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

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Abstract

This paper studies how revisions in demand expectations affect oil prices and propagate through the global economy, with particular attention to their impact on Emerging Markets (EMEs). To do so, we introduce a new high-frequency instrument to identify global demand shocks using changes in oil futures around U.S. and Euro Area labor report releases, interpreted as surprise revisions in global economic expectations. Using a proxy-SVAR framework our results suggest that a global demand shock has positive effects in world industrial production and reduces oil inventories as well as global uncertainty. In EMEs, the upward revision in the macroeconomic outlook leads to higher industrial production and inflation, real exchange rate appreciation, and lower EMBI spreads. Our findings offer a credible empirical strategy for isolating global demand shocks and have direct implications for empirical macroeconomic modeling in the context of emerging market economies.

Keywords: *Proxy SVAR; oil futures prices; global demand shocks; Emerging Markets; high-frequency identification; labor reports releases*
JEL Classification: *C3; E4; E6; F3; Q4*

*The views expressed are those of the authors and do not necessarily represent the views of the Inter-American Development Bank, the International Monetary Fund or either of both board members.

1 Introduction

Understanding the role of global demand in driving commodity prices and macroeconomic fluctuations is fundamental to both economic research and policymaking. Recent volatility in oil markets has renewed interest in how fluctuations in oil prices affect emerging market economies (EMEs) and the global business cycle more broadly. Throughout late 2024 and into 2025, oil prices have experienced renewed swings, reflecting a combination of stronger-than-anticipated global growth and persistent supply-side uncertainties, the latter particularly concentrated in the United States and parts of Asia. Tensions in the Middle East and disruptions to shipping routes in the Red Sea and Strait of Hormuz have contributed to risk premiums, while ongoing OPEC+ production discipline has kept global supply tight.

At the same time, shifting expectations around the pace of monetary easing in advanced economies have influenced both commodity demand and financial conditions in EMEs. These dynamics have reinforced the need to better understand the source of oil price movements, especially for economies highly exposed to terms-of-trade shocks and external vulnerabilities. However, this remains a complex issue. Oil prices are endogenous and respond to changing global economic conditions, geopolitical risks, and financial speculation. A meaningful empirical analysis requires distinguishing between the underlying drivers of these price movements. In particular, supply and demand shocks can exert markedly different, and often opposing effects on macroeconomic outcomes. From a policy point of view, the distinction is crucial as supply shocks can trigger contractionary dynamics, whereas demand shocks may reflect stronger underlying growth.

Despite substantial progress, the precise identification of global demand and supply shocks remains an ongoing challenge. Studies such as Kilian (2009), Kilian and Murphy (2012), and more recently Baumeister and Hamilton (2019) have highlighted the difficulties in isolating demand-side movements in oil prices from other structural forces. Structural vector autoregressions (SVARs) have traditionally relied on timing, sign, and long-run restrictions, which are often hard to justify or test empirically. In the last few decades, high-frequency identification strategies, based on market surprises around specific announcements, have been successfully applied in monetary policy settings (e.g.,Gürkaynak, Sack, and Swanson (2005); and Faust, Rogers, Wang, and Wright (2007)) but remain underused in the analysis of commodity price fluctuations[1]. Crucially, to the best of our knowledge, we have found no previous studies using oil futures surprises as instruments to identify global demand shocks.

This paper aims to fill this gap by proposing a new high-frequency instrument to identify global demand shocks in the context of a proxy SVAR[2]. In particular, we use changes in oil futures prices around labor market announcements from the United States and the Euro

[1]Känzig (2021) is a notable exception, who uses a high-frequency methodology to identify oil supply news shocks

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

Area as external instruments to identify global demand shocks. This identification strategy rests on the premise that labor market surprises from these two major economic blocs serve 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, and improved investment prospects. 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. This approach builds on insights from recent research that uses macroeconomic surprises to identify structural shocks in financial markets (e.g. Stock and Watson (2012); Mertens and Ravn (2013); and Miranda-Agrippino and Ricco (2021)) and extends this logic to the identification of global demand shocks in the context of oil markets.

Our empirical results demonstrate that labor-report-induced movements in oil futures prices provide a powerful and valid instrument for global demand shocks. A positive global demand shock leads to a significant and broad expansion in real activity, with both world industrial production and emerging market output rising sharply in the months following it. Financial markets respond accordingly. The VIX declines, sovereign spreads compress, and real exchange rates appreciate across emerging markets, suggesting improved risk sentiment and stronger external positions. Consumer prices also increase moderately, though the inflationary response varies by country depending on external trade structure. In fact, we document meaningful heterogeneity in the transmission of global demand shocks between oil-importing and oil-exporting economies, particularly in the magnitude and persistence of output, inflation, and sovereign risk responses. These estimated impulse responses are consistent with theoretical expectations and related literature. The instrument passes multiple robustness checks, including weak instrument diagnostics, change in the maturity of oil future markets and separating effects between US and Euro Area labor report releases.

The remainder of the paper is organized as follows. Section 2 situates our contribution within the existing literature on oil price shocks, 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 emerging markets, and highlighting the heterogeneity of 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 Literature Review

The relationship between oil prices and macroeconomic performance has long been a central theme in empirical research. Early work by Hamilton (1983) demonstrated that oil price shocks have significant effects on output and inflation. Over time, however, the literature has increasingly emphasized that the macroeconomic consequences of oil price movements depend critically on their underlying source. Kilian (2009) notably decomposed oil shocks into demand, supply, and precautionary demand components, showing that demand-driven oil price increases, that often reflect stronger global economic activity, have markedly different macroeconomic effects than supply-driven disruptions. This insight has since become foundational in macroeconomic modeling and empirical analysis, with follow-up contributions from Kilian and Murphy (2012), Baumeister and Peersman (2013), and Baumeister and Hamilton (2019), among others. Even more, some of these authors document that much of the persistent variation in oil prices in the last several decades is attributable to shifts in global demand shocks. Our paper aligns with this strand of the literature and extends it by contributing to identify global demand shocks using information from the oil futures market.

A central challenge in this literature is the identification of structural shocks. Traditional SVARs often rely on zero short- or long-term restrictions (Read (2022), and Baumeister and Hamilton (2022)), which can be difficult to justify in the presence of overlapping global dynamics. Recently, a growing number of studies have adopted the external or proxy SVAR approach (Mertens & Ravn, 2013; Stock & Watson, 2012), which leverages external instruments correlated with the shocks of interest but not correlated with other structural disturbances. This methodology has become especially influential in monetary economics, where high-frequency financial market surprises around scheduled announcements (e.g., interest rate decisions, labor market reports) are used to identify policy shocks (Gertler & Karadi, 2015; Miranda-Agrippino & Ricco, 2021). Importantly, these techniques have recently been extended to emerging markets. Beltrán (2025) analyzes how monetary policy surprises in the US impact emerging market economies, disentangling interest rate movements between pure monetary policy and information shocks. Similarly, Beltrán and Coble (2024) use a high-frequency instrument to identify monetary and news shocks in Chile. These studies show that external instruments and proxy-based identification are both feasible and informative in EMEs contexts, an insight that we build on in this paper.

Despite its success in other areas, high-frequency identification has been relatively underutilized in the analysis of oil markets, and to the best of our knowledge, it has been absent in identifying global demand shocks. Notably, Känzig (2021) used changes in oil futures prices around OPEC announcements to construct surprise-based shock series, which is arguably attributable to oil supply shocks. Similarly, Pan, Huang, and Lee (2024) develops an estimator that leverages OPEC's institutional characteristics and high-frequency data to identify oil supply shocks in the Chinese economy. Their findings suggest that such shocks lead to higher interest rates and inflation, underscoring the transmission of oil market disruptions into domestic monetary conditions. On the geopolitical side, Pinchetti (2024), using a combination of sign restrictions and high-frequency identification, finds that geopolitical shocks can generate heterogeneous economic responses depending on the context and the nature of the shock, particularly on inflation. No literature is yet available that uses oil futures price changes to pin down neither global nor oil demand shocks.

Our paper contributes to this literature by proposing a novel high-frequency instrument to identify global demand shocks. Specifically, we use changes in oil futures prices within a short time window around labor market data releases from both the United States and the Euro Area. These announcements, the Employment Situation Report and Eurostat's Unemployment Statistics release, are among the most closely followed macroeconomic indicators globally and regularly elicit strong, immediate responses in financial markets. Prior studies have exploited labor market surprises to identify monetary policy shocks (e.g. Nunes, Ozdagli, and Tang (2022)), but their use as instruments for identifying global demand shocks remains novel. We argue that oil futures price reactions to these announcements reflect updated beliefs about the strength of global economic activity and are thus suitable proxies for demand-side developments.

Beyond identification, our study contributes to the literature on oil shocks and their differential impact across countries. Emerging market economies, in particular, are highly exposed to global commodity price swings, with transmission channels running through trade balances, inflation, fiscal revenues, and capital flows (e.g. Arezki and Blanchard (2014); Basher, Haug, and Sadorsky (2012); and Mohaddes and Raissi (2019)). Demand-driven oil futures price increases may benefit these economies by raising export demand and improving terms of trade, while supply shocks often bring stagflationary pressures and increased external vulnerabilities. However, these effects can only be properly assessed if the underlying nature of the shock is correctly identified. Our framework offers a transparent and empirically grounded approach to this problem, providing a tool for better understanding how external demand shocks propagate in emerging economies.

3 Identification Strategy and Data

3.1 Econometric Framework

To examine the dynamic effects of global demand shocks on EMEs 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 key economic variables. In our 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) and Känzig (2021), consider X_t a vector of variables; P and Q_j $\forall i \geq 1$ 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 study the first column of P^{-1}, which traces the effects of the identified structural shock across variables. To compute the impulse-response functions associated with the instrumented global demand shocks, we proceed by estimating the following equation:

$$Y_t = \sum_{i=1}^{p} R_j Y_{i-j} + p_k^{-1} e_{k,t} \tag{3}$$

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, $\epsilon_t^{r\neq1}$:

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

$$E\left(W_t \epsilon_t^{r\neq1}\right) = 0 \tag{5}$$

A wide range of methodologies has been developed to identify oil 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 oil 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 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 previous methodologies restrictions alone (Känzig (2021)). Consequently, the structural interpretation of identified shocks may 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, limiting the interpretability and policy relevance of the results.

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. In this context, a positive labor market surprise is interpreted as an indicator of stronger global demand, prompting immediate adjustments in oil futures markets.

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 demand driven movements in oil markets, allowing us to capture shifts in global economic conditions without confounding them with supply side or uncertainty factors. The use of the 3-month-horizon futures 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; Känzig, 2021) Gertler and Karadi (2015), Lakdawala (2019).

Our main assumption is that, within the time window immediately following labor market data releases, 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).

Our instrument may also exhibit some limitations. While these releases are highly informative and widely followed, they may not fully reflect the breadth of forces that drive global demand. For instance, fiscal policy shocks, such as changes in public investment plans or the increase of debt ceiling debates, can significantly affect aggregate demand but may not be immediately incorporated into labor market data. Similarly, unconventional monetary policy measures, shifts in global financial conditions, and fluctuations in business or investor sentiment can all influence global demand dynamics through channels not directly proxied by employment-related surprises. As such, our instrument may only capture a subset of demand shocks, those that are salient to market participants in the context of scheduled macroeconomic releases, potentially overlooking more diffuse or latent sources of demand variation.

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 released information 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[4]. 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.

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

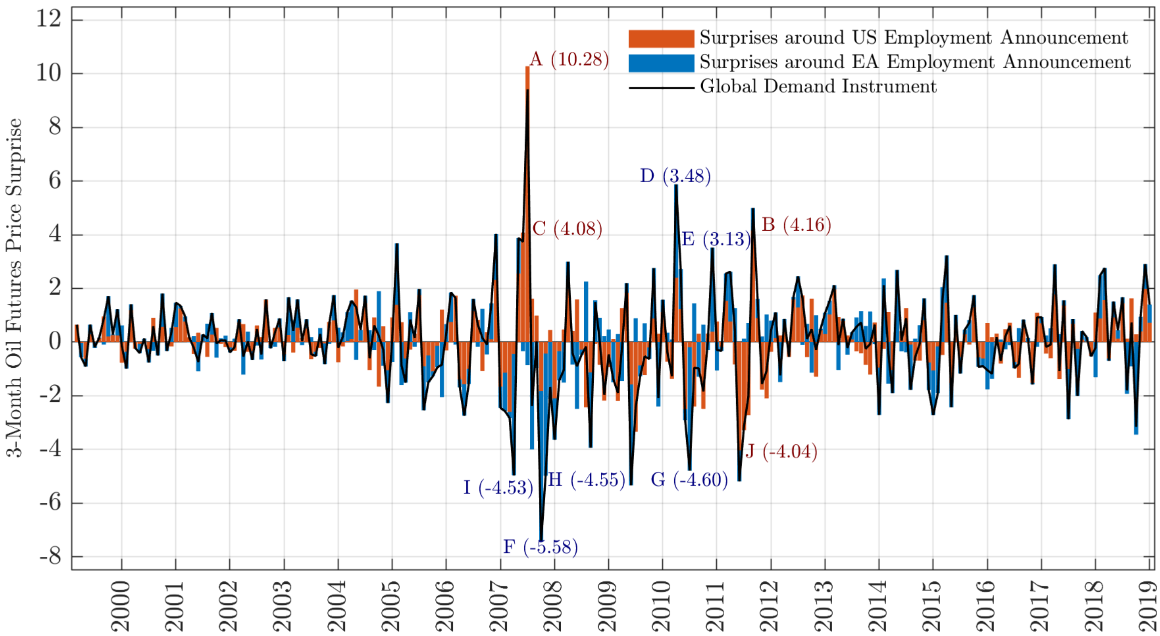
Figure 1 shows the time series for the global demand instrument in monthly frequency. The instrument reflects the surprise content of employment releases. Points A through J highlight the most extreme episodes across the 2000–2019 sample, each tied to large surprises in labor market data that led to significant oil futures price reactions. These events capture some of the most extreme shifts in oil price expectations over the sample period and reflect the sensitivity of oil futures to labor market news embedded in broader macro-

[3] We allow our instrument to exhibit measurement error, as other macroeconomic events could potentially influence oil futures prices in the same 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] If the previous day of the release coincides with a non-working day, we take the immediately previous business day to make the calculation.

financial developments.

Figure 1: Global Demand Instrument



Note: The global demand instruments are shown at a monthly frequency (2000–2019) and measured as changes in the U.S. 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. The figure highlights the most extreme changes. Full details on each episode, including day, region, and context, are available in Table B.1.

Point A (June 2008) corresponds to the largest positive movement in the series, with oil prices rising over 10 dollars amid a sharp decline in global equity markets and fears of stagflation. The backdrop included a sharp deterioration in labor market conditions, as the US unemployment rate posted its largest one-month increase in 22 years, jumping to 5.5 percent. Point B (August 2012) reflects a sizable increase in oil prices driven by strong US nonfarm payrolls and expectations of further monetary stimulus. The better-than-expected July jobs report was widely perceived as relieving pressure on the Federal Reserve to inject additional stimulus, though not precluding further easing steps. Point C (May 2008) similarly captures a broad commodity price surge on the back of robust global demand, particularly from China, and tightening concerns in EMEs. While labor market conditions remained weak, the employment report surprised to the upside, with job losses smaller than anticipated and the unemployment rate holding below expectations. Point D (March 2011) marks a reaction to the Fukushima disaster in Japan, which triggered global risk-off sentiment and drove up demand for safe-haven assets. Point E (November 2011) reflects rising tensions in the Euro Area amid surging Italian bond yields and renewed fears of sovereign contagion, contributing to rising unemployment concerns across peripheral economies.

On the downside, point F (September 2008) represents the sharpest decline in the instrument, coinciding with the collapse of Lehman Brothers and a broad sell-off across equities and commodities. Point G (June 2011) follows mass protests in Greece against fiscal austerity, which heightened political instability and weighed on employment prospects in the region. Point H (October 2008) captures falling oil prices in response to rising U.S. inventories and intensifying recession fears, with labor market indicators deteriorating sharply in advanced economies. Point I (March 2008) is associated with the emergency sale of Bear Stearns, prompting heightened market anxiety and a steep drop in oil futures, as job market stability came into question. Finally, point J (May 2012) reflects a decline in oil prices amid renewed political uncertainty in the Euro Area ahead of elections, with markets reacting to rising fiscal instability. Overall, these extreme episodes illustrate the richness and time variation of the instrument, capturing both sharp positive and negative revisions to global demand, often linked to the interplay between labor market surprises and broader macro-financial developments.

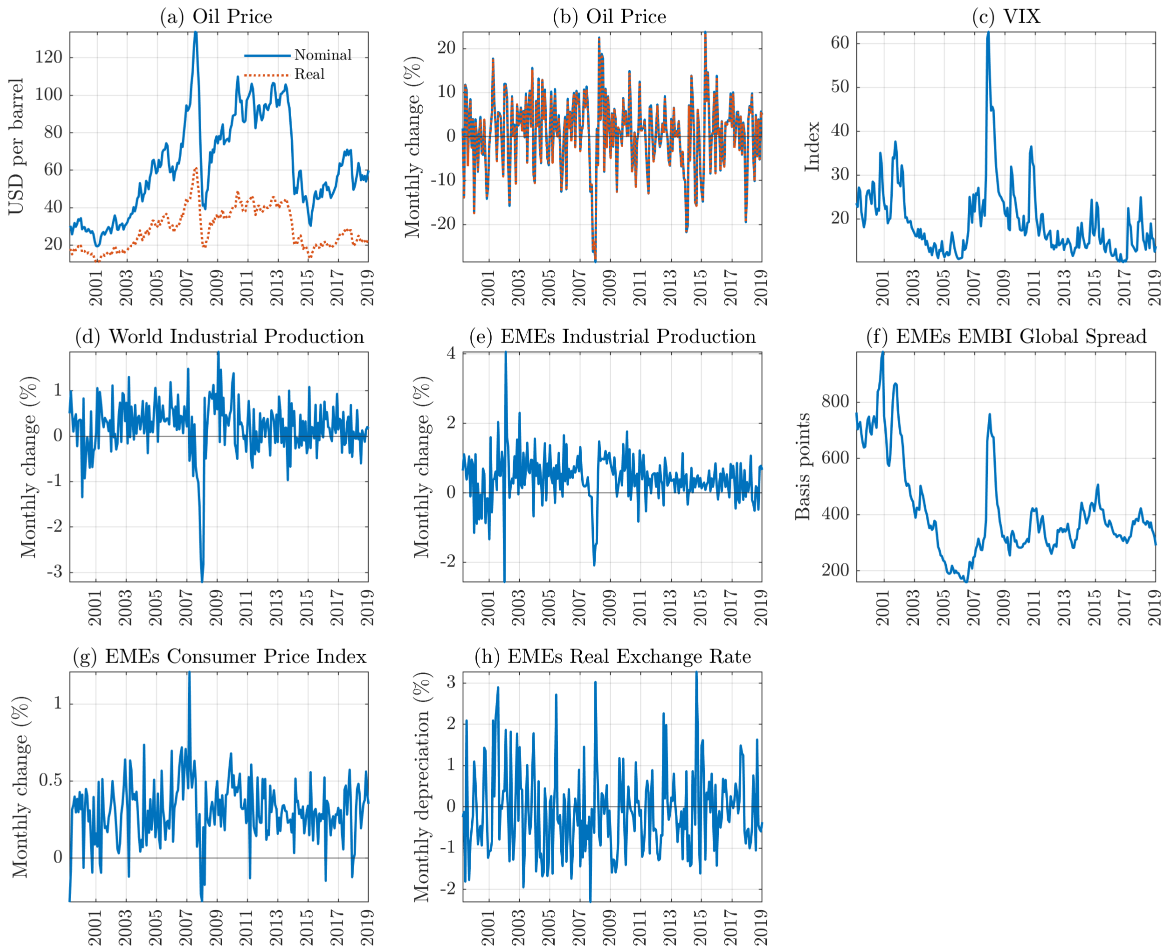
3.3 Data

We use monthly data spanning February 2000 to December 2019. The baseline specification includes seven variables: the real price of oil, world industrial production, VIX, and four EMEs aggregates: industrial production (IP), consumer prices (CPI), real effective exchange rates (REER), and sovereign credit spreads (EMBI Global). Throughout the paper, an increase in the REER is interpreted as a depreciation of EMEs' currencies. All variables, with the exception of the VIX, are included in log levels. The lag order is set to two months based on the Hannan–Quinn criterion (Table B.3). For a detailed data description see Appendix A.

Figure 2 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) and (d) display global indicators: the VIX, capturing financial market volatility, 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 (e)-(h) 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 2: 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 U.S. CPI) price of WTI spot oil price in USD per barrel and monthly percent changes. Panels (c)-(d) present the global variables: the CBOE Volatility Index (VIX) and monthly growth (in percent) of world industrial production from Baumeister and Hamilton (2019). Panels (e)–(h) 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. The coexistence of these offsetting dynamics highlights the importance of uncovering the nature of oil price shocks. When driven by stronger global demand, oil 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 tighteness, 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. Finally, we test the robustness of our baseline results across a range of alternative specifications and instruments.

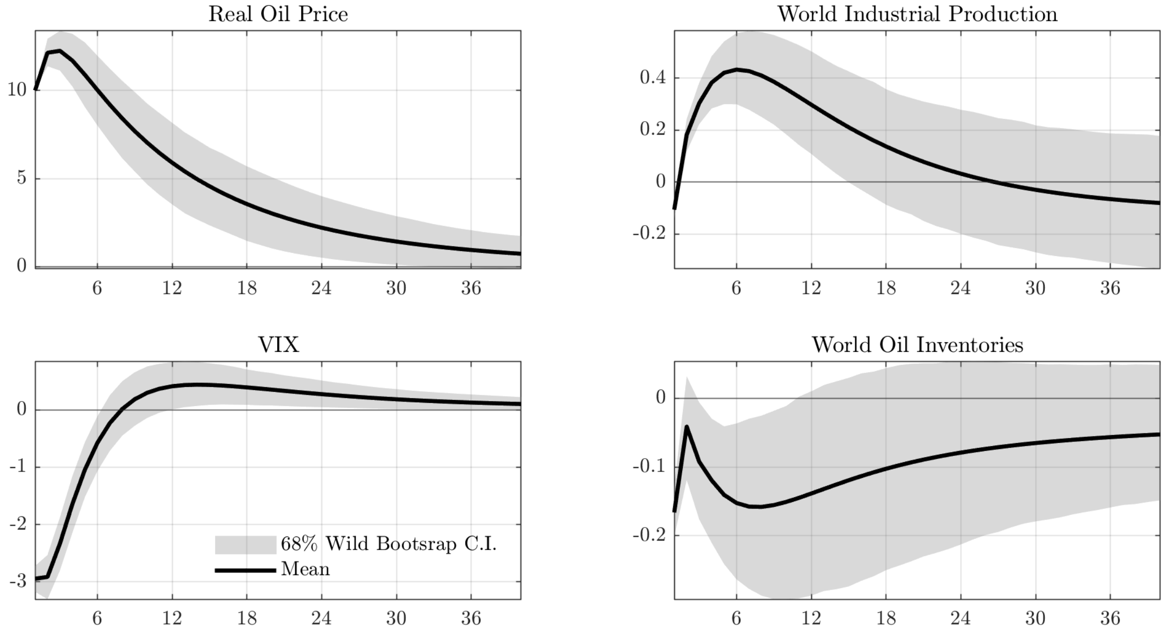
Across all specifications, the impulse response is normalized to generate a 10% increase in the real price of oil on impact. All variables, except the VIX, are expressed in logs and can be interpreted as elasticities. The solid lines in the figures denote point estimates, while the shaded areas represent 68% confidence intervals based on robust standard errors, following Mertens and Ravn (2013) and Nakamura and Steinsson (2018). We also report first-stage F-statistics to assess the strength of the instrument. [5]

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, the VIX, and global oil inventories. Figure 3 presents the corresponding impulse responses.

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

Figure 3: Effect of a 10% oil price demand shock on a Global VAR



First-stage F-statistic = 26.04.

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 U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and world oil inventories. All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.2.

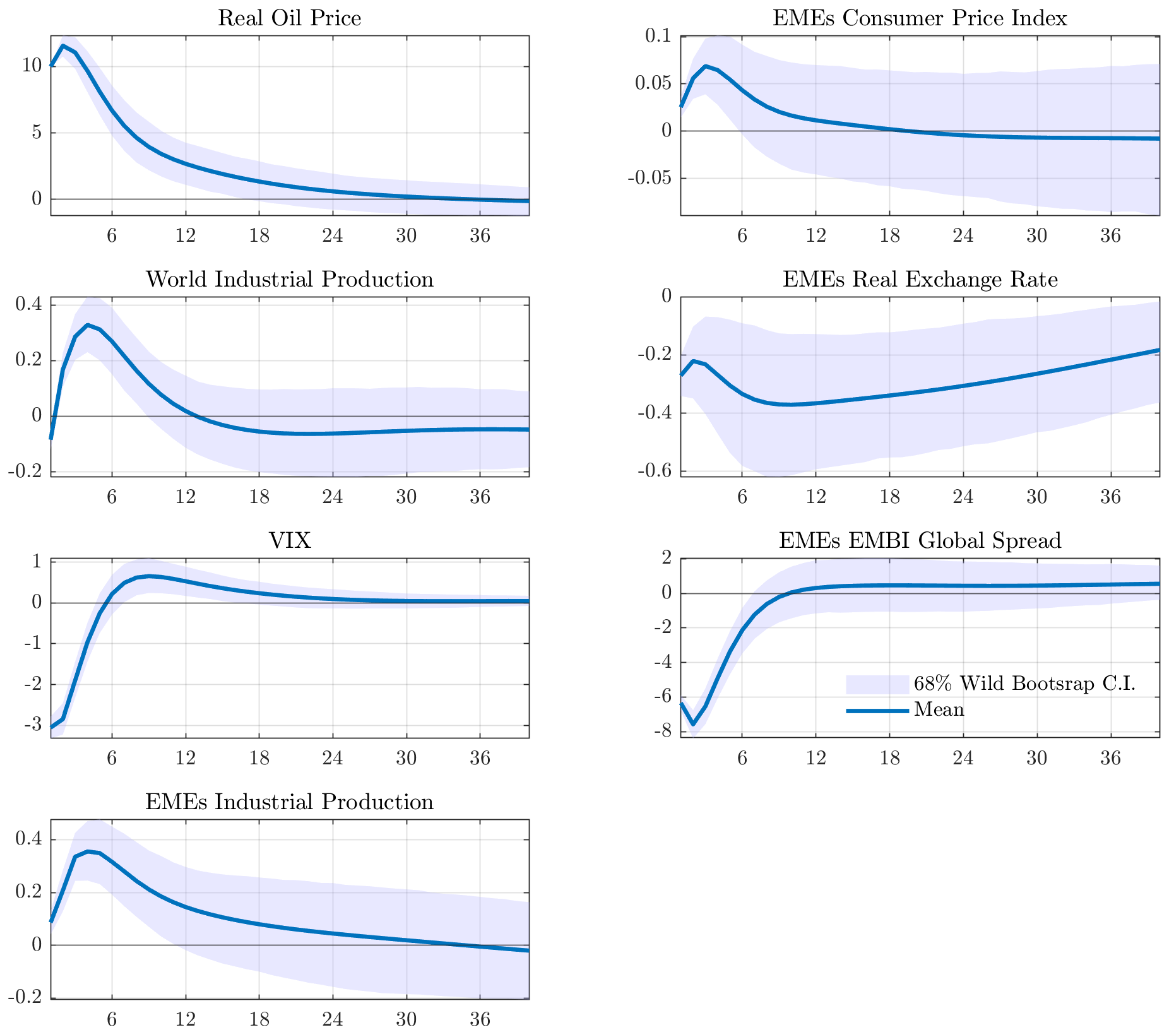
World industrial production rises sharply, peaking at around 0.4% in the fourth month and gradually returning to baseline thereafter, consistent with a short-term boost in global activity. The VIX falls significantly, reflecting a reduction in global uncertainty and increased investor risk appetite. 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 oil price movement, associated with improved growth expectations and a positive shift in the global outlook.

4.2 Macroeconomic Effects in Emerging Markets

We next turn to the macroeconomic and financial effects of the same global demand shock on EMEs. Figure 4 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 0.3% 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 an upward revision of the global macroeconomic outlook, where stronger external demand and a booming global economy stimulate a broad expansion in real activity across EMEs, typically accompanied by a transitory increase in 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 EMEs' real exchange rates.

Figure 4: Effect of a 10% oil price demand shock on Emerging Markets



First-stage F-statistic = 30.91.

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 U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and EMEs aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate (increase means EMEs' currency depreciation). All figures show percent responses to the initial shock over a 40-month horizon. Further instrument relevance statistics are reported in Table B.2.

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. 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

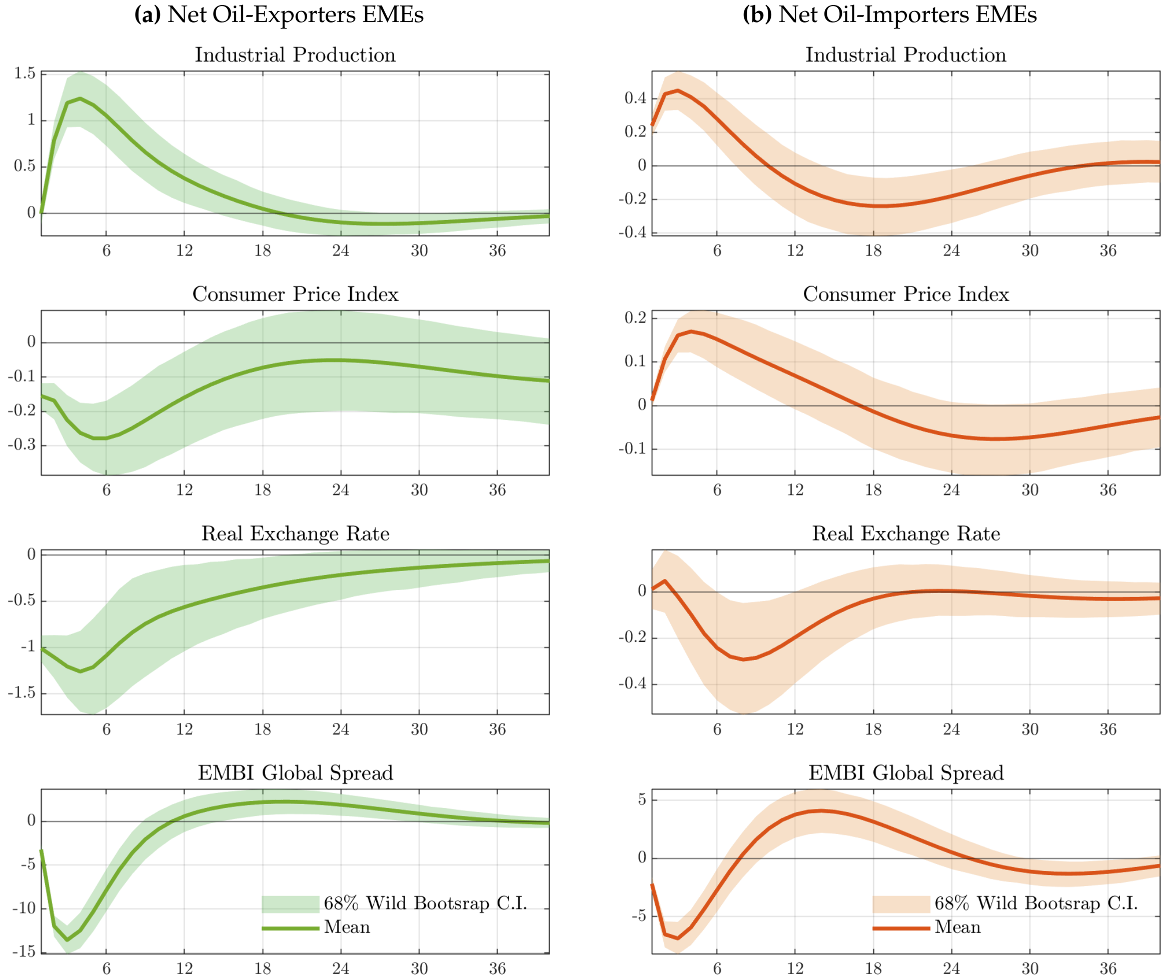
To explore potential asymmetries in the transmission of global demand shocks, we classify EMEs based on their net oil trade position, using the latest data from the US Energy Information Administration (EIA). Details on the classification are provided in Table A.1 in the Appendix.

The impulse responses differ notably between oil exporters and oil importers, as seen in Figure 5. 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 1.2% compared to 0.4% 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 13% for exporters, compared to about 6% 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 also raises 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. Taken together, this interpretation aligns with our empirical findings.

Figure 5: Effect of a 10% oil price demand shock on emerging markets



First-stage F-statistic = (a) 19.91 and (b) 27.57.

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 U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and EMEs aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate (increase means EMEs' currency depreciation). 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.2.

4.4 Robustness Checks

We run a series of robustness checks to assess the sensitivity of our baseline results for EMEs (Figure 4). First, we increase the number of lags in the VAR specification, from 2 (baseline) to 3 and 12 months, to examine the role of dynamic structure. Second, we test the robustness of the instrument itself by varying the maturity of the oil futures contract (using 1- and 2-month horizons instead of 3-month) and by estimating the model separately for US and Euro Area employment announcements. Across all cases, the impulse responses remain stable in direction and temporal dynamics, with only minor differences in magnitude or statistical significance.

Figures B.2 and B.3 presents the impulse responses estimated using 3 and 12 lags, respectively, in the VAR instead of the baseline specification with 2 lags. The main dynamics are preserved: EMEs industrial production rises on impact, the consumer price index increases moderately, the real exchange rate appreciates over time, and sovereign spreads compress sharply. One minor difference can be seen in the model with 12 lags, where the real exchange rate initially depreciates slightly in the first few months. This effect is somewhat counterintuitive, although not statistically significant, and is followed by a sustained appreciation. In general, confidence intervals are somewhat wider, as expected with a larger lag structure, but the responses remain broadly significant.

Results are also highly robust to changing the maturity of the oil futures contract used in the instrument. Figures B.4 and B.5 show the impulse responses using 1-month and 2-month oil futures, respectively, instead of the baseline 3-month contract. The responses across all emerging market variables are virtually identical to the baseline, confirming that the results are not sensitive to the particular horizon chosen in the futures curve.

We also estimate the model using only employment announcements from each region separately, rather than combining surprises from the US and the Euro Area. Figure B.6 displays the IRFs using US announcements and 3-month oil futures. The results for EMEs remain highly consistent, with increases in EMEs industrial production, moderate inflation, currency appreciation, and a significant decline in EMBI spreads. Figure B.7 presents the results based on Euro Area announcements. The dynamics are again very similar, suggesting that both regions' announcements provide valid high-frequency information about global demand conditions relevant to EMEs.

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 proposed instrument captures changes in expectations about global economic activity in real time and builds on the growing literature in proxy SVAR frameworks. It addresses a gap in the empirical analysis of oil market dynamics, where the distinction between supply- and demand-driven price movements remains critical.

Our findings are theoretically consistent with the observed transmission of global demand shocks to emerging markets. The results show a global expansionary and stabilizing effect of a positive global demand shock on output, exchange rates, sovereign risk, and inflation, with important 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 suggests 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 hope 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. **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).

7. **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).

8. **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.

9. **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).

10. **Employment Announcements:** Data are obtained from Bloomberg using the USURTOT Index and UMRTEMU Index tickers. These indices capture the release dates of the U.S. 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.

11. **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 U.S. 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.

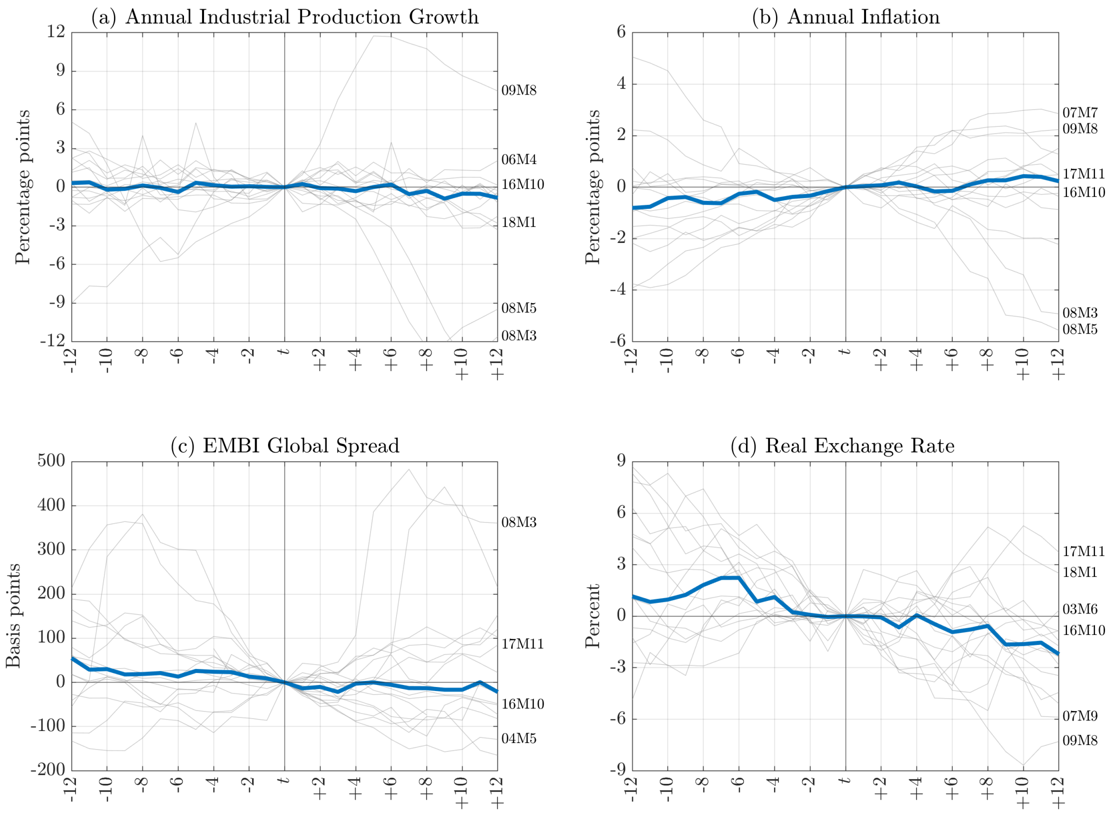
Table A.2: Summary statistics of key variables and instruments

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
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
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	Δ Price	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: Most Extreme Oil Futures Changes and Economic Events

Label	Rank	Date	Region	Price Variation	Event Description
A	Highest 1st	06/06/2008	US	10.28	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. The US unemployment rate jumped to 5.5%, marking the largest one-month increase in 22 years.
B	Highest 2nd	08/03/2012	US	4.16	Oil prices rose sharply, driven by expectations of further monetary stimulus in the US and positive US economic data. Investors also reacted to strong nonfarm payrolls, fueling speculation about future Fed policy. Strong July payroll data eased pressure on the Fed to act immediately, though further easing remained on the table.
C	Highest 3rd	05/02/2008	US	4.08	Prices of major commodities surged broadly, with Brent crude reaching record highs. Market participants cited strong global demand, particularly from China, as well as rising inflation concerns and expectations of monetary tightening in emerging markets. Employment data came in better than expected, with smaller job losses and a lower unemployment rate than forecast.
D	Highest 4th	03/17/2011	EA	3.48	Markets responded to the escalating crisis at Japan's Fukushima nuclear plant following the earthquake and tsunami. Risk sentiment deteriorated globally, with increased demand for safe-haven assets and falling equity prices.
E	Highest 5th	11/16/2011	EA	3.13	Italian sovereign debt came under pressure as 10-year bond yields rose to unsustainable levels. The euro area crisis intensified, triggering concerns about contagion and further political instability in the region.
F	Lowest 1st	09/15/2008	EA	-5.58	The collapse of Lehman Brothers marked a critical point in the global financial crisis. Severe disruptions in credit markets and heightened risk aversion led to a sharp sell-off across global equities and commodities.
G	Lowest 2nd	06/15/2011	EA	-4.60	Massive protests erupted in Greece amid growing resistance to fiscal austerity. Concerns over political instability and sovereign default risk triggered a sharp decline in the euro and increased volatility across European markets.
H	Lowest 3rd	10/16/2008	EA	-4.55	Oil prices fell sharply following reports of rising US inventories. The drop was compounded by mounting fears of a global recession and heightened financial stress in the aftermath of the Lehman collapse.
I	Lowest 4th	03/17/2008	EA	-4.53	The emergency sale of Bear Stearns to JPMorgan, backed by the Fed, raised alarm about the depth of the financial crisis. Markets reacted with extreme caution as liquidity dried up and confidence collapsed.
J	Lowest 5th	05/04/2012	US	-4.04	Oil prices declined to a four-month low as renewed political uncertainty in the euro area, particularly surrounding upcoming elections, raised concerns about fiscal stability. Markets reacted with increased caution amid deteriorating risk sentiment.

Note: The table shows the most extreme daily changes in 3-month oil futures prices following United States (US) and Euro Area (EA) employment data releases. For each event, we identify the label in Figure 1, the corresponding date, region, the magnitude of the change, and associated economic news or developments.

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

Instrument	EMEs		Global		Exporter		Importer	
	L=2	L=12	L=2	L=12	L=2	L=12	L=2	L=12
US Employment Announcement								
Chng. in 1-month WTI future	24.48	10.90	21.08	13.55	15.48	13.16	20.86	5.19
Chng. in 2-month WTI future	23.59	10.59	21.10	13.70	14.53	12.66	20.13	5.06
Chng. in 3-month WTI future	22.98	10.57	21.01	13.87	14.35	12.38	19.80	4.83
EA Employment Announcement								
Chng. in 1-month WTI future	9.42	6.87	7.45	7.07	6.62	3.42	8.76	6.02
Chng. in 2-month WTI future	9.22	7.08	7.00	6.50	6.35	3.37	8.49	5.84
Chng. in 3-month WTI future	9.38	7.49	7.07	6.42	6.52	3.37	8.67	5.95
US and EA Employment Announcement								
Chng. in 1-month WTI future	32.92	17.41	27.20	20.11	21.49	15.10	29.28	10.81
Chng. in 2-month WTI future	31.35	17.17	26.14	19.31	19.94	14.35	27.73	10.40
Chng. in 3-month WTI future	30.91	17.54	26.04	19.30	19.91	14.05	27.57	10.24

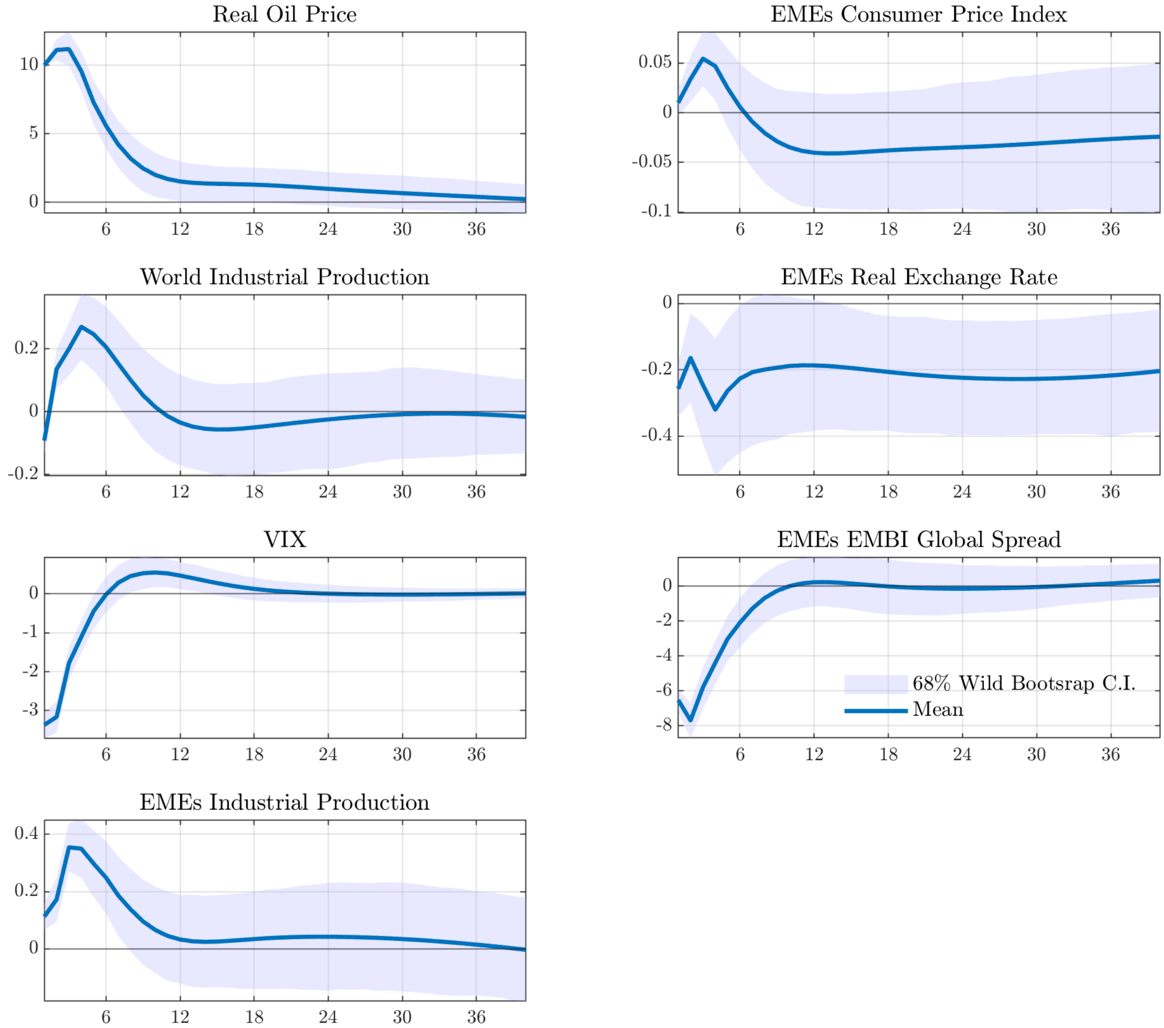
Note: The EMEs specification uses data from February 2000 to December 2019, while the Exporter and Importer models are estimated from January 2006 to December 2019 due to limited data availability. The EMEs model includes real oil prices, world industrial production, VIX, and emerging markets aggregates (industrial production, CPI, EMBI Global, and REER). The Global model includes world oil inventories instead of emerging market aggregates. Exporter and Importer models disaggregate EMEs variables by net oil trade position. Results are shown for VAR models with 2 lags (L=2) and 12 lags (L=12).

Table B.3: Lag length selection criteria for baseline model

Lag	Log-likelihood	LR	FPE	AIC	SIC	HQ
1	3591.0	5397.3	7.0e-23	-31.1	**-30.3**	-30.8
2	3674.8	156.6	5.2e-23	-31.5	-29.9	**-30.8**
3	**3732.5**	**104.2**	**4.8e-23**	**-31.5**	-29.2	-30.6
4	3768.2	62.2	5.4e-23	-31.4	-28.3	-30.2
5	3805.2	62.3	6.1e-23	-31.3	-27.5	-29.8
6	3837.7	52.6	7.2e-23	-31.2	-26.6	-29.3
7	3859.6	34.2	9.2e-23	-30.9	-25.6	-28.8
8	3880.1	30.7	1.2e-22	-30.7	-24.7	-28.2
9	3920.1	57.5	1.4e-22	-30.6	-23.8	-27.9
10	3968.2	66.1	1.4e-22	-30.6	-23.1	-27.6
11	3995.0	35.2	1.8e-22	-30.4	-22.1	-27.1
12	4038.3	54.1	2.1e-22	-30.3	-21.4	-26.7

Note: This table reports the lag length selection criteria for the baseline VAR model using monthly data from February 2000 to December 2019. Selection is based on log-likelihood, the sequential modified likelihood ratio test (LR), the final prediction error (FPE), and the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria. The bold entries indicate the selected lag order under each criterion.

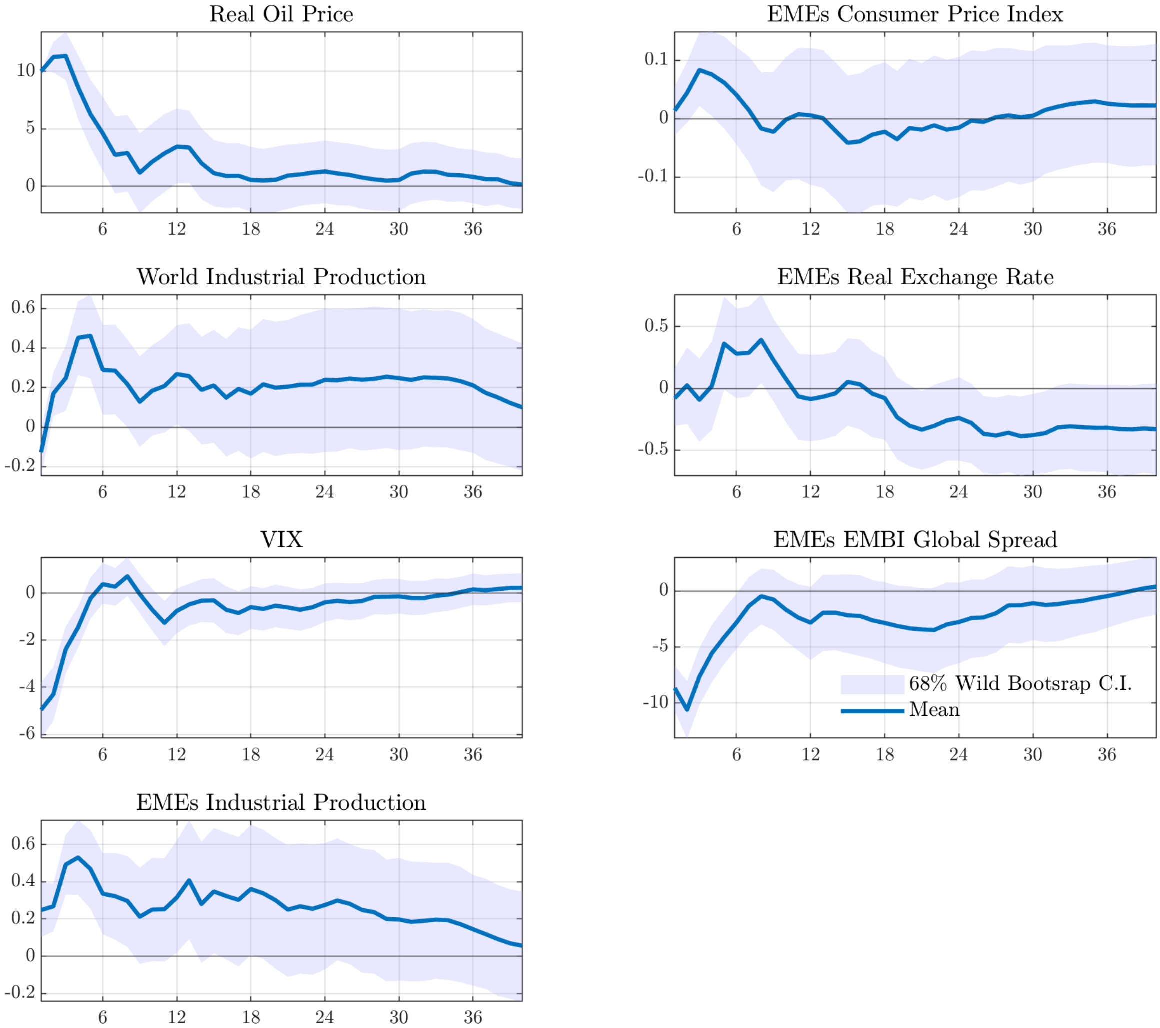
Figure B.2: Impulse Response - 3 lags VAR - Baseline Instrument



First-stage F-statistic = 28.63.

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 U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.

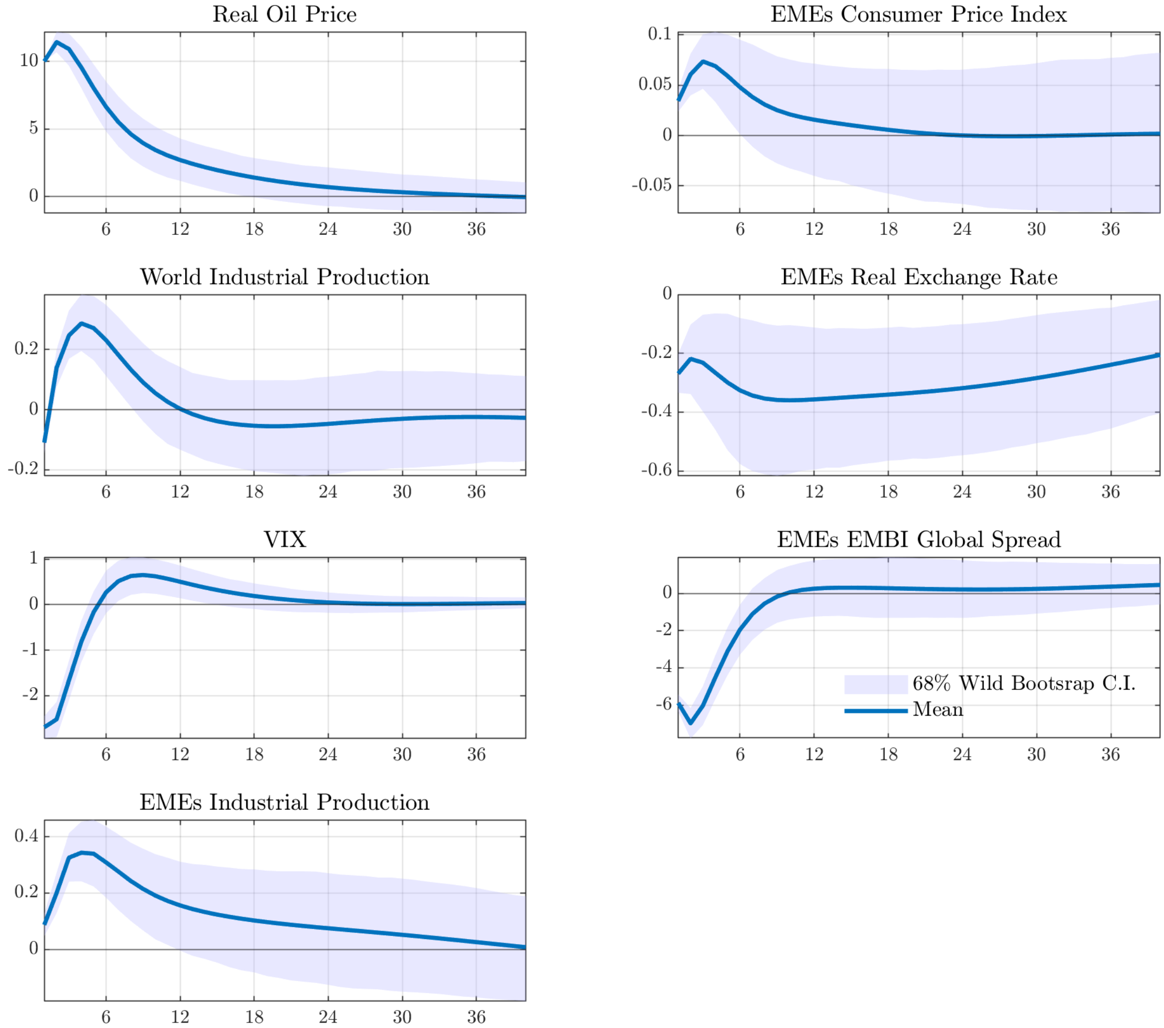
Figure B.3: Impulse Response - 12 lags VAR - Baseline Instrument



First-stage F-statistic = 17.54.

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 U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.

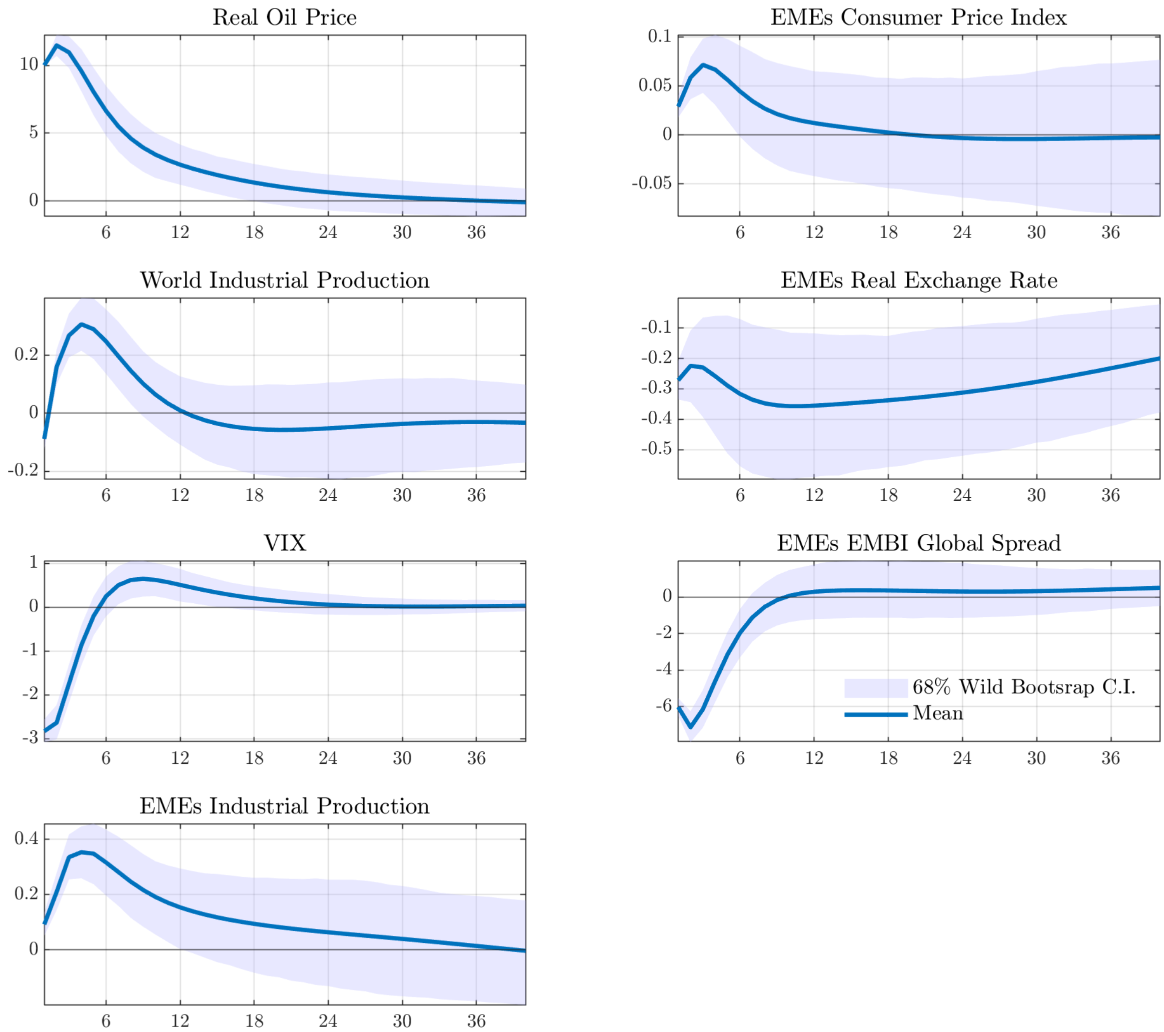
Figure B.4: Impulse Response - Baseline Instrument using 1-month futures



First-stage F-statistic = 32.92.

Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the **1-month** futures price variation around U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.

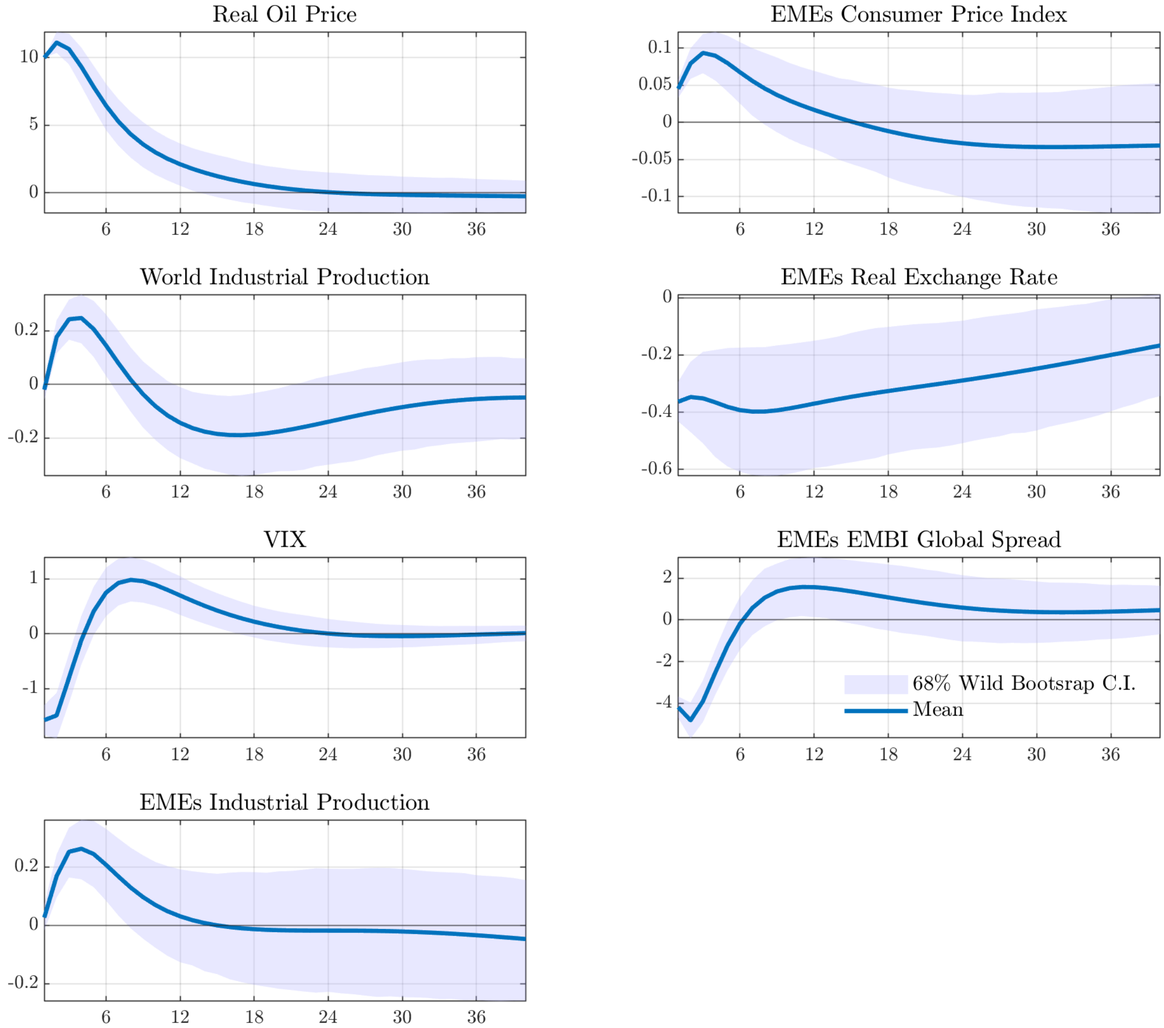
Figure B.5: Impulse Response - Baseline Instrument using 2-month futures



First-stage F-statistic = 31.35.

Note: The figures shows the estimated impulse responses to a 10% increase in the real price of oil, instrumented using the **2-month** futures price variation around U.S. and Euro Area employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.

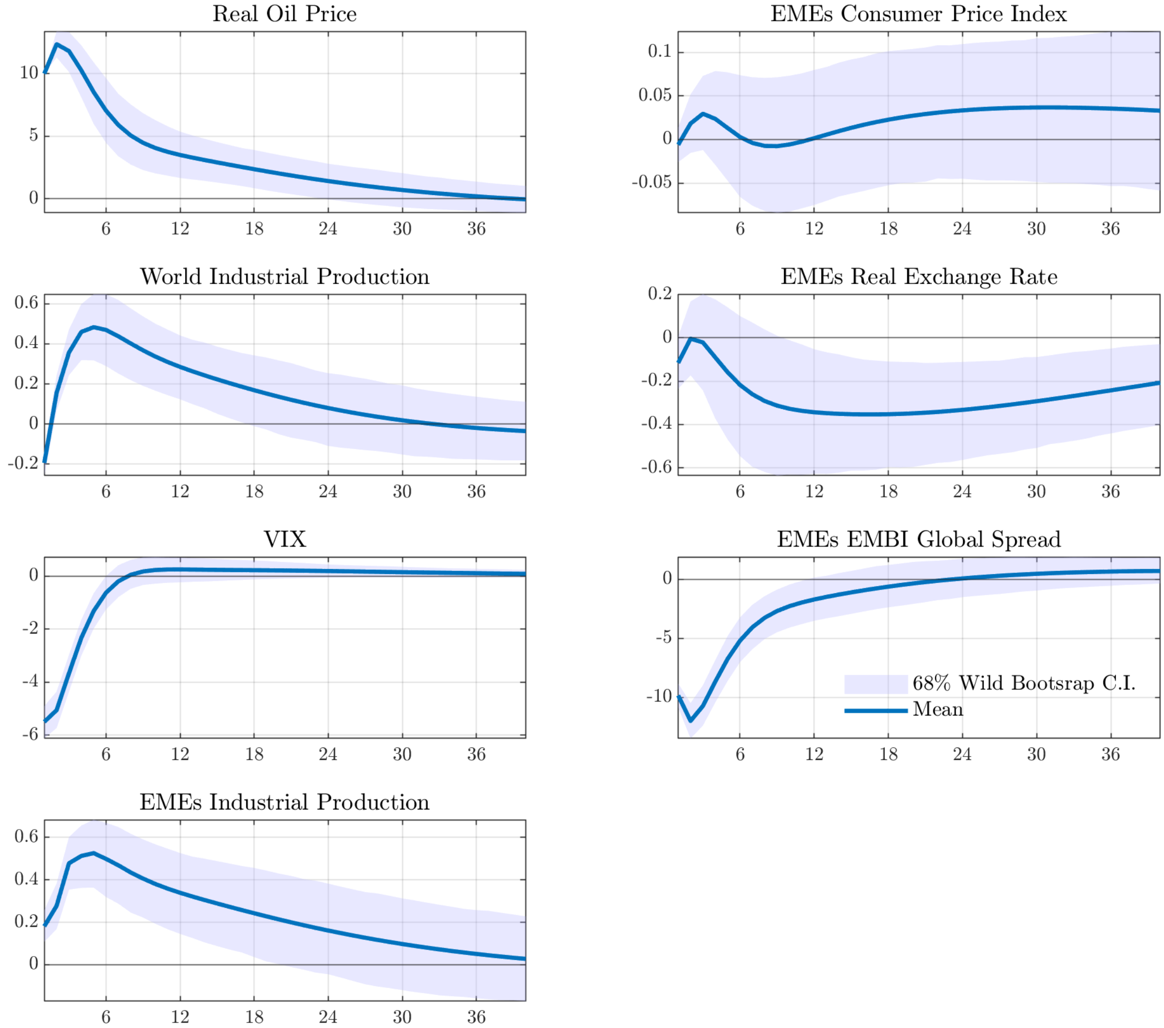
Figure B.6: Impulse Response - Instrumented using U.S. Only (3-month futures)



First-stage F-statistic = 22.98.

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 **U.S.** employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.

Figure B.7: Impulse Response - Instrumented using Euro Area Only (3-month futures)



First-stage F-statistic = 9.38.

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 **Euro Area** employment announcements, as described in Section 3.2. The Baseline specification includes the logged variables: real oil price, world industrial production, CBOE Volatility Index (VIX), and emerging market aggregates for industrial production, consumer price index, EMBI Global spread, and real exchange rate. An increase in the REER is interpreted as a depreciation of EMEs' currencies. All figures show percent responses to the initial shock over a 40-month horizon.