The Effect of OPEC News on Job Creation and Destruction*

Ryan Hanson †
University of Tennessee

Ana María Herrera ‡
University of Kentucky

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Abstract

Using confidential establishment-level data from the Annual Survey of Manufactures and the Census of Manufactures, we study how job creation and destruction in US manufacturing respond to OPEC news. We identify the shock with a quarterly Proxy-VAR that implements the corrections proposed by Kilian (2024) and conduct inference that is robust to weak instruments. At the quarterly frequency, OPEC news behaves like a flow-demand shock. First, the aggregate response is small and imprecisely estimated, as aggregation across industries obscures offsetting movements in job creation and destruction. Second, behind this muted response lies considerable heterogeneity across industries, with the motor vehicle industries bearing the brunt of the adjustment. Lastly, panel local projections show that the heterogeneity is systematically related to industry characteristics such as energy intensity, capital expenditures per worker, establishment size, and the share of mature establishments.

Keywords: Job flows, job reallocation, OPEC announcements, high-frequency identification, Proxy-VAR.

JEL: E24, E32, Q43.

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†University of Tennessee, Department of Economics, 1000 Volunteer Blvd, Knoxville, TN 37916, USA. Email: rchanson@utk.edu.

‡University of Kentucky, Department of Economics, 550 South Limestone, Lexington, KY 40506-0034, USA. Email: amherrera@uky.edu.

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 example, on 24 February 2022, Russia invaded Ukraine and, as part of a coordinated package of sanctions, the United States and several other countries banned imports of Russian crude oil; within two weeks, the price of West Texas Intermediate (WTI) had risen by more than 30 percent. Five weeks later, the Organization of the Petroleum Exporting Countries (OPEC) announced that global oil demand, which had plunged in 2020, was expected to reach 100.9 million barrels per day in 2022, surpassing its pre-pandemic level, and that monthly production would increase by 0.432 million barrels per day in May. Both announcements moved expectations about future oil prices, yet the first conveyed news about oil supply and the second news about oil demand. How does OPEC news affect the creation and destruction of jobs in US manufacturing? Do all industries respond alike? And has the response changed over time?

These questions matter for three reasons. First, oil is an input whose expected price enters the hiring, firing, and investment decisions of establishments; thus, labor demand can adjust before an increase in the price of oil is realized, and the dynamic response of job flows to OPEC news about future oil prices need not mirror those that follow realized price changes. Second, the net change in employment, on which most of the literature focuses, provides an incomplete summary of the adjustment: two industries with the same net employment growth (NET hereafter) can differ widely in the number of jobs they create (POS) and destroy (NEG) in response to the shock. We therefore study job creation and destruction separately, as well as gross job reallocation (SUM) and excess job reallocation (EXC), which measures job changes across establishments over and above those needed to accommodate the net change in employment. Understanding the dynamics of job flows is crucial because reallocation is costly for workers and firms, a point that goes back to the view that oil price movements raise unemployment by inducing costly shifts of labor across sectors (Lilien, 1982; Hamilton, 1988). Lastly, knowing which industries bear the brunt of the adjustment, and why, is key to the design of policies, such as worker assistance and retraining programs or measures aimed at reducing the use of oil, whose effects depend on where jobs are created and destroyed.

Despite the large literature on the macroeconomic effects of oil demand and supply shocks and a smaller literature on how sectoral job creation and destruction respond to oil price changes (Davis and Haltiwanger, 2001; Herrera and Karaki, 2015; Karaki, 2018), less is known about how changes in expectations about future oil prices affect job flows. In addition, the existing evidence on job flows is based on samples that end before the fracking revolution and on short-run restrictions that identify a combination of oil supply and oil demand disturbances. Hence, such estimates could understate the role that the shale boom has played in how the labor market adjusts to OPEC news.

To address these questions, we use confidential establishment-level data from the Annual Survey

of Manufactures (ASM) and the Census of Manufactures (CMF) to compute quarterly job creation and destruction rates for total manufacturing, 21 three-digit NAICS industries, and four four-digit sub-industries of the transportation equipment sector, following Davis and Haltiwanger (2001). We compute these series from 1980Q2 onward and use data from 1987Q2 to 2021Q4 in our baseline estimation. Thus, our sample starts before the public Business Employment Dynamics (BED) data, which begin in 1992Q2, and, hence, spans the 1990–1991 Gulf War; they can also be linked to establishment characteristics, such as energy and capital expenditures and age, which we use to investigate the sources of cross-industry heterogeneity. Because the sample ends in 2021Q4, it covers the shale oil boom, the lifting in December 2015 of the 40-year-old ban on US crude oil exports, and the COVID-19 recession.

We estimate the response of job flows to OPEC news with an industry-by-industry Proxy-VAR. Following Davis and Haltiwanger (2001), the job creation and destruction rates of each industry enter a near-VAR whose macroeconomic block does not depend on lagged sectoral flows, so that macroeconomic responses are common to all industries while sectoral responses vary freely. We depart from their approach in how the shock is identified and in the specification of the macroeconomic block. The block is the four-variable global oil market model of Kilian (2024), which comprises the real price of oil, world oil production, a measure of global real economic activity, and the change in global crude oil inventories (see also Kilian and Murphy, 2014), and the shock is identified via an external instrument built from surprises in oil futures prices around OPEC announcements (Känzig, 2021). Because job flows are only available at the quarterly frequency, we estimate quarterly Proxy-VARs, whereas Känzig (2021) and Kilian (2024) estimate monthly models.

This identification strategy that uses daily oil futures data to construct proxies has recently been questioned. Kilian (2024) makes three points about monthly proxies constructed from daily futures data around OPEC announcements. First, the principal component (PC) surprises proposed by Känzig uses futures contracts with longer maturities that did not trade continuously before April 1989. Second, treating daily surprises as monthly news ignores that the day of the month on which a surprise occurs matters for its effect on the average price. Third, the reduced-form oil market model is informationally deficient (see also Mori and Peersman, 2024). To address these concerns, we use only surprises from April 1989 onward: our VARs start in 1987Q2 and, with eight lags, the instrument enters from 1989Q2. In addition, our baseline proxy, which we call the *Kilian-type* proxy, maps each daily surprise in the 12-month futures price into its accounting effect on the average quarterly price. For comparison, we also report results for a *Känzig-type* model where we sum the daily surprises within each quarter to construct the proxy. While we find that the two proxies are positively correlated (0.52), as expected the *Känzig-type* proxy is more volatile (a standard deviation of 2.8 versus 1.8). In that sense, the temporal aggregation of the surprises is not innocuous at the quarterly frequency.

The remaining concerns are related to the strength and exogeneity of the instrument. To address concerns regarding the weakness of the instruments, we base our inference on the weak

instrument-robust confidence sets of Montiel Olea et al. (2021), which we extend to our block-exogenous near-VAR by deriving the sandwich covariance estimator of the corresponding system of seemingly unrelated regressions. Regarding exogeneity, Mori and Peersman (2024) argue that the *Känzig-type* monthly PC proxy is predictable by past financial conditions and that augmenting the VAR with a short-term interest rate, stock prices, and implied volatility restores both the invertibility of the system and the limited lead-lag exogeneity of the instrument in the sense of Miranda-Agrippino and Ricco (2023). Two distinct channels are at work in their argument. The first channel concerns the instrument: if z_t is correlated with lagged financial variables omitted from the VAR, the identified shock inherits that predictable component. The second channel concerns the information set: if the financial variables carry information about the oil market and the macroeconomy that the four-variable VAR specification of Känzig (2021) omits, then the reduced-form innovations themselves are not fundamental. While our baseline results are based on the four-variable oil block of Kilian (2024), we show that purging the *Kilian-type* proxy of lagged financial conditions leaves the responses of the oil market essentially intact, preserves the cross-industry pattern of the job flows responses, and identifies the same industries as bearing the brunt of the adjustment. The main difference is a smaller response of aggregate net employment. In contrast, adding the financial variables to the macro block (at the risk of overparameterizing the quarterly model) shifts the adjustment toward job destruction and reallocation: in the seven-variable model, the decline in aggregate net employment is statistically significant and stems mainly from higher job destruction.[1]

What shock do we identify? Because OPEC announcements can reveal information about oil demand as well as oil supply, we refer to the identified shock as an OPEC news shock rather than an oil supply news shock, and let the oil market block speak about its nature.[2] The responses discussed in Section 4.1 indicate that, at the quarterly frequency, the shock is not an oil supply shock. A shock that raises the real price of oil by 10% on impact leaves the price 3-4% above its initial level five years later, is accompanied by a small short-run increase in world oil production, raises global real economic activity on impact, and draws down oil inventories. This combination of higher prices, stronger global economic activity, and shrinking inventories is the signature of a flow-demand shock in the sense of Kilian and Murphy (2014). What the evidence highlights is a different interpretation of the shock and, therefore, the labor market effects that one should expect. Because price increases that stem from stronger flow demand are initially accompanied by higher activity, we do not expect a large contraction (expansion) in aggregate job creation (destruction) on impact; instead, the question is whether the higher cost of oil eventually erodes hiring and fosters

[1] Concerns of facing a curse of dimensionality by including the three financial variables in the monthly model of Mori and Peersman (2024), which includes data starting in 1974, are less crucial than in our quarterly setup; therefore, we opt to use the parsimonious model as the baseline. The cross-industry pattern of the responses and the industries that bear the brunt of the adjustment are robust across specifications; the margin of adjustment in total manufacturing, however, shifts toward job destruction in the seven-variable model (Section 4.4).

[2] Känzig (2021) labels the shock an oil supply news shock. We avoid this label because, as emphasized by Degasperi (2023) and Kilian (2024), the information content of OPEC announcements is not limited to oil supply, and because an oil supply news shock is not the same as an oil supply shock.

lay-offs, which is consistent with the notion that demand-driven oil price increases carry the seeds of their own destruction (Barsky and Kilian, 2002; Kilian, 2009).

Two findings emerge from our analysis. First, aggregation obscures the heterogeneity in the response of job flows to OPEC news. For total manufacturing, the cumulative responses of job creation and destruction are small and, in the Kilian-type model, statistically insignificant beyond the first quarter after the shock; in the Känzig-type model, job creation declines in the medium run, and net employment growth is 0.56 percentage points lower two years after the shock. Behind this muted aggregate response lie offsetting movements across industries. On impact, job creation rises significantly in several industries (e.g., food, beverage and tobacco, wood products, and plastics and rubber) and falls significantly in computer and electronic equipment and in furniture; two years after the shock, net employment growth is lower in 16 of the 21 three-digit industries, and the decline is statistically significant in textile product mills, apparel, printing, and furniture. The transportation equipment sector, which accounts for 12.1% of manufacturing employment in our sample, plays a pivotal role. OPEC news triggers an immediate and statistically significant increase in job destruction in motor vehicles and motor vehicle parts and a decline in job creation in motor vehicle bodies and trailers, consistent with the view that OPEC news affects motor vehicle manufacturing mainly through the demand for its products (Lee and Ni, 2002). Two years after the shock, the cumulative response of gross job reallocation in motor vehicles equals 2.32 percentage points, roughly 6,600 jobs reshuffled, whereas the change in net employment is statistically insignificant; a study focusing on net employment growth would miss this restructuring. In motor vehicle bodies and trailers, by contrast, the adjustment is mainly a contraction: net employment growth falls by 4.2 percentage points, roughly 6,400 jobs.

Second, the heterogeneity in the responses is systematically related to industry characteristics. Using panel local projections with instrumental variables (panel LP-IV) in the spirit of Almuzara and Sancibrián (2024) for 86 four-digit industries, we find that net employment growth falls more in industries with larger establishments and higher energy costs, whereas industries with a higher ratio of capital expenditures to labor experience a short-lived increase in net employment. Excess reallocation is greater in the short run in industries with larger establishments, lower capital expenditures per worker, and a lower share of mature establishments, and in the medium run, in industries with higher energy intensity. The energy intensity is thus the characteristic that stands out for the intensity of restructuring in the medium run.

Our estimates are smaller than those reported in earlier studies. Several explanations are plausible: the shale boom (Kilian, 2016, 2017), the documented decline in labor market fluidity (Davis and Haltiwanger, 2014; Decker et al., 2020), OPEC's declining share of global oil supply, or a change in the composition of the news conveyed by OPEC announcements. We also examine whether the responsiveness of job flows to OPEC news has changed over time by re-estimating the model on expanding and rolling windows (Online Appendix H). Rolling windows suggest that the decline in job creation that follows OPEC news was larger in windows ending around 2010 than in more recent ones. However, the instrument is too weak in samples ending before 2010 to yield

informative estimates; hence, whether job flows have become less responsive to OPEC news is a question left for future research.

Our results differ from those of Davis and Haltiwanger (2001) in substance and not only in method. First, the margin of adjustment differs: Davis and Haltiwanger (2001) estimate that the contraction in manufacturing employment following an oil price increase stems mainly from the destruction of jobs in contracting and exiting establishments, whereas, in our baseline specification, the aggregate responses of both job creation and job destruction to OPEC news are small and imprecisely estimated. When financial variables are added to the oil market block, the adjustment shifts toward job destruction (Section 4.4), bringing our results closer to theirs. Second, the nature of the shock differs: their short-run restrictions capture a combination of oil supply and demand shocks, while our identification isolates the component of oil market news that moves expected and actual oil prices and, as discussed above, is associated with higher global economic activity. Third, our estimates are smaller than those of earlier studies, and the restructuring is concentrated in a few industries, most notably the motor vehicle industries, a feature that aggregate data cannot reveal. To our knowledge, ours is also the first paper to study how expectations about future oil prices shape the creation and destruction of jobs with establishment-level data.

Our paper contributes to two strands of literature. The first strand investigates the macroeconomic effects of oil demand and supply shocks and, in particular, of changes in expectations about oil market conditions. We build on the work of Kilian and Murphy (2014), who first stressed the role of oil price expectations, and of Känzig (2021), who proposed the use of changes in oil futures prices around OPEC announcements; we also draw on the critiques and refinements of this approach by Degasperi (2023), Kilian (2024), and Mori and Peersman (2024). We depart from Känzig (2021) in that we do not interpret the identified shock as an oil supply shock and in that we leverage confidential data to document the response of job flows to investigate whether cross-industry variation in these responses is systematically related to industry characteristics. The second strand studies the effects of oil price shocks on the creation and destruction of jobs in the United States. Starting with Davis and Haltiwanger (2001), several studies have shown that unexpected increases in oil prices lead to declines in employment growth and to increased job reallocation (see also Herrera and Karaki, 2015; Karaki, 2018), and industry-level evidence suggests that oil price increases operate predominantly through the demand channel for most manufacturing industries (Lee and Ni, 2002; Jo et al., 2019). Our work complements Bjørnland and Skretting (2024), who use a time-varying parameter factor-augmented VAR to document a change in the transmission of oil supply shocks since the shale boom; because they examine employment at the industry and state level, their work is silent on the reallocation of jobs across establishments, which is the focus of our study.

We close with three caveats. First, our estimates are linear and, therefore, abstract from the asymmetry between oil price increases and decreases that is central to Davis and Haltiwanger (2001); whether the reallocative effects we document are asymmetric is a question left for future research. Second, because each industry's job flows are rotated through the same macroeconomic block, we abstract from spillovers across industries. Third, disclosure rules limit the level of dis-

aggregation at which we can report responses: with the exception of the four four-digit industries in the transportation equipment sector, sectoral impulse response estimates can only be released at the three-digit level. This is why we study heterogeneity with industry-level responses and characteristics rather than with establishment-level regressions. With these caveats in mind, our findings suggest that policies aimed at cushioning the effects of oil market news, as well as models of the transmission of oil shocks, need to account for the concentration of the adjustment in a few industries and for the heterogeneity across establishments.

The remainder of this article is organized as follows. Section 2 describes the construction of the job flows, their comparison with public data, and the construction of the Kilian- and Känzig-type quarterly proxies and the oil market variables. Section 3 describes our empirical strategy: the near-VAR specification, the identification of OPEC news shocks, and weak-instrument-robust inference. Section 4 discusses the dynamic responses to OPEC news, whereas Section 5 investigates the industry characteristics that account for the cross-industry heterogeneity in the responses. Section 6 concludes.

2 Data

In this paper, we explore the effect of OPEC news shocks on job flows using confidential data from the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CMF) spanning from 1987:Q2 through 2021:Q4. In this section, we first detail the computation of job flows, compare these flows with publicly available measures of job gains and losses, and conclude with the oil market data.

2.1 Construction of Job Flows

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 establishment age from the Longitudinal Business Database (LBD).[3]

We follow the methodology proposed by Davis et al. (1996) to calculate job flows for total manufacturing, 21 three-digit sectors of the North American Industrial Classification System (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:

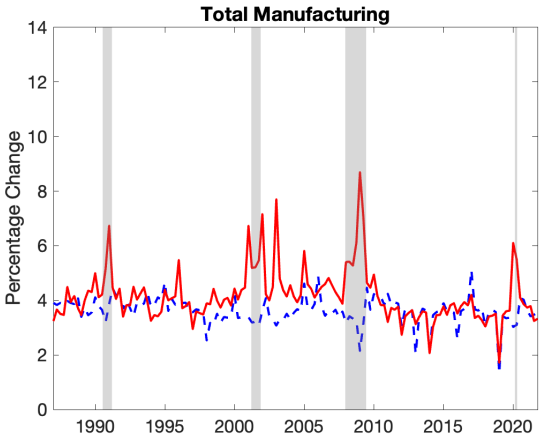
$$g_{it} = \frac{(EMP_{it} - EMP_{it-1})}{Z_{it}} \tag{1}$$

where

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

[3]Following Foster, Haltiwanger and Kim (2006), we identify establishment births and deaths using the LBD age and initial year. Establishments are considered new births only if the year of observation matches the initial year and the LBD age is equal to one, which minimizes the risk of mislabeling an establishment as a new birth when, in reality, it does not appear in the previous ASM panel but was sampled in an earlier one.

Figure 1: Total Manufacturing Job Flows



Notes: This figure reports quarterly rates of US manufacturing job creation (POS, dashed blue) and destruction (NEG, solid red). Data are seasonally adjusted with seasonal trend decomposition using LOESS (STL). Recessionary periods shaded in gray.

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., 1996). 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:

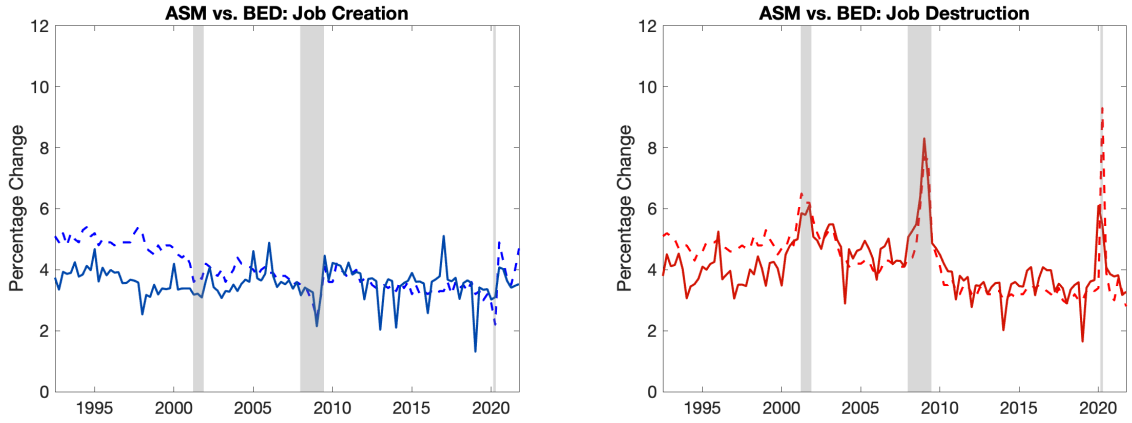
$$POS_{jt} = C_{jt}/Z_{jt} = \sum_{i \in j^+} (Z_{ijt}/Z_{jt})\, g_{ijt}$$
$$NEG_{jt} = D_{jt}/Z_{jt} = \sum_{i \in j^-} (Z_{ijt}/Z_{jt}) |g_{ijt}|.$$

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. EXC is a key statistic in understanding labor market fluidity as it reflects the difference between job turnover and net employment growth in a particular industry or the simultaneous job contraction and expansion happening at different establishments even when the number of jobs remains stable.

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.[4] Note that

[4]Flows for individual sectors and transportation subsectors can be seen in Online Appendix A and are available

Figure 2: Comparison of US Manufacturing Job Creation and Destruction



Notes: This figure compares the job creation rates (left) and job destruction rates (right) for both the ASM/CMF (solid) and the BED (dashed) for the common samples spanning from 1992Q2 to 2021Q4.

these rates represent movements in the employment of production workers, because only data on these workers are reported on a quarterly basis. As expected, job destruction rates largely exceeded job creation rates during recessions; pronounced and persistent spikes during economic downturns are evident for all recessions. The figure also shows that while US manufacturing experienced a fairly steady job creation rate since 1987, job destruction was much more volatile.

Table 1 reports summary statistics for the job flow rates over 1987Q2–2021Q4. On average, job destruction (4.14 percent per quarter) exceeded job creation (3.59 percent) in manufacturing, so that net employment growth was negative (−0.54); only food manufacturing and motor vehicle bodies recorded positive average net growth. Rates vary considerably across industries, from 2.40 (creation) and 2.91 (destruction) in paper to 5.02 and 5.77 in food and apparel, respectively, and motor vehicles and motor vehicle bodies exhibit some of the highest rates of both. Gross and excess reallocation, 7.73 and 7.19 percent in manufacturing, are large relative to net employment growth, which suggests that most reallocation takes place across establishments within the same industry rather than across industries.

2.2 Comparison to Other Job Flows Measures

Our use of the ASM and CMF data to study the dynamic effect of OPEC news shocks has two advantages compared to publicly available data from the Business Employment Dynamics (BED). First, the ASM/CMF series extend back to 1980Q2, whereas the BED begins in 1992Q2. Even though our baseline estimation uses data only from 1987Q2 onward (see Section 2.3), these additional years span the 1990-1991 Gulf War oil shock, one of the largest oil-news episodes of the modern sample, and are not observed in the publicly available BED data. 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 OPEC news.

upon request.

Table 1: Summary Statistics for Job Creation and Job Destruction, 1987:Q2-2021:Q4

		Emp.	**POS**		**NEG**		**NET**	**SUM**	**EXC**
Sector	NAICS	Share	Mean	S.D.	Mean	S.D.			
Total Manufacturing	311-339	100	3.59	(1.48)	4.14	(2.13)	-0.54	7.73	7.19
Nondurables									
Food Manufacturing	311	10.48	5.02	(2.41)	4.97	(2.57)	0.05	9.99	9.94
Beverages & Tobacco	312	1.87	4.48	(2.02)	4.74	(2.89)	-0.26	9.23	8.97
Textiles & Fabrics	313	1.77	2.58	(1.55)	3.83	(2.56)	-1.26	6.41	5.15
Textile Mills	314	1.18	3.70	(1.54)	4.42	(2.67)	-0.72	8.12	7.40
Apparel & Accessories	315	2.60	3.50	(1.84)	5.77	(3.94)	-2.27	9.27	7.00
Leather & Allied	316	0.71	3.61	(1.92)	4.62	(3.15)	-1.01	8.24	7.23
Paper	322	3.39	2.40	(0.98)	2.91	(1.36)	-0.51	5.31	4.80
Printing Matter	323	4.28	3.09	(1.47)	3.93	(2.23)	-0.84	7.02	6.18
Petroleum & Coal	324	0.85	2.94	(1.57)	3.34	(2.22)	-0.40	6.29	5.89
Chemicals	325	6.16	2.81	(1.99)	3.24	(2.22)	-0.43	6.05	5.62
Plastics & Rubber	326	5.37	3.60	(1.56)	3.92	(2.03)	-0.32	7.52	7.20
Durables									
Wood Products	321	3.31	3.76	(1.58)	4.24	(2.42)	-0.48	7.99	7.52
Nonmetallic Minerals	327	3.19	3.82	(1.63)	4.29	(2.47)	-0.46	8.11	7.65
Primary Metals	331	3.38	2.56	(1.18)	3.16	(1.92)	-0.60	5.72	5.13
Fabricated Metals	332	10.39	3.63	(1.47)	4.10	(2.15)	-0.47	7.73	7.26
Machinery, Non-Elec.	333	8.41	3.82	(2.00)	4.33	(2.22)	-0.51	8.16	7.65
Computer & Elec.	334	9.42	3.49	(2.52)	4.49	(3.46)	-1.01	7.98	6.97
Electrical Equip.	335	3.24	3.19	(1.51)	3.83	(2.22)	-0.64	7.02	6.38
Transportation Equip.	336	12.10	3.72	(1.96)	4.27	(2.57)	-0.55	7.98	7.44
Motor Vehicles	3361	1.63	4.39	(3.31)	4.59	(3.97)	-0.21	8.98	8.77
Motor Vehicle Bodies	3362	1.02	4.69	(2.77)	4.65	(3.19)	0.03	9.34	9.31
Motor Vehicle Parts	3363	4.38	3.59	(1.92)	4.31	(2.78)	-0.72	7.89	7.17
Other Transp. Equip.	3369	0.44	3.77	(2.29)	4.58	(3.65)	-0.82	8.35	7.54
Furniture & Fixtures	337	3.45	3.48	(1.52)	4.07	(2.29)	-0.59	7.54	6.95
Miscellaneous Other	339	4.43	3.61	(1.73)	4.09	(2.58)	-0.48	7.70	7.22

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 the average annual percent of workers within each 3-digit NAICS industry as a share of total manufacturing workers. Employment share data comes from the Bureau of Labor Statistics - Business Employment Dynamics for 1990-2021. Data prior to 1990 is unavailable for most 3-digit NAICS industries. Standard deviations are reported in parentheses where applicable.

Table 2: Comparison of Average Labor Flows by Industry

	ASM/CMF		**BED**		**DH2001**	
	1987 - 2021		*1992 - 2021*		*1972 - 1988*	
NAICS Description	POS	NEG	POS	NEG	POS	NEG
Total Manufacturing	3.59	4.14	4.00	4.27	5.2	5.5
Nondurables						
Food Manufacturing	5.02	4.97	5.23	5.20	9.0	9.0
Beverages & Tobacco	4.48	4.74	5.78	5.37	-	-
Textiles & Fabrics	2.58	3.83	3.45	4.73	-	-
Textile Mills	3.70	4.42	5.19	5.84	3.5	4.1
Apparel & Accessories	3.50	5.77	6.56	8.45	5.4	6.3
Leather & Allied	3.61	4.62	4.58	5.62	4.8	6.1
Paper	2.40	2.91	2.71	3.18	3.6	3.8
Printing Matter	3.09	3.93	4.36	5.06	4.5	4.5
Petroleum & Coal	2.94	3.34	3.75	3.99	4.9	5.3
Chemicals	2.81	3.24	2.94	3.03	3.6	4.0
Plastics & Rubber	3.60	3.92	3.76	3.84	5.4	5.3
Durables						
Wood Products	3.76	4.24	5.09	5.28	6.6	6.9
Nonmetallic Minerals	3.82	4.29	4.94	5.13	5.3	5.7
Primary Metals	2.56	3.16	2.88	3.37	3.7	4.6
Fabricated Metals	3.63	4.10	4.41	4.50	5.3	5.6
Machinery, Non-Electrical	3.82	4.33	3.66	3.84	4.9	5.3
Computer & Electronics	3.49	4.49	3.06	3.46	-	-
Electrical Equipment	3.19	3.83	3.19	3.51	4.7	4.9
Transportation Equipment	3.72	4.27	3.25	3.47	5.5	5.7
Furniture & Fixtures	3.48	4.07	4.76	5.20	5.1	5.3
Miscellaneous Other	3.61	4.09	4.53	4.64	6.7	7.1

Notes: Average seasonally adjusted 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. All samples start in quarter 2 of the initial year and end in quarter 4 of their final year.

However, the reader may wonder how the job creation and destruction rates computed from the ASM/CMF data compare with their BED counterparts. Figure 2 plots the job creation and destruction rates for the ASM/CMF and BED data. The two sources agree closely on job destruction and net growth, with correlations of 0.71 and 0.79, respectively, although the correlation for job creation is lower (0.32). Differences in coverage of these two sources and the use of different seasonal adjustment methods account for these differences.[5]

The ASM/CMF rates exhibit higher variation and slightly lower mean. The standard deviation of job creation (job destruction) in the BED is 0.70 (1.06) compared to 1.56 (2.19) in the ASM/CMF covering the same time period. The average job creation and destruction rates are 4.00 and 4.27 in the BED data versus 3.59 and 4.14 in the ASM/CMF.[6] On average, measures computed from the BED are about 0.27 percentage points higher than their ASM/CMF counterparts.

Earlier work by Davis and Haltiwanger (2001) used data from the Longitudinal Research Database (LRD) spanning 1972Q2 to 1988Q4 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

[5]BED data is seasonally adjusted using the X-13 ARIMA program while the ASM/CMF data is seasonally adjusted using local estimated scatterplot smoothing (STL) method.

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

reported by Davis and Haltiwanger (2001). Table 2 documents the job creation and destruction rates for our 1987Q2-2021Q4 sample, the BED sample spanning 1992Q2 to 2021Q4, and Davis and Haltiwanger (2001) LRD rates covering the period between 1972Q2 and 1988Q4. As the table shows, the average cross-industry rates for 1972-1988 exceed the ASM/CMF rates and BED estimates for the later sample by about 1.5 percentage points and 0.9 percentage points, respectively. 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 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 Construction of the Proxy and Oil Market Data

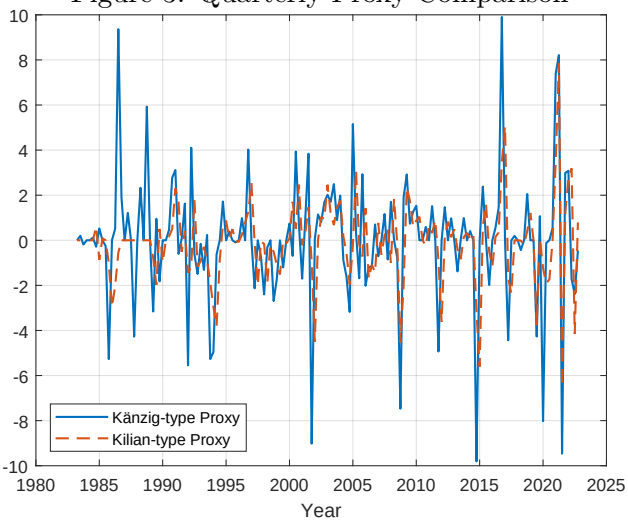
Construction of the Quarterly Proxy. Recent investigations on the effects of OPEC news shocks construct proxies by temporally aggregating daily futures market surprises around OPEC announcements (e.g., Känzig, 2021; Kilian, 2024). Most OPEC meetings are scheduled, narrow-window events that are ideal for high frequency identification: the core producers meet monthly, and the calendar of announcements is known well in advance while the content of each decision is not. Aggregation is typically done in two different ways. Känzig sums up daily surprises in the month (or quarter), whereas Kilian focuses on the average monthly increase in the daily log futures price caused by the surprises relative to the baseline of zero. Because job flows can only be computed at the quarterly level, we map daily surprises into the average quarterly changes caused by the surprise. Thus, we adapt Kilian (2024) methodology, which allows us to capture the accounting relationship between daily surprises and average quarterly oil prices.[7]

Specifically, consider a daily surprise of size α that takes place on day d during the first quarter of the year, where T denotes the number of days in the quarter and d the day of the quarter on which the OPEC announcement took place. Then, the average quarterly increase in the daily log futures price in the first quarter equals $\alpha(T-d+1)/T$. Additionally, a secondary surprise of $\alpha - \alpha(T-d+1)/T$ is attributed to the second quarter, since the econometrician would have expected the average quarterly price to be below the price that prevails in the second quarter. If two OPEC announcements of size α and β take place on days d_1 and d_2 of the quarter with $d_1 < d_2$, then the effect of the announcements on the quarterly log oil futures price in the first and second quarters will be $\alpha(T-d_1+1)/T+\beta(T-d_2+1)/T$ and $\alpha+\beta-\alpha(T-d_1+1)/T-\beta(T-d_2+1)/T$, respectively. As in Kilian, we use the 12-month futures to compute the quarterly surprises.

Figure 3 plots the quarterly proxy constructed as described above, which we denote by *Kilian-type* proxy and the proxy computed by summing the daily surprises from Känzig's principal component IV (PC-IV) in each quarter, which we denote by *Känzig-type* proxy. As the figure illustrates,

[7] This approach contrasts with the work of Känzig (2021) who sums up the surprises in each quarter to investigate the effect of oil shocks on quarterly outcomes such as real GDP, investment, and consumption.

Figure 3: Quarterly Proxy Comparison



Notes: This figure compares the two quarterly proxies obtained via two different aggregation methods.

the two quarterly proxies differ in two respects: (a) the *Känzig-type* proxy exhibits more volatility (standard deviation of 2.8 versus 1.8), which is evident but not limited to the first years of the sample, and (b) their contemporaneous correlation is 0.52, indicating that differences in magnitude and timing in the monthly proxies uncovered by Kilian (2024) also extend to the quarterly proxies. The differences in 1983-1984 stem from the lack of consistent data for the 12-month contract. Recall that one-month oil futures contracts started trading in 1983 but longer maturities were introduced later. Replacing the price for the longer contract with zero to extract a principal component, PC, (see Känzig (2021)) can affect the extracted PC. Following Kilian (2024), we discard the earlier part of the sample in our baseline analysis. We use only data starting in April 1989 when the oil futures market traded longer futures contracts in a non-intermittent manner and the volumes traded were large enough to allow for price discovery (see Kilian (2024) for a detailed discussion). Accordingly, although our job flows series start in 1980Q2, all VARs in the paper use data from 1987Q2 to 2021Q4. With eight lags, the effective estimation sample, and hence the period over which the proxy enters the model, is 1989Q2–2021Q4. The only exception is the robustness exercise in Online Appendix D, which uses all the available job flows data.

Other Oil Market Variables. The remaining oil market variables are defined in a manner similar to Kilian (2024) and Kilian and Murphy (2014) but aggregated to a quarterly frequency. As a measure of real oil prices, we employ the spot price of the refiners acquisition cost (RAC) deflated by the Consumer Price Index (CPI). Data for the RAC is obtained from the Energy Information Administration (EIA) and the CPI is obtained from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis. We average the monthly observations in the quarter. Data on world oil production (including lease condensate production) are obtained from the EIA, measured in thousands of barrels per day, and aggregated by summing monthly data to compute quarterly production. To construct a measure of crude oil inventories, we obtain monthly data on total crude oil inventories and petroleum stocks for the U.S. and on OECD petroleum

stocks from the EIA. Then, following Hamilton (2009) and Kilian and Murphy (2014), we calculate world inventories by scaling the total US crude oil inventories by the ratio of OECD petroleum stocks to U.S. petroleum stocks. Inventories enter the Proxy-VAR as the first difference of the quarterly sum of monthly stocks. As in Kilian and Murphy (2014) and Kilian (2024), the real price of oil (p_t^{oil}) enters in log levels and oil production (Δq_t^{oil}) in log growth. Real global economic activity is measured using Kilian's index (rea_t) obtained from FRED, averaged over the quarter.

We also provide estimation results for total manufacturing using a quarterly version of Känzig (2021)'s model, where we use the world industrial production as a measure of global economic activity,[8] the West Texas Intermediate (WTI) as a measure of oil prices, the sum of the extracted PC as a proxy, and inventories enter as the first difference of the log.

3 The Effect of OPEC News on Manufacturing Job Flows

The estimation strategy used in this paper resembles Davis and Haltiwanger (2001) in the use of a near-VAR, but is crucially different in the identification of the shock via an external instrument. We take a two-pronged approach to investigating the effect of OPEC news. In this section, we first estimate a Proxy-VAR sector-by-sector to investigate the dynamic responses across three-digit NAICS sectors. The advantage of this strategy is that it allows the dynamics to be heterogeneous across sectors. In the next section, we exploit more granular data to estimate the average response across four-digit sectors and investigate which characteristics drive the heterogeneity in the industry-level responses.[9]

Estimation. Let y_t^m denote the $n_m \times 1$ vector of macroeconomic variables. In our baseline specification, these variables comprise the quarterly version of the four-variate oil market block of Kilian (2024), so that $n_m = 4$. Similarly, $n_m = 4$ for the alternative specification following Känzig (2021). Let $y_{i,t}^s = (POS_{i,t}, NEG_{i,t})'$ denote the quarterly job creation and destruction rates of industry i (e.g., total manufacturing, a 3-digit, or a 4-digit NAICS industry). For each industry, we estimate the n-variable system, with $n = n_m + 2$ given by

$$y_{i,t} \equiv \begin{pmatrix} y_t^m \\ y_{i,t}^s \end{pmatrix} = \mu_i + \sum_{q=2}^{4} \delta_{i,q} D_{q,t} + \sum_{l=1}^{p} A_{i,l}\, y_{i,t-l} + u_{i,t}, \tag{3}$$

where $D_{q,t}$ are quarterly dummies, used to control for seasonality in the job flows, $p = 8$ to capture for delays in adjustment of job flows and economic activity (see e.g., Hamilton and Herrera (2004)), and $u_{i,t}$ is the vector of reduced-form innovations with $E[u_{i,t}u_{i,t}'] = \Sigma_i$.[10] Partitioning each

[8] 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.

[9] With the use of this two-pronged approach, we are able to comply with Federal Statistical Research Data Center (FSRDC) disclosure guidelines, while being able to investigate the role of industry characteristics, constructed from establishment-level data, in explaining the responsiveness of sectoral job flows to OPEC news.

[10] We opt to use quarterly dummies instead of adjusting the series using the X-12-ARIMA filter employed by Census to avoid possible forward contamination induced by the two-sided filter in our news-shock study.

coefficient matrix conformably with the macro and sectoral blocks, we have

$$A_{i,l} = \begin{pmatrix} A_l^{mm} & A_{i,l}^{ms} \\ A_{i,l}^{sm} & A_{i,l}^{ss} \end{pmatrix}, \tag{4}$$

where we impose a block-exogeneity restriction similar to Davis and Haltiwanger (2001), so that

$$A_{i,l}^{ms} = 0 \quad \text{for all } l = 1, \ldots, p \text{ and all industries } i. \tag{5}$$

That is, the lagged sectoral job flows do not enter the macro equations.

Two features of (5) are worth noting. First, because the zero-restrictions are placed only on the lag coefficients and the innovation covariance Σ_i is left unrestricted, contemporaneous correlation between macro and sectoral innovations is allowed. In this respect, we depart from Davis and Haltiwanger (2001), whose identification is block-recursive. Second, because under (5) the macro equations contain only μ^m, the seasonal dummies, and lags of y_t^m, the estimated macro block $\hat{A}_l^{mm}$ and its residuals $\hat{u}_t^m$ are identical across the sectoral systems; only the two sectoral equations differ by industry. The system is therefore a seemingly unrelated regression with two nested regressor sets, $X_t^m = (1,\, D_t',\, y_{t-1}^{m\prime}, \ldots, y_{t-p}^{m\prime})'$ and $X_{i,t}^s = (1,\, D_t',\, y_{i,t-1}', \ldots, y_{i,t-p}')'$, for the macro and sectoral equations, respectively, and we estimate it equation by equation by OLS.

Identification. We assume that the reduced-form innovations are linear combinations of structural shocks, $u_{i,t} = B_i \varepsilon_{i,t}$, $E[\varepsilon_t \varepsilon_t'] = I$, and we are interested in the first column $b_{i,1} = B_i e_1$, the impact response to the OPEC news shock $\varepsilon_{1,t}$. Let z_t be the external instrument. Under the relevance and contemporaneous exogeneity conditions

$$E[z_t \varepsilon_{1,t}] = \phi \neq 0, \qquad E[z_t \varepsilon_{j,t}] = 0 \quad \text{for } j \neq 1, \tag{6}$$

we have

$$\Gamma_i \equiv E[u_{i,t} z_t] = \phi\, b_{i,1}, \tag{7}$$

so that $b_{i,1}$ is identified up to scale by the covariance between the residuals and the instrument. We normalize the shock to raise the real price of oil by 10 percent on impact. Note that since $\hat{u}_t^m$ does not vary with i and, given assumption (5), the $h-$step moving average matrix, $C_{i,h}$, inherits the block structure of $A_{i,l}$. In addition, the macro responses $\lambda_{i,j}(h)$, $j \leq n_m$, are common across industries whereas the sectoral responses of job creation (POS) and destruction (NEG) differ because they depend on both $A_{i,l}^{sm}$ and $A_{i,l}^{ss}$. In turn, impulse responses for net employment growth, gross, and excess reallocation are computed as functions of the responses for POS and NEG.

To facilitate comparisons with previous studies, we report cumulative responses for job flows; the cumulative excess reallocation for horizons $h = 0, \ldots, H$ is defined as the cumulative reallocation less the absolute value of the cumulative net change, in the spirit of Davis and Haltiwanger (2001).

Inference. An issue with using OPEC news as an external instrument to identify the target shocks in monthly Proxy-VARs is that the IV can be weak (Kilian (2024)). We tackle this prob-

lem and avoid size-distortions that stem from pretesting by conducting inference that is robust to weak instruments and compute weak-instrument-robust confidence sets following Montiel Olea et al. (2021), which inverts an Anderson-Rubin-type test. Throughout the paper, we refer to a response as statistically significant when its 68% weak-instrument-robust confidence set excludes zero. Because the instrument is weak, these sets can be wide and, in some subsamples, unbounded; hence, we emphasize patterns that hold across horizons and industries rather than individual estimates. The construction of the test is based on the asymptotic variance of $\left(\text{vec}(\hat{A}_i)', \hat{\Gamma}_i'\right)'$. However, one difference with respect to Montiel Olea et al. (2021) is that (5) makes the regressor sets differ between the macro and sectoral equations instead of assuming that all equations have the same regressors as in the typical VAR. Hence, we derive the corresponding sandwich estimator for the SUR system in (3), treating the restricted coefficients in (5) as known zeros with no sampling variability, and use it in place of the VAR formula. In practice, this amounts to assembling the sandwich formula equation by equation rather than with one Kronecker formula.

4 The Effect of OPEC News on Job Reallocation

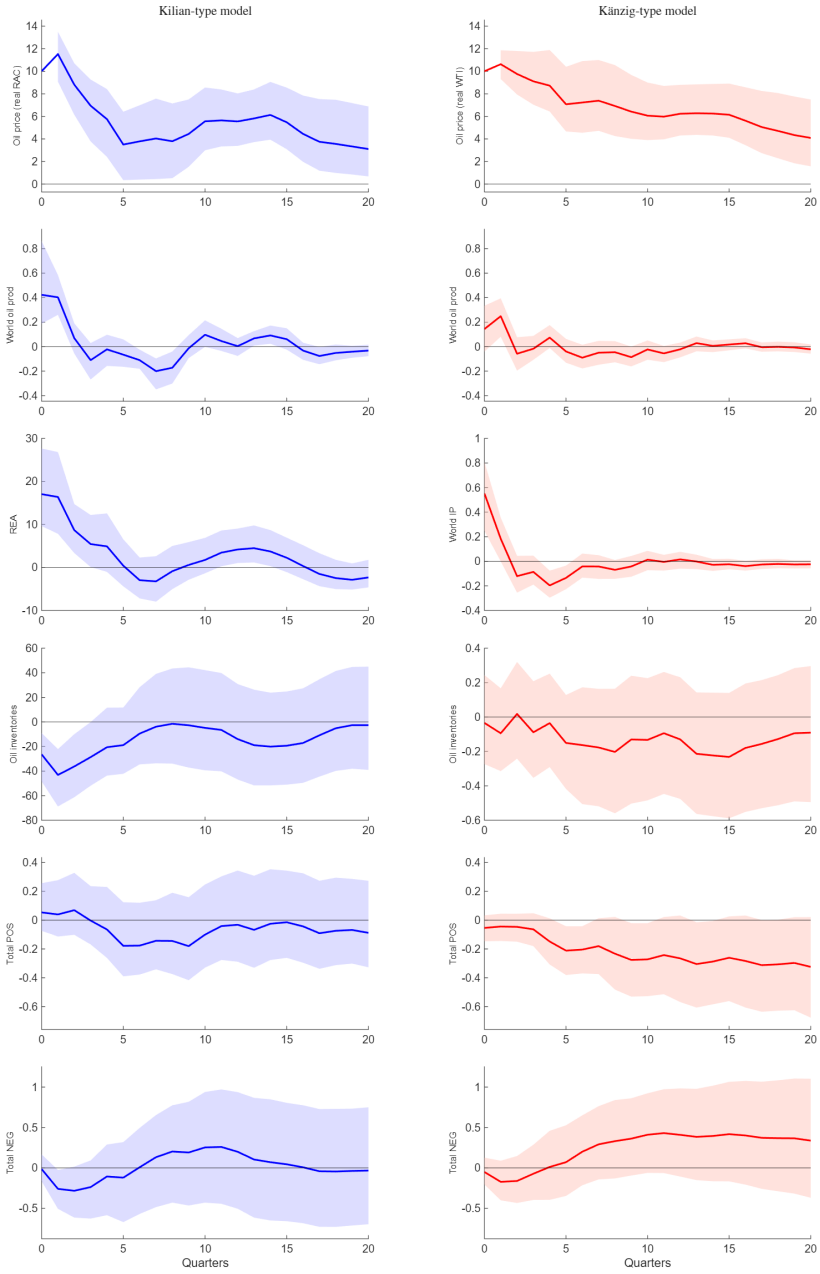
This section first describes the estimated responses of the oil market and of aggregate manufacturing. It then discusses the estimates for the three-digit NAICS industries and explores the responses of four four-digit sub-industries in the transportation equipment sector. We close by examining whether our results are robust to the concerns regarding the validity of the instrument and the invertibility of the system raised by Mori and Peersman (2024).

4.1 Oil market and aggregate manufacturing responses

Figure 4 plots the responses for the macro block as well as the cumulative response of manufacturing job creation and destruction. The left and right panels correspond to Kilian-type and Känzig-type models, respectively. Both specifications are estimated using data from 1987Q2 to 2021Q4 and 8 lags, which ensures that the instrument starts in 1989Q2. For comparison, we report 68% MSW weak-IV-robust sets.

As the figure illustrates, in both models an OPEC shock that leads to a 10% increase in the real oil price on impact has a statistically significant and persistent, albeit decreasing, effect. Regardless of the model, five-years after the shock, the price remains above its original level, reaching a plateau of about 3-4%. Thus, while persistence is somewhat higher for the Känzig-type specification, the dynamic response of the real oil price is similar. The second row suggests that the OPEC shock is associated with a small positive response of world oil production in the short run. In the Kilian-type model, oil production declines about a year and a half after the shock, while it is statistically insignificant in the Känzig-type model for all horizons but $h = 1$. This is a first piece of evidence suggesting that, as is the case in the monthly model of Kilian (2024), the quarterly Proxy-VAR does not identify an oil supply shock. The second piece of evidence comes from the response of the global demand indicator. Note how in both specifications OPEC news is associated with an increase in global economic activity on impact, which is consistent with expectations of higher oil demand and oil prices. Combined with oil inventories being drawn down in the short run, these results

Figure 4: Responses of oil market variables and U.S. manufacturing job flows in Kilian- and Känzig-type Proxy-VARs



Notes: This figure reports impulse response functions for the oil market variables and total manufacturing job creation (Total POS) and destruction (Total NEG). The solid line represents the responses and the shaded areas correspond to MSW 68% weak-IV-robust sets. The real oil price in the *Kilian-type* and *Känzig-type* models is measured by the refiners acquisition cost and WTI, respectively. We report cumulative responses for oil inventories and job flows.

further support the flow-demand narrative: OPEC news is followed by a drawdown of inventories as the demand for oil increases, while world oil production responds only modestly.[11] This flow-demand reading is familiar from recent events. In the time after Russia's February 2022 invasion of Ukraine, the WTI price rose by more than 30% while OPEC revised global demand above pre-pandemic levels, a combination where higher prices and stronger activity occurred together, rather than one causing the collapse of the other.

What do the differences in proxies and model specification imply for the response of total U.S. manufacturing job flows? As the last row of Figure 4 illustrates, the aggregate responses are small. In the *Kilian-type* model, job destruction declines briefly after the shock, so that net employment growth rises in the first quarter, but the cumulative responses of job creation and destruction are statistically insignificant at longer horizons. The responses in the *Känzig-type* specification are larger and more persistent: the 68% weak-instrument-robust set for the cumulative response of job creation excludes zero at several horizons between five and fourteen quarters after the shock, and, two years after the shock, net employment growth is 0.56 percentage points lower, compared with an insignificant decline of 0.35 percentage points in the Kilian-type specification. To put this magnitude in perspective, applying the cumulative decline of 0.56 percentage points to average manufacturing employment in the first quarter of 2026 (about 12.6 million workers) implies roughly 70,000 fewer jobs over the two years that follow the shock.[12] That the responses of total manufacturing job flows to OPEC news are statistically insignificant in the short run, but net employment declines in the medium run, at least in the Känzig-type model, aligns with the notion that oil price increases resulting from increases in flow-demand carry the seeds of their own destruction (Barsky and Kilian, 2002; Kilian, 2009). The initial boost in demand masks a slowdown in the rate at which establishments expand and create jobs; only in the medium run, when global demand declines and world oil production contracts, does the slowdown in job creation materialize. As we show next, however, the small aggregate response hides considerable heterogeneity across industries.

In brief, our estimation results indicate that OPEC news identify shocks to flow demand and have a small and imprecisely estimated effect on total manufacturing job flows. This result contrasts with the findings of Davis and Haltiwanger (2001) who estimate that the contraction in employment following an oil price shock stems mainly from the destruction of jobs in contracting and exiting establishments. These differences can be attributed both to methodological and economic reasons. Regarding the methodological differences, Davis and Haltiwanger (2001) identified the oil price shock via short-run restrictions and did not directly model the global oil market. In a world where

[11] That OPEC announcements convey news about global demand does not invalidate the instrument: identification only requires that the futures surprises on announcement days be uncorrelated with the other structural shocks, not that they convey news solely about oil supply. The effects of this news on US job flows, whether through the price of oil or through global economic activity, are part of the responses we estimate. Consistent with the narrow-window construction of the surprises, the identified shock is not predictable by lagged world industrial production or by lagged manufacturing job flows (Online Appendix G.3).

[12] Because our job flows are computed for production workers, this calculation assumes that net employment growth of nonproduction workers responds in a similar manner. Applying the same decline to the 8.8 million production and nonsupervisory employees in manufacturing yields roughly 49,000 fewer jobs.

oil prices are endogenous, the assumption that oil prices do not respond to global economic activity within the quarter is questionable and the identification scheme captures a linear combination of supply and demand shocks. Instead, in the Proxy-VAR setup, OPEC news identifies flow demand shocks. This is consistent with Jo et al. (2019), who examine industry-level evidence in a factor-augmented VAR estimated over a substantially longer sample and find that oil price increases operate predominantly through the demand channel for the large majority of U.S. manufacturing industries. That the flow-demand interpretation is consistent across different identification schemes and two additional decades of data supports our reading of the OPEC news shocks.

In addition, Davis and Haltiwanger (2001) include a nonlinear transformation of the oil price change (its absolute value) not only in the macro and job flows equations, but also in the oil price equation, yet they compute impulse responses as in a linear VAR. A subsequent literature has shown that this approach is not valid. In models with nonlinearly transformed regressors, the response to a shock depends on its size, its sign, and the history of the variables, and it must be computed by Monte Carlo integration, averaging over histories (Kilian and Vigfusson, 2011; Herrera et al., 2011; Gonçalves et al., 2021). Computing the responses as in a linear model can result in severely biased estimates (Kilian and Vigfusson, 2011). We therefore opt for a linear model, where the average response does not depend on the history of the shocks or on initial conditions.

Last but not least, their sample spans 1972Q2–1988Q4, whereas our estimation sample spans 1989Q2–2021Q4, a period during which the oil futures market matured, the fracking revolution led to a massive increase in US oil production, and the 40-year-old ban on US crude oil exports was lifted. Unfortunately, the instrument is too weak in samples ending before 2010 to tell whether a shorter sample would have yielded a larger impact of OPEC news on the reallocation of US manufacturing jobs (Online Appendix H).

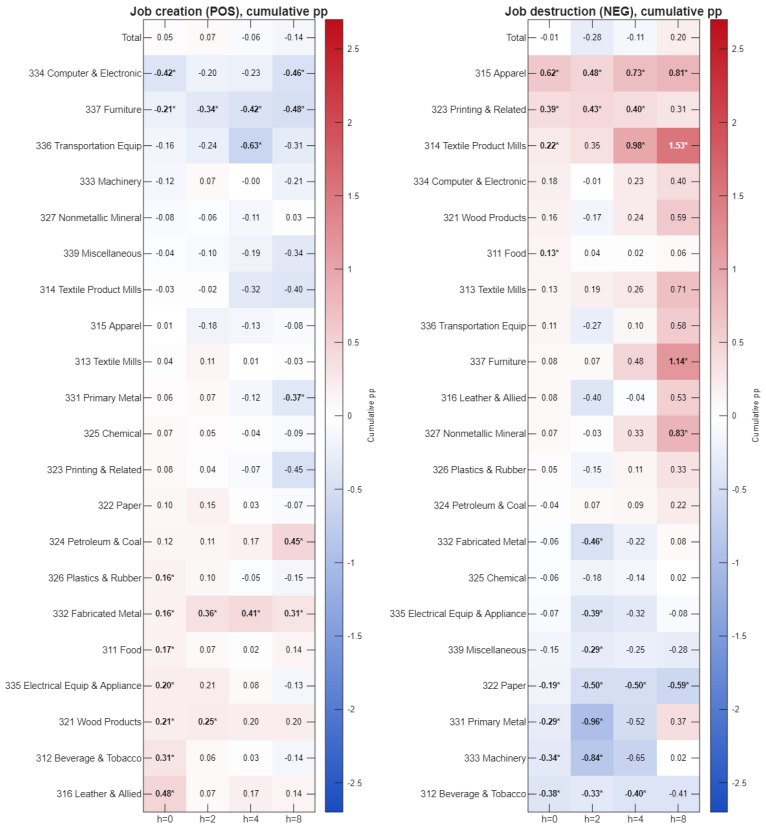
The two methodological differences discussed above are also the reason why we do not re-estimate the Davis and Haltiwanger (2001) specification on our sample to separate the role of the sample period from that of the estimation strategy. First, doing so would replicate a computation of impulse responses that the later literature has shown to be invalid. Second, even a linear version of their model, with the oil price ordered first, would identify an average of oil supply and oil demand shocks, with weights that depend on the relative importance of each shock in the sample. Because these weights are likely to differ between 1972–1988 and 1989–2021, a comparison of the two sets of estimates would confound the change in the sample with a change in the composition of the identified shock, which is precisely what such a comparison is meant to isolate. Moreover, neither set of estimates would be comparable with the response to OPEC news. Instead, we isolate the role of the sample by holding the identification fixed and re-estimating our Proxy-VAR on expanding and rolling windows (Online Appendix H).

4.2 Sectoral Job Flows

Figure 5 summarizes the cumulative responses for all three-digit manufacturing sectors. For the sake of brevity and to facilitate comparisons, we report the cumulative responses at select

horizons ($h = 0, 2, 4, 8$) for all sectors in one heatmap and relegate the impulse response functions to Figures B.1–B.3 of the Online Appendix. The responses of job creation (destruction) are sorted in ascending (descending) order based on their impact response, with red denoting increases and blue decreases. For reference, the total manufacturing responses are reported in the first row.

Figure 5: Sectoral responses of job creation and destruction to OPEC news in Kilian-type Proxy-VAR



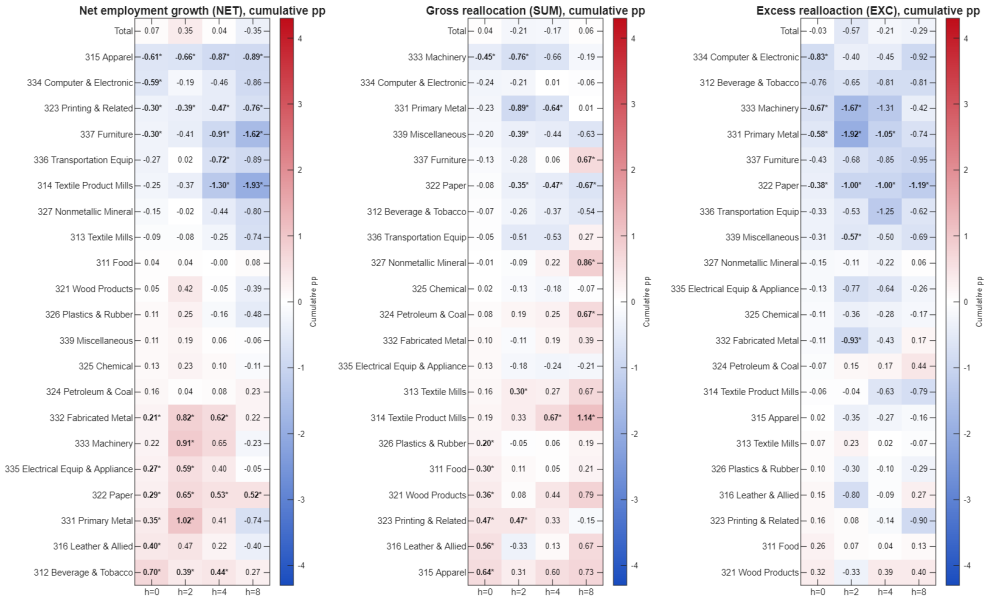
Notes: This heatmap reports cumulative responses (in percentage points) of *POS*, and *NEG* to OPEC news. Sectors are sorted in ascending and descending order, respectively, based on their impact response. Bold numbers with an asterisk denote significance based on MSW 68% weak-IV-robust sets.

A considerable degree of heterogeneity is evident in the responses to OPEC news. On impact, new and expanding establishments in several industries (e.g., food, beverage & tobacco, leather, wood products, plastics & rubber, fabricated metals, and electrical equipment) create additional jobs. At the same time, the shock leads to a statistically significant reduction in job creation for computer & electronic equipment, an energy-intensive sector, and for furniture production; for computer & electronic equipment, the impact response would represent about 4,100 fewer jobs created. Job creation also falls on impact in transportation equipment, although the decline is not statistically significant at the three-digit level; as we show in Section 4.3, it is concentrated in motor vehicle bodies & trailers. This is in line with work by Lee and Ni (2002) showing that oil

price shocks operate primarily as demand disturbances for industries such as motor vehicles, where oil enters through the household's purchase decision rather than production. In this regard, the decreases in job creation that we estimate could reflect the anticipated contraction in demand for their products.

All in all, the combination of some sectors where jobs are created at faster rates and others where job creation slows down explains why the impact effect on total manufacturing is insignificant. Yet, as time passes, the demand-driven oil price boom results in lower job creation rates in most sectors: two years after the shock, the point estimate is negative in 15 of the 21 three-digit industries, as evidenced by the preponderance of blue cells on longer horizons ($h = 4, 8$). However, the decline is statistically significant only for primary metals, computer & electronic equipment, and furniture, and the response of job creation in total manufacturing remains insignificant.

Figure 6: Sectoral responses of net employment growth, gross and excess reallocation to OPEC news in Kilian-type Proxy-VAR



Notes: This figure reports cumulative responses (in percentage points) of NET, SUM, and EXC to OPEC news. Sectors are sorted based on the on-impact response. Bold numbers with an asterisk denote significance based on MSW 68% weak-IV-sets. Confidence sets for $EXC = SUM - |NET|$ are based on the 68% weak-instrument-robust sets for NET and SUM (i.e., lower bound $SUM_{lo} - \max|NET|$, upper bound $SUM_{hi} - \min|NET|$).

The heatmap for job destruction provides additional evidence of heterogeneity at the sectoral level and evidence that job losses at contracting and exiting firms constitute an important part of the story for some sectors. Note that this negative effect of OPEC news on job growth is obscured when aggregating across sectors; that is, the response of total manufacturing is insignificant. On impact, increases in destruction are concentrated in the nondurable industries (textile mill products, apparel, printing, and food), whereas paper, beverage & tobacco, primary metals, and machinery experience a decrease in job losses. As time passes, increases in job destruction are estimated for most industries (17 of the 21 after two years), although the cumulative effect on job losses is

only statistically significant for four industries: textile product mills, apparel, nonmetallic mineral products, and furniture.

The heat maps reported in Figure 6 summarize the responses of net employment growth (NET), gross reallocation (SUM) and excess reallocation (EXC). Recall that NET represents the overall change in the number of jobs in manufacturing, SUM measures the total sum of jobs created by expanding or new firms plus jobs destroyed by downsizing or closing firms in manufacturing, whereas EXC measure the additional simultaneous firing and hiring activity above and beyond that needed to accommodate net employment growth. EXC gives a measure of how much "reshuffling" of jobs is taking place between different establishments in a sector (or the economy). In these heatmaps, we have sorted the sectors in ascending order according to their response on impact.[13]

Focusing first on the response of net employment growth reveals a pattern that resembles that of job creation. At $h = 0$ the responses are about equally distributed between negative (blue) and positive (red). Statistically significant declines are estimated for apparel, printing, computer & electronics, and furniture, whereas beverage & tobacco, leather, paper, primary metals, fabricated metals, and electrical equipment experience increases. However, as time passes and the positive effects of the demand boost fade out, higher oil prices result in lower net employment growth for most sectors. This shift is evidenced by the increased preponderance of blue cells as the horizon increases. Two years after the shock, net employment growth is lower in 16 of the 21 three-digit industries, although the decline is statistically significant only for textile product mills, apparel, printing, and furniture. On the other hand, on impact, the increase in job reallocation for more than half of the sectors suggests OPEC news leads to higher labor market turmoil, especially among nondurable industries. A year after the shock, the total volume of job changes remains significantly above its pre-shock level only in textile product mills, whereas it falls in paper and primary metals. For most sectors, the reallocation that takes place when OPEC news hits is just what is needed to accommodate the net change in employment (i.e., the change in excess reallocation is insignificant). For a few sectors, such as paper and, in the short run, primary metals, machinery, and computer & electronics, the cumulative decline in excess reallocation indicates a decline in the fluidity of labor markets.

A word of caution is in order. With 68% confidence sets, a response whose true value is zero has a 16% probability of being significant with a given sign; hence, by chance alone, we would expect three or four of the 21 three-digit industries to exhibit a significant decline in job creation two years after the shock. The three industries that we find are in line with this benchmark, as are the four with a significant increase in job destruction. We therefore refrain from interpreting individual cells of the heatmaps and base our conclusions on patterns that hold across horizons and industries, such as the sign of the responses in most industries and the large responses of the motor vehicle industries, and we complement this evidence with the panel LP-IV of Section 5, which tests

[13]Because $EXC = SUM - |NET|$ is not a linear combination of the impulse responses, its set is not computed directly as the Montiel Olea et al. (2021) results apply only to fixed linear combinations of shock loadings. Hence, we apply interval arithmetic to the 68% weak-instrument-robust sets for NET and SUM (lower bound $SUM_{lo} - \max|NET|$, upper bound $SUM_{hi} - \min|NET|$). This set is very conservative.

directly whether the responses vary systematically with industry characteristics.

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 OPEC news, which aggregation across sectors obscures. Sectors that have traditionally been considered to be intensive in the use of oil (transportation equipment, computer & electronics, and nonmetallic mineral products) experience declines in net employment growth two years after the shock, although these declines are imprecisely estimated. Second, the effect of OPEC news on sectoral job creation and destruction is consistent with the narrative that OPEC announcements identify flow-demand shocks: in the short-run some sectors experience booms but as time passes higher oil prices lead to job losses in several sectors. 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 OPEC news shocks on this sector.

4.3 Digging deeper into the response of the transportation sector

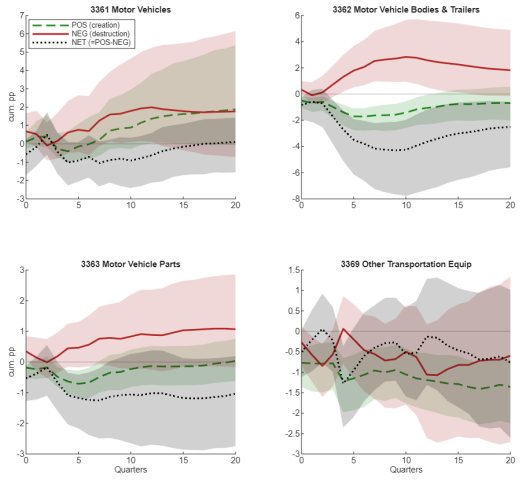
The results presented in the previous section suggest that the transportation equipment sector plays a key role in the dynamic adjustment of manufacturing jobs after an OPEC news shock. To further investigate the labor reallocation responses in this sector, we re-estimate our model for 4 four-digit sub-industries: 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 12.10% of manufacturing employment between 1987Q2 and 2021Q4, the largest share among all three-digit 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 OPEC news shocks impact overall manufacturing labor dynamics.

Figure 7 reports the impulse response functions for the four-digit NAICS sub-industries of interest. We estimate that OPEC news leads to an immediate and statistically significant increase in job destruction for motor vehicles and motor vehicle parts. In motor vehicle bodies & trailers, job losses increase gradually and reach a peak about two and a half years after the shock. On impact, motor vehicle bodies & trailers also experience a statistically significant decline in the rate of job creation, which persists: two years after the shock, the cumulative decline in job creation equals 1.6 percentage points. As a result, net employment growth drops considerably in motor vehicle bodies & trailers and, to a lesser extent, in motor vehicle parts, reaching a trough of 4.3 and 1.3 percentage points, respectively, nine and seven quarters after the shock.

The cumulative responses of net employment (NET), gross reallocation (SUM), and excess

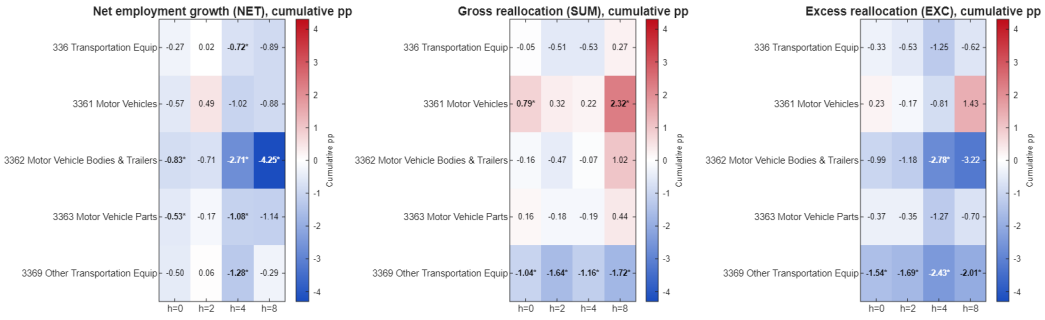
Figure 7: Cumulative responses of job creation, destruction and net employment growth to OPEC news in the transportation equipment sector



Notes: This figure reports cumulative responses (in percentage points) of POS (dashed green), NEG (solid red), and NET (dotted black) to OPEC news for four 4-digit industries in the transportation equipment sector. Shaded areas denote MSW 68% weak-IV-robust sets.

reallocation (EXC), reported in Figure 8, reveal an intense process of job reshuffling among establishments in the transportation equipment sector. Of note is the significant eight-quarter cumulative response of job reallocation in motor vehicles (2.32 percentage points); in motor vehicle bodies & trailers, the response of job reallocation (1.02 percentage points) is not statistically significant. To gauge the economic importance of the shock for job reallocation in these sectors, we express these responses in terms of current employment, as we did for total manufacturing in Section 4.1: in the first quarter of 2026, employment in motor vehicles and in motor vehicle bodies & trailers averaged approximately 282,900 and 151,600 jobs, respectively.

Figure 8: Cumulative responses of job flows to OPEC news in the transportation sector



Notes: This heatmap reports cumulative responses (in percentage points) of NET, SUM, and EXC to OPEC news for four 4-digit industries in the transportation equipment sector. Bold numbers with an asterisk denote significance based on MSW 68% weak-IV robust sets. Confidence sets for $EXC = SUM - |NET|$ are based on the 68% weak-instrument-robust sets for NET and SUM (i.e., lower bound $SUM_{lo} - \max|NET|$, upper bound $SUM_{hi} - \min|NET|$).

Thus, OPEC news would amount to the creation or destruction of about 6,600 jobs in motor vehicles. The nature of the adjustment differs across the two industries, however. In motor vehicles,

the cumulative response of net employment growth is statistically insignificant (−0.88 percentage points), while excess reallocation rises by about 1.4 percentage points, although the latter response is imprecisely estimated. That is, jobs are reshuffled across establishments rather than lost. Had we focused on the net employment growth response, we would have missed this restructuring, which suggests that, while the number of jobs in the industry remains roughly unchanged, workers may need to switch employers or occupations and learn new skills as establishments restructure. In motor vehicle bodies and trailers, instead, net employment growth falls by 4.25 percentage points (roughly 6,400 jobs) and excess reallocation declines, so the adjustment takes the form of a contraction rather than of churning.

4.4 Robustness Checks

The Online Appendix reports estimation results for a battery of robustness checks including: (a) *Känzig-type* Proxy-VAR (Appendix C); (b) Extended Sample (1982Q2-2021Q4; Appendix D); (c) Pre-COVID 19 sample (1987Q2-2019Q4; Appendix E); (d) Shorter Lag Length ($p = 4$; Appendix F); (e) Alternative Proxy-VAR specifications addressing the role of financial controls (Appendix G).[14] We find that the key results (i.e., heterogeneity in the sectoral responses and importance of motor vehicle sub-industries, primary metals, and nonmetallic minerals in driving the job flows response) are qualitatively unchanged across specifications. For the sake of brevity, in this section we only discuss the robustness checks that alleviate concerns regarding the validity of the instrument.

As noted in the introduction, a concern raised by Mori and Peersman (2024) is that monthly proxies computed from daily surprises around OPEC announcements are predictable by past financial conditions and that augmenting the VAR with a short-term interest rate, stock prices, and implied volatility restores both the invertibility of the system and the limited lead-lag exogeneity of the instrument in the sense of Miranda-Agrippino and Ricco (2023). Adding financial variables to the VAR addresses two channels simultaneously, a predictable component of the instrument and missing information in the VAR. To isolate the first channel, we keep our four-variable macro block specification unchanged and replace the *Kilian-type* proxy with the residual from a regression of the proxy on a constant and eight lags of the 1-year Treasury yield, 100 times the log of the real S&P 500, and the VXO, estimated over the effective sample of the VAR. We exclude contemporaneous values on purpose, since an OPEC news shock that moves oil futures within the quarter will also move stock prices within the quarter. We compare the resulting estimates with those of the baseline and of a 7-variable model that adds the three financial variables to the macro block.

We find that lagged financial conditions account for about 20% of the in-sample variation in the proxy, but the adjusted R^2 is 0.015 and a classical F-test does not reject the null that the lags are jointly insignificant ($p = 0.38$); only a HAC version of the test, which is prone to over-rejecting with 24 restrictions and 131 observations, does so. Purging, however, weakens the instrument: the

[14] We do not consider alternative oil shock series in this paper. For evidence on how US labor market outcomes respond to the oil supply and demand shocks identified by Baumeister and Hamilton (2019), see Zhao (2025).

Montiel Olea et al. (2021) strength statistic falls from 2.30 to 1.43, further below the 3.84 threshold (Online Appendix Table G.1).

Figure 9 overlays the three sets of estimates on the set of 68% weak-instrument-robust confidence from the baseline. Three takeaways are gleaned from these results. First, purging the proxy leaves the responses of the oil market variables virtually unchanged. The responses of the real price of oil, world oil production, real economic activity, and oil inventories obtained with the purged instrument lie inside the baseline confidence set at every horizon; the cumulative oil-price response over the first two years is 59%, compared with 56% in the baseline. In the model with the 7-variable macro block the oil-price response is markedly less persistent (2.6% above its pre-shock level after one year, compared with 5.9% in the baseline) and falls outside the baseline's confidence set in the second year. Moreover, the shock also retains the flow-demand signature on impact: global real activity rises and inventories are drawn down, while the responses of the real S&P 500 and the VXO are insignificant; stock prices fall (by 3.7% after four quarters) and implied volatility rises only after the second quarter, once the boost to global activity has faded, which is consistent with the notion that flow-demand-driven oil price increases carry the seeds of their own destruction.

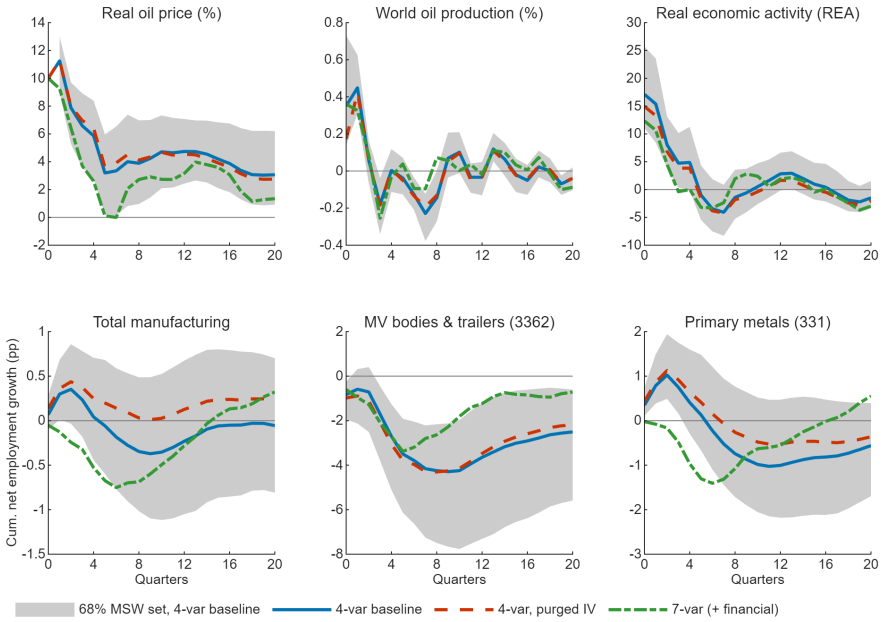
Second, purging the proxy preserves the cross-industry pattern of the job-flow responses. Across the 25 manufacturing industries in our sample, the correlation between the two-year cumulative net employment responses obtained with the raw and the purged proxy is 0.95, and the purged response lies inside the baseline confidence set at every horizon in 23 industries. The industries that bear the brunt of the shock are the same: motor vehicle bodies and trailers (-4.3% after two years, compared with -4.2% in the baseline), textile product mills, furniture, and apparel. Purging does shrink the typical response, as the median two-year decline falls from 0.48 to 0.26 percent, and the response of total manufacturing net employment growth, which is not significant under either instrument, goes from -0.35% to essentially zero.

Lastly, the purged responses do not move toward those of the 7-variable model. The latter lies inside the baseline set at every horizon in only 5 of the 25 industries and shifts the adjustment toward job destruction and reallocation, consistent with the allocative channel emphasized by Davis and Haltiwanger (2001). Taken together, these results suggest that the differences between the 4- and 7-variable specifications stem from the information content of financial conditions for the VAR innovations rather than from a predictable component of the instrument.

A related concern is that the Kilian proxy is predictable by lagged global economic activity, possibly because OPEC meetings respond to demand conditions. However, the shock that we identify is not predictable by lagged world industrial production ($p = 0.24$) or by lagged manufacturing job flows ($p = 0.27$), and while purging the proxy of lagged world industrial production strengthens the instrument (the strength statistic rises from 2.30 to 3.16), it leaves the impulse responses essentially unchanged.[15] For the sake of brevity, we relegate these tests, the industry-level estimates, and the analogous results for the Känzig (2021) proxy to Online Appendix Sections G.2–G.4.

[15]These results are available from the authors upon request.

Figure 9: Alternative Proxy-VAR specifications



Notes: This figure reports impulse response functions for the baseline model with a 4-variable macro block, a 4-variable model where the proxy is purged from financial variables and a 7-variable model where the macro block includes the financial variables. The shaded area is the 68% weak-instrument-robust confidence set of the 4-variable baseline (Montiel Olea et al., 2021).

5 Which Industry Characteristics Explain the Heterogeneous Response of Sectoral Job Flows to OPEC News?

The estimation results presented in the previous section reveal a significant degree of heterogeneity in the response of job creation and destruction to OPEC news shocks across three-digit NAICS sectors. What characteristics drive the 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.

To answer this question, we leverage restricted-use establishment-level data to compute 4-digit job flows, as well as measures of industry characteristics at this higher level of disaggregation and an empirical strategy designed to identify the margins that drive heterogeneity in the response of job flows. For the sake of brevity, in what follows we focus on net employment growth and excess job reallocation. Estimates for job creation and destruction, as well as gross job reallocation, can be found in Online Appendix I.

5.1 Possible Margins of Heterogeneity and Empirical Strategy

Industry Characteristics. We use the ASM/CMF data to capture variation across industry characteristics. In all cases, we take the average over the establishment's attribute in industry i at quarter t. We consider the following attributes as possible margins of heterogeneity:

Energy intensity is a likely determinant of the industry-level sensitivity and its importance is apparent from the estimation results reported in section 4. We measure the energy-intensity at the establishment level by dividing the cost of energy by the total value of the shipments (Davis and Haltiwanger, 2001). In addition, *fuel intensity* defined as the ratio of the cost of fuel to the total value of shipments is used to control for fuel dependence. *CAPEX/labor ratio* corresponds to expenditures reported by the establishment in acquiring and maintaining fixed assets 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.

We use three measures to proxy for the scale and growth of establishments in an industry. *Total value of shipments* is used to capture the average scale of establishments in an industry. *Establishment growth* defined as the first difference in the log of the number of establishments in industry is intended to capture differential rates of establishment growth, which could 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.[16] In addition, 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. Finally, we include the share of *mature* establishments in an industry, where we define establishments aged nine and above as mature.

Estimation Strategy. We depart from the strategy used in the previous sections in estimating the average response for the 86 four-digit NAICS industries and identifying the margins of heterogeneity via panel local projections with instrumental variables (panel LP-IV). Our estimation framework similar to Almuzara and Sancibrián (2024); yet it differs from their baseline setup in that the shock is not observed. Instead, the OPEC news shock is recovered from a regression of the target variable (the oil price change) on a target instrument (the OPEC news proxy). Thus, let us start by describing how the macro shock is identified.

Shock Identification. We identify OPEC news shocks following a quarterly proxy-SVAR model in the vein of Kilian (2024), which corresponds to the macro block used in the previous section for the sectoral VARs. Hence, the computation of the proxy and the oil market variables is as described in Section 2. That is, let $\mathbf{y}_t = (p_t^{oil}, \Delta q_t^{prod}, rea_t, \Delta inv_t)'$ denote the vector of quarterly macro variables, where p_t^{oil} is the log of the real price of oil, Δq_t^{prod} is world oil production growth, rea_t is Kilian's index of real global economic activity, and Δinv_t is the change in global oil inventories. The reduced-form VAR is given by

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

$$\mathbf{y}_t = \mathbf{c} + \sum_{\ell=1}^{p} \mathbf{A}_\ell \mathbf{y}_{t-\ell} + \mathbf{u}_t, \tag{8}$$

where $p = 8$ lags, $\mathbf{c}$ is a vector of constants, and $\mathbf{u}_t$ is the vector of reduced-form residuals with covariance matrix $\mathbf{\Sigma}$. The structural OPEC news shock ε_t^{oil} is the first element of the structural disturbance vector $\boldsymbol{\varepsilon}_t = \mathbf{B}^{-1}\mathbf{u}_t$, identified using the external instrument.

Panel LP-IV Specification. Let z_t denote the OPEC news proxy and u_{1t} the reduced-form residual of the real oil price from the VAR in equation (8). The first-stage regression

$$u_{1t} = \pi_0 + \pi_1 z_t + \eta_t \tag{9}$$

yields the fitted values $\hat{u}_{1t} = \hat{\pi}_0 + \hat{\pi}_1 z_t$, which we interpret as the identified OPEC news shock. By construction, $\hat{u}_{1t}$ varies over time only through the instrument. Let y_{it} denote the labor flow of interest (job creation, job destruction, net employment growth, gross reallocation, or excess reallocation) for industry i at quarter t, for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. Following Almuzara and Sancibrián (2024), we estimate the impulse response function at horizon h via the panel LP regression

$$y_{i,t+h} = \tilde{s}'_{i,t-1}\beta(h)\,\hat{u}_{1t} + \alpha_i + \delta_t + \varepsilon^h_{i,t+h}, \qquad h = 0, 1, \ldots, H, \tag{10}$$

where $\hat{u}_{1t}$ is the identified OPEC news shock common to all industries in quarter t; $\tilde{s}_{i,t-1}$ is a vector of industry characteristics, lagged one period and demeaned across industries within each quarter; $\beta(h)$ is the vector of heterogeneous response coefficients at horizon h; and α_i and δ_t denote industry and time fixed effects, respectively.[17] The error $\varepsilon^h_{i,t+h}$ is allowed to be heteroskedastic, serially correlated, and cross-sectionally correlated within each period, consistent with the aggregate shock structure. The panel regressions are estimated on the same effective sample as the Proxy-VAR, 1989Q2–2021Q4.

The time fixed effects δ_t absorb every term that is common to all industries in a given quarter, including the direct effect of the aggregate shock, $\hat{u}_{1t}$. As a result, equation (10) does not identify the average response of labor flows to the OPEC news shock; that response is given by the Proxy-VAR estimates in Section 4. What the panel regression does identify is how the response differs across industries. Because the characteristics are demeaned within each quarter, the interaction $\tilde{s}_{ij,t-1}\,\hat{u}_{1t}$ varies across industries in every period and is not absorbed by δ_t. Hence, $\beta_j(h)$, for $j = 1, \ldots, 6$, measures the differential response of an industry whose j-th characteristic is one unit above the cross-sectional mean, holding the other characteristics fixed.[18]

[17] We lag the characteristics by one period to ensure pre-determination. Since $s_{i,t}$ may itself respond to oil price movements within the period, using $s_{i,t-1}$ avoids a simultaneity problem between the characteristics and the current shock realization. This convention follows Almuzara and Sancibrián (2024) and David et al. (2026), among others.

[18] Following Almuzara and Sancibrián (2024), the characteristics enter equation (10) only through their interaction with the shock. Because the characteristics vary over time, the lagged characteristics $\tilde{s}_{i,t-1}$ may also have a direct effect on future labor flows that is not absorbed by the industry fixed effects. Such a direct effect does not bias $\hat{\beta}(h)$ as long as the identified shock is unpredictable: since $\hat{u}_{1t}$ varies only with the instrument z_t, it is uncorrelated with $\tilde{s}_{i,t-1}$ when z_t is uncorrelated with past information, and the direct effect then enters the error term, where it affects precision but not consistency. To the extent that the proxy is partly predictable by lagged global activity (see

For the same reason, the time fixed effects control for all aggregate influences on labor flows, including seasonal patterns. As recommended by Almuzara and Sancibrián (2024), we use lag augmentation: we include $p = 8$ lags of y_{it} and of each element of $\tilde{s}_{i,t-1}\hat{u}_{1t}$ at every horizon to match the information set of the macro VAR.[19]

Since $\hat{u}_{1t}$ is a generated regressor (i.e., the fitted value from equation (9)), identification requires the instrument z_t to be uncorrelated with the structural errors other than the OPEC news shock and with the leads and lags of all shocks in the system. Because u_{1t} is a VAR residual, $\hat{u}_{1t}$ is orthogonal to p lags of the macro variables, and the lags of y_{it} and of the interaction terms included in the panel regression condition on the past of the industry-level variables. Under these conditions, Almuzara and Sancibrián (2024) show that the panel LP-IV estimator recovers the same population estimand as in the case of a directly observed shock, and that the time-clustered lag-augmented sandwich standard errors (t-LAHR) remain asymptotically valid.[20]

The Panel LP-IV approach has three advantages. First, it accommodates time-varying industry characteristics interacted with the shock, taking into account that these characteristics evolve over time. Second, the time-clustered lag-augmented standard errors proposed by Almuzara and Sancibrián (2024) are valid even when the shock is common to all units, as is the case with the OPEC news shock, and, under certain conditions, when the shock is estimated in a first step. Third, because disclosure restrictions prevent us from reporting sectoral responses at a more granular level than the three-digit NAICS industries, with the exception of the four four-digit industries in the transportation equipment sector discussed in Section 4.3, pooling the 86 four-digit industries in a panel allows us to exploit within-sector variation in characteristics that would otherwise remain undisclosed.

Yet, this strategy has some drawbacks. The panel regression recovers differences in responses associated with the characteristics, not the average response, and it does not allow us to differentiate between particular sectors (e.g., motor vehicles versus other transportation equipment) beyond what their characteristics explain; time-invariant differences across industries are absorbed by the industry fixed effects α_i. In addition, as David et al. (2026) show, the linear interaction specification in equation (10) recovers a causal impulse response function if and only if the true functional coefficient $g_h(s)$ is linear in s. This condition holds broadly in the class of canonical heterogeneous-agent macro models solved by first-order perturbation, which encompasses the theoretical environments motivating our empirical design.

Online Appendix Section G.3), the lags of y_{it} and of the interaction terms included in the regression help absorb any remaining correlation.

[19] Fixing the lag count at p for all horizons, rather than using $\min(h, p)$ as in some implementations, ensures that the regressors span the same information set across horizons.

[20] Specifically, letting $\mathbf{X}_t = \sum_{i=1}^{N} \mathbf{X}_{it}$ denote the time-t aggregate of the score, the t-LAHR variance estimator takes the form

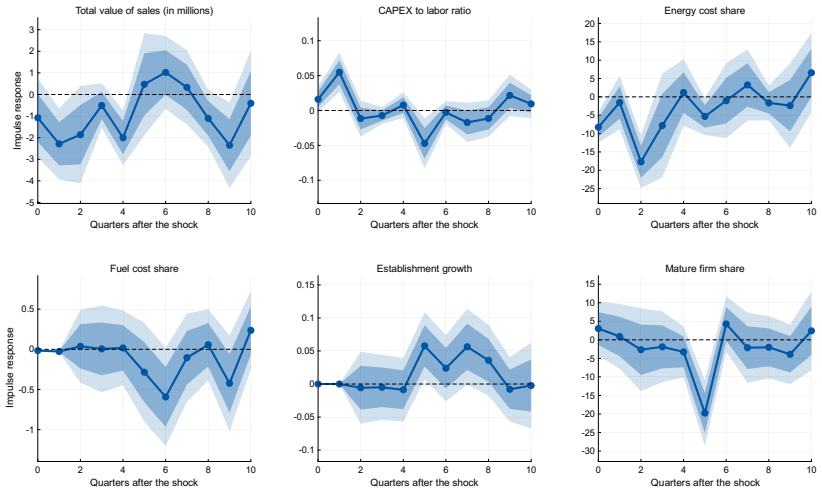
$$\widehat{\mathbf{V}}(h) = \left(\mathbf{X}'\mathbf{X}\right)^{-1} \left(\sum_{t=1}^{T} \mathbf{X}_t \mathbf{X}_t'\right) \left(\mathbf{X}'\mathbf{X}\right)^{-1}. \tag{11}$$

The estimator clusters by time period and thus accounts for the cross-sectional dependence induced by the common shock.

5.2 Estimation Results

Figures 10 and 11 report the $\hat{\beta}_j(h)$ for $j = 1, 2, ..., 6$, which capture the differential response relative to its cross-sectional mean. As Figure 10 illustrates, in the short run, the average scale of establishments in an industry (i.e., the total value of the shipments), the ratio of CAPEX to labor, and the share of energy costs drive the heterogeneous response of net employment growth. The larger the scale of establishments and the energy intensity of an industry, the greater the decline in net employment growth that follows the OPEC news. Estimation results reported in Online Appendix I indicate that this behavior is driven mostly by the faster rate at which closing and contracting establishments eliminate jobs (job destruction) and not by differences in the rate of job gains in expanding and entering establishments (job creation). In contrast, the larger the CAPEX/labor ratio in an industry, the greater the increase in net employment growth that follows the OPEC news. This short-term and short-lived increase in net employment, which lasts from the second to the third quarter after the shock, is largely explained by an increase in job creation. The greater increase in NET for industries with higher CAPEX/labor ratio is consistent with the notion that labor demand is more responsive in industries with lower capital adjustment costs (Cooper and Haltiwanger, 2006).

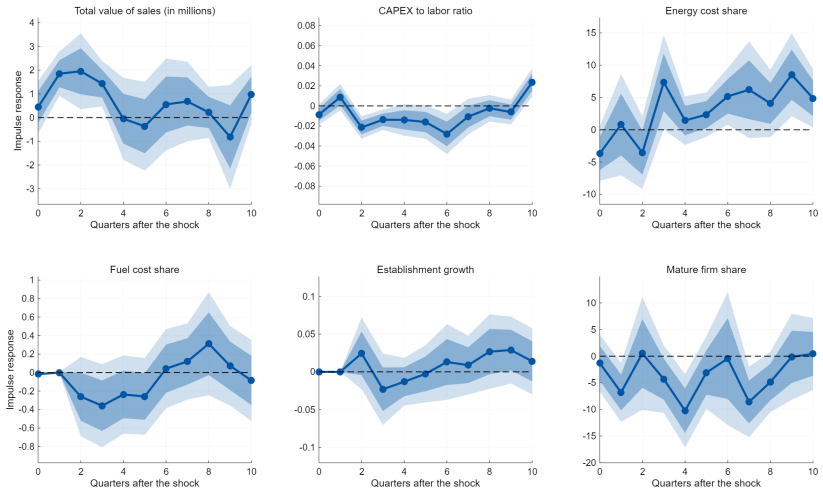
Figure 10: Margins of heterogeneity in the response of net employment growth



Notes: This figure reports the panel LP-IV estimates of $\hat{\beta}_j(h)$ for net employment growth (NET), 86 four-digit industries, 1989Q2–2021Q4. Each panel plots the differential response of an industry whose characteristic is one unit above the cross-sectional mean, holding the other characteristics fixed. "Total value of sales" denotes the average total value of shipments (effect per million dollars), "CAPEX to labor" denotes capital expenditures per production worker (effect per thousand of dollars), "energy cost share" denotes cost of energy as a percent of total value sales, "fuel cost share" denotes the cost of fuel as a percent of total value sales, "establishment growth" denotes the log difference of number of establishments, and "mature firm share" the share of establishments aged nine years or more. The dark and light shaded areas denote 68% and 90% confidence intervals based on time-clustered lag-augmented standard errors (Almuzara and Sancibrián, 2024).

A year after the shock, other characteristics, such as the cost of fuels, the percentage of mature establishments, and their rate of growth, contribute to explaining the heterogeneity in the response

Figure 11: Margins of heterogeneity in the response of excess job reallocation



Notes: This figure reports the panel LP-IV estimates of $\hat{\beta}_j(h)$ for excess job reallocation (EXC). See the notes to Figure 10.

of NET. More specifically, in industries that face higher fuel costs and have a higher share of mature establishments NET falls about a year after the shock and slightly increases in industries with higher average rates of establishment growth.

The characteristics driving heterogeneity in NET also play a key role in explaining differences in EXC across industries. In the short term, job churning is higher in industries where the average establishment size is larger, capital expenditure is lower, and the share of mature establishments is smaller. However, in the medium run, a crucial margin of heterogeneity in the response of EXC is cross-industry variation in energy intensity. That the process of reshuffling is more intense in industries where the share of mature establishments is lower is perhaps not surprising: rates of job creation and destruction are known to decline with age, and the well-documented "up-or-out" dynamics of young businesses suggest that shocks intensify the process of job reallocation where young establishments are more prevalent. Similarly, one would expect higher reallocation among industries facing higher energy costs. After all, as the price of oil increases, operation costs increase more for these industries, leading to a more intense restructuring process in these industries.

All in all, the panel LP-IV allows us to systematically investigate the question we posed at the beginning of this section: What drives the heterogeneity in the response of job flows to OPEC news? Focusing on the response of job flows, instead of net employment numbers, is key to understanding the process of restructuring/reshuffling of workers that takes place in response to OPEC news. Our estimation results indicate that characteristics such as the scale of the establishments, the CAPEX/labor ratio, and, especially, the degree of energy intensity, constitute important margins of heterogeneity in the intensity of the job reallocation process that follows OPEC news.

6 Conclusions

To investigate the effect of OPEC news on the creation and destruction of jobs in US manufacturing, we computed job flow rates from confidential establishment-level data for 1987Q2–2021Q4. These rates track closely their BED counterparts for job destruction and net employment growth, extend the sample back to cover the 1990–1991 Gulf War, and are lower than those reported by Davis and Haltiwanger (2001) for 1972–1988.

We then estimated a Proxy-VAR using movements in oil futures prices around OPEC announcements as an instrument, aggregating daily surprises to the quarterly frequency in two ways: a *Kilian-type proxy* that preserves the mapping between daily surprises and average quarterly prices, and a *Känzig-type proxy* that sums the surprises within each quarter. The responses of the oil market block in both specifications indicate that, at the quarterly frequency, OPEC news identifies shocks to flow demand rather than pure oil supply shocks. For total manufacturing, the responses are small and, in our baseline specification, statistically insignificant beyond the first quarter. We demonstrated that this muted aggregate response masks a great degree of heterogeneity across industries: in the short run, some sectors experience booms, but as time passes higher oil prices lead to lower net employment growth in most sectors. In addition, using panel LP-IV on 86 four-digit subindustries, we showed that the response of net employment growth and excess job reallocation is systematically related to the average scale of establishments, the capital expenditure to labor ratio, energy and fuel intensity, the share of mature establishments, and the rate of establishment growth. Of these, energy intensity stands out as the key driver of job reshuffling in the medium run.

While our results reveal important reallocative consequences of OPEC news, the responses we estimate are smaller than the increase in job reallocation documented by previous studies. We offered several plausible explanations for this muted response: the decline in the responsiveness of business-level employment (Decker et al., 2020), the role of the shale boom in altering the transmission of oil shocks (Kilian, 2016, 2017), the declining share of OPEC in global oil supply, and a change in the composition of the news conveyed by OPEC announcements. Because the instrument is too weak in samples ending before 2010 to yield informative estimates, we cannot establish whether the responsiveness of job flows to OPEC news has declined over time (Online Appendix H); disentangling the relative importance of these explanations is a question left for future research.

We close by highlighting three key aspects of the response of sectoral job creation and destruction to OPEC news shocks. First, there is a great degree of heterogeneity in responsiveness across industries, which aggregation obscures. Secondly, the motor vehicle industry stands out: OPEC news triggers the creation or destruction of roughly 6,600 jobs within two years with no significant change in net employment, a reshuffling that would be missed by focusing on net employment alone, whereas in motor vehicle bodies and trailers the adjustment takes the form of a sizable net contraction. Finally, cross-industry variation is systematically correlated with observable industry characteristics, constructed from establishment-level data, such as the cost of energy, capital ex-

penditures, the scale of establishments, and the share 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.

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