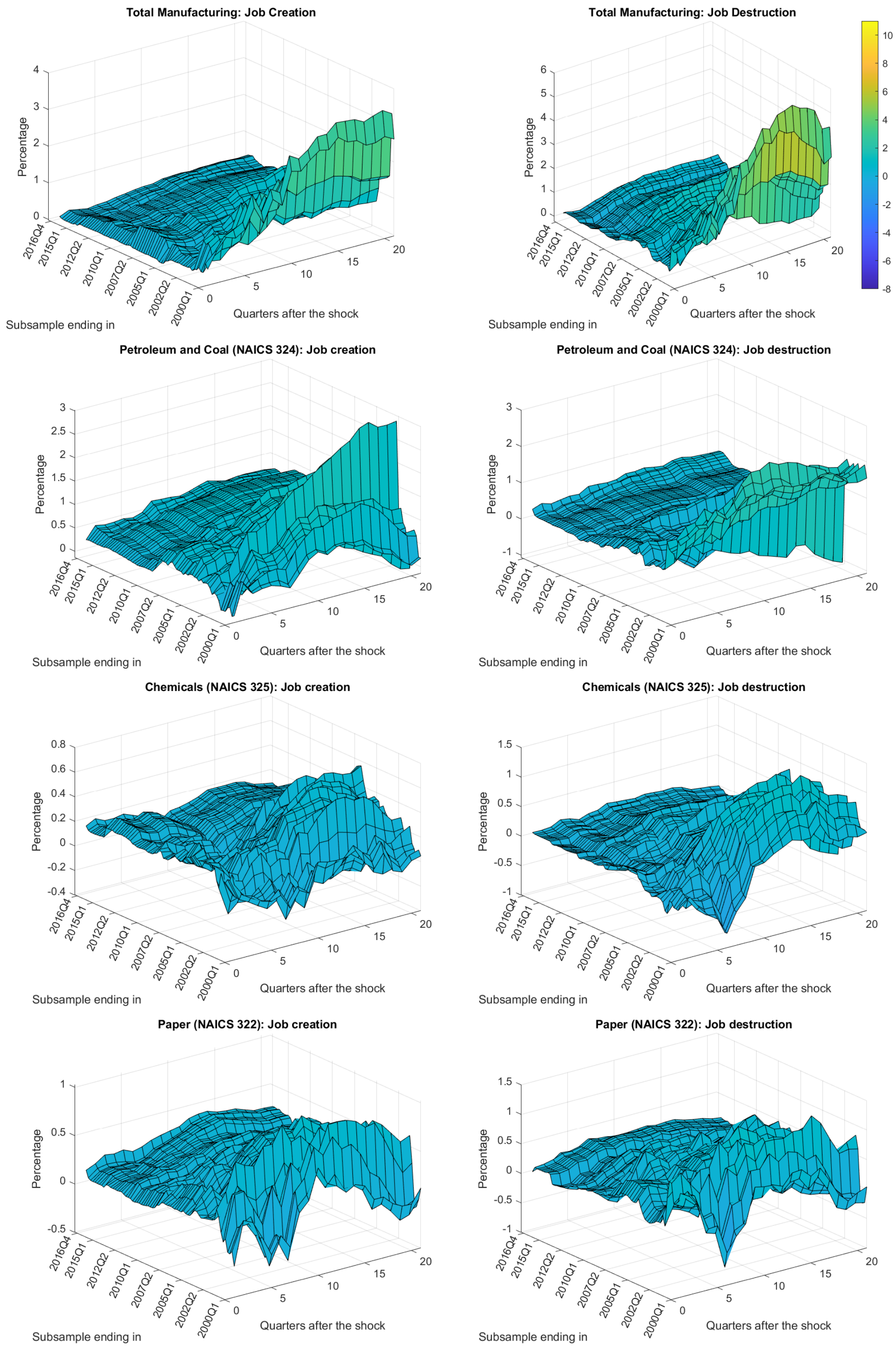
(a) Lowest Capital Intensity Quintile

(b) Highest Capital Intensity Quintile



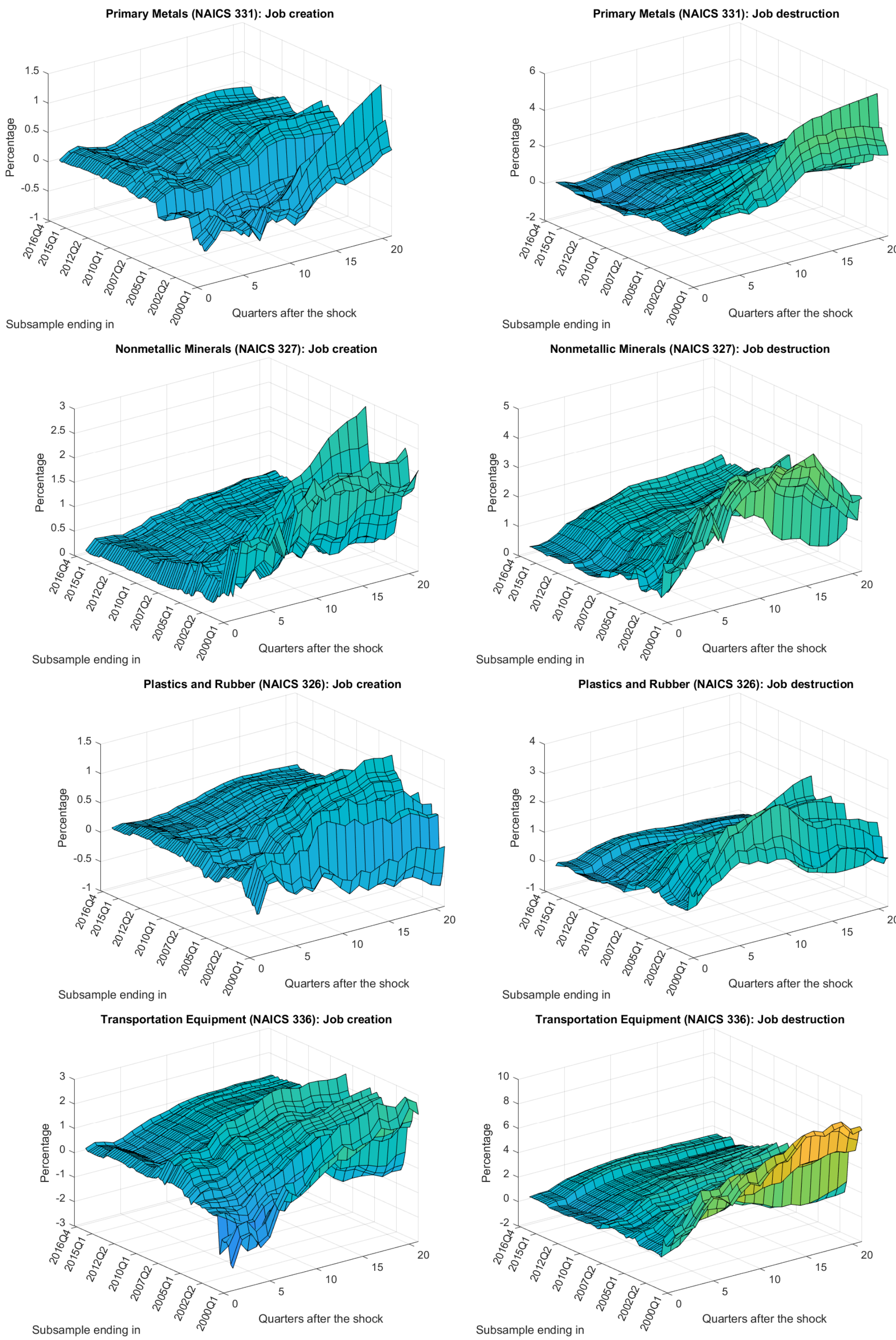
Notes: This figure reports the responses of job creation (dashed blue line) and destruction (solid red line) to an oil news shock. The shock is normalized to increase the real oil price by 10 percent on impact. Shaded areas represent 68 percent confidence bands obtained using a moving-block bootstrap with 10,000 repetitions.

Figure 10: Changes in Responsiveness of Job Flows Over Time



Notes: Surfaces illustrate the changes in the cumulative response of the job creation (left) and destruction (right) rates for subsamples that end on the date noted in the legend.

Figure 11: Changes in Responsiveness of Job Flows Over Time



Notes: Surfaces illustrate the changes in the cumulative response of the job creation (left) and destruction (right) rates for subsamples that end on the date noted in the legend.

A Appendices

A.1 Alternative Model Specifications

In this Appendix we discuss the results of a battery of robustness checks. To facilitate comparison across specifications, in Figures A.1-A.4 we plot the cumulative impulse responses for job creation and destruction in the baseline specification, corresponding 68% and 90% confidence intervals (light and darker blue-shaded areas, respectively), and the cumulative responses for alternative specifications.

Alternative measure of economic activity. We re-estimated the impulse response functions using Kilian's real economic activity (REA) index instead of the world industrial production index. The cumulative responses denoted by red-dashed lines are close to the baseline for most industries and fall inside the 90% confidence bands in all cases. For total manufacturing, estimates obtained using Kilian's REA suggest a slightly negative impact on net employment growth (-0.015 vs. 0.033) and a smaller increase in gross (0.192 vs. 0.541) and excess (0.177 vs. 0.509) job reallocation a year after the shock. The pattern of cross-industry variation is very similar to that observed in the baseline. More specifically, transportation equipment and energy-intensive sectors (e.g., primary metals, nonmetallic minerals) experience the largest declines in net employment and greater reduction in job fluidity.

Alternative measure of oil surprises. Kilian (2024) proposes an alternative way to compute the oil surprise IV. For most sectors, the yellow dashed-dotted line shows greater responsiveness of job creation and destruction than at the baseline. For instance, we estimate a small cumulative decline in net employment growth for total manufacturing (-0.057) a year after the shock compared to a small increase in the baseline, and the greater sensitivity is evidenced in aggregate manufacturing (standard deviation of net employment growth and gross reallocation is 2 and 1.5 times that of the baseline, respectively). Regarding the characteristics that account for cross-industry heterogeneity in responses, both the baseline model and the Kilian (2024) specification convey a very similar picture. As seen in Table A.1, the coefficients' signs are largely consistent between specifications. The main difference is the higher precision of the estimates for the share of mature firms within the industry, which has a small positive effect for almost all flows when we follow Kilian (2024).

Post-1989 data. A possible drawback of employing samples that include the 1980s when identifying oil news shocks using future oil prices is that WTI futures only started trading in 1983 and the market was rather illiquid in the early 1980s (Kilian, 2024). While this concern is alleviated by the fact that we exclude the 1970s data used in Känzig (2021), we reestimate our model using post-1989 (see solid black line). We note that the pattern is similar but the impulse responses are estimated with a lower degree of precision. Using only post-1989 data results in a negative impact on oil news on total manufacturing employment growth and a larger increase in gross and excess reallocation than estimated with the full sample. The degree of variation across industries is larger for net employment, but smaller for job reallocation. Yet, here –as with the other robustness checks– we find larger impacts on job flows for transportation equipment and the energy-intensive industries than for the less-energy intensive industries.

Lag length. The effect of oil news shock on job flows is shorter-lived than that of demand- and supply-driven shocks identified using short-run or sign restrictions. While setting the lag length to $p = 4$ could suffice to capture its dynamics, it has been argued that long cycles in the crude oil market requires to include up to two years of lags (see, e.g. Kilian (2009)). Increasing the lag length to 8 quarters leads us to estimate a larger fourth-quarter cumulative drop in employment for transportation equipment, nonmetallic minerals and total manufacturing. Yet, the industry level responses (solid black line) and cross-industry variation are very similar to the baseline.

A.2 Details on the Computation of Job Flows

Access to the ASM/CMF dataset used in this paper is restricted. Here, we detail information that may be relevant to reader understanding and allow reproducibility for researchers with access to the data.

Early-Mid 1980 Values. As noted in Section 2, job creation and destruction rates exhibit much greater variability in the 1980s than in any other decade covered in our sample. In particular, we observe large spikes in 1981-1982 for the job creation and destruction rates constructed from the ASM/CMF data that are not present in other data sources like the BDM. However, as Foster et al. (2006) note, "according to the researchers who developed the LBD, these two spikes are the result of a temporary change in the editing methodology of the LBD and should be ignored". Although we found it reassuring to observe the same spikes in the series constructed by Foster et al. (2006), and we opted to use the series without modifications in our analysis, we investigated the role of imputations in accounting for the spikes. Eliminating the establishments where the number of workers has been imputed and/or otherwise flagged by the U.S. Census does not eliminate these spikes in the job creation and destruction rates.

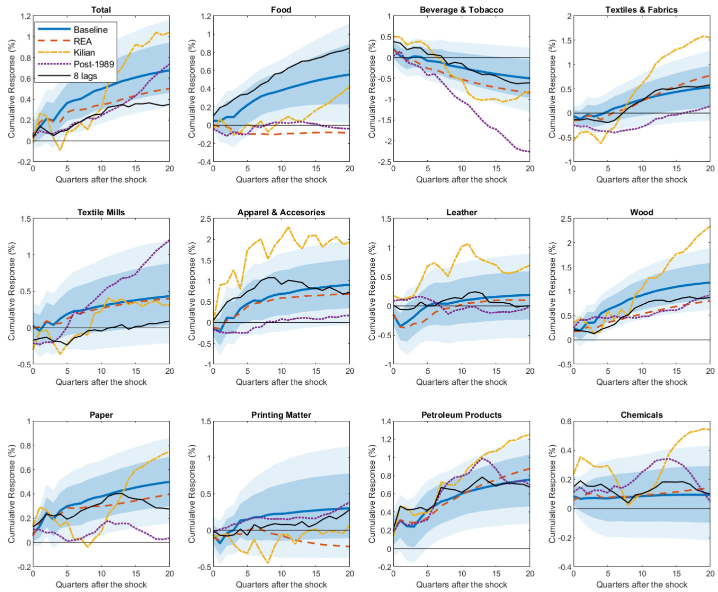
Bridging SIC to NAICS. Establishments were reclassified from the Standard Industrial Classification (SIC) to the North American Industrial Classification System (NAICS) starting in the 1997 CMF and the 1998 ASM. To link establishments across this break, we use a multi-tiered matching system. First, for establishments where the Census Bureau provides initial linkages for some establishments, we matched accordingly. When establishments did not have concrete measures for both SIC and NAICS, we did the following. First, if the establishment identification number occurs both before and after 1998, we define the earlier years industry code as the most recently observed NAICS code post-1998. For establishments that are only observed pre-1998, we use the SIC4-NAICS6 concordance table provided by the Census Bureau. However, only some codes have a one-to-one match. For industries where one SIC code is matched to multiple NAICS codes, we use the employment-weighted concordance table from Schaller and DeCelles (2021) and reallocate the number of production workers into each matched NAICS code according to the industry weight.

Table A.1: Relation between Firm-Level Characteristics and the Cumulative Response of Job Creation and Destruction to Oil News Shocks - Kilian (2024) Specification

	Job Creation		**Job Destruction**	
Quarters after the shock	4	12	4	12
Energy-Cost	0.0162***	0.0123***	0.0233**	0.00372
	(0.00603)	(0.00416))	(0.00935)	(0.00292)
Energy-Capital Ratio	-0.000239	-0.000038	-0.000458*	0.000424
	(0.000154)	(0.000106)	(0.000239)	(0.000747)
Mature Share	0.0143***	0.0105***	-0.0163**	0.00424*
	(0.00466)	(0.00321)	(0.00722)	(0.00226)
Establishment Growth	-0.0197*	0.0115	0.0247	0.00855
	(0.0107)	(0.0115)	(0.0166)	(0.00518)
	Net Employment Growth		**Excess Reallocation**	
Quarters after the shock	4	12	4	12
Energy-Cost	-0.00714	0.00857*	0.0373***	0.0129**
	(0.0108)	(0.00472)	(0.0118)	(0.00625)
Energy-Capital Ratio	0.00022	0.0000496	-0.000721**	0.000109
	(0.000276)	(0.000121)	(0.000301)	(0.00016)
Mature Share	0.0307***	0.00623*	0.0273***	0.0183**
	(0.00834)	(0.00365)	(0.00909)	(0.00483)
Establishment Growth	-0.04433**	0.00292	-0.0135	0.0224**
	(0.0191)	(0.00838)	(0.0209)	(0.0111)

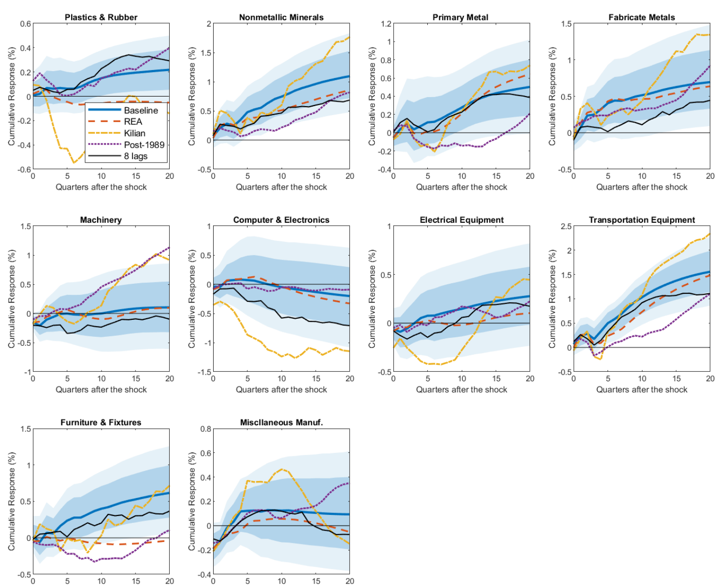
Notes: This table reports results from regressing industry-level cumulative responses to an oil news shock on the indicated industry characteristics, using the Kilian (2024) specifications. See text for full description of the variables. Robust standard errors are reported in parenthesis. *, **, and *** denote significance level at the 10%, 5% and 1%, respectively.

Figure A.1: Alternative Specifications: Cumulative Response of Job Creation to Oil News



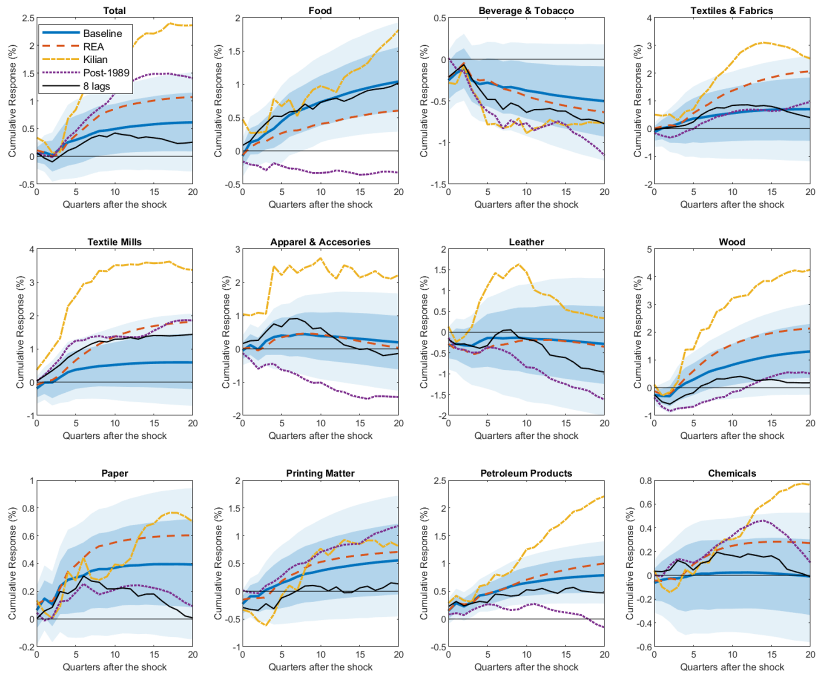
Notes: The solid blue lines, dark and light shaded areas are the response, 90% and 68% confidence bnads, respectively. The red dashed line is the response in the model with Kilian's Real Economic Activity, the dashed-dotted yellow line is the response using Kilian's (2024) specification, the dotted purple line is the response in the model using only post-1989 data, the solid black line is the response in the baseline model with 8 lags.

Figure A.2: Alternative Specifications: Cumulative Response of Job Creation to Oil News



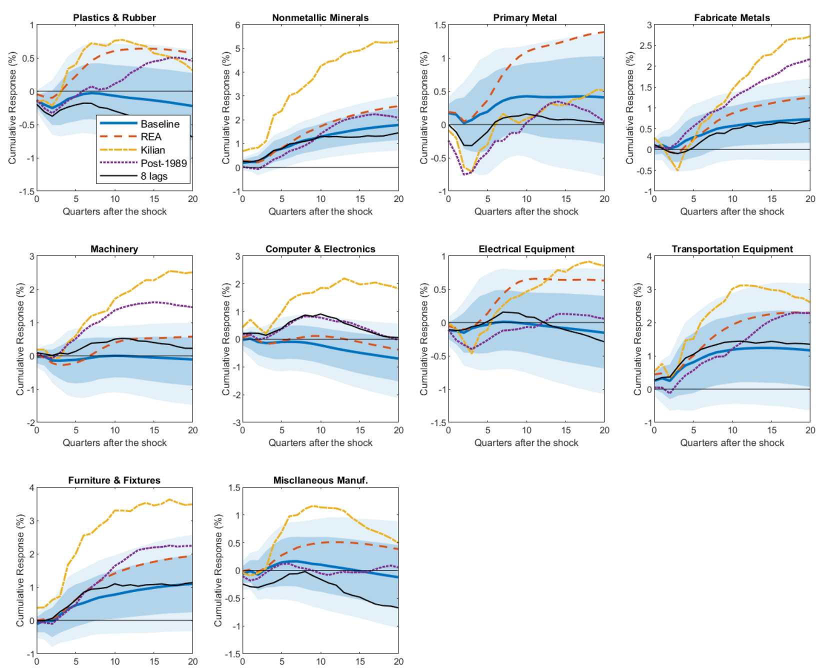
Notes: See notes for Figure A.1.

Figure A.3: Alternative Specifications: Cumulative Response of Job Destruction to Oil News



Notes: See notes for Figure A.1.

Figure A.4: Alternative Specifications: Cumulative Response of Job Destruction to Oil News



Notes: See notes for Figure A.1.

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