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Good News Travels Fast: Global Demand Shocks, Oil Futures, and Emerging Markets Dynamics

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ABSTRACT: In this paper we study how aggregate demand surprises affect and propagate to the global economy, with particular attention to their impact on Emerging Market Economies (EMEs). To do so, we introduce a new high-frequency external instrument to identify global demand shocks: the sensitivity of oil futures prices around labor market announcements from the US and the Euro Area, two events that consistently trigger strong revisions in global growth expectations across financial markets. Using a proxy-SVAR framework, our results suggest that a global demand shock has positive effects on world industrial production, reduces oil inventories and global uncertainty, and improves financial conditions. In EMEs, upward revision in macroeconomic outlook leads to higher industrial production and inflation, real exchange rate appreciation, and lower EMBI spreads. When the sample is split between oil-importers and exporters, we observe results consistent with the role of external trade exposure in shaping transmission, heterogeneity in the magnitude and persistence of output, inflation, real exchange rates, and sovereign risk responses. These results are consistent with theoretical expectations and the related literature. Our findings offer a credible empirical strategy for isolating global demand shocks and have direct implications for empirical macroeconomic modeling of emerging market economies.

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Abstract

In this paper we study how aggregate demand surprises affect and propagate to the global economy, with particular attention to their impact on Emerging Market Economies (EMEs). To do so, we introduce a new high-frequency external instrument to identify global demand shocks: the sensitivity of oil futures prices around labor market announcements from the US and the Euro Area, two events that consistently trigger strong revisions in global growth expectations across financial markets. Using a proxy-SVAR framework, our results suggest that a global demand shock has positive effects on world industrial production, reduces oil inventories and global uncertainty, and improves financial conditions. In EMEs, upward revision in macroeconomic outlook leads to higher industrial production and inflation, real exchange rate appreciation, and lower EMBI spreads. When the sample is split between oil-importers and exporters, we observe results consistent with the role of external trade exposure in shaping transmission, heterogeneity in the magnitude and persistence of output, inflation, real exchange rates, and sovereign risk responses. These results are consistent with theoretical expectations and the related literature. Our findings offer a credible empirical strategy for isolating global demand shocks and have direct implications for empirical macroeconomic modeling of emerging market economies.

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1 Introduction

Understanding the drivers of global demand fluctuations is central to macroeconomic research and policy. Global demand shocks affect industrial production, trade flows, commodity markets, and asset prices across countries, and are particularly consequential for emerging market economies (e.g. Boz, Gopinath, and Plagborg-Møller (2017); Sungurtekin Hallam (2022); Bems, Johnson, and Yi (2010)). Yet identifying the drivers and isolating these shocks remains empirically challenging, as global demand reflects a complex mix of monetary and fiscal policies, financial conditions, and expectations about future growth, often intertwined with endogenous macroeconomic dynamics. While structural models provide useful frameworks to interpret global co-movements, they typically rely on strong identifying assumptions or slow-moving aggregate indicators, limiting their ability to capture exogenous and timely shifts in global demand.

The empirical challenge lies in identifying a source of variation that captures unanticipated changes in global economic activity without being confounded by other structural shocks. Standard SVARs often rely on long-run or timing restrictions (e.g., Blanchard and Quah (1989); Christiano, Eichenbaum, and Evans (1999)), which can be difficult to defend in a global setting with overlapping policy regimes and simultaneous cross-country interactions. These challenges have motivated the development of alternative identification approaches, such as sign-restricted (e.g., Uhlig (2005); Peersman and Straub (2009)), or external-instrument SVARs that relax parametric assumptions while preserving structural interpretability (e.g., Stock and Watson (2012); Mertens and Ravn (2013)). While the latter approach has gained prominence in monetary policy research, its application to international macroeconomic shocks remains limited, particularly in identifying global demand shocks using timely financial market responses.

In this paper, we propose a novel high-frequency external instrument to identify global demand shocks. Our approach builds on the logic of high-frequency identification: asset prices react immediately to macroeconomic news and these reactions can be used to isolate structural shocks (Gürkaynak, Sack, and Swanson (2005); Faust, Rogers, Wang, and Wright (2007); Gertler and Karadi (2015); Nakamura and Steinsson (2018); and Miranda-Agrippino and Ricco (2021)). Specifically, we use changes in oil futures prices in a narrow time window surrounding major labor market announcements in the United States and the Euro Area.

This identification strategy rests on the premise that people's interpretation of the labor market information released to the market from these two major economic blocs serves as timely and credible signals of global economic activity. Given their substantial weight in global GDP and their central role in global trade and financial flows, stronger-than-expected labor reports are typically interpreted as indicators of strengthening global demand. Oil futures markets, which are forward-looking and globally integrated, respond quickly to such news, often registering immediate price increases that reflect revised expectations of future energy consumption, improved investment prospects, and higher expected global growth. Importantly, these announcements do not contain direct information about oil supply conditions, making it unlikely that the observed price responses are confounded by supply-side shocks. As such, the high-frequency response of oil futures prices to labor report surprises can be interpreted as isolating a demand-driven component of oil price variation. These announcements, the U.S. Employment Situation Report and Eurostat's unemployment release, are among the most anticipated macroeconomic indicators globally, as they regularly prompt immediate price adjustments in a wide range of asset markets.

Crucially, we do not interpret the oil futures response as an oil-market-specific signal, nor do we claim that global demand shocks operate primarily through the oil market. Rather, we treat the oil futures market as a liquid, forward-looking financial instrument that reflects updated expectations about global economic conditions. This distinction is important. Our goal is not to study oil demand per se, but to use oil futures price changes as a high-frequency financial proxy for revisions in beliefs about global demand. Oil futures are particularly well-suited to this role: they trade continuously, react quickly to macroeconomic news, and are sensitive to expectations about global industrial activity, shipping, and trade volumes, in addition to oil prices being a major driver of global business cycles, impacting economic activity, inflation, and unemployment worldwide (Alquist, Kilian, and Vigfusson (2013); Alquist and Kilian (2010); Gazzani, Venditti, and Veronese (2024)). In other words, this instrument makes a timely real-time barometer of global economic sentiment and an ideal financial proxy to isolate demand-driven components of price variation.

Our empirical results demonstrate that labor-report-induced movements in oil futures prices provide a powerful and valid instrument for global demand shocks. We incorporate this instrument into a Proxy SVAR framework to estimate the effects of global demand shocks on a range of global macroeconomic and financial variables. It proves both relevant and valid, passing multiple robustness checks, including weak instrument and placebo diagnostics, different lag specifications, change in the maturity of oil future markets, and separating effects between US and Euro Area labor report releases. The estimated shocks lead to broad-based expansionary effects, including increases in world industrial production, declining financial volatility, and improved macro-financial conditions. In the emerging world, industrial production increases, sovereign spreads compress, and real exchange rates appreciate, suggesting improved risk sentiment and stronger external positions[1]. Consumer prices also increase moderately, though these effects differ systematically between oil-exporting and oil-importing economies, consistent with the role of external trade exposure in shaping transmission.

Our findings contribute to several strands of the literature. First, we add to the work on the identification and transmission of global shocks by proposing a tractable and interpretable instrument that captures timely revisions in global demand expectations. Second,

[1]In this study, the emerging markets sample covers about 88 percent of the total EMEs GDP, and about 51 percent of global GDP.

we continue extending the high-frequency identification approach beyond its traditional use in monetary policy to the international macroeconomic domain. Finally, we contribute to the empirical literature on external instruments by proving the usefulness of financial market prices, such as oil future prices, not only as structural proxies for oil-supply shocks (Känzig (2021); Qureshi and Ahmad (2025)) or monetary policy news shocks but also for global demand shocks.

The remainder of the paper is organized as follows. Section 2 situates our contribution within the existing literature on global demand identification, and the use of high-frequency external instruments. Section 3 details the construction of our identification strategy, describing the proxy based on oil futures price movements around labor market announcements, and outlining the empirical framework. Section 4 presents the main results, documenting the macroeconomic and financial effects of global demand shocks on the global economy, its impacts on emerging markets, and the heterogeneous responses across oil-exporting and oil-importing economies. Section 5 concludes with a discussion of the broader methodological and implications of our findings, and points to potential avenues for future research.

2 Global Demand Shocks and Identification Challenges

A growing literature has emphasized the importance of identifying global demand shocks as distinct structural drivers of macroeconomic fluctuations (e.g. Kilian (2009); Boz et al. (2017)). These shocks, which capture unanticipated shifts in global consumption, investment, or economic sentiment, are critical to understanding international comovement, commodity prices, and capital flows. Yet, credible empirical identification of global demand shocks remains challenging. Traditional approaches, such as structural VARs with timing restrictions or long-run assumptions, often rely on low-frequency proxies that conflate structural shocks with endogenous responses or measurement error.

One prominent strand of research attempts to disentangle the sources of macroeconomic fluctuations using oil prices as a vehicle. In a foundational contribution, Kilian (2009) proposes a decomposition of oil price changes into different exogenous shocks, one of which is the global demand shock. His identification of global demand relies on an index of global real activity derived from dry bulk shipping freight rates. While highly influential, this index has been questioned on conceptual and empirical grounds. Baumeister and Hamilton (2019), for instance, critiques the index's dependence on freight market dynamics, its sensitivity to structural shifts in global trade, and its limited ability to track demand shocks in real time. Similarly, more recent work such as Rebei and Sbia (2021) introduces transitory and permanent components to shocks in the global oil market, and Jiménez-Rodríguez (2022) emphasizes the time-varying macroeconomic consequences of oil shocks across countries. These studies underscore the importance of distinguishing different types of global shocks, but also highlight the difficulties inherent in doing so with low-frequency and commodity-specific data.

In parallel, another literature has developed more timely identification strategies that exploit high-frequency financial market reactions to scheduled announcements. This high-frequency identification approach has become the dominant method in monetary policy research, where surprises in interest rate futures are measured within tight windows around central bank communications. Foundational work by Cochrane and Piazzesi (2002) and Faust et al. (2007) demonstrates that these intraday asset price movements can be used to extract monetary policy shocks without relying on recursive VAR restrictions. Nakamura and Steinsson (2018) extend this idea, showing that even short-window surprises often reflect both pure policy shocks and broader information effects. Their findings suggest that financial markets respond not only to policy actions, but also to new information about economic fundamentals, a feature that is central to our interpretation of oil futures price movements as a valid identification strategy of global demand shocks.

Outside monetary policy, high-frequency identification has recently gained traction in other domains. Phillot (2025) uses surprises around Treasury auctions to identify supply shocks in the bond market. Gazzani et al. (2024) introduce a method to identify oil shocks at daily frequency, while Alsalman, Herrera, and Rangaraju (2023) use oil futures surprises in proxy-VARs to study the impact of oil news on stock markets. These papers demonstrate that high-frequency financial data can be used to isolate structural shocks in real time, even outside traditional policy domains. A recent paper by Gazzani et al. (2024) approaches the identification of a global demand shock using a high-frequency methodology in a daily Proxy SVAR, by exploiting the close connection between oil and stock prices. Despite this progress, global demand shocks remain vastly underrepresented in the high-frequency identification literature. Most existing work focuses on monetary or commodity-specific events, and to our knowledge, no study has applied high-frequency identification to capture global demand shocks using futures data around macroeconomic announcements.

Our paper aims to fill this gap. We propose a novel external instrument that captures revisions in global demand expectations by exploiting the response of oil futures prices to labor market announcements in the United States and the Euro Area. Crucially, we do not interpret oil as the transmission channel of the shock, nor do we take a stand on whether global demand shocks operate primarily through commodity markets. Instead, we use the oil futures curve, a liquid, forward-looking financial asset, as a barometer of global growth expectations.

Consequently, we focus on oil futures markets as a viable instrument for the identification of global shocks. Crude oil is an internationally traded commodity with deep and highly liquid futures markets. Among these, West Texas Intermediate (WTI) futures are the most actively traded contracts worldwide, currently exceeding 1 million contracts per day[2]. Oil prices are inherently forward-looking and respond swiftly to macroeconomic

[2] Information extracted from the CME Group website on October 24, 2025:

news, aggregating information from multiple economies rather than reflecting conditions in a single country or sector. This global integration allows oil futures to serve as a real-time barometer of economic sentiment. Importantly, oil markets play a central role in global economic dynamics during both expansions and downturns (Baumeister and Hamilton (2019)), reinforcing their relevance for empirical macroeconomic analysis. These features make WTI futures particularly well-suited for isolating global demand shocks using high-frequency financial data.

While our identification strategy builds on the logic of high-frequency identification, it also engages with recent critiques. Mori and Peersman (2024) warn that surprises in commodity futures can be contaminated by overlapping financial variables, calling into question the exclusion restriction in proxy SVARs. Brennan, Jacobson, Matthes, and Walker (2024) similarly show that different high-frequency surprise series can yield uncorrelated shock measures, underscoring the sensitivity of results to instrument construction. We address these concerns by implementing a set of robustness checks designed to test the strength of our instrument. In particular, we examine the behavior of our instrument across different types of announcements, oil futures maturities, and geographic sources of macroeconomic news. We also test for financial market spillover effects and include controls that aim to isolate the impact from broader market movements.

In doing so, our contribution is threefold. First, we offer a new, high-frequency instrument that isolates unanticipated changes in global demand expectations using data readily available to policymakers and researchers. Second, we extend the proxy SVAR framework to the identification of global demand shocks, a domain where credible instruments remain scarce. Third, we apply this identification to study the propagation of global demand shocks to emerging market economies, highlighting differential responses across oil-exporting and oil-importing countries. In this way, we connect the macro identification literature with ongoing debates on global spillovers and policy transmission in emerging markets (e.g., Ahmed, Coulibaly, and Zlate (2017); Fernández, Schmitt-Grohé, and Uribe (2017)), offering new evidence on the role of global expectations in shaping real and financial outcomes.

3 Identification Strategy and Data

3.1 Econometric Framework

To examine the dynamic effects of global demand shocks on macroeconomic and financial variables, we adopt a vector autoregression model identified through external instruments. This methodology, originally introduced by Stock and Watson (2012) and further refined by Mertens and Ravn (2013), has become a standard tool in the literature aiming to uncover the fundamental sources of variation in high-frequency situations. In our

https://www.cmegroup.com/education/courses/introduction-to-crude-oil/product-overview/wti-overview.html context, we apply it to identify global demand shocks using an external instrument. In other words, an exogenous variable that is strongly correlated with the shock of interest but uncorrelated with other structural innovations in the system. The following subsection outlines the identification framework and the empirical procedures employed in our analysis.

Based in Gertler and Karadi (2015), consider X_t a vector of variables; P and Q_i $\forall i \geq 1$ coefficient matrices. Then, the structural form of the VAR model is given by:

$$PX_t = \sum_{i=1}^{p} Q_i X_{t-i} + \epsilon_t \tag{1}$$

The elements of the disturbance vector ϵ_t are considered mutually uncorrelated and interpreted as structural innovations. Without loss of generality, assume that the shock of interest, a global demand shock, is the disturbance in the first equation of (1). Assuming that P is invertible, we can pre-multiply both sides by P^{-1} to obtain the reduced-form VAR as follows:

$$X_t = \sum_{i=1}^{p} R_i X_{t-i} + u_t \tag{2}$$

It is important to note that the residual vector u_t incorporates the effects of global demand shocks as well as any other innovations, and they are assumed to have zero mean with a covariance matrix given by $\Omega = \mathrm{E}[u_t u_t']$. To disentangle the effects of the first structural disturbance, we aim to estimate the first column of P^{-1}, which traces the effects of the identified structural shock across variables, as follows:

$$X_t^{(1)} = \sum_{i=1}^{p} R_i^{(1)} X_{t-i}^{(1)} + p_{(1)}^{-1} \epsilon_t^{(1)} \tag{3}$$

In the context of a proxy SVAR framework, identifying global demand conditions through movements in the oil equation residual, requires the use of external instruments that meet two fundamental criteria. The relevance condition, which requires that the instrument be sufficiently correlated with the structural shock of interest, namely the global demand shock. The second is the exclusion restriction, which stipulates that the instrument must be orthogonal to all other structural innovations (Caldara and Herbst (2019), and Lakdawala (2019)). Let W_t denote our external instrument and $\epsilon_t^{r=1}$ represent the innovation of the first equation. For W_t to serve as a valid instrument, it must exhibit a strong correlation with $\epsilon_t^{r=1}$ while remaining uncorrelated with all other structural shocks, $\epsilon_t^{r\neq 1}$:

$$E\left(W_t \epsilon_t^{r=1}\right) = \phi \tag{4}$$

$$E\left(W_t \epsilon_t^{r\neq 1}\right) = 0 \tag{5}$$

A wide range of methodologies has been developed to identify demand shocks, with structural vector autoregressions (SVARs) employing sign restrictions, narrative approaches and structural identifications being among the most prominent (Brüggemann & Braun, 2022; Kilian, 2009; Liu, Meng, & Wang, 2020). While these approaches have advanced our understanding of international market dynamics, they face some limitations when applied to the identification of global demand-driven oil price movements. A key challenge lies in the fact that oil future prices often respond to a complex mix of factors, including expectations about future supply, demand, shifts in global uncertainty, and other macrofinancial variables that are difficult to disentangle using the restrictions alone (Känzig (2021)). Consequently, the structural interpretation of identified shocks could be confounded, which may introduce concerns regarding the robustness and interpretability of the empirical findings.

An additional concern arises in studies that use demand shocks but do not explicitly differentiate between the nature or origin of the underlying shocks (e.g. Kilian (2009), Stock and Watson (2012) and others following their methodology). These approaches often treat all price movements as homogeneous, implicitly assuming that observed fluctuations reflect a single structural source. This assumption is problematic, as oil demand price movements may respond to a variety of shocks, including shifts in global demand, precautionary motives, economic uncertainty, among others, each with distinct macroeconomic implications. Without a clear separation of these components, the estimated impulse responses may suggest different mechanisms.

We propose, as instrument for global demand shocks, the use of changes in the oil futures prices around a small time window after announcements of labor report releases from the United States and the Euro Area. The key identification assumption is that these surprises provide timely and credible signals of global economic activity, given the central role of these two regions in global output, trade, and financial markets. What matters for our identification is not whether the labor market surprise originates from supply- or demand-side developments in the labor market itself, but how market participants interpret the news in relation to future global economic activity. Oil futures markets are forward-looking, and any residual adjustment in oil prices immediately following the announcement is interpreted as a revision in beliefs about future demand for oil. Stronger-than-expected labor market data are typically understood as signaling higher expected global growth and energy consumption, regardless of the underlying source of the labor market shock. As such, the price reaction reflects a demand-side adjustment in expectations, consistent with movements in key indexes followed by global market analysts.

Based on the intensity of market interest among many different indicators, labor market releases in the US (non-farm payrolls, jobless claims, and unemployment rate releases) and in the Euro Area (unemployment rate) are among the most relevant information drivers for private forecasters and market analysts in the two regions (see Table B.3 for details).

3.2 External instrument designed for global demand shocks

The identification strategy relies on oil 3-month futures changes around labor market news in United States and Euro Area. Specifically, global demand shocks are defined as the combined change in 3-month oil futures prices in response to surprises in labor market data releases. This approach isolates global demand-driven movements captured by oil markets, allowing us to capture shifts in global economic conditions without confounding them with supply side or uncertainty factors. The use of 3-month-horizon future prices aligns with the one typically influenced by near-term macroeconomic developments, policy expectations, as it has been broadly used in the literature (Alquist & Kilian, 2010; Gertler & Karadi, 2015; Känzig, 2021; Lakdawala, 2019).

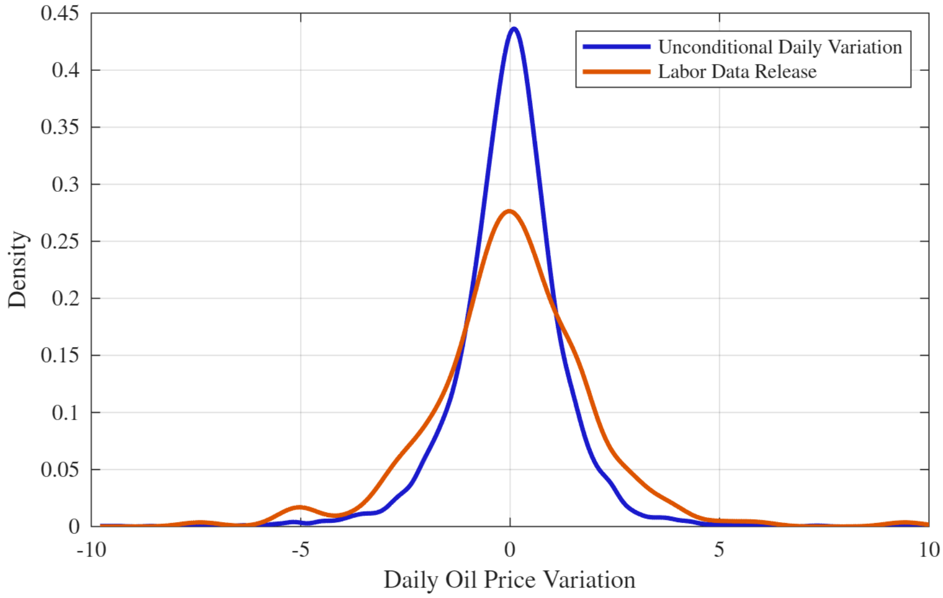
Our main assumption is that, within the time window immediately after the publication of labor market data, no other structural shocks occur that could *systematically* affect market expectations about future oil prices[3]. In other words, we assume the exclusion restriction holds, as any other structural innovation (e.g, oil supply news, geopolitical tensions, supply-chain disruptions, etc) does not happen *repeatedly* within a small window of time after the labor data releases. This enables us to isolate the causal effect of labor market news on oil price expectations (Känzig, 2021; Lakdawala, 2019).

To assess the distinct variation captured by our approach, we compare the distribution of three-month oil futures changes, following labor market data releases with the unconditional distribution of daily changes over the 2000–2019 period. Figure 1 presents the densities for both series. The distribution associated with futures price changes around labor announcements exhibits greater dispersion and fatter tails than its unconditional counterpart, indicating that employment-related news triggers larger adjustments in oil price expectations. This contrast suggests that our instrument isolates demand-driven movements in oil prices that go beyond regular market fluctuations[4].

[3]We allow our instrument to exhibit measurement error, as other macroeconomic events could potentially influence oil futures prices in the same narrow time window. However, we claim that such events are unlikely to be systematically correlated with the instrument, thus validity of our identification strategy remains.

[4]As a robustness check, we shift the event window to +4, +5, +6, and +7 days after each release, corresponding to the following Tuesday to Friday, since announcements usually occur on Fridays. The placebo results are not statistically significant, supporting the validity of our identification and indicating that markets react promptly to labor data releases.

Figure 1: Labor Data Releases versus Daily Oil Price Variation



Note: Kernel densities of daily changes in the level of the three-month oil futures contract. The series Labor Data Release corresponds to the combined changes around US and Euro Area labor market announcements, while Unconditional Daily Variation represents unconditional changes over 2000–2019.

Equation (6) outlines the construction of the global demand shock variable. Let W_t represent the instrumental variable. We define d as the specific day of the announcement, O as the closing price of the 3-month oil futures contract on that day. If the information released is consistent with market expectations, oil futures prices should exhibit minimal movement. However, when the labor market report deviates from expectations, it can lead to a reassessment of the economic outlook, particularly regarding future oil consumption. To isolate the effect of the labor release, we analyze the immediate market response by measuring the change in oil futures prices within a one-day window surrounding the release[5]. Given that the labor market reports for the United States and the Euro Area are released on different dates, we construct a unified measure by aggregating the respective components across both zones. As the VAR is estimated in a monthly frequency (t), the observed daily change is assigned uniformly across the corresponding month to serve as the instrument.

$$W_t = O_{t,d} - O_{t,d-1} \tag{6}$$

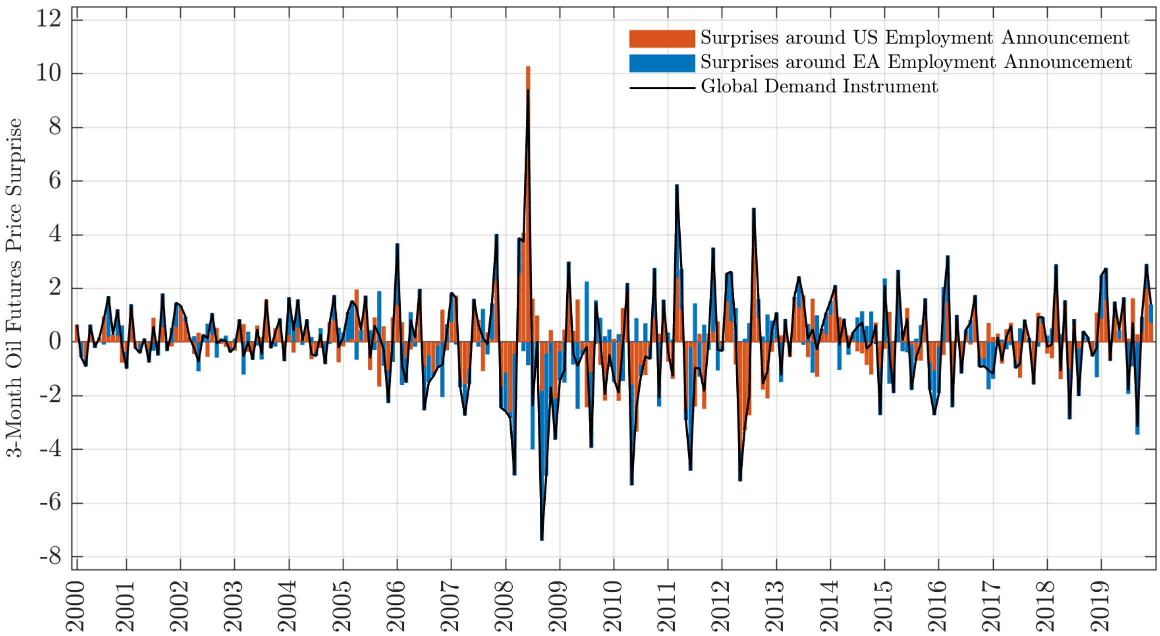
Figure 2 shows the time series for the global demand instrument in monthly frequency. The responsiveness of oil futures to employment surprises is evident in the following cases. In May 2008[6], the US employment release reported smaller job losses and a lower unemployment rate than anticipated, leading oil futures to rise by more than 4 dollars, over four times the average absolute change (0.91) observed around US announcements

[5] If the previous day of the release coincides with a non-working day, we take the immediately previous business day to make the calculation.

[6] Employment releases in month t report labor market outcomes for month $t-1$ (e.g., the May 2008 release refers to April 2008 unemployment).

(see Table A.2). In June 2012, unemployment came in higher than expected, and oil futures fell by more than 3 dollars, over three times the average response. For the Euro Area, in September 2008, weaker-than-expected labor market conditions were associated with a sharp fall of more than 5 dollars in oil futures, nearly six times the average absolute response (0.88). A more recent case is September 2019, when unemployment was higher than expected, coinciding with a decline of about 3.5 dollars in oil futures, roughly four times the average response. These episodes underscore that large surprises in employment releases are mirrored in oil futures markets, consistent with the interpretation of the instrument as capturing demand-driven revisions to oil price expectations.[7]

Figure 2: Global Demand Instrument



Note: The global demand instruments are shown at a monthly frequency (2000–2019) and measured as changes in the US dollar price of the 3-month oil futures contract. The Global Demand Instrument is constructed as the sum of the movements in oil futures around employment announcements in the United States (US) and the Euro Area (EA), within the same month.

3.3 Data

We use monthly data spanning February 2000 to December 2019. The baseline specification includes five variables: the real price of oil, world industrial production, world financial conditions index, VIX, and world oil inventories. For EMEs, we include industrial production (IP), consumer prices (CPI), real effective exchange rates (REER), and sovereign credit

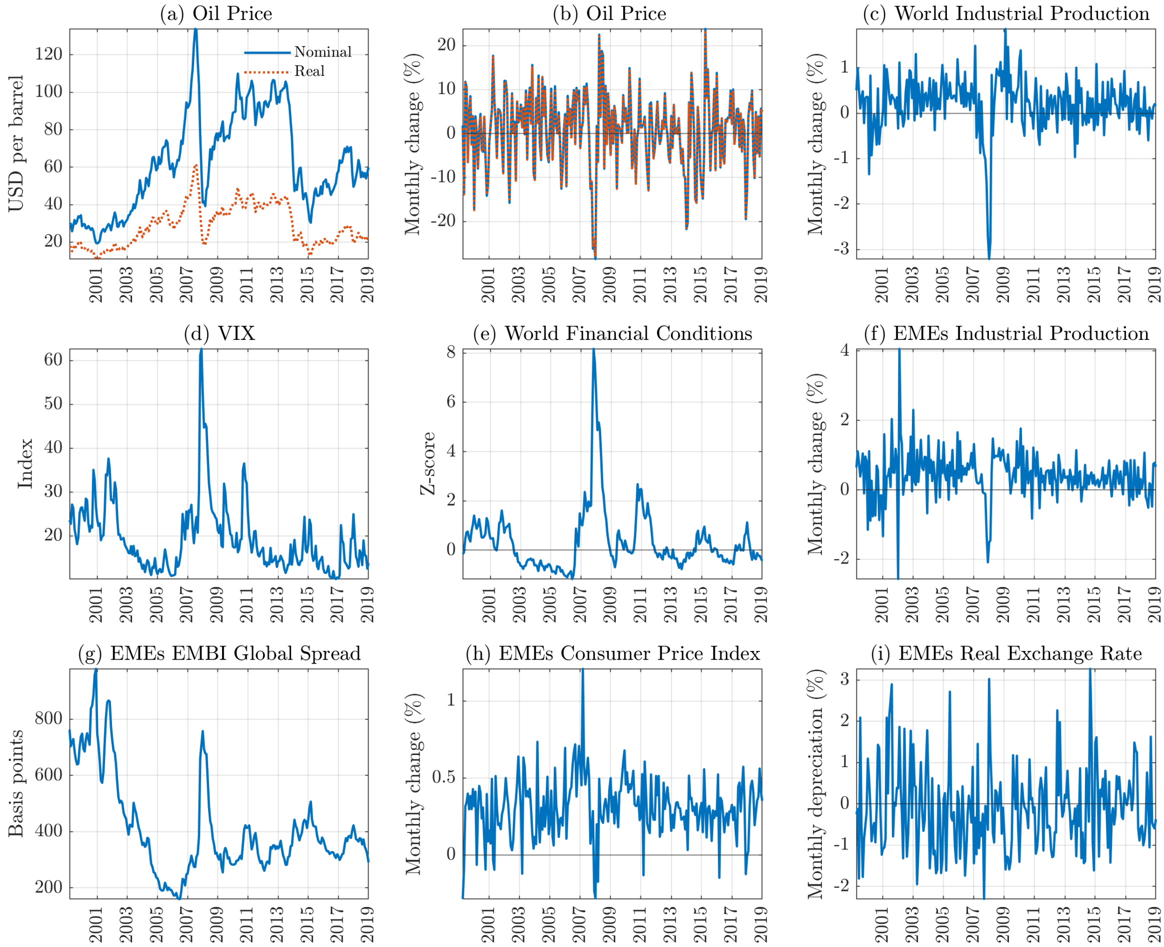
[7] The largest spike occurred in June 6th, 2008. This day, global equity markets plunged, with the Dow Jones losing nearly 400 points and widespread weakness in Asian markets. Oil prices surged, contributing to fears of stagflation and reinforcing concerns over a global economic slowdown. Exactly the same day, the US Census Bureau announced that the unemployment rate *jumped* to 5.5%, marking the largest one-month increase in 22 years. In this case, oil future prices *increased*, contradicting the usual expectation of lower global demand after bad news from the labor market. In reality, this happened at the onset of the Global Financial Crisis. This data point exhibits a measurement error in our instrument. However, since this episode is neither systematic nor recurrent, the relevance condition of the instrument still holds.

spreads (EMBI Global). The emerging markets sample covers about 88 percent of the total EMEs GDP, and about 51 percent of global GDP. Throughout the paper, an increase in the REER is interpreted as a depreciation of EMEs' currencies. All variables, with the exception of the world financial conditions index and the VIX, are included in log levels. The lag order is set to two months based on the Hannan–Quinn criterion (Table B.2). For a detailed data description see Appendix A.

Figure 3 provides an overview of the time series used in the baseline model, and Table A.2 reports summary statistics. Panels (a) and (b) show the nominal and real price of oil in levels and monthly percent changes, respectively. Oil prices exhibit considerable volatility, with an average absolute monthly change of 6.6% and maximum swings of 28.6% during the global financial crisis. Panels (c)-(e) display global indicators: the VIX which captures financial market volatility, the world financial conditions index capturing the degree of financial accomodation and world industrial production growth, sourced from Baumeister and Hamilton (2019). On average, global industrial production grew by 0.2% per month (approximately 2.4% annualized), while the VIX fluctuated widely, with an average absolute monthly change of 12.5%.

Panels (f)-(i) focus on EMEs aggregates. Industrial production averaged 0.4% monthly growth (roughly 5.2% annualized), while consumer price inflation remained moderate at 0.3% per month (3.7% annualized). The average monthly appreciation of the REER was 0.11%, with a standard deviation exceeding 1%. Sovereign spreads ranged from 160 to nearly 980 basis points, with a notable decline in the early 2000s and stabilization around 400 basis points during the second half of the sample.

Figure 3: Oil Prices and Macroeconomic Variables for Baseline Model



Note: The figure shows the data used for the baseline model. Panels (a)-(b) display the nominal and real (deflated by US CPI) price of WTI spot oil price in USD per barrel and monthly percent changes. Panels (c)-(e) present the global variables: the CBOE Volatility Index (VIX), world financial conditions and monthly growth (in percent) of world industrial production from Baumeister and Hamilton (2019). Panels (f)–(i) show emerging market aggregates: industrial production, sovereign spread, inflation, and real exchange rate, all in monthly percent changes except for the EMBI Global spread, which is expressed in basis points. For a detailed data description see Appendix A.

To understand the empirical behavior of EMEs aggregates around general large oil price movements, Figure B.1 presents the median dynamics over the 12 months surrounding episodes of sharp increases in the real price of oil, defined as monthly changes of $10 \pm 1\%$. Based on 16 episodes between 2000 and 2019, the median EMEs annual industrial production growth declines by 0.8 percentage points twelve months after the shock, while inflation rises by approximately 0.2 percentage points. Sovereign spreads exhibit a mild decline of 22 basis points after one year, and the REER appreciates by 2.2% over the same horizon.

The heterogeneous effects and mixed evidence in terms of macrofinancial dynamics of EMEs underscore the complex and multifactorial nature of unidentified oil price shocks. These may reflect a combination of underlying drivers, including shifts in global demand and supply conditions, changes in economic uncertainty, and other macroeconomic developments. In general terms, for net oil importers, higher oil prices increase input costs and depress output, while inflation rises through energy pass-through channels. In contrast, oil exporters and financially open EMEs can experience improved terms of trade and capital inflows, leading to stronger currencies and reduced risk premia. When driven by stronger global demand, oil futures price increases are typically associated with good news: rising world output, falling uncertainty, and improved macroeconomic conditions in the EMEs. In contrast, oil supply shocks are characterized by lower output, inflation pressures, and financial tightness, particularly in oil-importing economies.

4 Results

This section examines the effects of a global demand shock captured through our instrument. In subsection 4.1, we begin our analysis with an baseline VAR for the global economy to assess the broad macroeconomic effects. Then, in subsection 4.2 we extend our baseline model, by focusing on emerging market economies (EMEs), which provides a more detailed view of the transmission to real activity, prices, exchange rates, and sovereign risk. Subsection 4.3 proceeds to analyze potential heterogeneity in the response of EMEs based on their net oil trade position. Subsection 4.4 highlights the relative importance of our identification when we use an alternative methodology to identify global demand shocks. Finally, we test the robustness of our baseline results across a range checks.

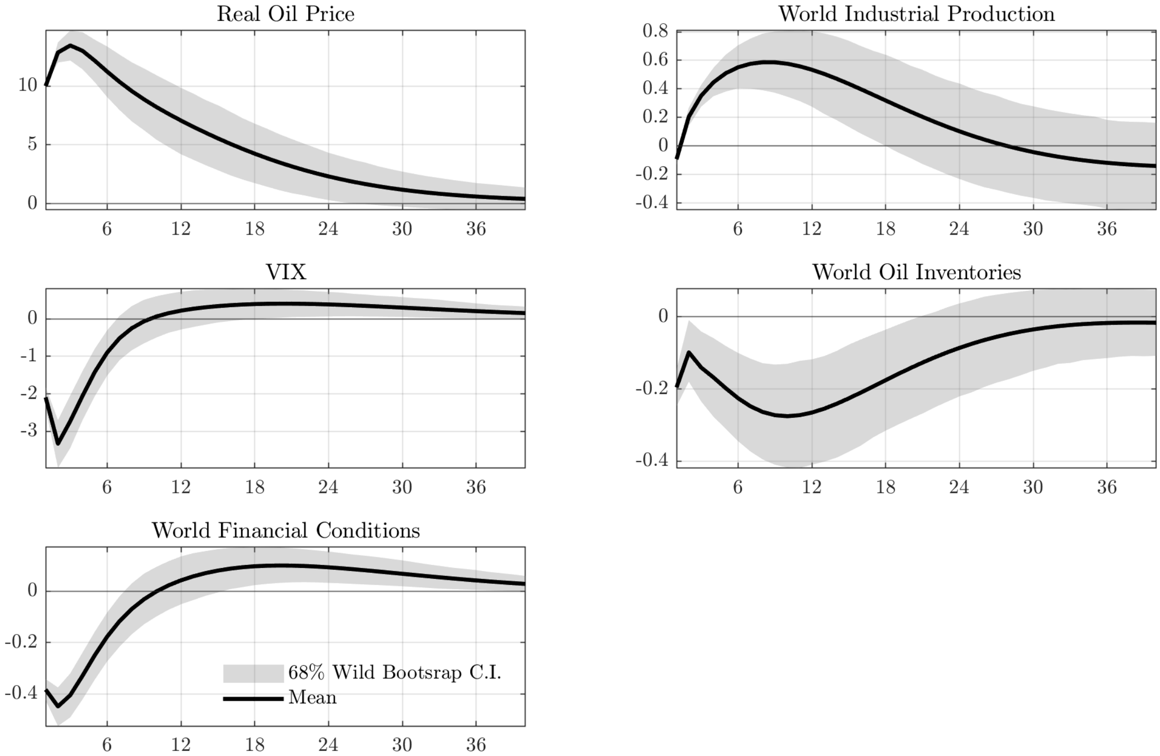
Across all specifications, the impulse response is normalized to generate a 10% increase in the real price of oil on impact. All variables, except the world financial conditions index and the VIX, are expressed in logs and can be interpreted as elasticities. The solid lines in the figures denote point estimates, while the shaded areas represent 68% confidence intervals based on robust standard errors. We also report first-stage F-statistics to assess the strength of the instrument. [8]

4.1 Dynamic Effects from the Global VAR

We start by examining the global macroeconomic response to the demand shock using a VAR model that includes the real oil price, world industrial production, world financial conditions index, VIX, and global oil inventories. Figure 4 presents the corresponding impulse responses.

[8] Following Stock, Wright, and Yogo (2002), a value of less than 10 represents a weak instrument.

Figure 4: Effect of a 10% oil price demand shock on a Global VAR



First-stage F-statistic = 22.34

Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world oil inventories and world financial conditions (FCI). All variables are in logarithms, except the VIX and FCI, which are in levels. All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.1.

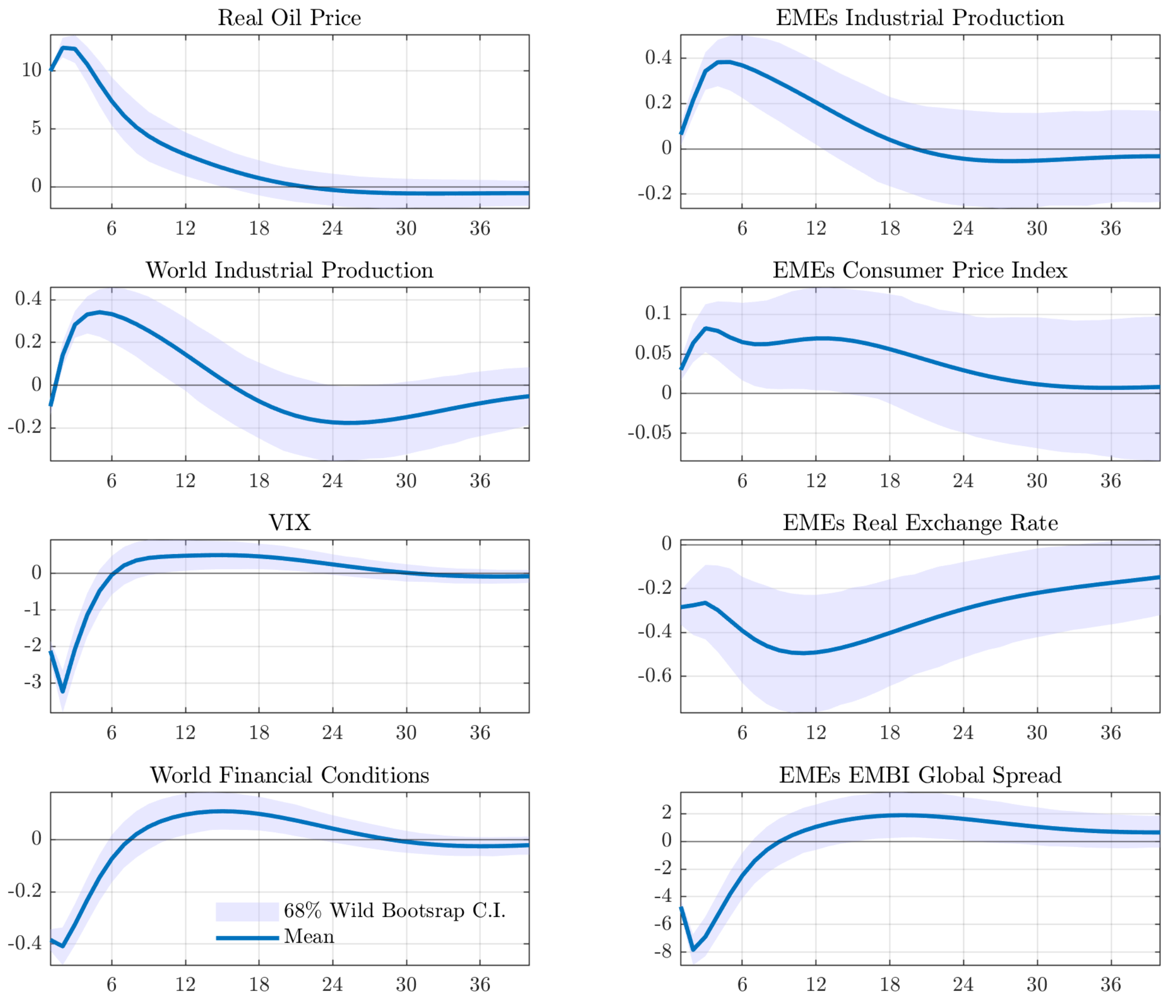
World industrial production rises sharply, peaking at around 0.6% in the ninth month and gradually returning to the baseline thereafter, consistent with a short-term boost in global activity. The VIX falls significantly, reflecting a reduction in global uncertainty and increased investor risk appetite, which is consistent with more relaxed global financial conditions and the upward revision of the macroeconomic outlook. Oil inventories initially dip slightly during the first months, followed by a gradual return to baseline, consistent with transitory imbalances between supply expectations and realized demand. These patterns support the interpretation of a demand-driven movement, associated with improved growth expectations and a positive shift in the global outlook.

4.2 Macroeconomic Effects in Emerging Markets

We turn to the macroeconomic and financial effects of the same global demand shock on EMEs. Figure 5 reports the impulse responses for industrial production, consumer prices, real exchange rates, and sovereign spreads (EMBI) in EMEs.

EMEs industrial production rises significantly, with a peak around 0.4% in month four, in line with the global IP response. This activity boost seems to last between 18 and 24 months, longer than the global industrial production boost. This pattern reflects a strengthening of global growth prospects, where stronger external demand and a booming global economy stimulate a broad expansion in real activity across EMEs, accompanied by a transitory increase in the CPI. The VIX declines markedly, following the shock, not merely indicating lower uncertainty, but pointing to a risk-taking or portfolio rebalancing channel that triggers capital inflows into EMEs. This mechanism is consistent with the observed appreciation of the real exchange rates of the EMEs.

Figure 5: Effect of a 10% oil price demand shock on Emerging Markets



First-stage F-statistic = 27.35.

Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI), and EMEs aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate (increase means EMEs' currency depreciation). All variables are in logarithms, except the VIX and FCI, which are in levels. All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.1.

Consumer prices in EMEs increase moderately and significantly on impact, before gradually returning to pre-shock levels. However, the aggregate response disguises some underlying heterogeneity, with inflationary dynamics varying across countries depending on the net oil trade position. This aspect will be explored in more detail in the next section. The real exchange rate appreciates persistently after the shock, supported by improved terms of trade, capital inflows, and stronger fundamentals. This response is also consistent with the shift in global risk sentiment captured by the decline in the VIX and improved world financial conditions. As with inflation, it is expected that the magnitude of the exchange rate adjustment vary across countries in ways that likely reflect differences in oil trade structure. Finally, sovereign spreads in EMEs (EMBI) fall strongly and persistently, reflecting improved credit conditions and investor sentiment. The response is both statistically and economically significant, and aligns with the idea that good news about global demand translates into reduced perceived risk in EMEs' sovereign debt markets.

Together, these responses point to an overall improvement in macroeconomic and financial conditions across EMEs following a global demand shock. However, the behavior of inflation and exchange rates suggests that the transmission of the shock may vary across countries, depending on their external trade position. We explore these heterogeneous effects in the next section.

4.3 Dynamic Effects Across Net Oil Exporting and Importing Economies

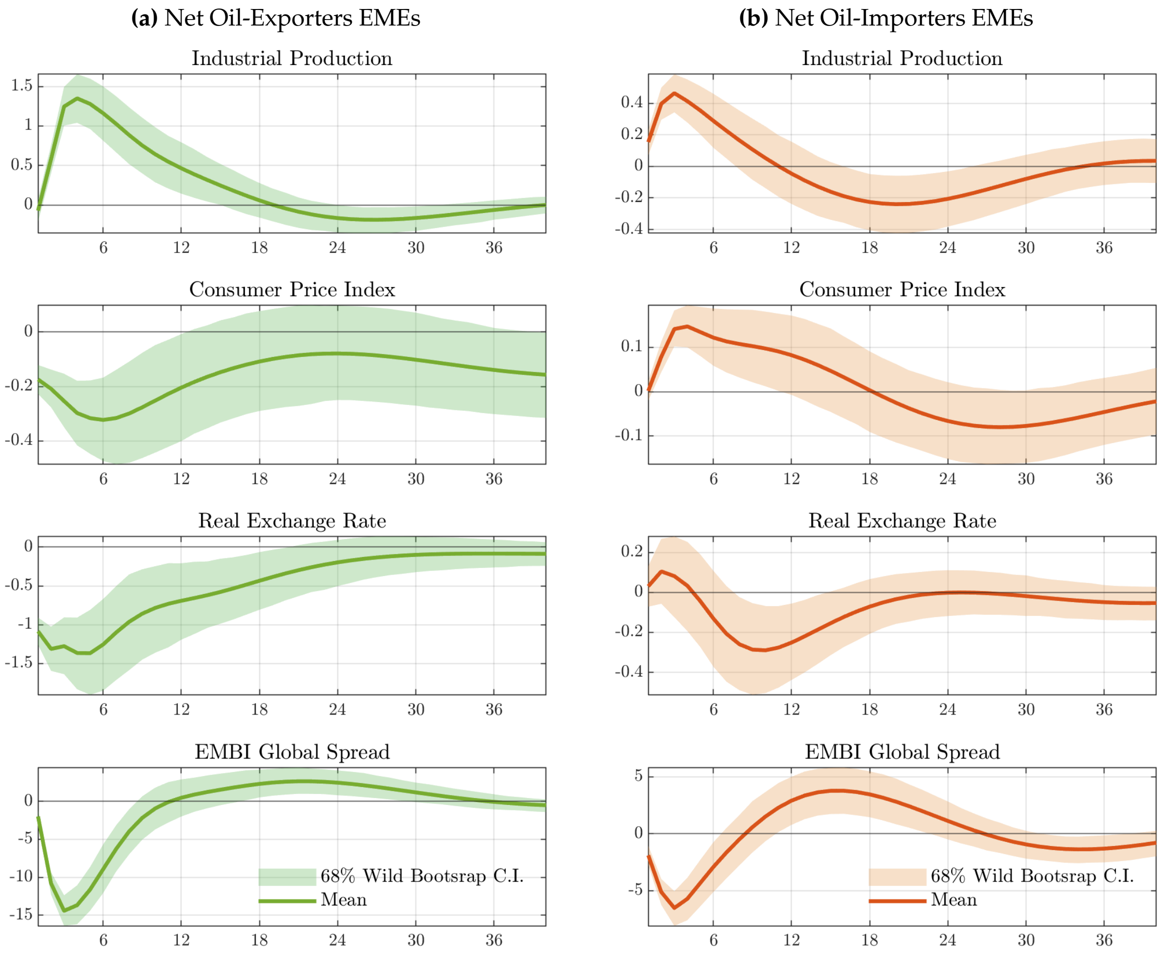
To explore potential asymmetries in the transmission of global demand shocks, we classify EMEs based on their net oil trade position, using the latest data from the US Energy Information Administration (EIA). Details on the classification are provided in Table A.1 in the Appendix.

The impulse responses differ notably between oil exporters (Figure 6a) and oil importers (Figure 6b). The contrast between the two groups is consistent with broader increases in global commodity prices, which tend to benefit commodity-exporting economies more directly. Industrial production rises sharply in both groups but is substantially stronger among exporters, peaking at around 1.3% compared to 0.5% for importers. This stronger response reflects the greater dependence of oil-exporting economies on oil prices, both through industry linkages and fiscal revenues. Moreover, the expansion is more persistent in exporters, while the response in importers reverses quickly after the initial surge.

Consumer prices also diverge. While CPI increases modestly for oil importers, it falls mildly for exporters. This pattern is consistent with differences in terms-of-trade dynamics, with oil exporters benefiting from higher oil prices, while importers face upward cost pressures. The real exchange rate appreciates significantly and persistently for exporters, consistent with stronger external balances and larger capital inflows. For importers, however, the response is weaker, less persistent and with larger confidence intervals, suggesting a less homogeneous exchange rate adjustment. Finally, while EMBI spreads decline in both groups, the compression is notably stronger among exporters. Sovereign spreads fall by nearly 14% for exporters, compared to about 7% for importers, reflecting a greater improvement in credit risk perceptions among oil-exporting economies.

These results are intuitive. Oil-exporting economies benefit broadly from a global demand shock: higher oil prices improve terms of trade, support fiscal revenues, and increase output. Currency appreciation, increased output, reduced inflation, and declining sovereign spreads are patterns consistent with a positive productivity shock that yields large and persistent gains. For oil-importing economies, the response is more nuanced. Rising oil prices increase import costs and inflationary pressure, potentially weakening the currency. However, stronger global demand should also raise prices for other exported commodities, supporting output and external balances. These opposing forces can coexist, leading to modest appreciation, higher inflation, and a partial initial decline in risk premia. In order to verify the last claim, we performed an alternative specification of the Global VAR, which reveals that in response to a global demand shock, not only do oil prices rise, but so do prices of other non-oil commodities, including agricultural goods, livestock, industrial metals, and precious metals (see Figure B.5). This broader commodity-price response reinforces the interpretation that the identified shock reflects global demand forces rather than oil-specific demand shocks. This interpretation is consistent with our empirical findings for emerging markets.

Figure 6: Effect of a 10% oil price demand shock on emerging markets



First-stage F-statistic = (a) 14.64 and (b) 22.22.

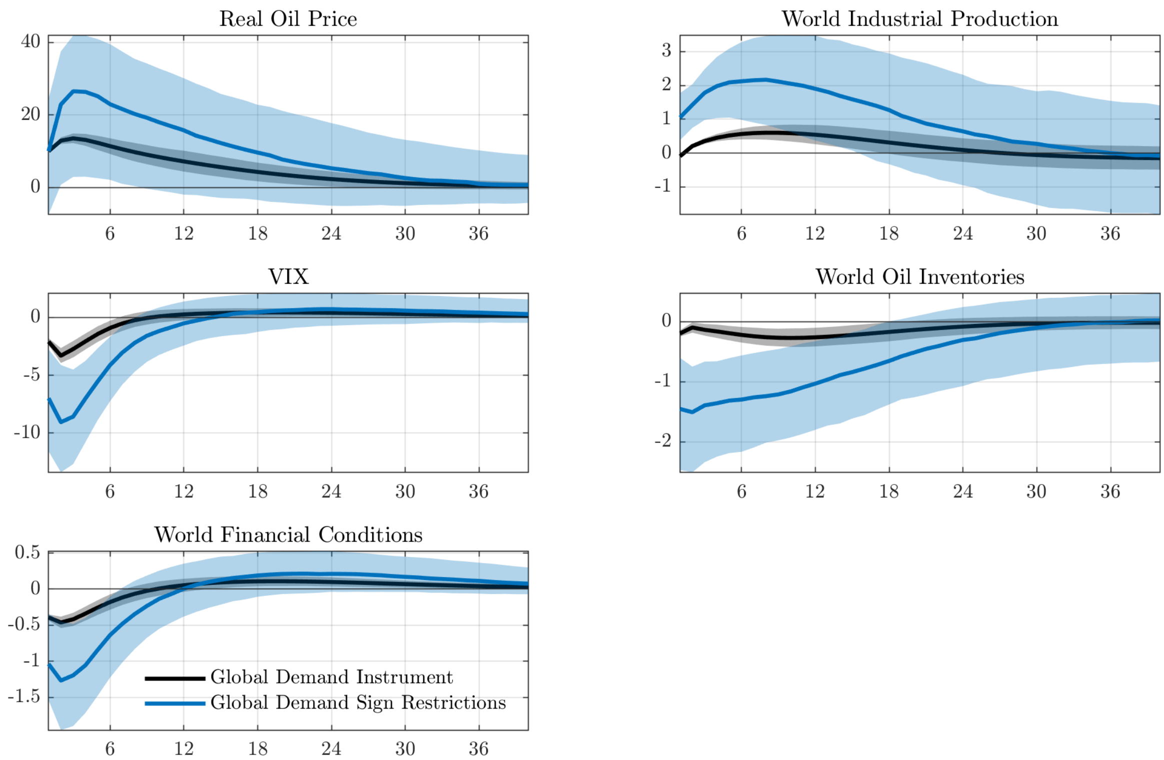
Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions, and EMEs aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate (increase means EMEs' currency depreciation). All variables are in logarithms, except the VIX and FCI, which are in levels. The classification between oil exporters and oil importers countries is based on EMEs net oil trade position, using data from the International Energy Agency (further details can be found in Table A.1). All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.1.

4.4 Sign-Restriction VAR Identification of Global Demand Shocks

When we include an alternative source of variation in oil prices, the relative importance of our identification strategy becomes even more evident. Employing a sign-restriction approach, an alternative methodology commonly used in the literature to analyze spillovers of global demand shocks, we compare our baseline results to a broader global demand component. Our claim is that a global demand shock increases world industrial production, reduces oil inventories, and contemporaneously lowers the VIX, with these sign restrictions imposed over a six-month horizon. To focus on the dynamics of oil and global financial conditions, we remain agnostic about the contemporaneous sign of their immediate responses. As our paper uses exclusively high-frequency movements of oil futures to isolate the specific driver of the shock, the sign restriction VAR captures the same underlying global-demand variation but in a broader sense that aggregates multiple macroeconomic signals.

The comparison shows that our results are not substantially different from the narrative in the previous subsection: Global demand shocks produce expansionary effects on the global economy. Figure 7 displays a 10 percent increase in the real oil price associated with the sign-restriction Global Demand shock; the restricted variables reveal higher economic activity and lower uncertainty and oil inventories (roughly 2%, -5 points, and -1.5% over six months, respectively). Non-restricted variables follow a pattern similar to the external-instrument identification, with an improvement in global financial conditions of about -0.6 percentage points by month sixth. When we implement a sign-restriction VAR framework, the resulting effects are even more pronounced than those derived from our employment-news-based identification.

Figure 7: Impulse Responses using sign restrictions - Global VAR



Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, using our Global Demand Instrument (as described in Section 3.2 and a sign restrictions specification for the 6-month horizon over world industrial production (+), VIX (-) and world oil inventories (-). The specification includes the logged variables: real oil price, world industrial production, the CBOE Volatility Index (VIX), world oil inventories and world financial conditions (FCI). All variables are in logarithms, except the VIX and FCI, which are in levels. All figures display percent responses to the initial shock over a 40-month horizon.

4.5 Robustness Checks

We run a series of robustness checks to assess the sensitivity of our results across different model specifications and instrument variations. Specifically, we test (i) alternative lag structures in the VAR, increasing from the baseline two lags to one, three and twelve lags; (ii) alternative maturities for the oil futures contract used in the instrument, ranging from the baseline 3-month horizon to 1, 2, 6, and 12 months; and (iii) alternative instruments based on employment announcements from the US and the Euro Area separately.

For the Global VAR, the results are highly robust to changing the number of lags (Figure B.2), with the direction of the dynamics remaining unchanged. The main patterns persist: world industrial production rises following the shock and gradually returns to baseline, the VIX declines, and oil inventories fall initially before reverting, all consistent with a demand-driven boost to global activity. Varying the maturity of the futures contract also preserves these dynamics, with longer maturities reinforcing the same qualitative responses (Figure B.3). Interestingly, when we increase the maturity of futures contracts in the instrument, the results remain robust. In particular, the effects on activity and financial variables tend to be more persistent when employment news impacts larger maturities, which can be interpreted as news that incorporate expected structural shifts in economic outlook rather than transitory spikes. Finally, when using instruments based on US and Euro Area announcements separately, the dynamics remain stable, though the effects are more pronounced when the instrument is constructed from Euro Area surprises compared to those based on US announcements (Figure B.4).

Turning to the EMEs specification, the robustness checks confirm the stability of the results as well. Using alternative lag structures (Figure B.6), we again find that industrial production, consumer prices, exchange rates, and sovereign spreads all move consistently with the baseline, with only minor changes in magnitude or significance. Similarly, the choice of futures maturity does not alter the direction or timing of the responses (Figure B.7), and instruments based on either US or Euro Area announcements produce nearly identical patterns, with Euro Area surprises generating somewhat larger effects (Figure B.8).

For the exporters-importers split, the results follow the same pattern of robustness. Changing the number of lags leaves the direction of the responses unchanged (Figure B.9). The main dynamics remain: industrial production increases in both groups, more persistently for exporters than for importers; consumer prices rise for importers but fall slightly for exporters; the real exchange rate appreciates strongly and durably for exporters while the appreciation for importers is weaker and less persistent; and sovereign spreads decline in both groups, with a stronger and more consistent reduction among exporters. Again, using longer futures maturities does not alter the direction of the responses, but tends to strengthen the same qualitative patterns (Figure B.10). Finally, when separating the instrument between US and Euro Area announcements, the direction and timing of the responses are stable, but effects are systematically more pronounced when the Euro Area instrument is used (Figure B.11).

5 Conclusion

This paper proposes a new high-frequency external instrument to isolate global demand shocks using oil futures price reactions to labor market announcements from the United States and the Euro Area. The labor-report-induced change in oil futures prices captures changes in expectations about global economic activity in real time and builds on the growing literature in proxy SVAR frameworks. This instrument offers a robust and credible approach to identifying global demand shocks, addressing a key gap in the empirical literature on international market dynamics, where timely and precise identification remains essential.

Our findings are theoretically consistent with the observed transmission of demand shocks to global and emerging markets. Global demand shocks lead to a significant and broad expansion in real activity, improved international financial conditions, reduced global uncertainty, and oil inventories reductions. In EMEs, industrial production and consumer prices increase, sovereign spreads compress, and real exchange rates appreciate, suggesting improved risk sentiment and stronger external positions, with intuitive asymmetries between oil-exporting and oil-importing economies.

Beyond the specific findings, our paper contributes to a broader methodological agenda that seeks to improve the identification of structural shocks in a globalized and information-rich environment. It further supports the idea that high-frequency financial data around well-defined macroeconomic announcements offer an underexploited source of credible instruments, beyond monetary policy, extending to international and commodity market analysis. Future work may extend this approach to other forms of macroeconomic news, incorporate cross-country interdependencies more explicitly, or investigate other transmission mechanisms of global demand shocks. We expect that our contribution leads to a deeper understanding of the global economic forces that shape oil markets and macroeconomic dynamics more broadly.

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A Data sources and description

The following list describes the primary data series used in the analysis, including their sources and relevant details such as frequency, measurement units and treatment:

1. **Oil Price**: Spot Crude Oil Price: West Texas Intermediate (WTI), measured in dollars per barrel, monthly frequency, not seasonally adjusted (WTISPLC from FRED).

2. **Oil Futures**: Daily Light Sweet Crude Oil Futures Price for the 3-month contract settlement (end-of-period), measured in dollars per barrel. Data obtained from CME via Haver Analytics (PZTEXF3@DAILY).

3. **World Oil Inventories**: Monthly proxy for global crude oil inventories based on OECD petroleum stocks, following Kilian and Murphy (2014). The series is obtained from the US Energy Information Administration (EIA).

4. **World Industrial Production**: Global industrial production index constructed by Baumeister and Hamilton (2019).

5. **VIX**: CBOE Volatility Index, reported monthly and not seasonally adjusted (VIXCLS from FRED).

6. **World Financial Conditions Index**: Average of the Bloomberg Financial Conditions Indices for the United States (BFCIUS Index), Euro Area (BFCIEU Index), United Kingdom (BFCIGB Index), and Asia excluding Japan (BFCIAXJ Index). The average is multiplied by -1 so that a positive (negative) value indicates tighter (accommodative) financial conditions relative to pre-crisis levels. Each index is a z-score indicating how many standard deviations current financial conditions deviate from normal (pre-crisis) levels.

7. **Emerging Markets Industrial Production Index**: Monthly Industrial Production index, excluding construction, seasonally and working day adjusted, obtained via Haver Analytics. The index is constructed as a GDP-weighted average across EMEs (see Table A.1 for details).

8. **Emerging Markets Consumer Price Index**: Monthly Consumer Price Index, seasonally adjusted, obtained via Haver Analytics. The index is constructed as a GDP-weighted average across EMEs (see Table A.1 for details).

9. **Emerging Markets Real Exchange Rate Index**: Monthly Bruegel's Real Effective Exchange Rate index, not seasonally adjusted, obtained via Haver Analytics. The index is constructed as a GDP-weighted average across EMEs (see Table A.1 for details). Through the study, an increase in real exchange rate is an EMEs currency depreciation.

10. **Emerging Markets J.P. Morgan EMBI Spread**: Emerging Markets Bond Index Global Spread, sourced from Bloomberg using the JPEGSOSD ticker. The series is constructed as a GDP-weighted average across EMEs (see Table A.1 for details).

11. **Employment Announcements:** Data are obtained from Bloomberg using the USURTOT Index and UMRTEMU Index tickers. These indices capture the release dates of the US Bureau of Labor Statistics' Employment Situation Report, which is published monthly (typically on the first Friday of each month) and provides key labor market indicators such as the unemployment rate, nonfarm payrolls, and labor force participation. For the Euro Area, it refers to Eurostat's Unemployment Statistics, which are published monthly and harmonized across member countries.

12. **Net Oil Exporter and Importers Classification:** Countries are classified as net oil importers or exporters based on the most recent annual data on crude oil trade from EIA.

Table A.1: Emerging Markets classification

Country	Weight	Net Oil Position
China	36.5%	Importer
India	15.5%	Importer
Russia	6.6%	Exporter
Brazil	4.5%	Exporter
Indonesia	4.5%	Importer
Türkiye	3.3%	Importer
Mexico	3.2%	Exporter
Egypt	2.1%	Exporter
Saudi Arabia	2.0%	Exporter
Poland	1.8%	Importer
Thailand	1.7%	Importer
Islamic Republic of Iran	1.6%	Exporter
Bangladesh	1.6%	Importer
Vietnam	1.6%	Importer
Pakistan	1.5%	Importer
Nigeria	1.4%	Exporter
Malaysia	1.3%	Exporter
Philippines	1.3%	Importer
Colombia	1.1%	Exporter
South Africa	0.9%	Importer
Romania	0.9%	Importer
United Arab Emirates	0.8%	Exporter
Kazakhstan	0.8%	Exporter
Algeria	0.8%	Exporter
Iraq	0.7%	Exporter
Chile	0.6%	Importer
Ukraine	0.6%	Importer
Peru	0.6%	Importer
Argentina*	0.0%	Exporter
Venezuela*	0.0%	Exporter

Note: The 30 countries shown are the largest emerging markets (EMEs), selected based on their GDP in PPP terms from the IMF's WEO. *Argentina and Venezuela are excluded due to persistent inflation and data inconsistencies, and are assigned a GDP share of zero. The column Weights reports each country's share of total EMEs GDP, normalized to sum to 100%. Net Oil Position classifies countries as net importers or exporters using the latest crude oil trade data from the US Energy Information Administration (EIA). Data availability for the macroeconomic variables used in the analysis (IP, CPI, REER, EMBI) covers 73%, 95%, 99%, and 88% of total EMEs GDP, respectively.

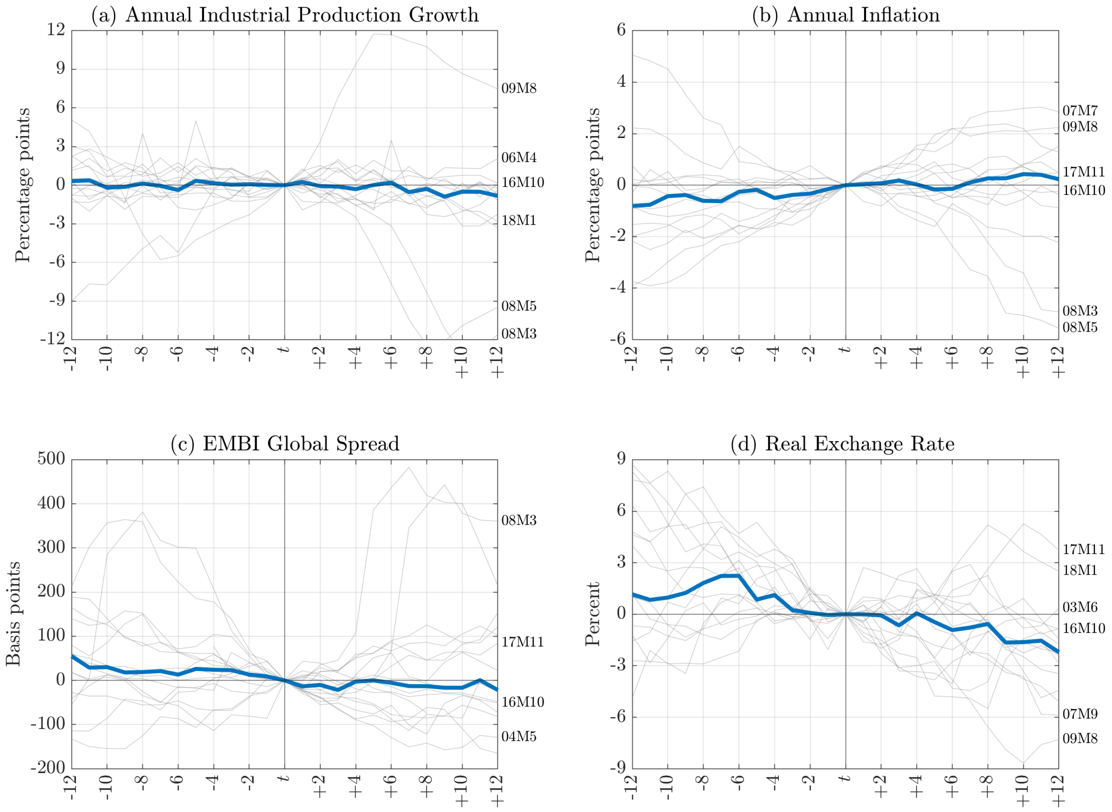
Table A.2: Summary statistics of key variables and instruments

Variable	Unit	Mean	Abs. Mean	Std	Min	P25	Median	P75	Max
WTI Price	Δ%	0.67	6.56	8.44	-28.59	-4.74	1.72	5.82	23.85
WTI Price	ΔPrice	0.01	0.90	1.29	-9.79	-0.61	0.04	0.67	10.28
World IP	Δ%	0.19	0.48	0.62	-3.21	-0.13	0.23	0.55	1.86
VIX	Δ%	1.27	12.54	19.15	-31.13	-9.55	-2.22	7.21	103.07
World FCI	Z-score	0.37	0.80	1.31	-1.17	-0.39	-0.01	0.75	8.17
EMEs IP	Δ%	0.42	0.62	0.68	-2.57	0.14	0.43	0.78	4.06
EMEs CPI	Δ%	0.31	0.32	0.19	-0.29	0.20	0.31	0.42	1.21
EMEs REER	Δ%	-0.11	0.78	1.00	-2.31	-0.79	-0.19	0.39	3.28
EMEs EMBI	bps	411.81	411.81	173.49	159.95	303.51	360.69	443.04	979.21
US Announcement Surprise	ΔPrice	0.09	0.91	1.33	-4.04	-0.57	0.11	0.75	10.28
EA Announcement Surprise	ΔPrice	-0.07	0.88	1.25	-5.58	-0.58	0.10	0.65	3.48
Combined Surprise	ΔPrice	0.03	1.34	1.88	-7.40	-0.91	0.06	0.96	9.42

Note: Summary statistics are based on monthly data from 2000 to 2019. The first set of variables (WTI Price, World IP, VIX, EMEs IP, EMEs CPI, EMEs REER) are expressed as month-over-month percentage changes. The EMBI is expressed in basis points. An increase in the REER is interpreted as a depreciation of EMEs' currencies. The last three variables correspond to our instruments, surprise movements in oil futures prices around employment announcements in the US and Euro Area, and are expressed as daily changes in oil prices.

B Figures and Tables

Figure B.1: Emerging markets dynamics around a 10% real oil price increase



Note: The figure shows the empirical dynamics over 12 months around a 10±1% month-to-month real oil price increase. The bold blue line represents the median across all events depicted by the gray lines. All figures are expressed as deviations relative to the value at time *t*. The analysis includes 16 episodes identified in the 2000–2019 sample: Jun 2000, Jun 2003, May 2004, Aug 2004, Aug 2005, Jan 2006, Apr 2006, Jul 2007, Sep 2007, Mar 2008, May 2008, Aug 2009, Oct 2016, Nov 2017, Jan 2018, and Apr 2019. An increase in the REER is interpreted as a depreciation of EMEs' currencies.

Table B.1: First stage F-statistic (t^2)

Instrument	Global			EMEs			Exporter			Importer		
	L=1	L=2	L=3	L=1	L=2	L=3	L=1	L=2	L=3	L=1	L=2	L=3
US Employment Announcement												
Chng. in 1-month WTI future	25.30	22.57	18.32	28.48	25.03	20.98	20.44	16.13	15.24	28.70	22.69	18.91
Chng. in 2-month WTI future	25.45	22.09	18.49	27.98	23.61	19.82	19.79	14.56	14.07	27.25	21.30	18.10
Chng. in 3-month WTI future	25.25	21.79	18.43	27.51	22.78	19.24	19.65	14.09	13.70	26.60	20.64	17.48
EA Employment Announcement												
Chng. in 1-month WTI future	10.89	4.25	5.15	11.07	6.68	6.79	10.17	2.78	3.13	5.12	4.34	4.59
Chng. in 2-month WTI future	10.17	4.15	4.86	10.66	6.74	7.04	9.37	2.76	3.16	5.10	4.39	4.63
Chng. in 3-month WTI future	10.08	4.28	5.00	10.61	6.99	7.38	9.20	2.95	3.32	5.17	4.63	4.87
US and EA Employment Announcement												
Chng. in 1-month WTI future	35.67	23.42	21.61	38.77	29.31	26.18	30.91	16.26	16.24	29.89	23.88	21.44
Chng. in 2-month WTI future	34.27	22.46	20.95	37.14	27.77	25.16	28.70	14.76	15.09	28.12	22.44	20.45
Chng. in 3-month WTI future	33.81	22.34	21.00	36.49	27.35	25.03	28.23	14.64	14.98	27.61	22.22	20.23

Note: The Global and EMEs specification uses data from February 2000 to December 2019, while the Exporter and Importer models are estimated from January 2006 to December 2019 due to limited data availability. The Global model includes real oil prices, world industrial production, VIX, world oil inventories and world financial conditions. Instead of world oil inventories, the EMEs model includes emerging markets aggregates (industrial production, CPI, EMBI Global, and REER). Exporter and Importer models disaggregate EMEs variables by net oil trade position. Results are shown for VAR models with 1 lag (L=1), 2 lags (L=2) and 3 lags (L=3).

Table B.2: Lag length selection criteria for baseline model

	Global		**EMEs**		**Exporter**		**Importer**	
Lag	SIC	HQ	SIC	HQ	SIC	HQ	SIC	HQ
1	**-10.40**	-10.67	**-29.76**	-30.41	**-25.05**	-25.89	**-28.38**	**-29.21**
2	-10.35	**-10.84**	-29.28	**-30.51**	-24.75	**-26.33**	-27.6	-29.18
3	-10.02	-10.74	-28.34	-30.14	-23.79	-26.11	-26.48	-28.80
4	-9.70	-10.65	-27.27	-29.64	-22.33	-25.40	-24.96	-28.03
5	-9.30	-10.47	-26.21	-29.17	-20.76	-24.57	-23.52	-27.33
6	-8.83	-10.23	-25.06	-28.59	-19.21	-23.76	-22.06	-26.61
7	-8.46	-10.08	-23.85	-27.95	-17.78	-23.07	-20.68	-25.97
8	-8.03	-9.87	-22.62	-27.30	-16.57	-22.60	-19.66	-25.69
9	-7.62	-9.68	-21.54	-26.80	-15.83	-22.61	-18.68	-25.46
10	-7.18	-9.48	-20.6	-26.44	-14.8	-22.32	-17.65	-25.17
11	-6.71	-9.23	-19.49	-25.90	-13.65	-21.92	-16.71	-24.98
12	-6.23	-8.98	-18.46	-25.45	-12.90	-21.91	-16.03	-25.04

Note: This table reports the lag length selection criteria for the baseline VAR model using monthly data. The Global and EMEs specification uses data from February 2000 to December 2019, while the Exporter and Importer models are estimated from January 2006 to December 2019 due to limited data availability. Selection is based on the Schwarz (SIC), and Hannan-Quinn (HQ) information criteria. The bold entries indicate the selected lag order under each criterion.

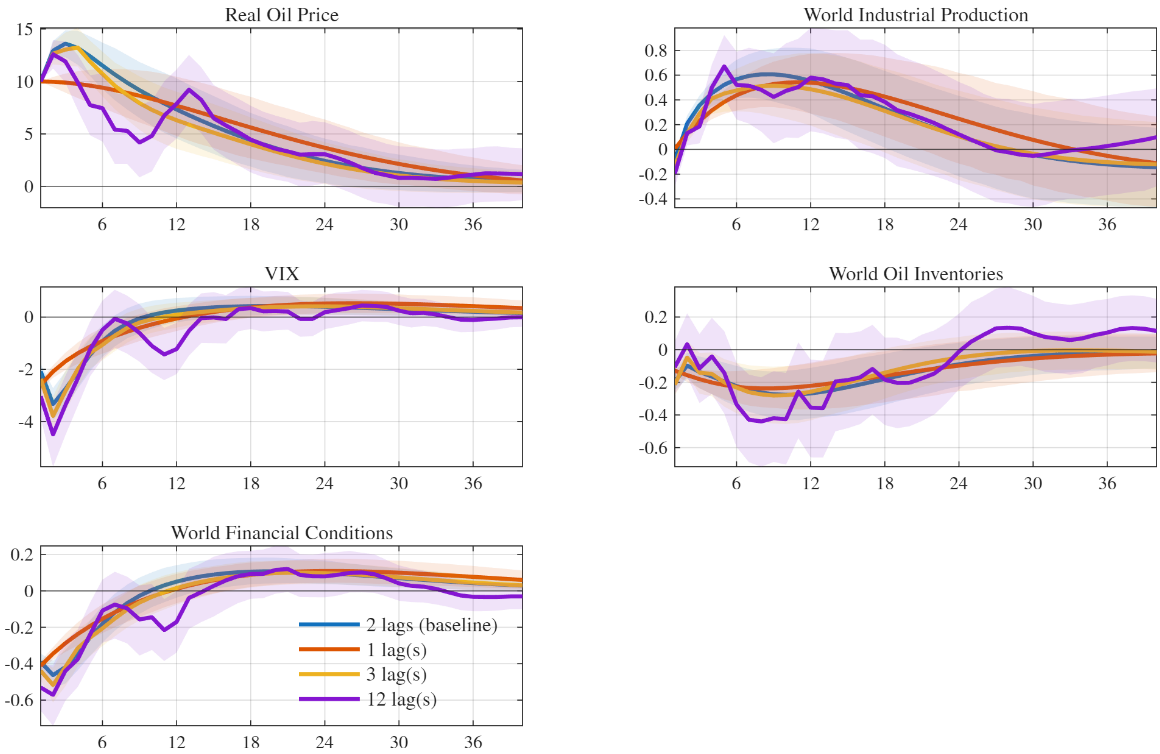
Table B.3: Selected Events and Bloomberg Relevance Values

Event	Bloomberg Ticker	Relevance Value
(a) United States		
Change in Nonfarm Payrolls	**NFP TCH Index**	**99.3**
Initial Jobless Claims	INJCJC Index	98.6
FOMC Rate Decision	FDTR Index	98.0
CPI MoM	CPI CHNG Index	97.3
GDP Annualized QoQ	GDP CQOQ Index	96.6
ISM Manufacturing	NAPMPMI Index	95.2
Retail Sales Advance MoM	RSTAMOM Index	93.9
Conference Board Consumer Confidence	CONCCONF Index	91.8
Unemployment Rate	USURTOT Index	89.4
New Home Sales	NHSLTOT Index	88.4
Leading Index	LEI CHNG Index	83.7
CPI Ex Food and Energy MoM	CPUPXCHG Index	77.8
Employee Cost Index QoQ	ECI SA% Index	76.9
PPI Ex Food and Energy MoM	FDIDSGMO Index	70.1
Capacity utilization	CPTICHNG Index	62.9
(b) Euro Area		
ECB MRO Announcement Rate	EURR002W Index	97.6
EA Real GDP QoQ	EUGNEMUQ Index	90.5
HCOB EA Manufacturing PMI SA	MPMIEZMA Index	90.0
EA MUICP All Items MoM NSA	ECCPEMUM Index	85.7
ECB Marginal Lending Facility Announcement Rate	EUORMARG Index	81.0
Eurostat IP EA Industry Ex Construction MoM SA	EUITEMUM Index	79.2
ECB M3 Annual Growth Rate SA	ECMAM3YY Index	78.6
HCOB EA Composite PMI Output SA	MPMIEZCA Index	73.8
Eurostat EA Core MUICP YoY NSA	CPEXEMUY Index	71.4
Eurostat Unemployment EA SA	**UMRTEMU Index**	**69.0**
European Commission Consumer Confidence EA	EUCCEMU Index	66.7
ZEW EA Expectation of Economic Growth	GRZEEUEX Index	61.9
Eurostat Retail Sales Volume EA MoM SA	RSSAEMUM Index	54.8
Eurostat PPI EA Industry Ex Construction YoY	EUPPEMUY Index	50.0
Eurostat Labor Costs Nominal EA YoY WDA	LNTNEMUY Index	19.0

Note: Bloomberg's Relevance Value is the share of user alerts for this event relative to all events in the same country. Values for selected United States in (Panel (a)) and Euro Area (Panel (b)) indicators retrieved on August 20, 2025.

B.1 Robustness: Global VAR

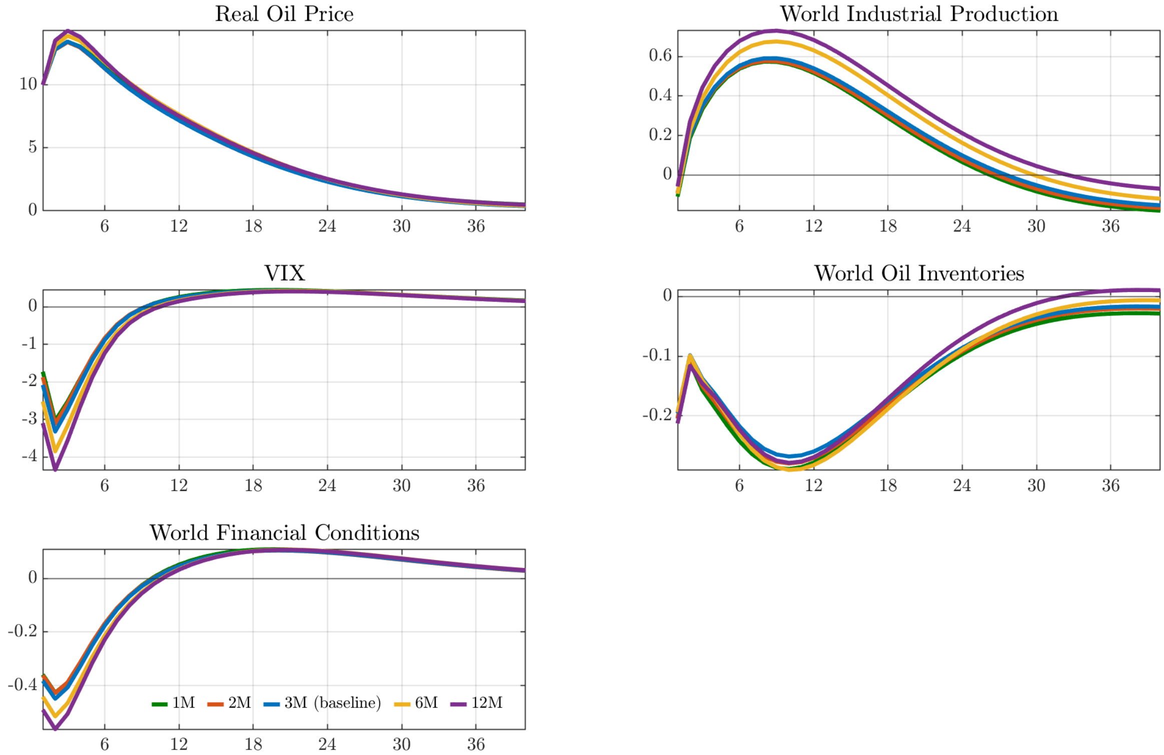
Figure B.2: Impulse Responses under Alternative Lag Specification - Global VAR



First-stage F-statistic = 33.81 (1 lag), 22.34 (2 lag), 21.00 (3 lag) and 15.32 (12 lag).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. We consider four alternative lag specifications (1, 2, 3, and 12 lags). The specification includes the variables: real oil price, world industrial production, the CBOE Volatility Index (VIX), world financial conditions (FCI) and world oil inventories. All variables are in logarithms, except the VIX and FCI, which are in levels. All figures display percent responses to the initial shock over a 40-month horizon.

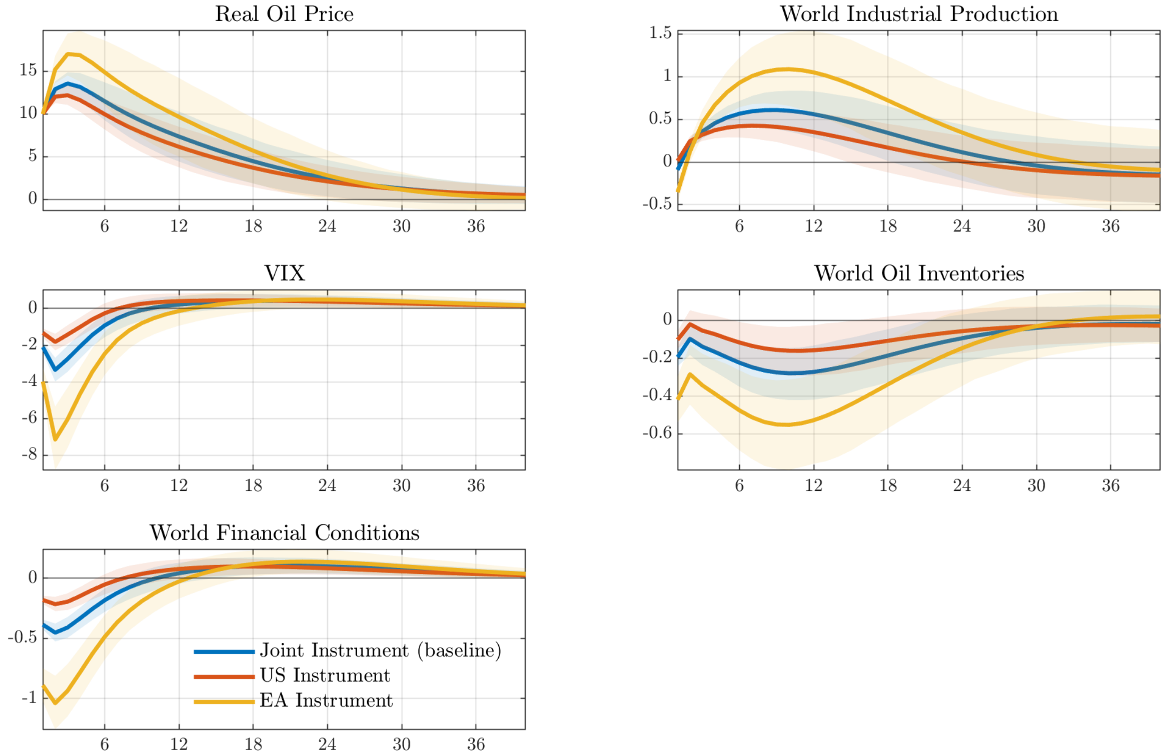
Figure B.3: Impulse Responses under Alternative Futures Maturities - Global VAR



First-stage F-statistic = 23.42 (1M), 22.46 (2M), 22.34 (3M), 19.96 (6M) and 21.31 (12M).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 1, 2, 3, 6 and 12-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, the CBOE Volatility Index (VIX), world financial conditions (FCI) and world oil inventories. All variables are in logarithms, except the VIX and FCI, which are in levels. All figures display percent responses to the initial shock over a 40-month horizon.

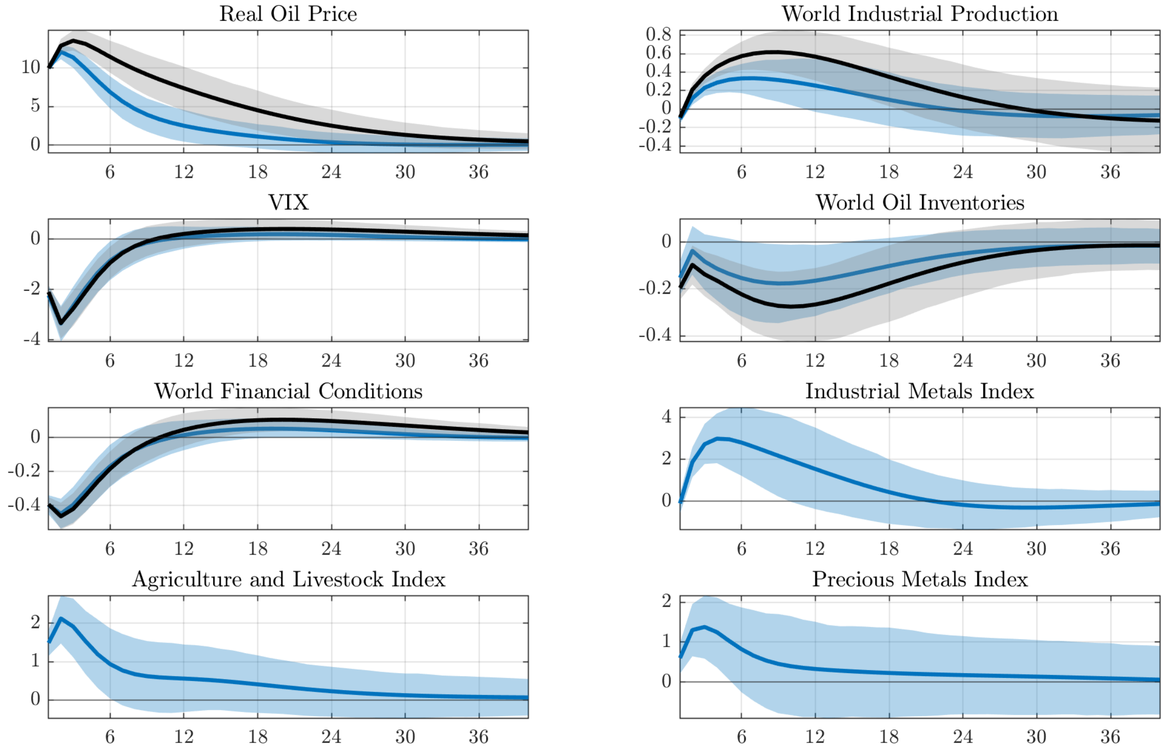
Figure B.4: Impulse Responses Using Separate Instruments for US and Euro Area — Global VAR



First-stage F-statistic = 22.34 (Joint Instrument), 21.79 (US) and 4.28 (EA).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, separately and jointly, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, the CBOE Volatility Index (VIX), world financial conditions (FCI) and world oil inventories. All variables are in logarithms, except the VIX and FCI, which are in levels. All figures display percent responses to the initial shock over a 40-month horizon.

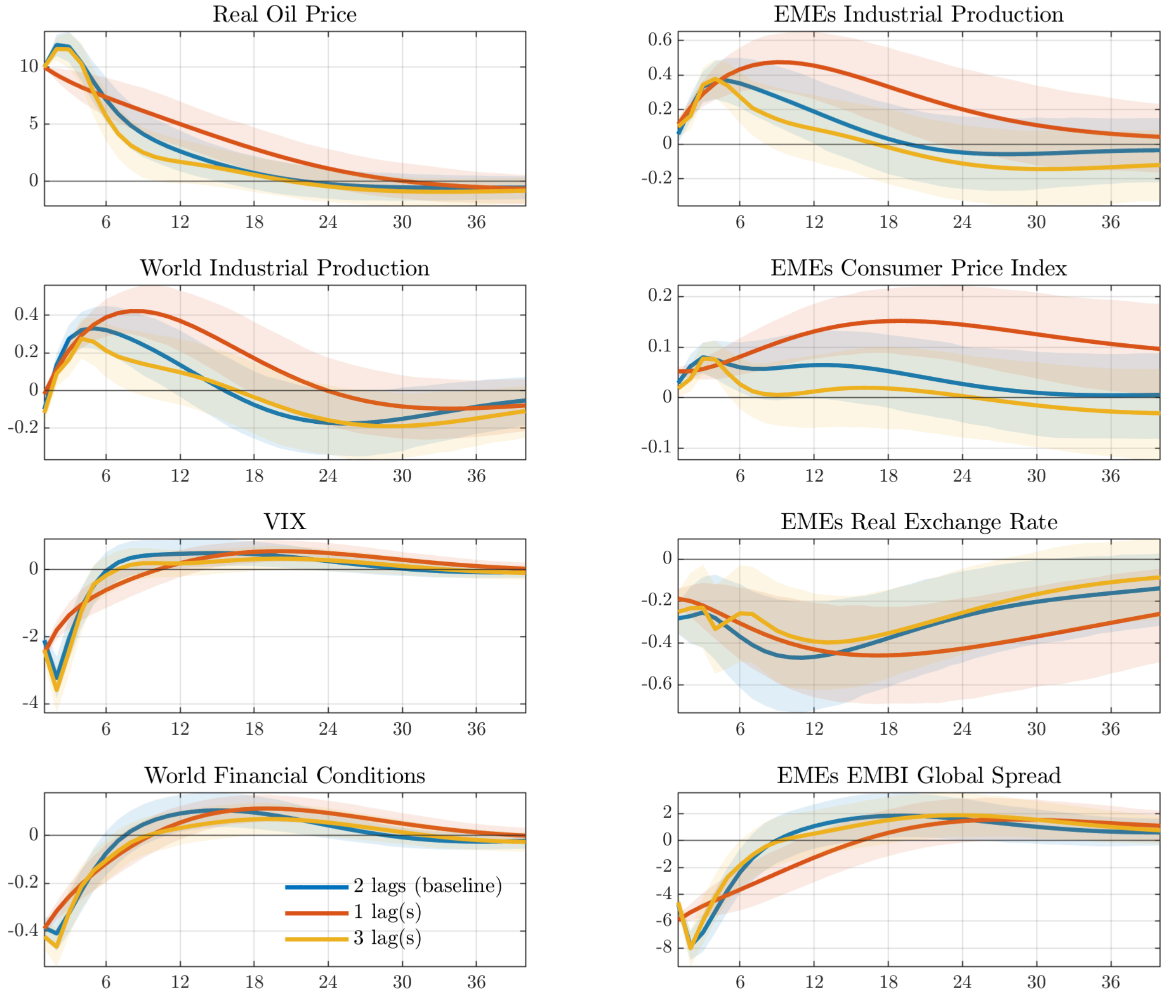
Figure B.5: Effect of a 10% oil price demand shock on a Global VAR



Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2 compared to a specification that includes three real commodity indexes. The baseline specification (black line) includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI), and EMEs aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate (increase means EMEs' currency depreciation). All variables are in logarithms, except the VIX and FCI, which are in levels. All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.1.

B.2 Robustness: EMEs VAR

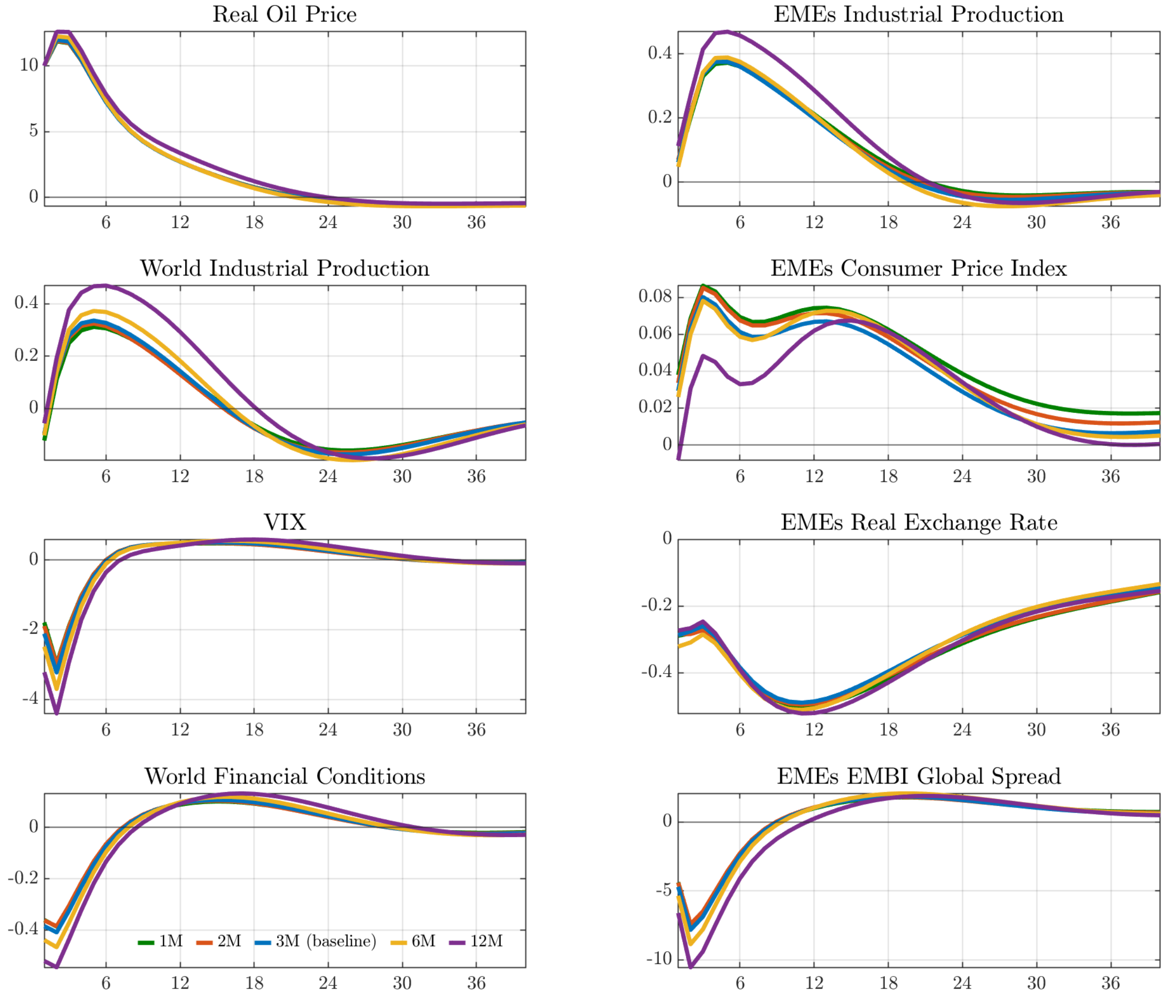
Figure B.6: Impulse Responses under Alternative Lag Specification - EMEs



First-stage F-statistic = 36.49 (1 lag), 27.35 (2 lag) and 25.03 (3 lag).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. We consider three alternative lag specifications (1, 2, and 3 lags). The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures display percent responses to the initial shock over a 40-month horizon.

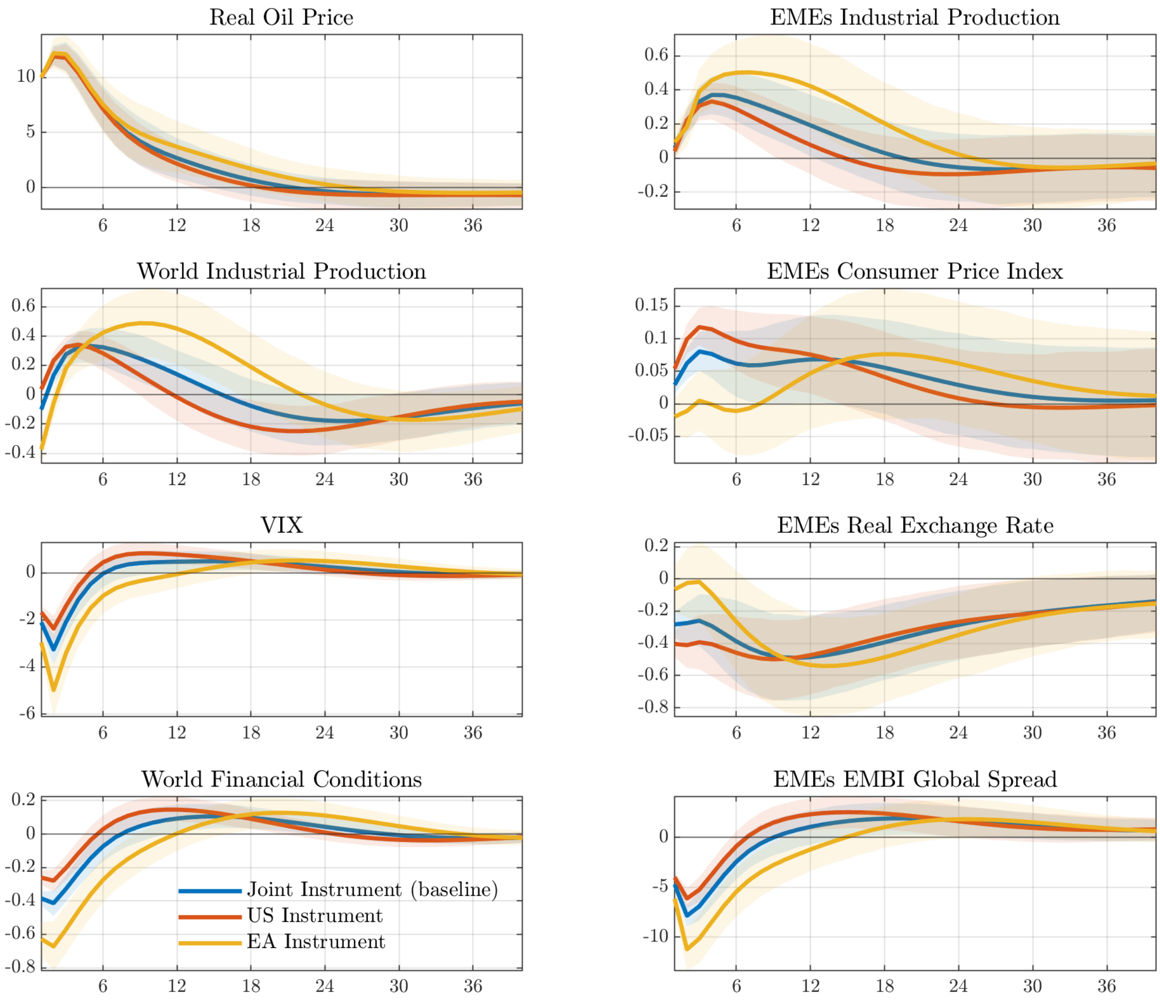
Figure B.7: Impulse Responses under Alternative Futures Maturities - EMEs



First-stage F-statistic = 29.31 (1M), 27.77 (2M), 27.35 (3M), 23.95 (6M) and 21.93 (12M).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 1, 2, 3, 6 and 12-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures display percent responses to the initial shock over a 40-month horizon.

Figure B.8: Impulse Responses Using Separate Instruments for US and Euro Area — EMEs

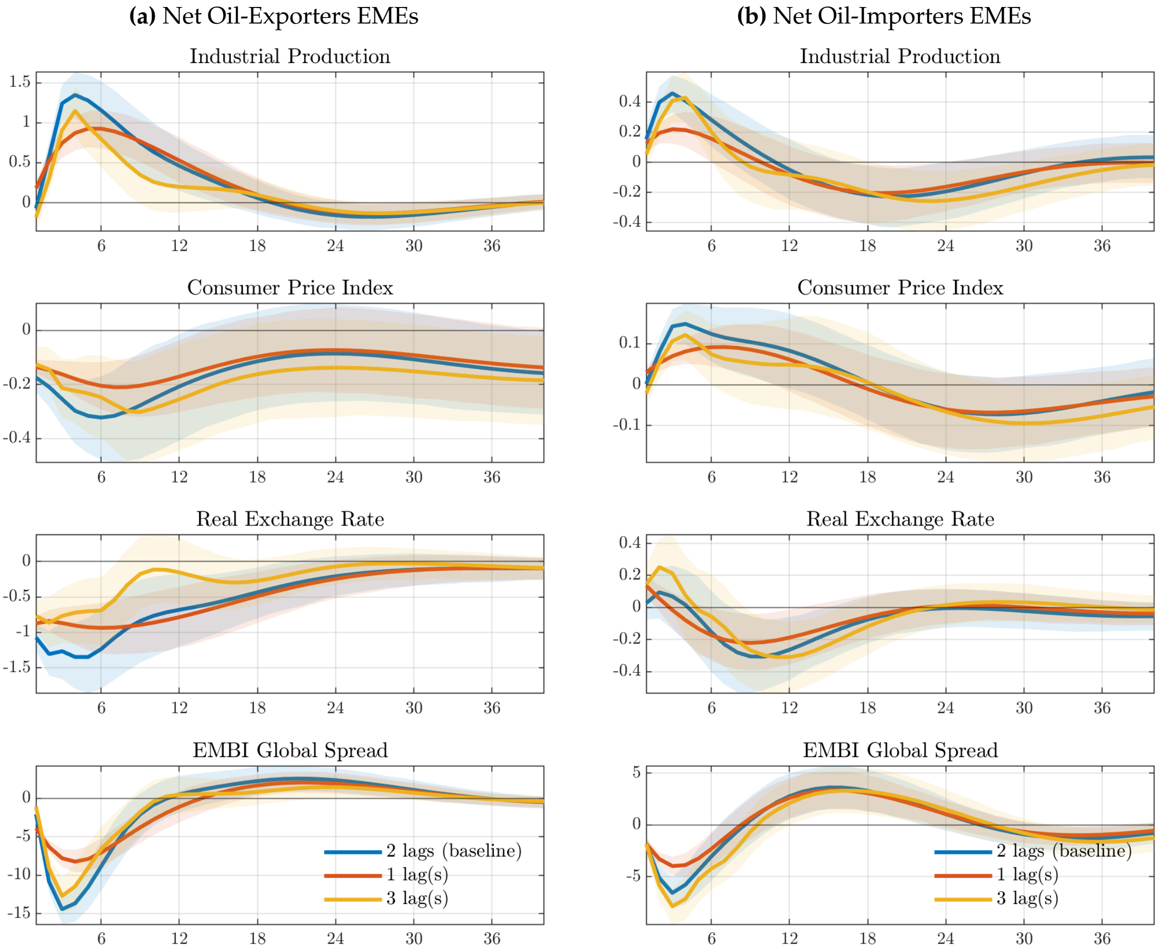


First-stage F-statistic = 27.35 (Joint Instrument), 22.78 (US) and 6.99 (EA).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, separately and jointly, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures display percent responses to the initial shock over a 40-month horizon.

B.3 Robustness: EMEs Disaggregation VAR

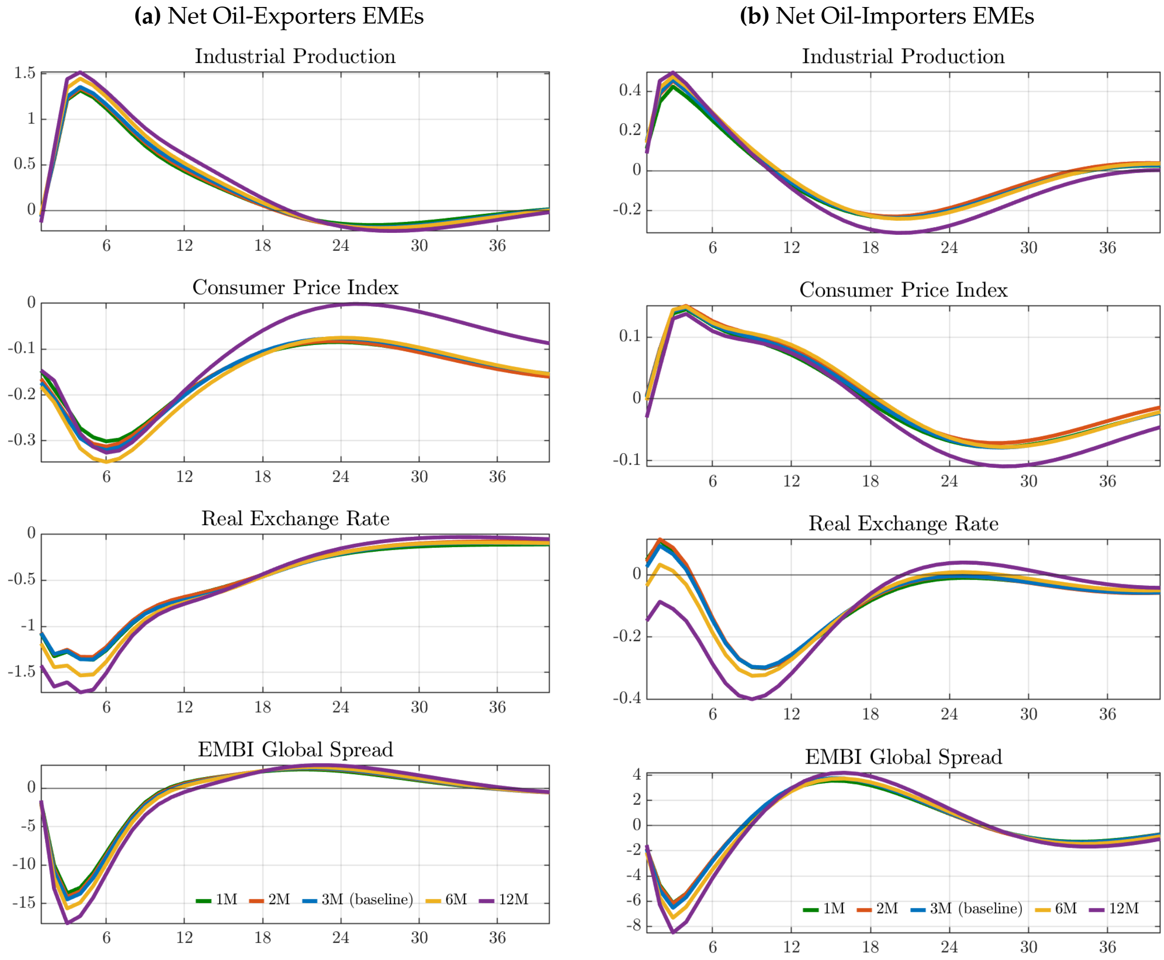
Figure B.9: Impulse Responses under Alternative Lag Specification - EMEs



First-stage F-statistic = (a) 28.23 (1 lag), 14.64 (2 lag) and 14.98 (3 lag). (b) 27,61 (1 lag), 22.22 (2 lag) and 20.23 (3 lag).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. We consider three alternative lag specifications (1, 2, and 3 lags). The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. The classification between oil exporters and oil importers countries is based on EMEs net oil trade position, using data from the International Energy Agency (further details can be found in Table A.1). All figures show percent responses to the initial shock over a 40-month horizon.

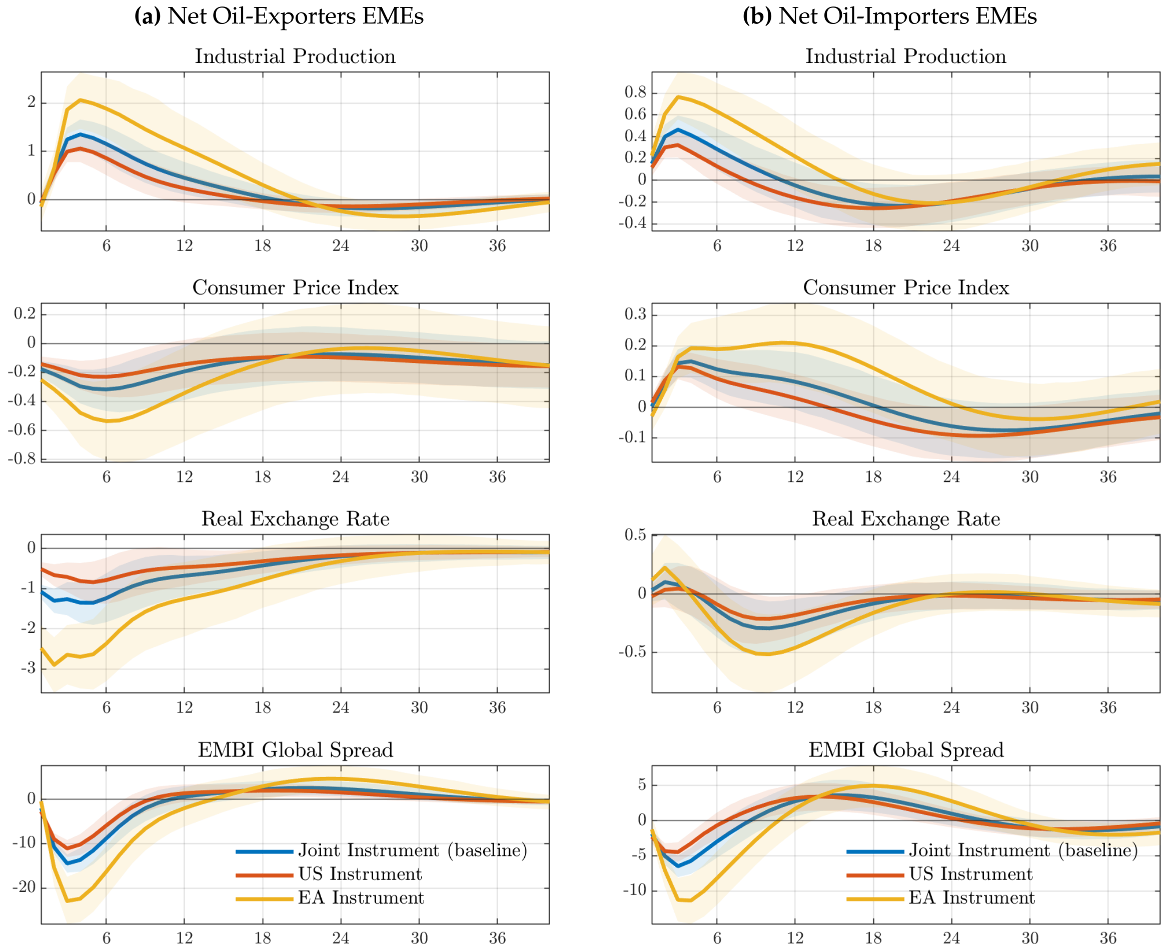
Figure B.10: Impulse Responses under Alternative Futures Maturities - EMEs



First-stage F-statistic = (a) 16.26 (1M), 14.76 (2M), 14.64 (3M), 12.80 (6M) and 11.61 (12M). (b) 23.88 (1M), 22.44 (2M), 22.22 (3M), 19.40 (6M) and 17.00 (12M).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 1, 2, 3, 6 and 12-month futures price variation around US and Euro Area employment announcements, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. The classification between oil exporters and oil importers countries is based on EMEs net oil trade position, using data from the International Energy Agency (further details can be found in Table A.1). All figures show percent responses to the initial shock over a 40-month horizon.

Figure B.11: Impulse Responses Using Separate Instruments for US and Euro Area — EMEs



First-stage F-statistic = (a) 14.64 (Joint Instrument), 14.09 (US) and 2.95 (EA). (b) 22.22 (Joint Instrument), 20.64 (US) and 4.63 (EA).

Note: The figures show the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the 3-month futures price variation around US and Euro Area employment announcements, separately and jointly, as described in Section 3.2. The specification includes the variables: real oil price, world industrial production, CBOE Volatility Index (VIX), world financial conditions (FCI) and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. All variables are in logarithms, except the VIX and FCI, which are in levels. An increase in the REER is interpreted as a depreciation of EMEs' currencies. The classification between oil exporters and oil importers countries is based on EMEs net oil trade position, using data from the International Energy Agency (further details can be found in Table A.1). All figures show percent responses to the initial shock over a 40-month horizon.

PUBLICATIONS

Good News Travels Fast: Global Demand Shocks, Oil Futures, and Emerging Markets Dynamics

Working Paper No. WP/2025/253