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The Changing Vulnerability of the U.S. Economy to Oil Shocks

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Abstract:
The United States has gone from heavy oil dependence to being a net petroleum exporter. Time-varying parameter regressions show that macroeconomic associations with oil price increases have weakened, especially for employment. State-level instrumental variables local projections suggest a source: An oil supply shock raising the real oil price by one standard deviation lifts employment in a state at the 90th percentile of oil production intensity by about 0.2 percentage point more over two years than in a nonproducing state. These relative gains, visible in non-extraction employment and house prices, point to regional offsets that may dampen the aggregate inflation–real activity tradeoff.

JEL Classifications: E23, E3, Q34, Q43
Keywords: Oil shocks, inflation, employment, state-level oil production, regional employment offsets

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1 Introduction

Historically, large oil price increases have been stagflationary: they raise costs throughout the economy and weigh on real activity, while generating inflationary pressures that can become persistent through second-round effects on non-energy prices. As a result, monetary policymakers have typically faced a tradeoff between containing inflation and supporting employment. The relevance of this tradeoff today, however, depends on how the economy's exposure to oil has changed—an issue of particular importance currently, given the surge in oil prices sparked by the U.S.–Iran conflict in early 2026. In fact, as noted in the minutes of the April 28–29, 2026, Federal Open Market Committee meeting, two structural changes—the substantial rise in domestic oil production and the lower oil intensity of economic activity—may have altered the economy's response to an increase in oil prices.[1]

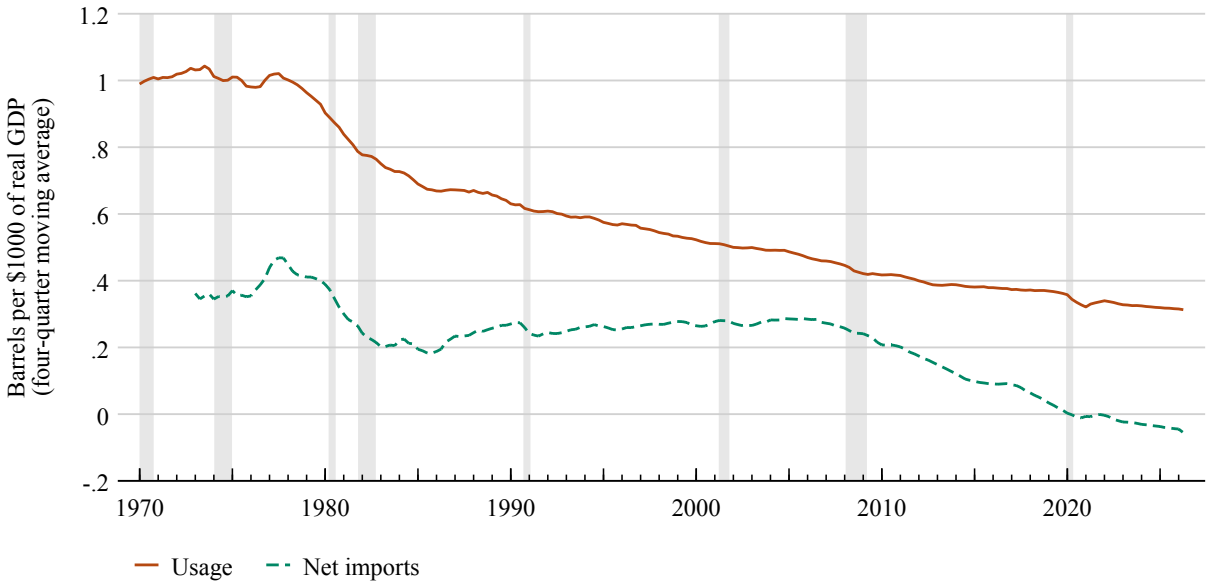
This paper provides empirical evidence on how these changes have affected the vulnerability of the U.S. economy to oil price increases. We first document how the relationship between *net* oil price increases—a nonlinear measure that tracks how much the current price of oil exceeds the highest price reached over a previous reference period (see Hamilton, 1996, 2003)—and aggregate macroeconomic outcomes has evolved over the past five decades. Using instrumental variables (IV) local projections, we then exploit state-level variation in oil production—together with identified oil supply news shocks (see Känzig, 2021)—to assess whether domestic oil production has helped alter the relationship between oil and the macroeconomy in more recent decades.

Our main finding is that the state-level evidence is consistent with regional offsets dampening the national employment response to oil price shocks since the late 1990s. According to our IV local projections, an oil supply news shock that raises the real oil price by 1 standard deviation leaves employment in a state at the 90th percentile of oil production intensity about 0.2 percentage point higher after two years than in a state that does not produce oil. These relative job gains extend beyond mining and logging and are accompanied by significantly higher house prices—an indication of positive demand spillovers. Although this approach identifies only relative effects and does not quantify the impact on aggregate outcomes, it suggests that employment gains in oil-producing states can offset losses elsewhere, leaving little net effect on national employment.

Consistent with this interpretation, our time-varying parameter estimates show that the national employment response to net oil price increases has largely vanished. In the 1970s and 1980s, a 1 standard deviation net oil price increase was associated with a 0.5 percentage point reduction in national employment over the subsequent year, whereas the association today is essentially nil. The oil–inflation association has also moderated, though by less; a 1 standard deviation increase is now associated with a 0.4 percentage point rise in year-ahead total PCE inflation, down from almost 0.6 percentage point through the early 1970s, though the decline is modest relative to the estimation uncertainty. The attenuation is sharper for core PCE inflation. This is consistent with the lower oil intensity of U.S. production reducing the pass-through from oil to non-energy prices,

[1] See Federal Open Market Committee (2026).

FIGURE 1: U.S. Oil Intensity and Net Import Reliance



NOTE: The solid line shows the number of oil barrels used per $1,000 of real GDP, whereas the dashed line shows the net number of oil barrels imported per $1,000 of real GDP (in 2017 dollars); both series are four-quarter moving averages. As our measure of usage, we use the crude oil and petroleum products supplied series, which approximately represents oil consumption in the entire U.S. economy (see the U.S. Energy Information Administration Glossary for details). Net imports are defined as the difference between imports and exports of crude oil and petroleum products, with negative values indicating that the U.S. is a net exporter of oil and petroleum products. The gray-shaded vertical bars represent NBER-dated recessions.
SOURCE: Authors' calculations using data from the U.S. Bureau of Economic Analysis and the U.S. Energy Information Administration.

just as the rise in domestic oil production has created regional offsets on the employment side.

Our work complements a recent literature documenting the positive effects of oil and gas booms on local economies and on their resilience to oil supply shocks (see Feyrer et al., 2017; Allcott and Keniston, 2018; Alsalman and Rangaraju, 2026). Most closely, Känzig et al. (2026) find that oil shocks have become expansionary for the U.S. economy over time but attribute little role to regional offsets. We instead show that exploiting state-level time variation in oil intensity uncovers economically and statistically significant regional differences in the response to oil supply shocks.

The remainder of the paper is structured as follows. Section 2 documents how the relationship between oil and the macroeconomy has changed over the past five decades. Section 3 investigates the regional offsets that arise from domestic oil production. Section 4 concludes.

2 Changing Relationship between Oil and the Macroeconomy

The U.S. economy has become much less dependent on oil. As shown by the solid line in Figure 1, the economy used about one barrel of oil for each $1,000 of real output through most of the 1970s. Today, that figure is less than one-third of its earlier level, reflecting greater efficiency in oil usage and a shift away from energy-intensive manufacturing toward services.

Reliance on foreign oil has also declined, but along a different timeline. According to the dashed line in Figure 1, net oil imports per $1,000 of real GDP fell sharply between the late 1970s and the early 1980s, as oil usage dropped. They then remained roughly flat through the 2000s, even as usage per unit of output continued to decline. Net import reliance began to fall again around 2010, as the shale boom sharply expanded domestic production. By 2019, the U.S. had become a net oil exporter.[2]

Lower oil intensity and reduced net import reliance suggest that the U.S. economy is less exposed to oil price increases than in the 1970s. We therefore examine whether the association between oil and the macroeconomy has weakened. Not every oil price increase, however, constitutes a shock that disrupts economic planning. Following Hamilton (1996, 2003), we focus on price jumps that exceed the highest level observed over the preceding 12 months, so that only movements beyond recent experience are treated as "shocks."[3] Purple spikes in Figure 2 depict these "net oil price increases," derived from the real price of West Texas Intermediate (WTI) crude oil (shown by the blue line), the U.S. benchmark—the average monthly WTI price deflated by the PCE price index and expressed in August 2026 dollars. The right panel cumulates them over the most relevant historical episodes.[4] Although the Hamilton measure is not a structural supply shock and reflects a mix of supply and demand forces, these episodes—from the 1973 OPEC embargo through the 2026 U.S.–Iran war—line up closely with clearly identifiable disruptions to oil supply, so in practice, the measure tends to flag episodes in which supply-side forces appear to have played an outsized role.

Using these price increases, we estimate the following time-varying parameter regression:

$$y_{t+12} - y_t = \beta_{0,t} + \beta_{1,t}\text{NetOil}_t^{(+)} + u_{t+12}, \tag{1}$$

where y_t is an outcome variable in logs (times 100) and $\text{NetOil}_t^{(+)}$ is the 12-month Hamilton net oil price increase in month t. The intercept and slope are assumed to evolve as random walks:

$$\beta_{k,t} = \beta_{k,t-1} + \epsilon_{k,t}, \text{ where } \epsilon_{k,t} \sim \mathcal{N}(0, \sigma_k^2), \quad k \in \{0, 1\}.$$

The intercept $\beta_{0,t}$ captures time variation in the conditional mean of the growth rate of the outcome variable y_t from month t to month $t + 12$, while the slope $\beta_{1,t}$ measures changes in the sensitivity to net oil price increases. The random-walk specification is consistent with the low-frequency movements in oil intensity and import reliance shown in Figure 1.

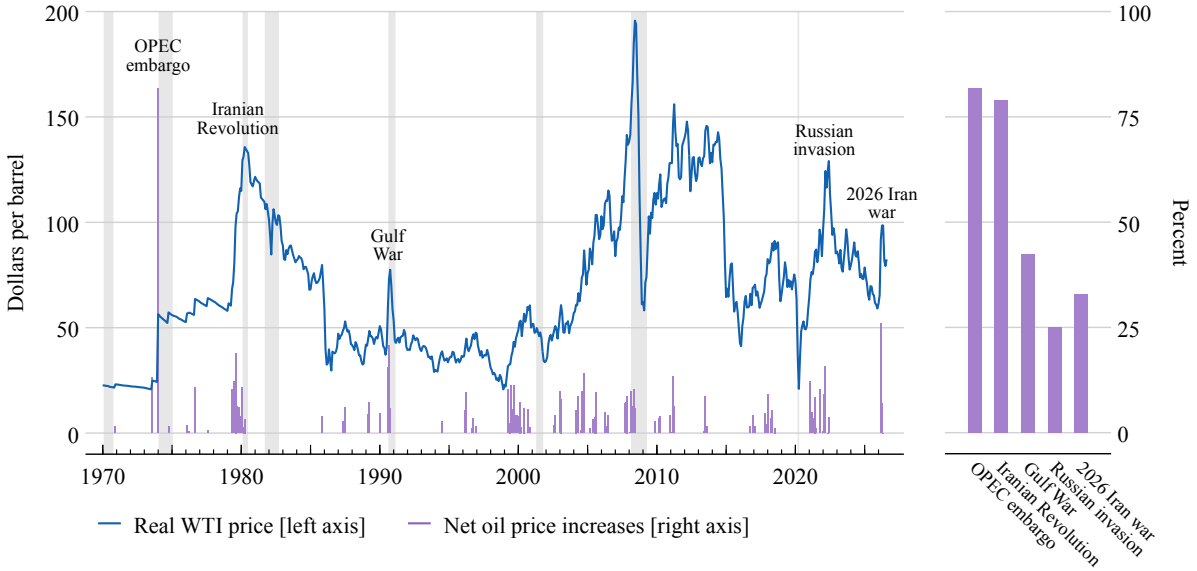
The specification also incorporates stochastic volatility—to account for the well-documented

[2]This shift is primarily driven by exports of processed petroleum products. The U.S. still imports crude oil on net, though these imports have also decreased notably as domestic production has risen.

[3]The intuition is that agents form expectations from recent prices, so increases within the recent range are anticipated, while increases that break through that range are more likely to catch agents off-guard and force costly adjustments. The approach is backward-looking and avoids reliance on structural models or assumptions about future prices. The choice of look-back window involves a tradeoff, as shorter windows flag more frequent but less dramatic increases, while longer windows isolate only the most extreme departures from recent experience; we use 12 months as our baseline, matching typical planning horizons.

[4]Our dating of the 1973–1974 OPEC oil embargo and the 1978–1980 Iranian Revolution episodes follows Kilian (2008).

FIGURE 2: The Real Price of Oil and Hamilton Net Oil Price Increases



NOTE: The blue line in the left panel shows the average monthly price of a barrel of WTI crude oil in August 2026 dollars. The purple spikes depict the associated net oil price increases of Hamilton (1996, 2003), calculated using a 12-month look-back reference price. The gray-shaded vertical bars represent NBER-dated recessions. The purple vertical bars in the right panel show the cumulative net increases for (1) the OPEC embargo (1973:M10–1974:M3), (2) the Iranian Revolution (1978:M10–1980:M8), (3) the Gulf War (1990:M8–1991:M2), (4) the first two months of the Russian invasion of Ukraine (2022:M2–2022:M3), and (5) the current episode resulting from the U.S.–Iran war (2026:M3–2026:M8).
SOURCE: Authors' calculations using data from the U.S. Bureau of Economic Analysis, the CME Group, and the U.S. Energy Information Administration.

decline in macroeconomic volatility since the 1980s—and an outlier component to limit the influence of extreme observations (for example, the COVID-19 pandemic) on the estimated coefficient paths. In particular,

$$u_t \sim \mathcal{N}(0, o_t^2 \times e^{h_t}), \text{ where } h_t = h_{t-1} + \nu_t, \text{ with } \nu_t \sim \mathcal{N}(0, \omega^2),$$

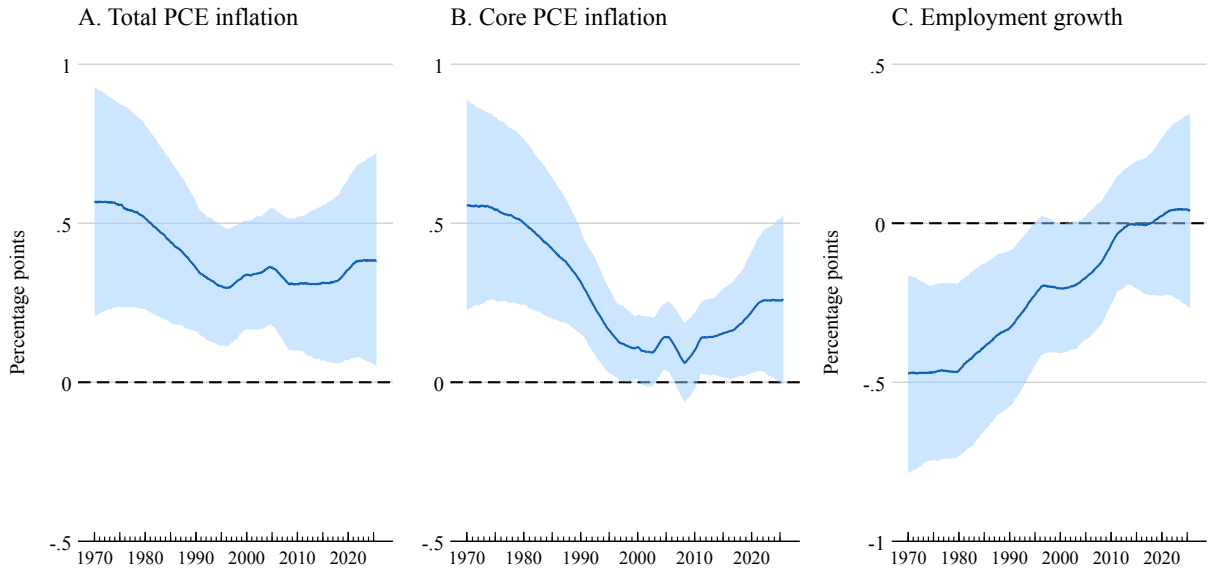
and where, following Stock and Watson (2016), the outlier term is given by

$$o_t = \begin{cases} 1 & \text{with probability } (1-\chi); \\ \mathcal{U}_{[a,b]} & \text{with probability } \chi. \end{cases}$$

The time-varying parameter regression in (1) is estimated by Bayesian methods using monthly data from 1960:M1 through 2026:M8. Specifically, we use the Gibbs sampler to simulate the posterior distribution of the parameters and latent states, the Carter and Kohn (1995) algorithm to sample the time-varying coefficients, and the mixture-of-densities approach of Kim et al. (1998) to sample the stochastic volatility state.[5]

[5]We use an Inverse-Wishart prior for the covariance matrix of the coefficient innovations, $\text{diag}[\sigma_0^2, \sigma_1^2]$, and an Inverse-Gamma prior for the variance of the log-volatility innovations ω^2. The prior hyperparameters for $\text{diag}[\sigma_0^2, \sigma_1^2]$

FIGURE 3: Time-Varying Oil–Macroeconomy Associations



NOTE: The figure shows the association between the 12-month net oil price increase in month t and the specified outcome over the subsequent 12 months. The solid line in each panel depicts the time path of the posterior median ($P50$) of the slope coefficient $\beta_{1,t}$ multiplied by 8.5, the standard deviation of the net oil price increase (in percent) over the 1960:M1–2025:M12 sample period. The shaded bands depict the associated $[P10, P90]$ credible intervals.

Figure 3 shows the estimated time paths of the slope coefficients $\beta_{1,t}$ for different aggregate outcomes: total and core PCE inflation (Panels A and B) and private nonfarm employment growth (Panel C), each measured over the following 12 months. We scale the coefficients by 8.5, the standard deviation of net oil price increases in percent.

The estimates point to a weakening of these associations, though with varying precision across outcomes.[6] For total PCE inflation (Panel A), a 1 standard deviation net oil price increase was associated with about 0.55 percentage point of additional year-ahead inflation through the 1970s, compared with about 0.4 percentage point at the end of the sample. The credible intervals overlap substantially, leaving the decline imprecisely estimated.[7]

The attenuation is more pronounced for year-ahead core PCE inflation (Panel B). The estimated association declined steadily from the early 1980s through the late 1990s and was weakest from the late 1990s through the mid-2000s, when the credible intervals generally include zero. It has risen

are $\vartheta = 10^3$ and $\varrho = \frac{1}{12} \times \text{diag}[1, 0.05]$; for ω^2, they are $\vartheta_\nu = 10^3$ and $\varrho_\nu = 0.01 \times (\vartheta_\nu - 1)$. Finally, the outlier probability χ has a Beta prior, $\chi \sim \mathcal{B}(\alpha_o, \beta_o)$, with $\alpha_o = 2.5$ and $\beta_o = 117.5$, following Stock and Watson (2016).

[6] Our regression sample starts in 1960:M1, but we plot coefficients only from 1970:M1 because Hamilton net oil price increases cumulated to just 5.17 percentage points over the 1960s. With so little variation to identify $\beta_{1,t}$, the random-walk prior simply extends the 1970 estimate backward.

[7] This result is consistent with previous studies that have employed time-varying parameter structural vector autoregressions with stochastic volatility to measure the macroeconomic effects of oil price shocks. For instance, Baumeister and Peersman (2013) find that a supply shock normalized to a 10 percent real crude oil price increase yields a volatile consumer price response characterized by considerable estimation uncertainty, particularly before 1990. More recently, Känzig et al. (2026) show that the responses of U.S. CPI and industrial production to adverse oil shocks moderated since the 1980s. On the other hand, Herrera and Rangaraju (2025) document only modest time variation in inflation responses, where the credible intervals could also accommodate time-invariant responses.

gradually since about 2015, to roughly 0.25 percentage point at the end of the sample. Because core inflation excludes food and energy prices, this response reflects second-round effects, whereby higher energy costs pass through to the prices of other goods and services and may also feed into wage setting and inflation expectations.

In the labor market (Panel C), a net oil price increase of this size was associated with a decline of about 0.5 percentage point in year-ahead employment growth during the 1970s and early 1980s. The association remained negative through the 1990s and 2000s but has moved to roughly zero since about 2010, coinciding with the acceleration of domestic shale oil production.

Regional heterogeneity in oil production is a natural candidate explanation: higher oil prices may raise employment in producing states by enough to offset losses elsewhere. The inflation responses documented above lend some indirect support to this hypothesis. Rather than continuing their gradual decline—as one might have expected given the downward trend in economy-wide oil usage (the solid line in Figure 1)—the inflation responses have stabilized since the late 1990s—rising somewhat for core inflation—suggesting some positive demand effects from higher oil prices. Aggregate time series cannot test this explanation directly. The regional-offsets hypothesis is intrinsically a cross-state proposition, and the net oil price increases used in this exercise reflect both supply and demand forces in any case. We therefore turn to state-level data and compare how employment responds to identified oil supply shocks in states with different degrees of oil production.

3 Regional Offsets from Domestic Oil Production

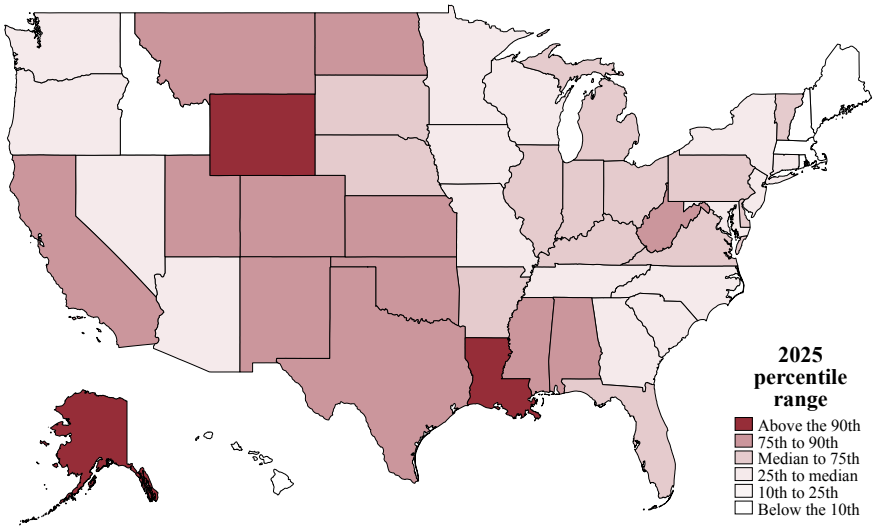
Domestic oil and gas extraction is geographically concentrated. Figure 4 shows the share of oil and gas extraction in gross state product (GSP) in 1997 (Panel A) and 2025 (Panel B).[8] In 2025, the industry accounted for about 1 percent of GSP on average across states, but is concentrated in a few: New Mexico, North Dakota, Alaska, Oklahoma, West Virginia, and Texas together account for 85 percent of the nation's oil and gas extraction output. The geography has also shifted since 1997. For instance, North Dakota, New Mexico, Oklahoma, and West Virginia rank higher in 2025, whereas Louisiana and Wyoming rank lower. This variation in exposure across states and over time is what we exploit to assess whether domestic oil production creates regional offsets.

Specifically, we use the local projection framework of Jordà (2005) to compare how economic outcomes evolve in states with different oil production intensity following the same national oil price change. The oil price change, however, is not exogenous. Oil prices fluctuate for many reasons: a supply disruption raises prices and depresses global activity, whereas a surge in global demand raises both prices and activity. If oil-intensive states respond differently to global demand conditions than do other states—because commodity-producing regions are more cyclical, for example—a regression on the observed oil price change would attribute that differential response to the price change itself.

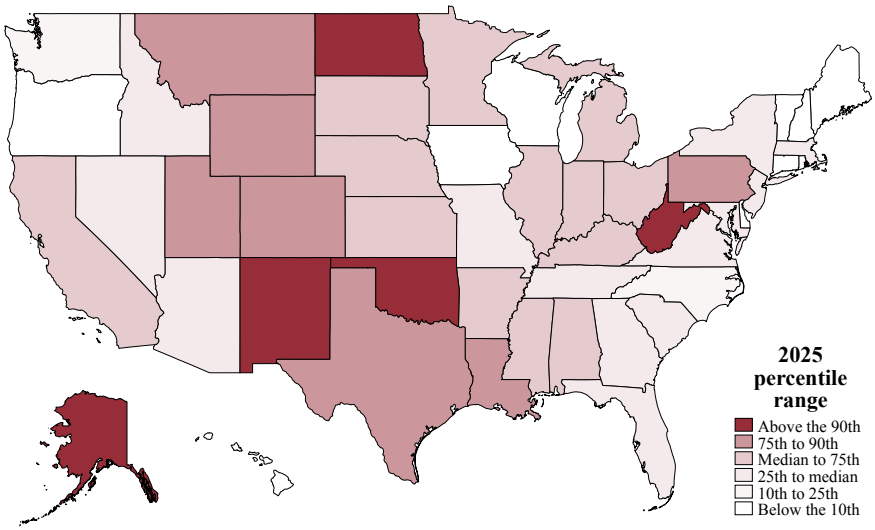
[8] We use the narrow oil and gas extraction category (NAICS 211) rather than a broader definition of the energy sector for two reasons: (1) data limitations at the state level and (2) to isolate the industry most directly linked to higher oil prices. Downstream industries that produce petroleum products may not move in parallel, because higher oil prices raise their input costs while their output prices may also rise.

FIGURE 4: State-Level Oil Production Intensity: 1997 and 2025

A. Oil and gas extraction as a share of GSP in 1997



B. Oil and gas extraction as a share of GSP in 2025



NOTE: The figure shows the geographic distribution of the share of oil and gas extraction in total gross state product (GSP) in 1997 (Panel A) and 2025 (Panel B). To facilitate comparison, percentile ranges in both panels correspond to 2025 shares.
SOURCE: Authors' calculations using data from the U.S. Bureau of Economic Analysis.

The resulting bias could go in either direction, depending on the mix of shocks.

We therefore instrument the national oil price change with the oil supply news shocks of Känzig (2021), which are designed to isolate price movements arising from news about oil supply—measured as changes in oil futures prices in a narrow window around OPEC announcements—and are plausibly unrelated to contemporaneous demand conditions. Both the price change and the instruments are interacted with each state's predetermined oil production intensity, generating a standard shift-share

design (see Borusyak et al., 2025). Formally, we estimate the following specification:

$$y_{i,t+h} - y_{i,t-1} = \alpha^{(h)}[\Delta\text{WTI}_t \times \text{OilInt}_{i,t-12}] + \beta^{(h)}\text{OilInt}_{i,t-12} + \sum_{p=1}^{12}\gamma_p^{(h)}[\Delta\text{WTI}_{t-p} \times \text{OilInt}_{i,t-12-p}] + \sum_{p=1}^{12}\mathbf{x}'_{i,t-p}\boldsymbol{\delta}_p^{(h)} + \eta_i^{(h)} + \lambda_t^{(h)} + \varepsilon_{i,t+h}^{(h)}, \quad (2)$$

where i indexes states, t indexes time (in months), and h is the projection horizon. The variable $y_{i,t}$ is 100 times the log of the state-level outcome, so the dependent variable is the cumulative percent change from month $t-1$ to month $t+h$. We consider three outcomes. The first is private nonfarm employment. The second is private nonfarm employment excluding mining and logging, which removes direct hiring by resource extraction firms, so that a relative gain reflects spillovers to other sectors rather than a mechanical effect on the extraction industry. And the third is house prices, which proxy for broader demand-driven effects at the state level, since monthly state-level price data are generally unavailable. Because house prices in principle capitalize expected local income, they should rise in places where oil revenues boost local demand.[9]

The vector $\mathbf{x}_{i,t}$ contains the log-levels of the state outcome variables and enters with 12 monthly lags, as does the interaction term $\Delta\text{WTI}_t \times \text{OilInt}_{i,t-12}$.[10] The specification also includes state fixed effects ($\eta_i^{(h)}$) and time fixed effects ($\lambda_t^{(h)}$). The state fixed effects absorb time-invariant state characteristics, such as geographic, demographic, and institutional factors, that may influence both economic outcomes and oil production intensity. The time fixed effects absorb all common monthly factors, including national monetary and fiscal policy and global conditions, as well as the average effect of the oil price change itself.

The endogenous explanatory variable in specification (2) is the interaction between ΔWTI_t—100 times the log-difference in the average monthly real price of a barrel of WTI crude oil from month $t-1$ to month t—and $\text{OilInt}_{i,t-12}$, state i's oil production intensity, measured as the share of oil and gas extraction in its GSP (in percent) 12 months earlier.[11] The coefficient of interest, $\alpha^{(h)}$, measures the differential response of the outcome at horizon h, in percentage points, to a 1 percent oil price increase for a state with a 1 percentage point higher oil share. A positive $\alpha^{(h)}$ means that states with higher oil production intensity fare relatively better—in terms of employment growth and house price appreciation—after an oil price increase.

To identify $\alpha^{(h)}$, we rely on the monthly oil supply news shocks of Känzig (2021), denoted OilShk_t,

[9] The sample begins in 1997, the first year for which the BEA reports GSP by industry on the NAICS basis—which we need to measure the oil and gas extraction share. All state-level data are seasonally adjusted, and we winsorize the monthly log-difference of each series at the 0.5th and 99.5th percentiles before cumulating them, to limit the influence of outliers. Monthly house prices are from the Federal Home Loan Mortgage Corporation (Freddie Mac). Summary statistics for all variables used in the analysis are reported in Table A-1 of the Appendix.

[10] Specifically, in the case of private employment, the vector $\mathbf{x}_{i,t}$ comprises the log-levels of private employment and house prices; in the case of employment outside mining and logging, $\mathbf{x}_{i,t}$ comprises the log-levels of employment excluding mining and logging and house prices; and in the case of house prices, $\mathbf{x}_{i,t}$ comprises the log-levels of house prices and private employment.

[11] State-level gross output of the oil and gas extraction industry is available only at annual frequency. We assign each annual share to all 12 months of the corresponding year. The share assigned to month $t-12$ is thus based on a calendar year that ended before month t.

to instrument the interaction term $\Delta\text{WTI}_t \times \text{OilInt}_{i,t-12}$ and thereby isolate exogenous variation in ΔWTI_t. The natural instrument is $\text{OilShk}_t \times \text{OilInt}_{i,t-12}$. However, ΔWTI_t itself displays mild serial correlation, so the WTI price response to a given news shock is spread over several months rather than realized at impact. To capture this transmission, we expand the instrument set to include the first two lags of the shock, each interacted with the correspondingly lagged oil intensity: $\{\text{OilShk}_{t-p} \times \text{OilInt}_{i,t-12-p}\}_{p=0}^{2}$. With three excluded instruments for one endogenous regressor, the model is overidentified.[12]

This approach identifies $\alpha^{(h)}$ from the interaction of state-level differences in oil intensity with the time series of oil price changes, assuming the response is linear in the oil share. The coefficient $\alpha^{(h)}$ therefore measures the response of oil-intensive states *relative* to non-producing states and tests a necessary condition for regional offsets, but it does not pin down the absolute effect of oil price changes or the size of the aggregate offset.

We estimate specification (2) using monthly data for the 50 states from 1997:M1 through 2025:M12 and for horizons $h = 0, 1, \ldots, 36$. Because the model is overidentified, we use two-step (efficient) GMM, which also allows us to test the overidentifying restrictions. At horizon $h = 0$, the sample with the largest number of observations, the Hansen J-statistic ranges from 2.2 to 2.8 across outcomes, so we do not reject the overidentifying restrictions; moreover, the Kleibergen–Paap Wald F-statistic is 129, indicating strong instruments. Lastly, all inference is based on standard errors clustered by state and time, thus allowing for serial correlation in the error term $\varepsilon_{i,t+h}^{(h)}$ within states, as well as for cross-sectional correlation across states within a month (see Cameron et al., 2011).[13]

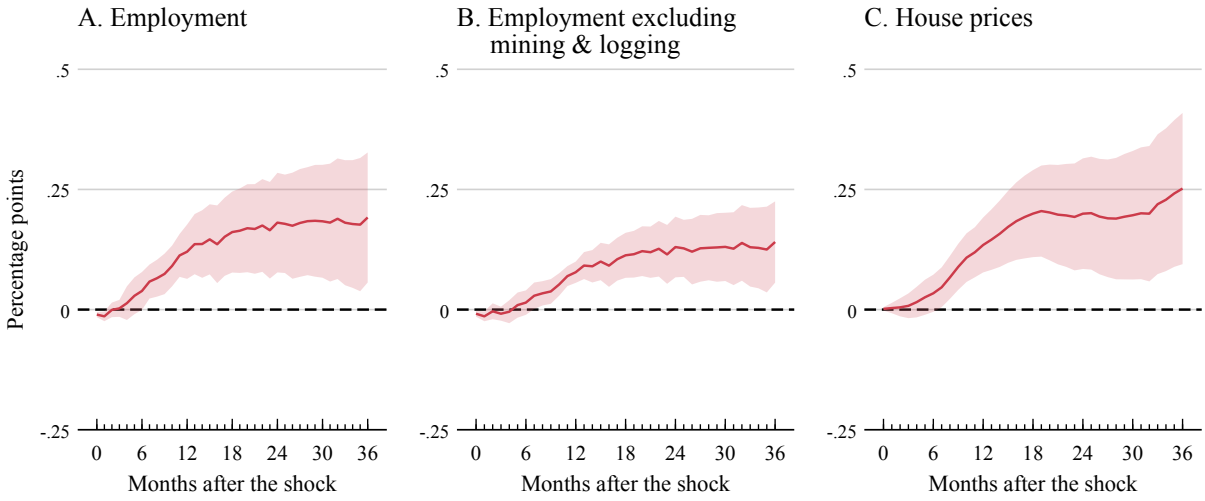
Figure 5 shows the estimated differential responses of our state-level outcome variables to an oil supply news shock that raises the real oil price by 10 percent in month 0, an increase of 1 standard deviation over the 1997:M1–2025:M12 sample period. Each response compares a state at the 90th percentile of oil production intensity (about 5 percent of GSP) with a state that does not produce oil. As Panel A shows, total employment in the oil-intensive state is essentially unchanged relative to the non-producing state for about six months. The differential then turns positive—the 90 percent confidence interval excludes zero after about seven months—and widens to roughly 0.2 percentage point by month 24, where it remains through the three-year horizon.

Employment gains are not confined to the extraction sector. Panel B shows that the response of employment excluding mining and logging follows the same path as total employment but is

[12] The effect of past shocks on the outcome operates through past oil price changes, which enter the specification through the 12 lags of the interaction term $\Delta\text{WTI}_{t-p} \times \text{OilInt}_{i,t-12-p}$. Lagged shocks thus serve as instruments for the current price change, not as separate determinants of the outcome. The 12-month lag of oil intensity ensures that it is predetermined with respect to the shocks in months t, $t-1$, and $t-2$.

[13] The results are robust along two dimensions. Instrumenting $\Delta\text{WTI}_t \times \text{OilInt}_{i,t-12}$ with the oil supply shocks of Baumeister and Hamilton (2019) in place of the Känzig (2021) oil supply news shocks yields very similar responses (see Figure A-1 in the Appendix), confirming that our main finding does not depend on which identified oil supply shock we use. Replacing ΔWTI_t with the raw Hamilton net oil price increases and estimating specification (2) by OLS likewise delivers a similar pattern of relative responses (see Figure A-2). These OLS estimates should be interpreted with caution. The Hamilton net oil price increases reflect both supply and demand forces, so the resulting coefficients cannot be given a clean causal interpretation. The estimated differential responses are also somewhat larger than those from the IV specification, consistent with a demand component in the Hamilton measure amplifying relative gains in oil-producing states—exactly the endogeneity concern that our IV strategy is designed to address.

FIGURE 5: Differential State-Level Effects of an Oil Supply News Shock



NOTE: The figure shows the relative effects of a 1 standard deviation increase in the real price of oil (10 percent) induced by an oil supply news shock in month 0 on the specified state-level outcome variable over the subsequent 36 months. The solid line in each panel depicts the estimated difference in the cumulative growth of the specified variable for a state at the 90th percentile of oil production intensity, relative to a state with no oil production. The shaded bands depict the associated 90 percent confidence intervals, computed using the asymptotic covariance matrix clustered by state and time.

smaller in magnitude, plateauing around 0.15 percentage point two years after the shock, consistent with higher oil revenues supporting local spending and hiring in other industries. Relative house price appreciation, shown in Panel C, reaches roughly 0.2 percentage point within 18 months and edges up slightly by the end of the horizon, further corroborating positive demand spillovers from domestic oil production and consistent with housing markets capitalizing the expected rise in local income.[14]

These regional patterns are consistent with the significantly attenuated response of national employment to net oil price increases in recent decades, documented in Section 2. Because higher oil prices transfer income from consumers to producers, a substantial part of that transfer went abroad when the United States was a large net importer of oil; in that case, employment gains in domestic oil-producing regions could offset only a fraction of the losses elsewhere. As the shale boom turned the country into a net exporter, domestic producers' gains became large relative to domestic consumers' losses, and employment gains in oil-producing states may now offset a larger share of the losses in non-producing states. These gains could also generate some additional inflationary pressure through positive demand spillovers. Because our estimates identify only the differential response across states, the results above are consistent with, but do not establish, a regional-offsets interpretation of the aggregate findings.

[14]These results are consistent with De Michelis et al. (2020), who exploit cross-sectional and time-series variation in state-level oil intensity to analyze how economic activity across the United States reacts to oil price shocks. Using new car registrations as a proxy for consumption, the authors find that states with higher oil dependency experience a more pronounced increase in consumption following an exogenous oil price decline.

4 Conclusion

The vulnerability of the U.S. economy to oil price increases has changed substantially over the past five decades. The association between a 1 standard deviation net oil price increase and year-ahead total PCE inflation has declined from about 0.6 to about 0.4 percentage points, and the association with employment growth has moved from about -0.5 percentage point to roughly zero. State-level instrumental variables estimates point to a source of the latter shift. Following an oil supply shock that raises the real price of oil by 1 standard deviation, employment in a state at the 90th percentile of oil production intensity grows about 0.2 percentage point more over two years than in a state with no oil production. These relative gains are consistent with regional offsets dampening the national employment response. This changed exposure matters for monetary policy: oil shocks today may now be more purely inflationary, in contrast to the stagflationary dynamics of the 1970s and early 1980s, when they weighed heavily on employment as well.

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Appendix

— For Online Publication Only —

The supplementary material below provides summary statistics of key variables used in the analysis and two robustness checks of the results referenced in the main text.

Summary statistics. Table A-1 provides summary statistics for the key state-level and aggregate variables used in the analysis.

TABLE A-1: Summary Statistics

		Std. Deviation[a]		
Variable	Mean	Tot.	Btw.	Wth.
A. *State-level variables*[b]				
Oil intensity shares (%)	1.32	3.41	3.04	1.58
Employment (%Δ)	0.11	0.38	0.04	0.38
Employment ex. mining & logging (%Δ)	0.11	0.38	0.04	0.37
House prices (%Δ)	0.36	0.54	0.06	0.54
B. *Aggregate variables*[c]				
Real WTI price (%Δ)	0.32	9.94	.	.
Oil supply news shocks (pps.)	0.02	0.65	.	.
Net oil price increase (%)	6.05	8.49	.	.

NOTE: Entries in the table report sample means and standard deviations of the main variables used in the analysis: Panel A = state-level economic outcomes; and Panel B = aggregate variables.

[a] Tot. = total standard deviation; Btw. = between standard deviation; and Wth. = within standard deviation. Data in Panel B have no cross-sectional dimension, so the concepts of between and within standard deviations are not applicable.

[b] For private nonfarm employment and house prices, unbalanced panel of 50 states from 1997:M1 through 2025:M12 ($\bar{T}$ = 344 and Obs. = 17,350). For private nonfarm employment excluding mining and logging, unbalanced panel of 47 states from 1997:M1 through 2025:M12 ($\bar{T}$ = 344 and Obs. = 16,165). Mining and logging employment data are not available for Delaware, Florida, and Hawaii for the entire sample and are available for Rhode Island starting in 2009:M1. Oil intensity data contains gaps for Connecticut, Hawaii, Idaho, Iowa, Maine, New Hampshire, Rhode Island, South Carolina, and Wisconsin. Monthly log-differences of state-level variables have been winsorized at the 0.5th and 99.5th percentiles.

[c] For real WTI price and Känzig (2021) oil supply news shocks, monthly data data from 1997:M1 through 2025:M12. For net oil price increases, monthly data from 1960:M1 through 2025:M12.

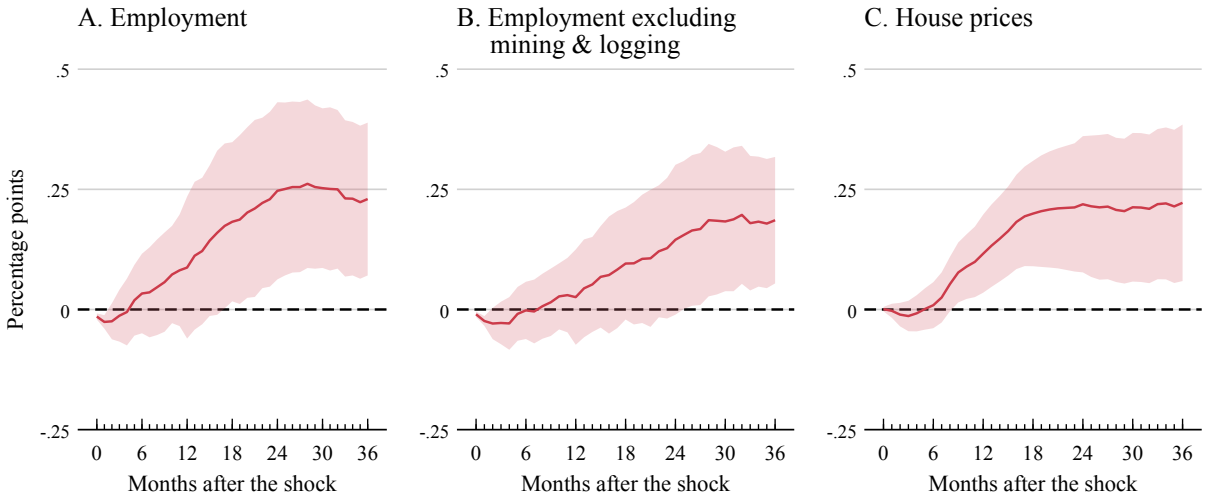
Sensitivity analysis. We conduct two sensitivity exercises for the state-level IV local projections of Section 3 in the main text.

The first replaces the Känzig (2021) oil supply news shocks with the oil supply shocks of Baumeister and Hamilton (2019) as the instrument. The two sets of shocks are identified from different sources of variation but share the goal of isolating movements in the real price of oil driven by supply fluctuations. Figure A-1 shows that the resulting responses are very similar in both magnitude and timing to those from the Känzig-based baseline, indicating that our main finding is not sensitive to the particular choice of identified oil supply shock.

The second exercise replaces ΔWTI_t in specification (2) in the main text with Hamilton's net oil price increases $\text{NetOil}_t^{(+)}$—the measure used in the aggregate analysis of Section 2—and estimates

the modified specification by OLS. Figure A-2 reports the resulting responses, which also show positive relative effects for oil-intensive states. The estimated magnitudes are somewhat larger than those from the IV baseline, consistent with the Hamilton measure capturing both supply- and demand-driven movements in oil prices; demand-driven increases amplify the relative gains in oil-producing states that OLS attributes to the price change itself. As noted in the main text, these OLS estimates cannot be interpreted causally. Taken together with the aggregate exercise in Section 2, they do, however, provide a consistent qualitative picture of a changing state-level response to oil price shocks over our sample period.

FIGURE A-1: Differential State-Level Effects of a Baumeister–Hamilton Oil Supply Shock



NOTE: The figure shows the relative effects of a 1 standard deviation increase in the real price of oil (10 percent) induced by an oil supply shock in month 0 on the specified state-level outcome variable over the subsequent 36 months. The solid line in each panel depicts the estimated difference in the cumulative growth of the specified variable for a state at the 90th percentile of oil production intensity, relative to a state with no oil production. The shaded bands depict the associated 90 percent confidence intervals, computed using the asymptotic covariance matrix clustered by state and time.

FIGURE A-2: Differential State-Level Effects of a Hamilton Net Oil Price Increase



NOTE: The figure shows the relative effects of a 1 standard deviation (8.5 percent) net oil price increase in month 0 on the specified state-level outcome variable over the subsequent 36 months. The solid line in each panel depicts the estimated difference in the cumulative growth of the specified variable for a state at the 90th percentile of oil production intensity, relative to a state with no oil production. The shaded bands depict the associated 90 percent confidence intervals, computed using the asymptotic covariance matrix clustered by state and time.