



Contents lists available at SciVerse ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/enecoOil prices, exchange rates and emerging stock markets[☆]Syed Abul Basher^a, Alfred A. Haug^b, Perry Sadorsky^{c,*}^a Department of Research & Monetary Policy, Qatar Central Bank, P.O. Box 1234, Doha, Qatar^b Department of Economics, University of Otago, P.O. Box 56, Dunedin, New Zealand^c Schulich School of Business, York University, 4700 Keele Street, Toronto, Ontario, Canada M3J 1P3

ARTICLE INFO

Article history:

Received 12 April 2011

Received in revised form 30 September 2011

Accepted 1 October 2011

Available online xxxx

JEL classification:

G15

Q43

Keywords:

Emerging market stock prices

Oil prices

Exchange rates

SVAR

ABSTRACT

While two different streams of literature exist investigating 1) the relationship between oil prices and emerging market stock prices and 2) the relationship between oil prices and exchange rates, relatively little is known about the dynamic relationship between oil prices, exchange rates and emerging market stock prices. This paper proposes and estimates a structural vector autoregression model to investigate the dynamic relationship between these variables. Impulse responses are calculated in two ways (standard and the recently developed projection based methods). The model supports stylized facts. In particular, positive shocks to oil prices tend to depress emerging market stock prices and US dollar exchange rates in the short run. The model also captures stylized facts regarding movements in oil prices. A positive oil production shock lowers oil prices while a positive shock to real economic activity increases oil prices. There is also evidence that increases in emerging market stock prices increase oil prices.

© 2011 Elsevier B.V. All rights reserved.

1. Introduction

The recent surge in oil prices over the past 8 years has generated a lot of interest in the relationship between oil prices, financial markets and the economy (see, for example, Blanchard and Gali, 2007, and Herrera and Pesavento, 2009). Crude oil spot prices, measured using West Texas Intermediate crude oil, closed out the year 2002 at \$29.42 per barrel. By June of 2008 spot oil prices had risen to \$133.93 per barrel. Over this same time period, the US dollar fell against other major traded currencies and emerging market stock prices rose (Fig. 1). While there exists a literature on the relationship between oil prices and stock prices, and a separate literature on the relationship between oil prices and exchange rates, the relationship between these two streams has, however, not been that closely studied, especially within the context of emerging market stock prices. The purpose of this paper is to use a structural vector autoregression (SVAR) model to bring these two literatures together.

Understanding the relationship between oil prices, exchange rates and emerging stock market prices is an important topic to study because as emerging economies continue to grow and prosper, they will exert a larger influence over the global economy. By some estimates, emerging economies will account for 50% of global GDP by 2050 (Cheng et al.,

2007) and the majority of economic growth. Over the period 1990 to 2007 real GDP in China and India grew at average annual rates of 10.0% and 6.3% respectively. By comparison, OECD countries grew at an average annual rate of 2.5% over this same period. At these growth rates the Chinese economy will double every 7 years and the Indian economy will double every 11 years. Along with this economic growth comes a voracious demand for energy products such as oil. In 2009, the US was the largest consumer of oil in the world, accounting for 22% of the global oil demand. China, at 10% of the world total, had overtaken Japan to become the second largest oil consuming nation (Table 1). While the demand for oil in developed economies is holding steady or declining slightly, the demand for oil in emerging economies is rapidly growing. The International Energy Agency (IEA) (2009, p. 81) predicts that between 2008 and 2030, China and India will have average annual growth rates in oil consumption of 3.5% and 3.9% respectively (compared to the 1.0% average annual growth rate for the world). China alone will account for 42% of the global increase in oil demand between 2008 and 2030.

Some emerging economies, like China, are accumulating large reserves of foreign currency (mostly US dollars) and this will make them a bigger player in the world financial markets. Some estimates place China's reserves of foreign exchange and gold at \$2.206 trillion as of December 2009. Managing this amount of money and protecting

[☆] The authors thank, without implicating, three anonymous referees, Daniel Mitchell and other participants at the WEAI Meeting in Portland (Oregon) for their helpful comments.

* Corresponding author.

E-mail addresses: bashers@qcb.gov.qa (S.A. Basher), alfred.haug@otago.ac.nz (A.A. Haug), psadorsk@schulich.yorku.ca (P. Sadorsky).

¹ <http://research.stlouisfed.org/fred2/data/OILPRICE.txt>.

² International Energy Agency (2009, p.62).

³ <https://www.cia.gov/library/publications/the-world-factbook/rankorder/2188rank.html>.

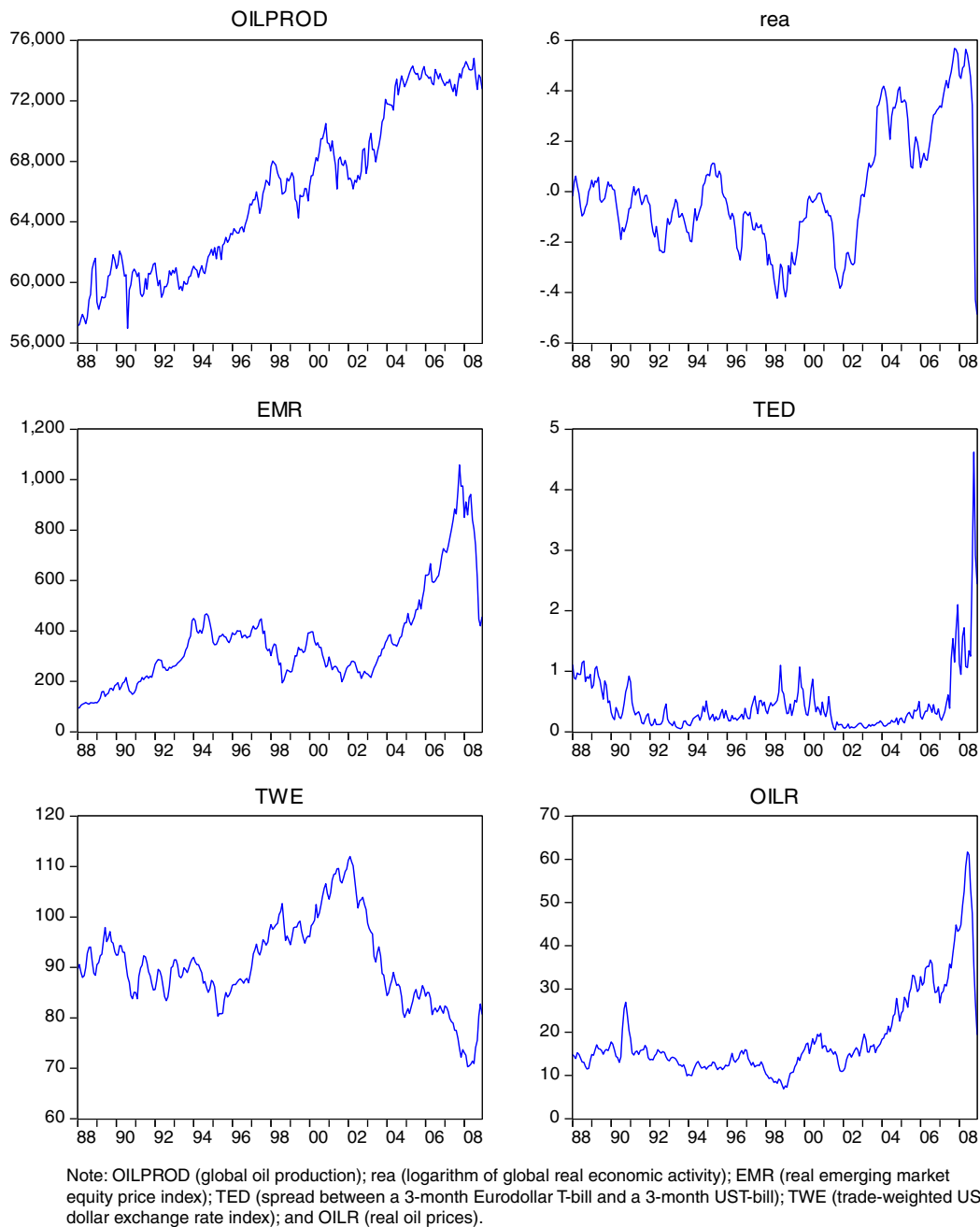


Fig. 1. Global oil production, real economic activity, emerging market stock prices, the US treasury/Euro interest rate spread, exchange rates, and oil prices.

its store of value will mean that China will have not only a greater participation but also a greater influence over global financial capital markets.

Shocks or unexpected price hikes originating from the oil market have been captured in different ways.⁴ Hamilton (2003) defines an oil price shock as a net oil price increase, which is the log change in the nominal price of oil relative to its previous 3 year high if positive, or zero otherwise. However, Kilian (2008a) argues that this measure of oil price shocks does not necessarily filter out oil price changes due to exogenous political events or wars because oil price shocks may be demand-driven.⁵ Furthermore, nominal oil price shocks do not mean that there are corresponding real oil price shocks. In order to account for these problems, Kilian (2009) uses a vector autoregression (VAR) with three variables, the oil supply,

the real price of oil and a proxy variable for global demand for industrial commodities measuring global real economic activity. He identifies, based on a recursive structure, three oil shocks: an oil supply shock, an oil-market specific shock and a global demand shock. Kilian (2009) treats these shocks as pre-determined in secondary ordinary least squares regressions analyzing their effects on the US economy.⁶ We model the oil market as in Kilian (2009), however, we use a much less restrictive set-up for the analysis of the effects of oil shocks that treats all variables as endogenous and allows for rich dynamics in the interrelations across markets.⁷

⁶ See also Kilian (2008b) for a different definition of oil shocks that are treated as strictly exogenous. These concepts correspond to weak and strong exogeneity in Engle et al. (1983).

⁷ We do not require the statistically un-testable assumption of pre-determinedness. Also, our approach does not cause problems with autocorrelated errors and generated regressors (the estimated oil shocks used in secondary regressions) when constructing confidence intervals (see Kilian, 2009).

⁴ This literature has been focusing on the US and European economies.

⁵ See Kilian and Vigfusson (2009) on empirical evidence against such price asymmetries. See also Hamilton (2010).

Table 1
The top 10 countries with the largest increase in oil consumption over the past 10 years.

| Oil consumption ('000 barrels per day) | 2008 | 2009 | Growth past 5 years | Growth past 10 years | Change 2009 over 2008 | 2009 share of total |
|--|--------|--------|---------------------|----------------------|-----------------------|---------------------|
| Qatar | 198 | 209 | 54.09% | 140.41% | 5.00% | 0.21% |
| China | 8086 | 8625 | 24.19% | 65.57% | 6.69% | 10.42% |
| Kazakhstan | 263 | 260 | 13.32% | 57.15% | −3.34% | 0.31% |
| Algeria | 311 | 331 | 32.00% | 57.06% | 6.49% | 0.38% |
| Kuwait | 370 | 419 | 24.79% | 54.33% | 9.79% | 0.49% |
| Saudi Arabia | 2390 | 2614 | 32.96% | 52.71% | 9.79% | 3.14% |
| United Arab Emirates | 475 | 455 | 22.28% | 51.81% | −4.95% | 0.56% |
| Ecuador | 207 | 216 | 42.62% | 49.90% | 5.24% | 0.25% |
| Singapore | 968 | 1002 | 29.23% | 48.14% | 3.49% | 1.34% |
| India | 3071 | 3183 | 21.25% | 39.99% | 3.70% | 3.83% |
| USA (ranked 52) | 19,498 | 18,686 | −10.39% | −4.36% | −4.87% | 21.71% |

Source: BP Statistical Review of World Energy, 2010.

Killian's approach has recently been used by several authors to investigate the impact of oil price shocks on stock prices or oil prices. Kilian and Park (2009) use four variables (the percentage change in world crude oil production, global real economic activity, the real oil price, and return on US stocks) to investigate the relationship between US stock prices and oil price shocks within the same modeling framework as in Kilian (2009). They find that while oil demand shocks do depress stock prices oil supply shocks have much less impact on stock prices. Apergis and Miller (2009) use a SVAR approach to analyze the effect of structural oil market shocks on the stock prices in eight developed economies (Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). They find that oil market shocks do not have a very large or significant impact on the stock prices in the countries studied. Killian's index of real economic activity has recently been used by He et al. (2010) to investigate the relationship between real economic activity and oil prices. They find that real oil future prices are cointegrated with the real economic activity index and a trade weighted US dollar index. They also find evidence of Granger causality running from the real economic activity index to real oil prices.

The approach taken in this paper is to use a SVAR to model the dynamic relationship between real oil prices, an exchange rate index for major currencies, emerging market stock prices, interest rates, global real economic activity and oil supply. The empirical results show that the six-variable SVAR model fits the data well in supporting some stylized facts. Impulse responses are calculated in two alternative ways (standard and local projection based methods) in order to check their robustness. The results presented in this paper help to further deepen our understanding of the relationship between oil prices, exchange rates and emerging market equity prices.

The rest of the paper is organized as follows. Section 2 discusses the theoretical and empirical relationship between oil prices, exchange rates and emerging stock prices. Section 3 describes the data and the identification of the structural VAR model. Section 4 presents the main results of the paper. It also includes the discussion of impulse responses based on the local projection methods and a discussion on the forecast error variance decomposition. Some concluding remarks appear in Section 5.

2. Relationships between oil prices, exchange rates and emerging stock markets

Theoretically, oil prices can affect stock prices in several ways. The price of a share in a company at any point in time is equal to the expected present value of discounted future cash flows (Huang et al., 1996). Oil prices can affect stock prices directly by impacting future cash flows or indirectly through an impact on the interest rate used to discount the future cash flows. In the absence of complete

substitution effects between the factors of production, rising oil prices, for example, increase the cost of doing business and, for non-oil related companies, reduce profits. Rising oil prices can be passed on to consumers in the form of higher prices for final goods and services, but this will reduce demand for final goods and services and once again reduce profits. Rising oil prices are often seen as inflationary by policy makers and central banks respond to inflationary pressures by raising interest rates which affects the discount rate used in the stock pricing formula.

There is a fairly sizable literature showing that oil price movements affect stock prices (see, for example, Basher and Sadorsky, 2006; Boyer and Filion, 2007; El-Sharif et al., 2005; Faff and Brailsford, 1999; Ferson and Harvey, 1994, 1995; Hammoudeh and Aleisa, 2004; Hammoudeh and Huimin, 2005; Hammoudeh et al., 2004; Henriques and Sadorsky, 2008; Huang et al., 1996; Huang et al., 2005; Jones and Kaul, 1996; Kaneko and Lee, 1995; Papapetrou, 2001; Park and Ratti, 2008; Sadorsky, 1999; Sadorsky, 2001).

While most of the research investigating the relationship between oil prices and stock prices has been conducted using developed economies, there is some research looking into the relationship between oil prices and emerging stock markets (see for example, Basher and Sadorsky, 2006; Hammoudeh and Aleisa, 2004; Hammoudeh and Huimin, 2005). On balance, these papers provide evidence that changes in oil prices affect emerging market stock prices.

Oil price movements are expected to depend upon the demand for oil. While the demand for oil in most developed economies is growing very slowly or hardly at all, demand for oil in emerging economies is rapidly increasing. Between 1999 and 2009, for example, oil consumption has grown the fastest in developing and emerging economies like Qatar, China, Kazakhstan, Algeria, Kuwait, Saudi Arabia, United Arab Emirates, Ecuador, Singapore, and India (Table 1). Over the past 10 years, most of these countries have experienced growth rates in oil consumption in excess of 50%. China is a particularly interesting country, because in 2009 China's share of global oil consumption was 10%, making it the second largest oil consuming country after the United States. For comparison purposes, the United States is included in Table 1. Notice that for the US, oil consumption growth is actually negative (−10.39%) in the period 1999–2009. The US is a very important player in the global oil market because it accounts for 22% of global oil consumption, but future growth and pricing pressure is likely to come from emerging economies. Over the past 5 years and 10 years, the fastest growing oil consuming region has been the Middle East (Table 2). The second fastest growing oil consuming region over the past 10 years has been Asia Pacific. Notice also, that as a region, Asia Pacific now accounts for approximately one third of global oil consumption. Regionally, the demand for oil is growing the fastest in the Middle East, Asia Pacific and Africa. Emerging market economic and financial activity is likely to be a factor behind oil

Table 2
Oil consumption growth by region.

| Oil consumption ('000 barrels per day) | 2008 | 2009 | Growth past 5 years | Growth past 10 years | Change 2009 over 2008 | 2009 share of total |
|--|--------|--------|---------------------|----------------------|-----------------------|---------------------|
| Total Middle East | 6864 | 7146 | 22.51% | 42.14% | 3.83% | 8.66% |
| Total Asia Pacific | 25,662 | 25,998 | 8.18% | 23.67% | 1.01% | 31.07% |
| Total Africa | 3045 | 3082 | 13.59% | 21.33% | 1.08% | 3.71% |
| Total S. and Cent. America | 5681 | 5653 | 14.88% | 14.20% | −0.82% | 6.59% |
| Total World | 85,239 | 84,077 | 2.18% | 10.56% | −1.70% | 100.00% |
| Total Europe and Eurasia | 20,193 | 19,372 | −3.88% | −1.99% | −4.21% | 23.54% |
| Total North America | 23,795 | 22,826 | −8.69% | −2.00% | −4.71% | 26.42% |

Source: BP 2010.

price movements. The idea that oil prices respond to strong economic growth in emerging economies, and especially Asia, has recently been discussed by [Benassy-Quere et al. \(2007\)](#).

The idea that there is a relationship between oil prices and exchange rates has been around for some time (early papers, for example, include, [Golub, 1983](#) and [Krugman, 1983a,b](#)). [Bloomberg and Harris \(1995\)](#) provide a good description, based on the law of one price, of how exchange rate movements can affect oil prices. Commodities like oil are fairly homogeneous and internationally traded. The law of one price asserts that as the US dollar weakens relative to other currencies, *ceteris paribus*, international buyers of oil are willing to pay more US dollars for oil. [Bloomberg and Harris \(1995\)](#) find that, empirically the negative correlation between commodity prices and the US dollar increased after 1986. In addition to the theoretical and empirical work by [Bloomberg and Harris \(1995\)](#), empirical papers by [Pindyck and Rotemberg \(1990\)](#) and [Sadorsky \(2000\)](#) find that changes in exchange rates impact oil prices. [Zhang et al. \(2008\)](#) find a significant influence of the US dollar exchange rate on international oil prices in the long run, but short-run effects are limited. [Akram \(2009\)](#) also finds that a weaker dollar leads to higher commodity prices. Current observations suggest that oil prices and exchange rates do move together. [Fig. 1](#), for example, shows a plot of oil prices (measured in US dollars) and a trade-weighted US dollar exchange rate (with a higher value indicating an appreciation of the US dollar while a lower value indicates a depreciation of the US dollar). From [Fig. 1](#), it appears that rising oil prices do coincide with a weakening of the US dollar.

[Golub \(1983\)](#) and [Krugman \(1983a,b\)](#) put forth arguments as to why movements in oil prices should affect exchange rates. Golub reasons that an increase in oil prices will generate a current account surplus for oil exporters (like OPEC) and current account deficits for oil importers. This creates a reallocation of wealth that may impact exchange rates. If OPEC's increased demand for dollars is less than the reduction in the demand for dollars by oil importing countries, then there will be an excess supply of dollars and the dollar will depreciate. Golub's formal model depends upon the crucial assumption that the demand for oil in oil-importing countries is price inelastic and if the price elasticity is greater than one (in absolute value) an increase in oil prices will lower total expenditure on oil and the demand for US dollars would fall. [Krugman \(1983a,b\)](#) develops six stylized models to show that the impact of higher oil prices on exchange rates is complicated and depends upon assumptions about trade balances, trade elasticities, capital flows and speculation. In [Krugman \(1983b\)](#), for example, a model with speculation is developed that shows how exchange rates can either rise or fall in the short-run in response to an increase in oil prices. Rising oil prices increases incomes for oil exporters and if these petro dollars are recycled back into dollars then the demand for dollars rises in the short-run. Alternately, the long-run expectation is that oil importers will experience a depreciation in their currencies because of the adverse terms of trade effect and this expectation of future depreciation is enough to produce a drop in the dollar in the short-run even if petro dollars are recycled.

Research by [Amano and van Norden \(1998\)](#), [Chen and Chen \(2007\)](#), [Chen and Rogoff \(2003\)](#), [Golub \(1983\)](#), [Huang and Guo \(2007\)](#), [Lizardo and Mollick \(2010\)](#) and [Zhou \(1995\)](#) find empirical support for the hypothesis that movements in oil prices affect exchange rates.

This discussion on the relationship between oil prices and exchange rates highlights that there are strong theoretical arguments for why exchange rates should affect oil prices and there are strong theoretical arguments for why oil prices should affect exchange rates. Ultimately, the relationship between these two variables can only be resolved through empirical analysis.

Interest rates may also affect oil prices through a connection with inflation. Unexpected inflation erodes the real value of investments like stocks and bonds. Central banks can respond to inflationary pressures by raising interest rates. International investors looking for better investments in inflationary times may prefer to invest in real assets like oil, which drives the price of oil up and puts further pressure on inflation. Recycled petro-dollars from oil rich countries can help to reduce the impact of increases in interest rates ([IEA, 2006, p.39](#)). [Akram \(2009\)](#) finds that commodity prices increase in response to reductions in real interest rates.

3. Model specification

3.1. Choice of variables

For this study, monthly data is collected on global oil production, oil prices, global real economic activity, exchange rates, emerging market stock prices and interest rates. Our monthly data cover the sample period from 1988:01 to 2008:12. Following a large body of research on the significant effect of energy supply disruptions on economic activity,⁸ an oil production variable is included in our model to capture oil supply shock. Following [Kilian \(2009\)](#), the oil supply shocks are defined as unpredictable innovations to global oil production. Data on global oil production over the 1987:12–2008:4 period were taken from [Hamilton \(2009\)](#),⁹ while the remaining data were updated from the US Energy Information Agency (EIA) database. In the EIA data, global oil supply is defined as crude oil including lease condensate.

Recent research has documented that the oil price reacts differently to oil demand shocks than oil supply shocks. In particular, [Kilian \(2009\)](#) finds that oil price increases due to surging global demand produce a less disruptive effect than those caused by losses in supply. Persistent increase in the (real) price of oil from 2002 to mid-2008 was mainly driven by strong and increasing global demand for crude oil particularly from India, China and other emerging countries

⁸ See [Hamilton \(2003, 2009\)](#) and the references therein. [Hamilton \(2009\)](#) concludes that "historical oil price shocks were primarily caused by significant disruptions in crude oil production that were brought about by largely exogenous geopolitical events."

⁹ The global oil production data can be downloaded from James Hamilton's homepage: <http://weber.ucsd.edu/~jhamilton/>.

(Hamilton, 2009; Kilian, 2008a). Therefore, to account for the effect of global demand on changes of oil price shocks, we have included a measure of global real economic activity. In so doing, we have followed Kilian (2009) and used the index of global real economic activity as a proxy for global demand for industrial commodities. The index is based on dry cargo single voyage ocean freight rates of different commodities: grain, oilseeds, coal, iron ore, fertilizer and scrap metal. It is likely to capture shifts in the demand for industrial commodities in global business markets. The detailed construction of the index is described in Kilian (2009). Unlike OECD indices of industrial production, used in some previous studies on the role of oil, Kilian's measure captures recent large increases in global demand for industrial commodities from emerging countries such as Brazil, China and India. Such a dry goods measure is more useful for gauging what is happening globally and the movements in economic and financial activity in emerging economies in particular, where manufacturing plays an important role. The index is deflated by the US consumer price index (CPI) and is linearly detrended in order to remove the effects of technological advances in ship-building and other long-term trends in the demand for sea-transport. The detrended index therefore should capture the cyclical variations in ocean freight rates. The index is available to download from Lutz Kilian's homepage.¹⁰

Oil prices are measured in dollars per barrel using spot market prices on West Texas Intermediate crude oil. Over the time period studied, West Texas Intermediate crude oil is widely seen as a benchmark for world oil markets. Exchange rates are measured using a trade-weighted exchange rate index which is a weighted average of the foreign exchange value of the US dollar against a set of the most widely traded currencies.¹¹ Globally, there are only a few currencies that have enough trading volume to affect the foreign exchange markets and oil prices. We therefore use an exchange rate that captures movements in the most widely traded currencies. Also, several other currencies not included peg or have pegged their domestic currency to the US dollar. Higher values of the exchange rate index indicate a stronger US dollar. Emerging market stock prices are measured using the MSCI emerging stock market index (measured in US dollars).¹² In this paper, the proxy variable for global interest rate movements is calculated as the difference in the yield spread between the 3 month Eurodollar LIBOR (London Interbank Borrowing Rate) and the 3 month US Treasury bill rate (the "TED spread"). The yield spread is an interesting variable to include because movements in the yield curve are often a good predictor of future economic performance. Further, fluctuations in the TED spread may capture fluctuations in global credit risks (Ferson and Harvey, 1994, 1995).

The data on oil prices, exchange rates and interest rates are available from the Federal Reserve Bank of St. Louis. Stock price data are

available from Datastream. Oil prices and stock prices are converted to real values by deflating by the US CPI. For modeling purposes, they are expressed in natural logarithms. A dummy variable, which takes on the value of one from September 1998, is included to capture structural change due to the Asian financial crises.

3.2. The structural VAR model

The empirical model uses global oil production (OILPROD), the natural logarithm of global real economic activity (rea), real emerging market stock prices (EMR), real oil prices (OILR), a trade-weighted exchange rate index expressed in US dollars (TWE) and an interest rate spread (TED). Our VAR model is based on monthly data for $y_t = (\text{oilprod}_t, \text{rea}_t, \text{emr}_t, \text{TED}_t, \text{twe}_t, \text{oilr}_t)'$. Except for TED, the logarithms of the remaining variables are expressed in lower case letters. The reduced form VAR is given by

$$y_t = c + \sum_{i=1}^p A_i y_{t-i} + D_t + u_t, \quad (1)$$

where c is a vector of constants, p denotes the lag length, A_i are the 6×6 parameter coefficient matrices, D_t is a dummy variable to capture the possible effect of the Asian financial crisis on emerging market stock prices and u_t is a vector of error terms. The structural representation of (1) is given by

$$A y_t = c + \sum_{i=1}^p A_i^* y_{t-i} + \varepsilon_t, \quad (2)$$

where ε_t denotes the vector of structural shocks. Note that the Asian financial crisis dummy variable does not enter in (2). Denote the total number of variables in the VAR by K . Assuming $E(\varepsilon_t \varepsilon_t') = D_K$, where D_K is a K -dimensional diagonal matrix that is restricting the structural shocks hitting the system to be mutually uncorrelated innovations, and premultiplying (1) with A yields the relationship between the reduced-form errors u_t and the structural shocks ε_t as¹³

$$A u_t = \varepsilon_t \text{ and } (A) E(u_t u_t') (A') = D_K. \quad (3)$$

After normalizing the K diagonal elements of A to 1s, an exact identification of the structural equation requires imposing $K(K-1)/2$ restrictions on A . We employ only short-run restrictions on contemporaneous relations and no long-run restrictions. Moreover, we do not impose any restrictions on the lagged coefficients in Eq. (2). The short-run restrictions impose some contemporaneous feedback effects among the variables in the model. Christiano et al. (2007) argue that structural VARs based on short-run restrictions perform "reasonably well". Since we do not attempt to test any particular model, we base our identification restrictions on different economic models as well as economic ad-hoc reasoning.

¹³ See e.g. Hamilton (1994, Ch. 11) for further details. The unobserved structural errors (shocks) have an economic interpretation, whereas the estimated reduced-form errors (shocks) do not.

¹⁰ <http://www-personal.umich.edu/~lkilian/>.

¹¹ We use the Federal Reserve Board trade weighted exchange index for major traded currencies index (TWEXMMTH). This index consists of the seven (euro, Canadian dollar, Japanese yen, British pound, Swiss franc, Australian dollar and Swedish krona) most widely traded currency markets outside of their respective home countries. The major currencies trade in liquid financial markets and the major currencies index can be used to gauge financial market pressures on the dollar. Details on the calculation of this index can be found in Loretan (2005).

¹² The MSCI emerging markets index is a free float-adjusted market capitalization index that is designed to measure equity market performance of emerging markets. MSCI classifies countries as emerging based on size and liquidity requirements and market accessibility criteria. MSCI has put together a very nice 20-year perspective on the MSCI emerging markets index (http://www.msicibarra.com/products/indices/em_20/msci_emerging_markets_index_20_year_anniversary_historical_timeline.html). The link above takes the reader to an interactive presentation and downloadable pdf file that shows the country additions/deletions to the index as well as the countries with the largest weight in the index. In 1988, the MSCI emerging markets index consisted of 10 countries (Argentina, Brazil, Chile, Greece, Jordan, Malaysia, Mexico, Philippines, Portugal and Thailand). Across time, countries have been added and subtracted from the index so that today the index consists of 21 countries (<http://www.msci.com/products/indices/tools/index.html#EM>).

3.3. Identification of structural shocks

The identification of A in Eq. (3) is achieved by imposing the following exclusion restrictions:

$$A = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{22} & 0 & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \\ 0 & a_{42} & 0 & a_{44} & 0 & a_{46} \\ 0 & a_{52} & a_{53} & 0 & a_{55} & a_{56} \\ a_{61} & a_{62} & 0 & 0 & 0 & a_{66} \end{bmatrix} \quad (4)$$

The restrictions on A may be motivated as follows. The identifying restriction in the equations for oil supply and global demand takes these two variables as being contemporaneously exogenous to the other variables in the system. We have thus assumed that both oil supply and global (oil) demand, due to real economic activity, do not contemporaneously react to shocks to other variables in the system within a month. These exclusion restrictions seem quite plausible since it is very unlikely for, say, Saudi Arabia to react immediately within the same month with a change to its crude production level following, for example, an oil price or an exchange rate shock. Likewise, it is quite probable that there might be a significant time delay before consumers and businesses revise their consumption plans following a shock. Needless to say, lagged values of oil supply and global demand are allowed to react to macroeconomic shocks after the first month has passed.¹⁴

Following the discussion in Section 2, emerging market equity prices are allowed to contemporaneously react to interest rate, exchange rate and oil price shocks, besides reacting to aggregate demand shocks. Unlike the long delay in adjustments in the goods sectors, financial markets react swiftly to changes in macroeconomic news. For example, energy based equities will react instantaneously to a positive change in the oil price, while a dollar appreciation effectively makes emerging equities less competitive than dollar-denominated assets. In the fourth equation, the interest rate spread is allowed to react contemporaneously to a global demand shock and an oil price shock, with the former predicted to generate a positive impact on interest rates while the latter is presumably inversely related to interest rates.

Changes in global demand, emerging market equity prices and oil prices result in a contemporaneous change in the trade-weighted US dollar index. Since oil is denominated in dollars, in the face of a declining dollar, with the relative price of oil being set in equilibrium, the dollar price of oil must rise instantaneously. Fig. 1, which depicts the time series of the oil price and the trade-weighted value of the dollar (along with the remaining model's variables), does seem to lend support to this idea, especially since the start of 2002. Relative strength in global demand is also likely to impact the US dollar within the same month because of the dollar's role as the dominant invoicing currency in international trade (see, Goldberg and Tille, 2008). In the sixth and final equation we assume that changes in global oil production and global aggregate demand contemporaneously affect real oil prices.

4. Empirical results

This section is divided into four parts. First, we present preliminary results on the time series properties of our data. Second, we present the main results of the paper, the restricted structural VAR analysis for the model discussed in Section 3.3. Third, we study the robustness of the impulse response analysis by employing local

¹⁴ Crude oil price shocks affect shipping freight rates because bunker fuel oil is an input to shipping services. However, following Kilian (2009), we assume that the effect occurs with a delay and not within the same month. Kilian (2009) found no contemporaneous correlation between the two time series.

projection instead of standard methods. Fourth, we present the results obtained from forecast error variance decomposition.

4.1. Preliminary results

4.1.1. Graphical and descriptive analysis

Fig. 1 shows a plot of global oil production (OILPROD), the logarithm of real global economic activity (rea), emerging market real stock prices (EMR), the TED spread, exchange rates (TWE) and real oil prices (OILR). Notice how closely oil prices and emerging market stock prices track each other. Both tend to rise and fall often at the same time. Also notice that exchange rates and oil prices tend, for the most part, to move in opposite directions. A lower US dollar coincides with higher oil prices and vice versa.

Table 3 presents some summary statistics of the model's variables. Some remarks are in order. The average real oil price during the sample period is \$18.59, with a maximum of nearly \$62 observed during mid-2008. A 5.863% decline in the rate of change of global oil production took place in August 1990, as a result of the Iraqi invasion of Kuwait (the first Gulf war). Interestingly, this decline is immediately compensated by a 4.473% increase in global oil production in the following month (September 1990). The yield spread between the 3-month Eurodollar LIBOR and the 3-month US T-bill (the TED spread) was generally higher during the end of the sample, reflecting the effect of the 2007–08 global financial crisis. For example, a 4.620 spread was observed in October 2008, a month after the collapse of Lehman Brothers, which is extremely large by comparison to the pre-2007 period. The coefficient of variation, a normalized measure of dispersion, which is defined as the ratio of the standard deviation to the absolute value of the mean, portrays the highest variability for real global activity followed by the TED spread. The US dollar exchange rate index (TWE) has the second least variability compared with other variables. Further, the skewness and kurtosis statistic for the dollar index is very close to normality, which is further supported by the Jarque–Bera test statistic, suggesting that the null hypothesis of normality is not rejected for the exchange rate, while the null of normality is strongly rejected for the remaining variables.¹⁵

4.1.2. Unit roots and cointegration

Table 4 presents results of unit root tests of the variables. We apply the DF-GLS test of Elliott et al. (1996) for our unit root test. When testing for $I(1)$, i.e., unit roots, we allow for a constant and deterministic time trend in the regression, except for the yield spread (TED) and log of the exchange rate (twe). The DF-GLS test is based on applying the well-known Dickey–Fuller τ -test to locally demeaned or demeaned and detrended series. It is generally more powerful than the standard Augmented Dickey–Fuller unit root test. Ng and Perron (2001) study the size and power properties of the DF-GLS test in finite samples. They recommended using a modified Akaike criterion (MAIC) for selecting the lag length. We applied the modification to MAIC suggested by Perron and Qu (2007). Results show that, save for oil production, the variables are non-stationary, as the null hypothesis of a unit root cannot be rejected at the conventional 5% level of significance.¹⁶

We tested the null hypothesis of no cointegration. We applied three commonly used cointegration tests: the Engel–Granger (with MAIC), Phillips–Ouliaris \hat{Z}_α and Johansen trace and maximum

¹⁵ VARs are generally quite robust to such non-normalities.

¹⁶ We also applied a break test suggested by Harris et al. (2009) that allows for a single unknown change in the intercept and slope of the trend function under both the null and alternative hypotheses when testing for a unit root. A unit root with a break is not rejected for all variables, except for oil production and the oil price. This test detects breaks in all series, towards the end of the 1990s and at the beginning of the 2000s. This likely reflects the impact of the Asian financial crisis and its aftermath. We therefore include in our impulse response models a dummy variable in order to account for this crisis.

Table 3

Summary statistics: January 1988 to December 2008.

| | OILPROD | rea | EMR | TED | TWE | OILR |
|--------------------------|------------|---------|----------|----------|---------|---------|
| Mean | 65,974.750 | −0.002 | 360.221 | 0.448 | 90.494 | 18.594 |
| Median | 66,105.720 | −0.040 | 329.882 | 0.300 | 89.615 | 15.295 |
| Maximum | 74,821.130 | 0.568 | 1058.376 | 4.620 | 111.990 | 61.709 |
| Minimum | 56,960.860 | −0.488 | 94.688 | 0.030 | 70.320 | 6.861 |
| Std. dev. | 5269.581 | 0.231 | 191.612 | 0.501 | 8.662 | 9.833 |
| Skewness | 0.167 | 0.607 | 1.445 | 3.911 | 0.239 | 2.025 |
| Kurtosis | 1.709 | 2.824 | 5.025 | 25.886 | 2.978 | 7.347 |
| Coefficient of variation | 0.080 | 126.701 | 0.532 | 1.117 | 0.096 | 0.529 |
| Jarque–Bera | 18.664 | 15.825 | 130.784 | 6142.212 | 2.412 | 370.583 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.299 | 0.000 |
| Observations | 252 | 252 | 252 | 252 | 252 | 252 |

Note: OILPROD (global oil production); rea (logarithm of global real economic activity); EMR (real emerging market equity price index); TED (spread between a 3-month Eurodollar T-bill and a 3-month US T-bill); TWE (trade-weighted US dollar exchange rate index); and OILR (real oil prices).

eigenvalue tests. We applied these tests to all possible pairs, triplets, quadruplets and quintuplets of variables and also to the six variables together. We found rather mixed evidence (not reported) depending on the test used, whether or not a linear time trend is considered, and on the lag selection method used. The VAR with all six variables shows two cointegrating vector with the trace test, however, only one with the maximum eigenvalue test, at the usual 5% significance level. Our conflicting evidence here is consistent with the findings of Gregory et al. (2004) for Monte Carlo simulations and for a comparison of alternative cointegration tests applied to 132 data sets from 34 studies.

The finding of unit roots in variables raises the question whether to estimate the structural VAR in levels (i.e., with variables in non-stationary form), first-differenced (i.e., with variables in stationary form) or in a VAR that imposes cointegration (i.e., in an error-correction model). A considerable literature on this issue tends to suggest that even if the variables have unit roots, it is still desirable to estimate a structural VAR in level. Sims et al. (1990) show that the estimated coefficients of a VAR are consistent and the asymptotic distribution of individual estimated parameters is standard (i.e., the asymptotic normal distribution applies) when variables have unit roots and there are some variables that form a cointegrating relationship.¹⁷ We do not impose possible unit roots and cointegration in our VAR. We justify the specification in levels based on the Monte Carlo results of Lin and Tsay (1996). The problem is that cointegration tests often indicate too many, or occasionally too few, cointegrating vectors and therefore lead to misspecification. On the other hand, a VAR specified in first differences assumes that variables are not cointegrated because no error-correction terms are included. If there is cointegration, then such a model in first differences is misspecified. The impulse response functions of the VAR model in levels are also consistent estimators of their true impulse response functions both in the short- and medium-run, except in the longer run. As shown by Phillips (1998), in the longer run the standard impulse responses do not converge to their true values with a probability of one when unit roots or near-unit roots are present and the lead time of the impulse response function is a fixed fraction of the sample size. For this reason, we apply an alternative method for estimating the impulse responses based on local linear projections suggested by Jordà (2005) that is robust to this problem.

4.2. The main SVAR model

The VAR consists of the six variables as defined previously: oilprod_t, rea_t, emr_t, TED_t, twe_t and oilr_t. The VAR lag length p is set at 4. The AIC chooses 3 lags. Following the approach of Toda and

Yamamoto (1995) one additional lag is added for unit roots. With this lag length, the residuals are randomly distributed and the VAR has stable roots. The identification system is given by (4). Abadir et al. (1999) study the analytical effects of including irrelevant variables in a VAR with non-stationary I(1) regressors and cointegration.¹⁸ They find that biases and mean-squared errors of the least squares and maximum likelihood estimators increase when economically irrelevant variables are added to such a VAR. This is in contrast to VARs with covariance-stationary variables, where adding irrelevant variables does not affect biases and only reduces efficiency. They recommend parsimonious modeling. For this reason, we considered reducing the dimension of the VAR. We dropped the interest rate spread (TED) because real economic activity (rea) and the exchange rate (twe) may possibly capture the same information as contained in TED. However, AIC chooses the specification with six variables over the specification with only five variables. Furthermore, the TED variable enters several of the equations in the VAR significantly, besides its own. The same results hold true when we tried dropping any one of the other variables. Hence, we employ the VAR with six variables.

Fig. 2 displays the response of global oil production, real economic activity, equity prices, interest rates, exchange rates and oil prices to a one-standard deviation structural innovation. The two-standard-error confidence intervals are shown by short-dashed lines. Our discussion of the impulse response functions (IRFs) mainly centers on the responses of oil supply, emerging equity prices, exchange rate, and oil prices to their own and other shocks, which is the main interest of the paper. Given oil production shocks and global demand shocks, as captured by global real economic activity shocks, are treated as contemporaneously exogenous to the other variables in the system, it is interesting to analyze how the two variables react to their own shock. As can be seen from Fig. 2, a positive oil supply shock causes a statistically significant increase in global oil production over a 20-month period.¹⁹ This possibly reflects the discovery of new oil fields, better extraction technologies or a decline in OPEC's control over the oil supply. By comparison, a positive global demand shock stimulates real economic activity in the first few months after the impact and then slowly winds down in a persistent fashion. It becomes statistically insignificantly different from zero after about 15 months, reflecting typical short-run macroeconomic multiplier effects over the business cycle from aggregate demand

¹⁸ We thank an anonymous referee for pointing out this issue to us.

¹⁹ Kilian (2009), among others, uses the percentage change in oil production instead of the log levels. We tried this measure but found no significant changes in the IRF graphs. In principle, one should treat all variables the same so that a log-level specification for oil production would seem preferable. Also, the two-standard-error confidence bands in our graphs are roughly equal to 95% confidence bands.

Table 4
DF-GLS unit root tests.

| Variables | DF-GLS statistic |
|--|------------------|
| Log of oil production (oilprod) | −3.61*** (trend) |
| Log of global real economic activity (rea) | −2.56 (trend) |
| Log of real emerging equity prices (emr) | −1.55 (trend) |
| TED spread (TED) | −0.59 |
| Log of US dollar index (twe) | −1.54 |
| Log of real oil prices (oilr) | −2.57 (trend) |

Note: the lag length is chosen using the modified AIC criteria, using the correction of Perron and Qu (2007). The maximum number of lags allowed is 15. *** denotes statistical significant at the 1% level. A deterministic linear time trend is included where noted.

stimulation.²⁰ A positive oil supply shock has little effect on emerging market equity prices and the effect is also not statistically significantly different from zero. On the other hand, an unanticipated demand expansion generates a small but persistently positive impact on equity prices. However, this effect is only statistically significant for the first 3 months. The reaction of equity prices to their own shock is corrected rather slowly. Following an unexpected increase, equity prices decline mostly linearly over the experiment period and reach a level that is insignificantly different from zero after about 18 months. This may indicate some inefficiencies in financial markets in emerging economies because one would expect shocks to dissipate more rapidly in well functioning markets. The effect of an unanticipated increase in the TED spread has a persistently negative and statistically significant effect for 16 months, from the time of the impact, on the real emerging market equity index. This is to be expected since a rising TED spread is an indication of a potential market downturn as liquidity is withdrawn, which negatively affects capital flows. Positive exchange rate shocks (measured by the trade-weighted US index) serve to place eventually downward pressure on emerging stock prices; however, the effect is not statistically significant.²¹ We should mention that the effects are somewhat imprecisely measured as reflected in the rather wide confidence band in the first half of the 24-month horizon. A stronger dollar encourages investors to invest in US dollar denominated assets, thereby slowing down investment activity in emerging markets.²² Finally, although the emerging stock price index reacts negatively to an oil price shock, quite surprisingly the effect is relatively small and not significant (or a borderline case at the beginning).

The responses of the US dollar trade-weighted exchange rate index to various macroeconomic shocks support fairly conventional theoretical views of open economy macroeconomics. Global oil supply shocks appear to have no visible effect on the exchange rate, judging by the nearly horizontal impulse function and its statistical insignificance. On the contrary, an unanticipated global demand expansion produces a lasting significant downward impact on the US dollar (i.e. depreciation) over the initial 15 months after the impact. This seems to suggest that the source of the global demand buoyancy

²⁰ Unanticipated demand expansion also leads to a sustained increase in oil production and in oil prices because of the associated increase in real economic activity. However, these effects are somewhat borderline cases in regard to their significance because the lower confidence band weaves along the horizontal axis, except for the oil price increases that are significantly different from zero over the first 12 months. Also, the exchange rate declines significantly over the first 15 months as demand expands.

²¹ A rising trade-weighted index indicates appreciation of the US dollar vis-à-vis trading partner currencies, and vice versa.

²² Many emerging countries, to some extent, tied their national currencies to the US dollar. Thus, another way to interpret the effect of the exchange rate shock on the emerging market price is that, if a stronger dollar is a consequence of tighter monetary policy in the USA, monetary authorities in the emerging markets would like to implement similar monetary tightening to maintain the fixed relation between the US dollar and their national currencies. Hence, tighter domestic monetary conditions could drag equity prices downward in emerging markets.

is not US originated. Indeed, the collapse of the US dollar over the 2002–2008 period combined with the simultaneous expansion of many emerging economies (e.g. Brazil, China and India) appears to be consistent with this evidence. The response of the US dollar index to an emerging market equity price shock is very small and insignificant. A positive TED spread shock only slightly rises at first the US dollar index for 5 months but then afterwards persistently increases it, though the effects are only of borderline significance. The eventual appreciation of the US dollar is likely a reflection of investors' deleveraging activity where a lasting rise in the TED spread leads investors to rush away from risky assets and favor dollar-denominated assets.²³ The exchange rate initially rises after the impact to its own shock and thereafter stays at the elevated level, indicating a permanent effect of the shock. This effect is statistically significant for 15 months after the shock occurred. The US dollar response to a positive oil price shock is negative, reflecting the *numeraire* effect as oil is priced in US dollar, and eventually dissipates. These effects are small and significant only for the first 5 months. This result is consistent with Krugman's (1983a) analysis that exchange rate movements are determined primarily by current account movements. In the case of a large net importer of oil like the United States, rising oil prices lead to a current account deterioration and then exchange rates will fall.

The reaction of the oil price to a positive oil production shock is negative for the first 8 months, as one would expect; effects are barely statistically significant for the first 5 months. A positive global demand shock increases the oil price after the impact for about 6 months, thereafter it stays at an elevated level and becomes insignificantly different from zero in 12 months after the impact. By contrast, the oil price displays a positive hump-shaped response to a positive equity shock but the effect is mostly not significant, except for the 2–8 month period after the impact, where it is of borderline statistical significance. A positive TED spread shock leads to a fall in oil prices after the impact for the first 3 months, staying permanently lower, though the effects fade into insignificance after the initial 8 months. Unanticipated exchange rate increases lower oil prices, the effect being significant for the first 8 months. Finally, oil prices increase after an oil price shock for 2–3 months and then fall steadily back to the original level. These effects are statistically significant for the first 15 months after the impact.

The results from our six-variable SVAR can be compared to the results for the oil market in Kilian's (2009) three-variable VAR with recursive identification. The data sets for the oil-market variables are not identical because we use updated data. The contemporaneous identification scheme for the three variables in our SVAR is almost identical, except that we set a_{21} equal to zero so that aggregate demand does not respond contemporaneously to an oil price shock, however, we explore in Section 4.3.2 whether this restriction affects our results. An oil supply shock (positive in our case) has very much the same effects on global oil production and on real oil prices as in Kilian (2009). It leads to a sharp increase in global oil production on impact, followed by a decline in months 5 to 8 after the shock but then stays at a higher level afterwards. However, an aggregate demand shock shows a somewhat different profile. It is persistent and highly significant as in Kilian (2009), but in our case the effect starts to decline already after 3–4 months instead of after 14 months in Kilian, and becomes insignificant after 15 months in our case but not in his case. An aggregate demand shock also increases oil prices for the first 6 months after the impact and then stays at an elevated level. In Kilian (2009) the increase is steady but significant only

²³ When the crisis intensified after the bankruptcy of Lehman Brothers, private foreign investors lowered the risk in their portfolios by turning to US Treasury securities. The global flight to safety into US Treasury bills during the recent financial crisis had in turn strengthened the US dollar (see, McCauley and McGuire, 2009). See also Melvin and Taylor (2009) for the implications of the deleveraging in financial markets on foreign exchange markets during the recent financial crisis.

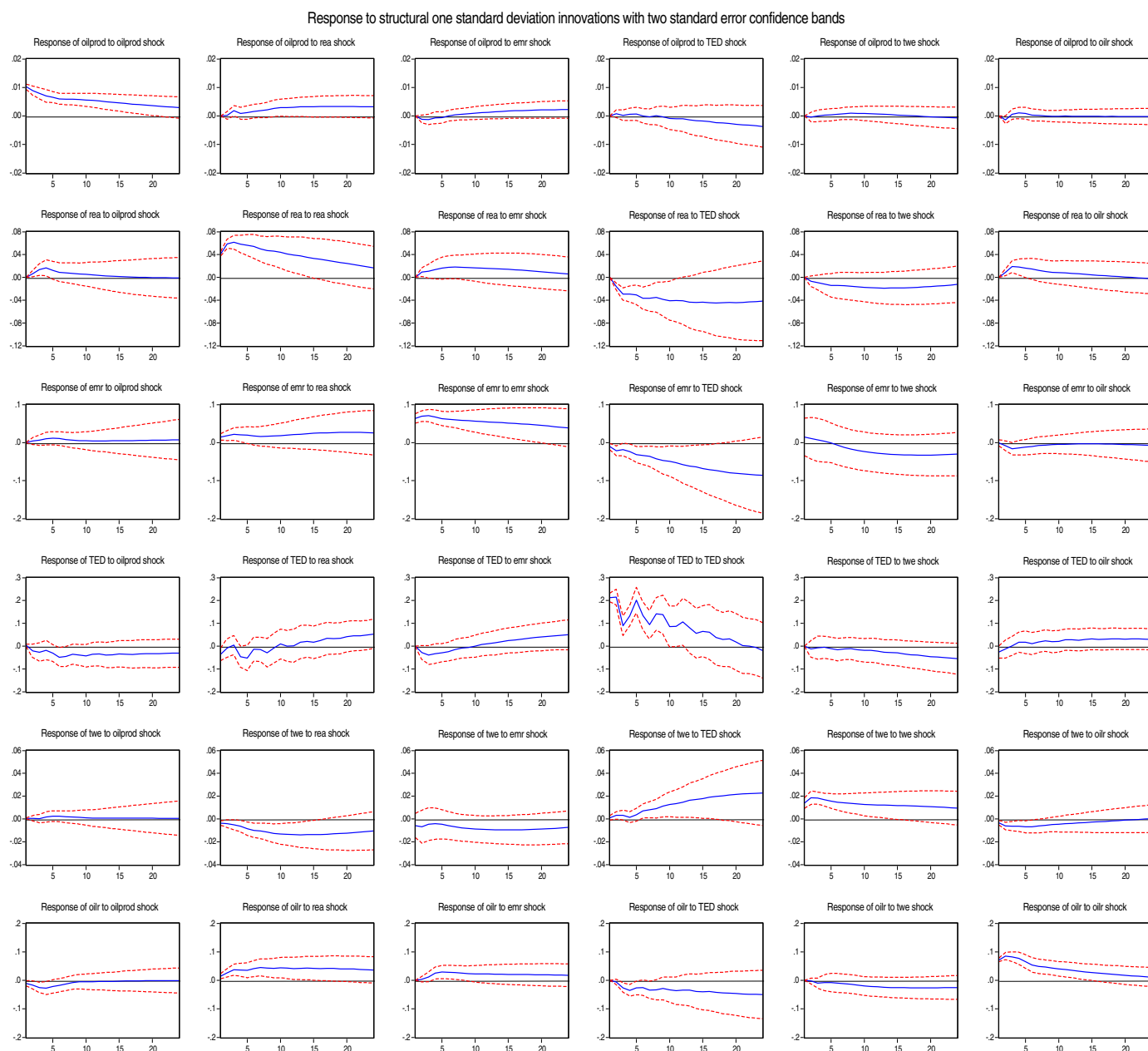


Fig. 2. Structural VAR impulse responses.

during the first 7–8 months, whereas in our case it is significant for 12 months. A positive oil price shock, interpreted by Kilian (2009) as a precautionary oil-specific demand shock, shows as similar profile over time in both analyses.²⁴ The effects of oil price shocks on real economic activity and oil production are not significant in our case, whereas Kilian (2009) found a positive but small effect on real economic activity.

²⁴ Hamilton (2009) questions the interpretation of these price shocks as precautionary demand shocks.

4.3. Robustness of the impulse responses

4.3.1. Different estimation method: local projection based impulse responses

The preceding impulse response functions were derived with standard impulse response function analysis. The standard method is based on a moving average representation of the VAR model. The VAR is estimated first and then a vector moving-average (VMA) is formed in order to derive the effects of experimental shocks on the variables over time. The impulse responses are derived iteratively, moving forward period-by-period, relying on the same set of original VAR parameter estimates each time. There are several problems with

the standard approach to impulse response analysis. These problems are magnified by the iterative process.

First, the true and generally unknown data-generating process of the economic model may be poorly approximated by a VAR, even with relatively long lag structures.²⁵ The reason is that moving average components in the data may not be captured adequately by the VAR. Second, VMA representations of the VAR may not be unique and different invertibility assumptions can lead to vastly different impulse responses.²⁶ Third, unit or near-unit roots and cointegration in the VAR can lead to inconsistent impulse responses at longer horizons when the lead time of the impulse response function is a fixed fraction of the sample size (Pesavento and Rossi, 2006; Phillips, 1998). These problems open various possibilities for misspecification of the VAR that might be relatively small. However, the highly non-linear transformations used in the derivation of standard impulse responses will amplify the effects of misspecifications and could lead to unreliable impulse response functions.

Jordà (2005) has proposed an alternative approach for deriving impulse response functions. Instead of non-linear transformations, local linear projections are applied in order to obtain impulse responses. An impulse response can be regarded as a revision in the forecast of a variable at a future horizon $t + s$ to a one-time experimental shock at time t . Jordà (2005) applies multi-step direct forecast for every horizon. The forecast or projection is local to the horizon, or put differently, a separate forecasting regression is run for every horizon. Jordà (2005) proves that impulse responses based on direct forecasts are consistent and asymptotically normal. Furthermore, he demonstrates in Monte Carlo simulations that local linear projections estimate impulse responses more accurately than standard methods, especially at medium to longer horizons. Also, the loss of efficiency from using local projection impulse responses (instead of a correctly specified VAR) appears to be very small. Local projection based impulse responses are more robust to misspecification than standard ones.

Jordà's (2005) local projection based impulses use a recursive causal ordering for structural shocks, which cannot be compared with the non-recursive identification schemes discussed in the previous section. Recently, Haug and Smith (forthcoming) have extended Jordà's (2005) method to a non-recursive identification scheme, which is appropriate for our purpose. Briefly, Jordà's (2005) method can be summarized as follows. Consider an n -dimensional vector y_t of random variables. Following Jordà (2005), we define the impulse response (IR) at time $t + s$ arising from the i th experimental shocks d_{it} at time t as:

$$IR(t, s, d_{it}) = E(y_{t+s} | \delta_t = d_{it}; X_t) - E(y_{t+s} | \delta_t = 0; X_t),$$

where $i = 0, 1, 2, \dots, n$; $s = 0, 1, 2, \dots$; $X_t \equiv (y_{t-1}, y_{t-2}, \dots)'$; d_i is a vector additively conformable to y_t ; and $\mathbf{0}$ is a vector of zeroes. The expectations are formed by linearly projecting y_{t+s} onto the space of X_t :

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + \dots + B_p^{s+1} y_{t-p} + u_{t+s}^s,$$

where α^s is a vector of constants and B_j^{s+1} are coefficient matrices at lag j and horizon $s + 1$. For every horizon $s = 0, 1, 2, \dots, h$, a projection or forecast regression is done in order to estimate the coefficients in B_j^{s+1} . The estimated IRF is then given by:

$$\widehat{IR}(t, s, d_i) = \widehat{B}_1^s d_{it}$$

with the normalization $B_1^0 = I$, the identity matrix. Thus, an innovation or impulse to the i th variable in the vector y_t , denotes d_{it} ,

produces an impulse response of $\widehat{B}_1^s d_{it}$. The horizon of the forecast is s and $E(y_{t+s} | \delta_t; X_t)$ shows the forecast after a shock in period t .

The impulse responses from local approximations can be calculated from univariate least squares regressions for each variable at every horizon. Jordà's (2005) demonstrates that inference can be performed with standard heteroscedastic and autocorrelation (HAC) robust standard errors, such as Newey–West standard errors that we apply. These HAC standard errors correct for the moving average terms that exist in forecast errors.

Issues of potential misspecification raised by Jordà (2005) apply to macroeconomic data but also more generally to time series data and are therefore relevant in our application in this paper. Our analysis involves the macroeconomic time series global output demand (rea), interest rates (TED) and the exchange rate, besides time series for the stock and oil markets. Jordà illustrates in Monte Carlo simulations that for a correctly specified VAR standard and projection based impulse responses are very similar, however, in the presence of misspecification they differ substantially, depending on the degree of misspecification. We therefore apply both methods for calculating impulse responses in order to find out whether our results are robust with respect to potential misspecification of our VAR.

We consider the impulse responses for the SVAR system with two standard error confidence bands and also with one standard error confidence bands, as is common in the literature (e.g., Kilian, 2009). These figures with two standard error confidence bands are shown in Appendix A and the figures with one standard error confidence bands are available on request from the authors. With some exceptions, the projection based IRFs generally follow a pattern remarkably similar to that of VMA-based IRFs. For example, emerging country stock markets respond similarly to positive shocks to global economic activity with a positive short-run effect as predicted by theory due to higher future cash flows that affect equity markets positively. IRFs are also similar to the effect of a positive shock to the TED spread on equity markets. It leads to a long-lasting negative effect as expected because of higher discount rates leading to lower present values of cash flows. One notable difference between local-projection and standard IRFs is that local-projection IRFs show less pronounced responses of the TED spread to an oil production shock, of oil prices to a real economic activity shock, of real economic activity to a TED shock, of oil prices to a TED shock and of the TED to an oil price shock. Most importantly, the response of equity prices to an oil price shock is statistically significant for projection based IRFs for the first 2 to 3 months. Theoretically, a positive oil price shock would likely lead to an increase of stock prices in oil exporting countries such as Mexico and Russia, at least for oil-related stocks. In other oil importing countries we would expect a fall in stock prices. Overall, oil importing countries have a larger weight in the MSCI for stock prices in emerging economies than oil exporting countries. Therefore, the overall effect of an oil price shock on emerging market share prices should be negative. The result with projection based impulse responses is hence consistent with theory.

Furthermore, a positive oil price shock leads to a more pronounced drop in the exchange rate that is statistically significant for the first 4 to 6 months after the impact. Aside from this, there are only small differences in the overall evolution of the IRF graphs over time. Further, confidence bands have similar coverage, with a few initial responses becoming less significant. Overall, the IRFs show considerable robustness with respect to the two different estimation methods. This demonstrates the reliability of our model as specified.

4.3.2. Different identification schemes

We consider two modified identification schemes to our baseline model given in Eq. (4).²⁷ We do not provide graphs in order to

²⁵ See, Kapetanios et al. (2007), among others.

²⁶ See, Fernández-Villaverde et al. (2007), Hansen and Sargent (1980), and Sims (2009).

²⁷ We tried other identification schemes for the contemporaneous relations but either could not estimate the matrix A^{-1} because of non-convergence or the IRF results did not make economic sense.

conserve space, but they are available on request from the authors. The first scheme does not restrict a_{21} to be equal to zero. This is motivated by Kilian's (2009) recursive (Choleski) scheme for his three-variable oil-market VAR that does not allow him setting a_{21} to zero. It means that we allow for the possibility that global aggregate demand responds to an oil supply shock within the same month. In other words, oil supply shocks have immediate effects. This change has no noticeable effect on all our IRFs reported in Fig. 2, consistent with our assumption in the baseline identification scheme that oil supply (production of crude oil) shocks stimulate or depress aggregate demand with a delay.

The second identification scheme restricts a_{56} to equal zero, i.e. the exchange rate does not respond contemporaneously to an oil price shock. We expect this to be an unrealistic assumption because foreign exchange markets are efficient markets. Unless oil price shocks are perceived in this market as irrelevant, we expect to see changes in the IRFs. Indeed, this change affects four IRF graphs in a significant way. A positive exchange rate shock has now a long-lasting and significant effect on the emerging stock market for about a year, even though the exchange rate itself is not reacting in any significant way to its own shock. Similarly, an emerging stock market shock has no significant effects on the stock market but seems to affect negatively the exchange rate in a significant and permanent way. Therefore, our baseline identification scheme that does not restrict a_{56} to equal zero seems more reasonable.

4.4. Variance decomposition

After discussing the findings for the impulse response functions in the previous sub-sections, we now turn to the results for the variance decomposition. Fig. 3 displays the forecast error variance decomposition results for all the variables involved in the SVAR model. It is based on a structural decomposition of the covariance matrix. From Fig. 3 it appears that both global oil production and the interest rate spread dominate the system to some extent as their forecast errors are largely attributable to their own innovations; about 70% of the forecast error variance is explained by their own innovations at the end of the 24-month period considered in the variance decomposition. Nevertheless, forecast errors of the interest rate spread are partly determined by the changes in global real economic activity, emerging stock market prices and US dollar exchange index – at least for longer term forecasts. This is consistent with the findings for the impulse responses of the previous sub-sections. Forecast errors of both global oil production and global real economic activity in the first month are purely explained by their own shock (100%), which reflects the contemporaneous identification scheme in Eq. (4). Among all the variables, changes in the US dollar exchange index are not fully explained by its own innovation (76%) in the first period, while by the end of 24-month horizon only a quarter of its movement is due to its own shocks and the remainder is due to shocks to the interest rate spread and global real economic activity. Likewise, over the medium to longer term (12–24 months), changes in real oil prices (aside from the effects of its own shock) are also explained by shocks to the interest rate spread and global real economic activity. The interest rate spread shock also accounts about for 26%–46% of changes in emerging stock returns over the 12–24 months horizon. Overall, the evidence from the variance decomposition supports the informational feedback process assumed for our structural identification scheme.

5. Conclusions

Recognizing the importance of the relationship between stock prices and oil prices and the relationship between oil prices and exchange rates, this paper combines these two streams of literature, discussed in Section 2 of our paper, together into one empirical

structural vector autoregression model. This differentiates our paper from prior studies. In doing so, it is possible to gain a more complete understanding of the dynamic relationship between oil prices, emerging market stock prices and exchange rates. This is important because emerging economies have, over the past ten years, been accounting for a larger proportion of global GDP and this trend is expected to continue. Emerging economies are among the fastest growing economies (with GDP growth rates much higher than the growth rates observed in developed economies) and this combination of size and growth is likely to influence the dynamics between oil prices, emerging market stock prices and exchange rates.

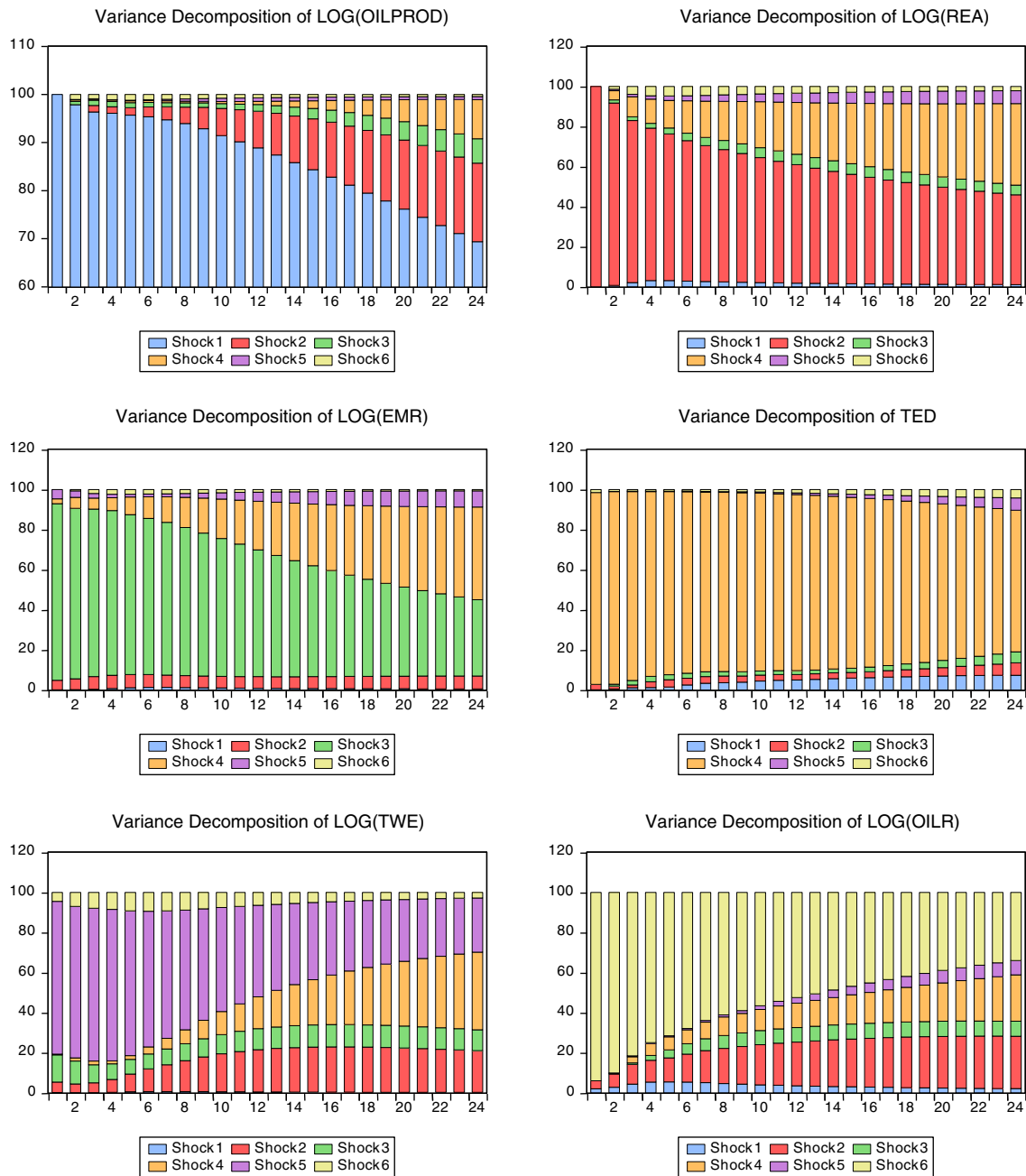
The short-term dynamics between oil prices, emerging market stock prices and exchange rates are analyzed using two sets of impulse response functions (standard and local projection based). In most cases the projection based IRFs provide similar results as the standard IRFs. Where the two approaches differ, the projection based approach tends to provide impulse responses that are more likely to adequately capture the cyclical response of a variable to an unexpected structural shock. Both approaches for example report that stock prices respond negatively to a positive oil price shock, and that oil prices respond positively to a positive emerging market shock. However, the first effect is only statistically significant for the projection based impulses for the first 2–3 months after the impact. The second effect is barely statistically significant in the period 2–8 months after the impact for standard impulses and is statistically significant in that period (4–13 months) for projection based responses with one standard error confidence bands. These results indicate that while increases in oil prices depress stock prices (a result widely supported by the literature documenting the effects of oil prices on stock markets, see for example Basher and Sadorsky (2006) and the references they cite) it is also the case that increases in emerging market stock market prices lead to an increase in oil prices (a result which to our knowledge has not been previously explored). This latter result makes sense within the context of global oil markets and global economic activity. Oil consumption in most developed economies is flat or in decline and as a result emerging market economic growth (as proxied by emerging market stock prices) is likely to be an important source of demand side pricing pressure in the oil market.

The results in this paper offer support for the hypothesis that exchange rates respond to movements in oil prices and that most of the dynamic interaction takes place in the short run. In particular, a positive oil price shock leads to an immediate drop in the trade-weighted exchange rate. This result has a statistically significant impact for about 5–6 months. These results are consistent with Krugman's (1983b) model of speculation.

Rising oil prices will generate a current account surplus for oil exporters and current account deficits for oil importers. The long-run expectation is that oil importers will experience a depreciation in their currencies because of the adverse terms of trade effect and this expectation of future depreciation is enough to produce a drop in the dollar in the short-run even if petro dollars are recycled. In comparison, no support is found for the hypothesis that oil prices respond to shocks to exchange rates.

The results in this paper show that oil prices respond negatively to an unexpected increase in oil supply and oil prices respond positively to an unexpected increase in demand. These results are consistent with the predictions from a demand and supply model for the oil market. Oil prices respond positively to a positive shock to emerging stock markets. These results are important in establishing, that in addition to global supply and demand conditions for oil, oil prices also respond to emerging market equity markets.

The results in this paper have a number of policy implications. As expected, oil prices respond to global oil production (supply) and real global economic activity (demand). Rapidly rising stock prices in emerging economies can also put pressure on oil prices to rise.



Note: Shock1 (logarithm of global oil production, oilprod); Shock2 (logarithm of global real economic activity, rea); Shock3 (logarithm of real emerging market stock prices, emr); Shock4 (interest rate spread, TED); Shock5 (logarithm of trade-weighted US dollar index, twe); and Shock6 (logarithm of real oil prices, oilr).

Fig. 3. Variance decomposition.

While it has typically been the case that macroeconomic policy in developed economies, like the G7, was seen as an important factor affecting the global economy, it now must be recognized that monetary and fiscal policy in large emerging economies (like China and India) can affect their own economic growth prospects as well as global financial markets. As the results in this paper have shown, oil prices respond not just to economic fundamentals like oil supply and real economic activity but also to movements in emerging stock prices. Stock markets are often seen as leading economic indicators. Rapidly rising stock prices in emerging markets signal the expectation of higher economic growth ahead. If emerging market stock prices get trapped in a bubble, however, oil prices will overshoot in relation to

economic fundamentals. This means that consumers in developed economies could end up paying more for oil and oil related products even if their own domestic economic growth remains sluggish and future realized economic growth in emerging economies is less than what the financial markets expected.

Finally, the framework presented in this paper could be used to analyze the oil, stock market and exchange rate relationship separately for major emerging countries, such as BRIC (Brazil, Russia, India and China) and/or major oil-exporting (e.g. Indonesia, Mexico and Russia) countries. Such country-specific study would allow for a more in-depth understanding of the effect of oil price shocks on equity prices in these countries. We leave this to future research.

Appendix A. Structural VAR local projection-based impulse responses with two-standard-error confidence bands

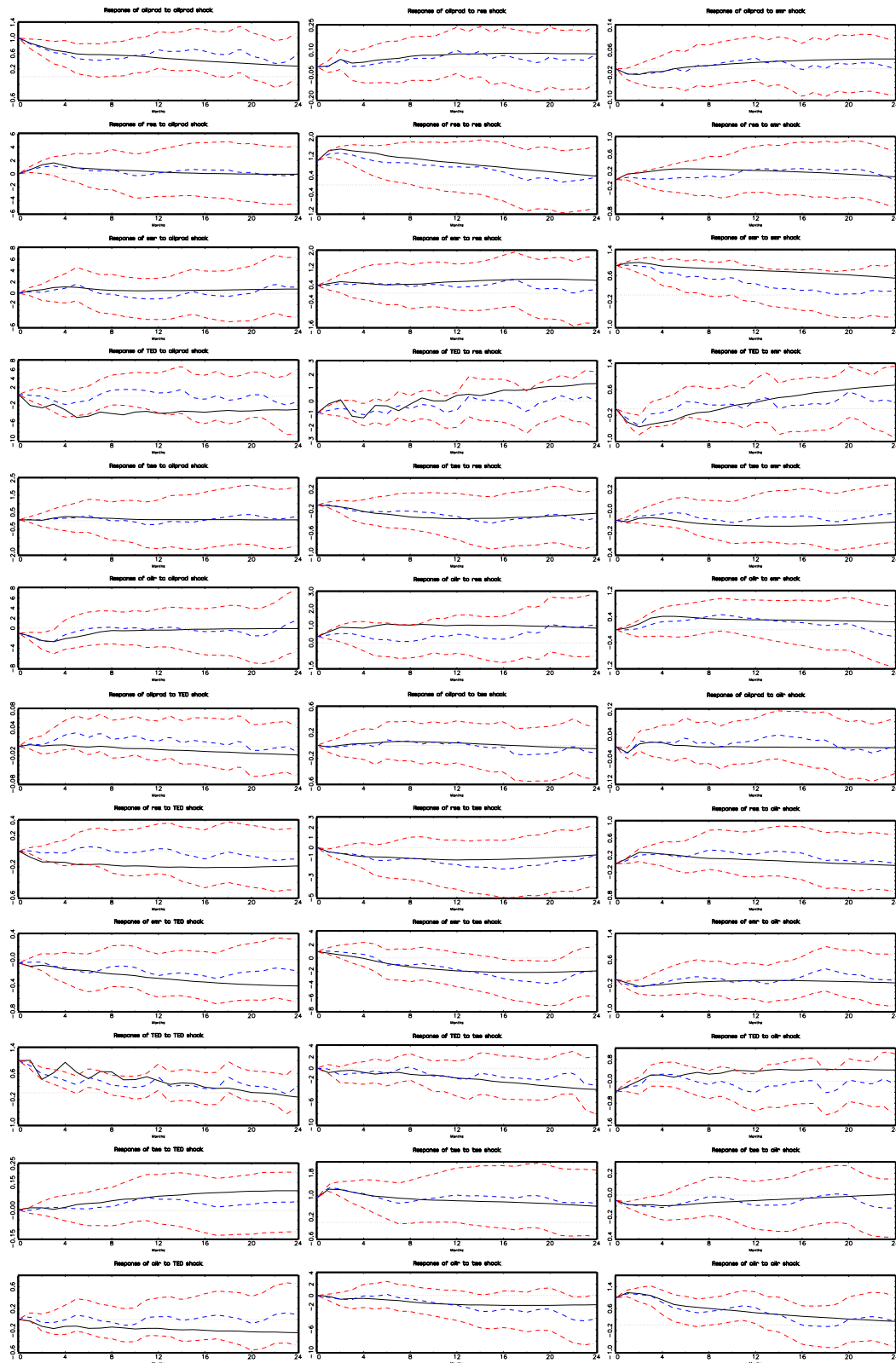


Fig. a1.

Note: see “Note” to Fig. 2 for an explanation of the abbreviations. Local projection-based IRFs are indicated by blue-dashed lines with red-dashed two standard error (approximately 95%) confidence bands. The solid black line denotes the impulse responses from standard IRFs from Fig. 2, repeated here for ease of comparison.

References

- Abadir, K.M., Hadri, K., Tzavalis, E., 1999. The influence of VAR dimension on estimator biases. *Econometrica* 67, 163–181.
- Akram, Q.F., 2009. Commodity prices, interest rates and the dollar. *Energy Econ.* 31, 838–851.
- Amano, R.A., van Norden, S., 1998. Oil prices and the rise and fall of the US real exchange rate. *J. Int. Money Finance* 17, 299–316.
- Apergis, N., Miller, S.M., 2009. Do structural oil-market shocks affect stock prices? *Energy Econ.* 31, 569–575.
- Basher, S.A., Sadorsky, P., 2006. Oil price risk and emerging stock markets. *Glob. Finance J.* 17, 224–251.
- Benassy-Quere, A., Mignon, V., Penot, A., 2007. China and the relationship between the oil price and the dollar. *Energy Policy* 35, 5795–5805.
- Blanchard, O., Gali, J., 2007. The macroeconomic effects of oil shocks: why are the 2000s so different from the 1970s? NBER Working Paper, 13368. National Bureau of Economic Research.
- Bloomberg, S.B., Harris, E.S., 1995. The Commodity–Consumer Price Connection: Fact or Fable? Federal Reserve Board of New York, Economic Policy Review, October, 21–38.
- Boyer, M.M., Filion, D., 2007. Common and fundamental factors in stock returns of Canadian oil and gas companies. *Energy Econ.* 29, 428–453.
- BP Statistical Review of World Energy, 2010. www.BP.com2010 (June).
- Chen, S.S., Chen, H.C., 2007. Oil prices and real exchange rates. *Energy Econ.* 29, 390–404.
- Chen, Y., Rogoff, K., 2003. Commodity currencies. *J. Int. Econ.* 60, 133–160.
- Cheng, H.-F., Gutierrez, M., Mahajan, A., Shachmurov, Y., Shahrokhi, M., 2007. A future global economy to be built by BRICs. *Glob. Finance J.* 18, 143–156.
- Christiano, L., Eichenbaum, M., Vigfusson, R., 2007. Assessing structural VARs. In: Acemoglu, D., Rogoff, K., Woodford, M. (Eds.), *NBER Macroeconomics Annual*, Volume 21. National Bureau of Economic Research, MIT–Press.
- Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. *Econometrica* 64, 813–836.
- El-Sharif, I., Brown, D., Burton, B., Nixon, B., Russell, A., 2005. Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. *Energy Econ.* 27, 819–830.
- Engle, R.F., Hendry, D.F., Richard, J.-F., 1983. Exogeneity. *Econometrica* 51, 277–304.
- Faff, R.W., Brailsford, T.J., 1999. Oil price risk and the Australian stock market. *J. Energy Finance Dev.* 4, 69–87.
- Fernández-Villaverde, J., Rubio-Ramírez, J.F., Sargent, T.J., Watson, M.W., 2007. ABCs (and Ds) of understanding VARs. *Am. Econ. Rev.* 97, 1021–1026.
- Ferson, W.W., Harvey, C.R., 1994. Sources of risk and expected returns in global equity markets. *J. Bank. Finance* 18, 775–803.
- Ferson, W.W., Harvey, C.R., 1995. Predictability and time-varying risk in world equity markets. *Res. Finance* 13, 25–88.
- Goldberg, L., Tille, C., 2008. Vehicle currency use in international trade. *J. Int. Econ.* 76, 177–192.
- Golub, S., 1983. Oil prices and exchange rates. *Econ. J.* 93, 576–593.
- Gregory, A.W., Haug, A.A., Lomuto, N., 2004. Mixed signals among tests for cointegration. *J. Appl. Econ.* 19, 89–98.
- Hamilton, J.D., 1994. *Time Series Analysis*. Princeton University Press, Princeton, NJ.
- Hamilton, J.D., 2003. What is an oil shock? *J. Econ.* 113, 363–398.
- Hamilton, J.D., 2009. Causes and consequences of the oil shock of 2007–08. *Brookings Papers on Economics Activity* 215–259 (Spring).
- Hamilton, J.D., 2010. Nonlinearities and the macroeconomic effects of oil prices. NBER Working Paper, No. 16186.
- Hammoudeh, S., Aleisa, E., 2004. Dynamic relationships among GCC stock markets and NYMEX oil futures. *Contemp. Econ. Policy* 22, 250–269.
- Hammoudeh, S., Huimin, L., 2005. Oil sensitivity and systematic risk in oil-sensitive stock indices. *J. Econ. Bus.* 57, 1–21.
- Hammoudeh, S., Dibooglu, S., Aleisa, E., 2004. Relationships among US oil prices and oil industry equity indices. *Int. Rev. Econ. Finance* 13, 427–453.
- Hansen, L.P., Sargent, T.J., 1980. Formulating and estimating linear rational expectations models. *J. Econ. Dyn. Control.* 2, 7–46.
- Harris, D., Harvey, D.I., Leybourne, S.J., Taylor, A.M.R., 2009. Testing for a unit root in the presence of a possible break in trend. *Econometric Theory* 25, 1545–1588.
- Haug, A., Smith, C., forthcoming. Local linear impulse responses for a small open economy. *Oxford Bulletin of Economics and Statistics*; available online at <http://dx.doi.org/10.1111/j.1468-0084.2011.00643.x>.
- He, Y., Wang, S., Lai, K.K., 2010. Global economic activity and crude oil prices: a cointegration analysis. *Energy Econ.* 32, 868–876.
- Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. *Energy Econ.* 30, 998–1010.
- Herrera, A.M., Pesavento, E., 2009. Oil price shocks, systematic monetary policy, and the 'Great Moderation'. *Macroecon. Dyn.* 13, 107–137.
- Huang, Y., Guo, F., 2007. The role of oil price shocks on China's real exchange rate. *China Econ. Rev.* 18, 403–416.
- Huang, R.D., Masulis, R.W., Stoll, H.R., 1996. Energy shocks and financial markets. *J. Futur. Mark.* 16, 1–27.
- Huang, B.-N., Hwang, M.J., Peng, H.-P., 2005. The asymmetry of the impact of oil price shocks on economic activities: an application of the multivariate threshold model. *Energy Econ.* 27, 455–476.
- International Energy Agency, 2006. *World Energy Outlook*, Paris.
- International Energy Agency, 2009. *World Energy Outlook*, Paris.
- Jones, C., Kaul, G., 1996. Oil and the stock markets. *J. Finance* 51, 463–491.
- Jordà, O., 2005. Estimation and inference of impulse responses by local projections. *Am. Econ. Rev.* 95, 161–182.
- Kaneko, T., Lee, B.S., 1995. Relative importance of economic factors in the US and Japanese stock markets. *Journal of the Japanese and International Economies* 9, 290–307.
- Kapetanios, G., Pagan, A., Scott, A., 2007. Making a match: combining theory and evidence in policy-oriented macroeconomic modelling. *J. Econ.* 136, 565–594.
- Kilian, L., 2008a. Exogenous oil supply shocks: how big are they and how much do they matter for the US economy? *Rev. Econ. Stat.* 90, 216–240.
- Kilian, L., 2008b. A comparison of the effects of exogenous oil supply shocks on output and inflation in the G-7 countries. *J. Eur. Econ. Assoc.* 6, 78–121.
- Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *Am. Econ. Rev.* 99, 1053–1069.
- Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. stock market. *Int. Econ. Rev.* 50, 1267–1287.
- Kilian, L., Vigfusson, R.J., 2009. Pitfalls in Estimating Asymmetric Effects of Energy Price Shocks, Manuscript. University of Michigan. available at <http://www-personal.umich.edu/~lkilian/kv14apr09.pdf>.
- Krugman, P., 1983a. Oil and the dollar. In: Bhandari, J.S., Putnam, B.H. (Eds.), *Economic Interdependence and Flexible Exchange Rates*. Cambridge University Press, Cambridge.
- Krugman, P., 1983b. Oil shocks and exchange rate dynamics. In: Frankel, J.A. (Ed.), *Exchange Rates and International Macroeconomics*. University of Chicago Press, Chicago.
- Lin, J.-L., Tsay, R.S., 1996. Co-integration constraint and forecasting: an empirical examination. *J. Appl. Econ.* 11, 519–538.
- Lizardo, R.A., Mollick, A.V., 2010. Oil price fluctuations and US dollar exchange rates. *Energy Econ.* 32, 399–408.
- Loretan, M., 2005. Indexes of the foreign exchange value of the dollar, Federal Reserve Bulletin Winter, available at http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf.
- McCauley, R.N., McGuire, P., 2009. Dollar appreciation in 2008: safe haven, carry trades, dollar shortage and overhedging. *BIS Q. Rev.* 85–93 (December).
- Melvin, M., Taylor, M.P., 2009. The crisis in the foreign exchange market. CESifo Working Paper Series No. 2707, Munich.
- Ng, S., Perron, P., 2001. Lag length selection and the construction of unit root tests with good size and power. *Econometrica* 69, 1519–1554.
- Papapetrou, E., 2001. Oil price shocks, stock markets, economic activity and employment in Greece. *Energy Econ.* 23, 511–532.
- Park, J., Ratti, R.A., 2008. Oil price shocks and stock markets in the US and 13 European countries. *Energy Econ.* 30, 2587–2608.
- Perron, P., Qu, Z., 2007. A simple modification to improve the finite sample properties of Ng and Perron's unit root tests. *Econ. Lett.* 94, 12–19.
- Pesavento, E., Rossi, B., 2006. Small sample confidence intervals for multivariate IRFs at long horizons. *J. Appl. Econ.* 21, 1135–1155.
- Phillips, P.C.B., 1998. Impulse response and forecast error variance asymptotics in non-stationary VARs. *J. Econ.* 83, 21–56.
- Pindyck, R.S., Rotemberg, J., 1990. The excess co-movement of commodity prices. *Econ. J.* 100, 1173–1189.
- Sadorsky, P., 1999. Oil price shocks and stock market activity. *Energy Econ.* 21, 449–469.
- Sadorsky, P., 2000. The empirical relationship between energy futures prices and exchange rates. *Energy Econ.* 22, 253–266.
- Sadorsky, P., 2001. Risk factors in stock returns of Canadian oil and gas companies. *Energy Econ.* 23, 17–28.
- Sims, E., 2009. Non-invertibilities and structural VARs, manuscript, University of Notre Dame available at <http://www.nd.edu/~esims1/2009>.
- Sims, C.A., Stock, J.H., Watson, M.W., 1990. Inference in linear time series models with some unit roots. *Econometrica* 58, 113–144.
- Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated process. *J. Econ.* 66, 225–250.
- Zhang, Y.-F., Fan, Y., Tsai, H.-T., Wei, Y.-M., 2008. Spillover effect of US dollar exchange rate on oil prices. *Journal of Policy Modelling* 30, 973–991.
- Zhou, S., 1995. The response of real exchange rates to various economic shocks. *Southern Journal of Economics* 936–954.