# What Drives the Oil-Dollar Correlation?

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**Abstract**

Oil prices and the US Dollar tend to move together: while the correlation between the WTI spot price and the US Dollar trade-weighted exchange rate has historically fluctuated between positive and negative values, it turned persistently negative in recent years. What explains this comovement? This paper investigates the relationship between oil prices and the US Dollar nominal effective exchange rate using a structural model that is fully identified by exploiting the heteroskedasticity in the data, following Rigobon (2003). We control for effects of US and global economic developments on oil prices and exchange rates by including measures of the surprise component of economic news releases. The results indicate that higher oil prices depreciate the Dollar both in the short run and over longer horizons. We also find that that Dollar depreciation is associated with higher oil prices in the short run. US short-term interest rates explain much of the long-run variation in oil prices and and the Dollar exchange rate.

**JEL classification:** F31, G15

**Keywords:** Oil prices, exchange rates, identification through heteroskedasticity

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# 1 Introduction

Oil prices and the US Dollar exchange rate tend to move together. Figure 1 plots oil prices against the US Dollar nominal effective exchange rate. No clear relationship is apparent for the early part of the sample, but oil prices and the US Dollar appear to be negatively related in recent years. As the Dollar depreciated between 2002 and 2008, oil prices surged. Conversely, during the financial crisis oil prices collapsed, while the Dollar appreciated. Figure 2 shows the correlation between oil prices and the Dollar, computed over 6-month moving windows. While the correlation fluctuates between negative and positive values for most of the sample, it turns more persistently negative after 2002. What economic relationships are behind this comovement? Do oil shocks drive exchange rates, or do exchange rates affect oil prices? Or does the comovement of oil prices and exchange rates reflect movements in other variables, such as for example the US or global growth outlook? Financial market commentary routinely suggests a causal relationship between oil price movements and changes in the value of the US Dollar as the following quotes illustrate: "Weak dollar central to oil price boom,"[1] "Strong Dollar presses crude oil,"[2] "Oil settles lower on stronger dollar, ample supply,"[3] "Dollar index strength may tumble oil prices in 2011,"[4] "Crude lower on stronger Dollar."[5]

While the relationship between oil prices and exchange rates is widely discussed in the popular press and among market practitioners, the academic literature on this topic is relatively scarce. One strand of the literature[6] investigates the long-run relationship between US Dollar real exchange rates and the real price of oil. Using monthly data on either US Dollar trade-weighted exchange rates or Dollar bilateral exchange rates versus advanced economies, this literature generally finds that real exchange rates and the real price of oil are cointegrated and exhibit a positive long-run equilibrium relationship: that is, higher oil prices are associated with an appreciation of the US Dollar. Furthermore, the literature generally finds that oil prices Granger-cause exchange rates, but not vice-versa. Coudert, Mignon and Penot (2008) present evidence that both real oil prices and the US Dollar real effective exchange rate are cointegrated with the US net foreign asset position, and argue that this suggests that the influence of oil prices on exchange rates runs through the effect of oil prices on US net foreign assets.[7] Cheng (2008) estimates a dynamic error correction model using data on commodity prices, the US Dollar effective exchange rate, world industrial production, the Federal funds rate, and commodity inventories. Dollar depreciation is associated

[1] See http://www.reuters.com/article/idUSL2576484820070926

[2] See http://www.profi-forex.us/news/entry4000000618.html

[3] See http://www.marketwatch.com/story/oil-lower-on-stronger-dollar-ample-inventories-2010-10-27

[4] See http://www.liveoilprices.co.uk/oil/oil_prices/11/2010/dollar-index-strength-may-tumble-oil-prices-in-2011.html

[5] See http://online.wsj.com/article/BT-CO-20101215-704928.html

[6] See for example Amano and van Norden (1998a, 1998b), Chaudhuri and Daniel (1998), Chen and Chen (2007), Benassy-Quéré, Mignon and Penot (2007) and Coudert, Mignon and Penot (2008).

[7] The literature typically employs (log-)linear models. In contrast, Akram (2004) estimates a model that allows for a non-linear relationship between oil prices and the trade-weighted value of the Norwegian Krone.

with higher oil prices, with the effect being strongest in the long run (after several years).

One common feature of this literature is that authors either focus on reduced-form models, or use potentially problematic zero restrictions on the contemporaneous feedback effects between oil prices and exchange rates. Akram (2009) estimates a structural VAR using quarterly data on OECD industrial production, real US short-term interest rates, the real trade-weighted US Dollar exchange rate, and a set of real commodity prices including the oil price. One finding is that Dollar depreciation is associated with higher commodity prices, which is consistent with the negative correlation between commodities and Dollar exchange rates observed in the data. The model is identified using standard exclusion restrictions; in particular, it is assumed that the real exchange rate does not respond to fluctuations in commodity prices within the same quarter.

A second strand of the literature asks whether exchange rates can help forecast commodity prices. Chen, Rogoff and Rossi (2010) study the relationship between commodity currencies and commodity prices, using quarterly data on the nominal Dollar exchange rates of a set of commodity exporting countries (Australia, Canada, South Africa, and Chile). They find that commodity currencies help to forecast commodity prices, both in-sample and out-of-sample. This result is consistent with the idea that exchange rates are determined by traders' expectations about future macroeconomic shocks; for small commodity exporters, commodity prices are an important and relatively exogenous source of economic fluctuations. In contrast, the authors argue that commodity prices are less forward-looking because commodity markets are more regulated and mainly influenced by current demand and supply conditions. Therefore, commodity prices are less successful in forecasting exchange rates.[8] Groen and Pesenti (2009) provide an extensive study of the forecasting power of exchange rates for a range of commodity prices. They find that commodity currencies help to forecast commodity prices, but across forecast horizons and across a range of commodity price indices do not robustly outperform naïve statistical benchmark models.

The contribution of this paper is to estimate a structural model that is fully identified, allowing for two-way contemporaneous comovements between oil prices and the trade-weighted US Dollar exchange rate. This is important because exchange rates and oil prices are asset prices which are likely to respond instantly to economic news and developments in financial markets. Following Rigobon (2003) and Ehrmann, Fratzscher and Rigobon (2010) identification is achieved by exploiting the heteroskedasticity of the data. Intuitively, in times when oil shocks (to take an example) are particularly volatile the effect of oil shocks on exchange rates is likely to dominate the correlation observed in the data; such high volatility periods can therefore be used to identify the influence of oil shocks on exchange rates. This paper focuses on short-run comovements, using weekly data on nominal variables, which exhibit more volatility and are therefore better suited for this methodology. It is of course possible that the comovement of oil prices and exchange rates reflects the influence of third variables. For example, the surge in oil prices between 2003 and 2008 could

[8] Chen and Rogoff (2003) present evidence that commodity prices are related to the exchange rates of three small commodity exporters (Australia, Canada and New Zealand).

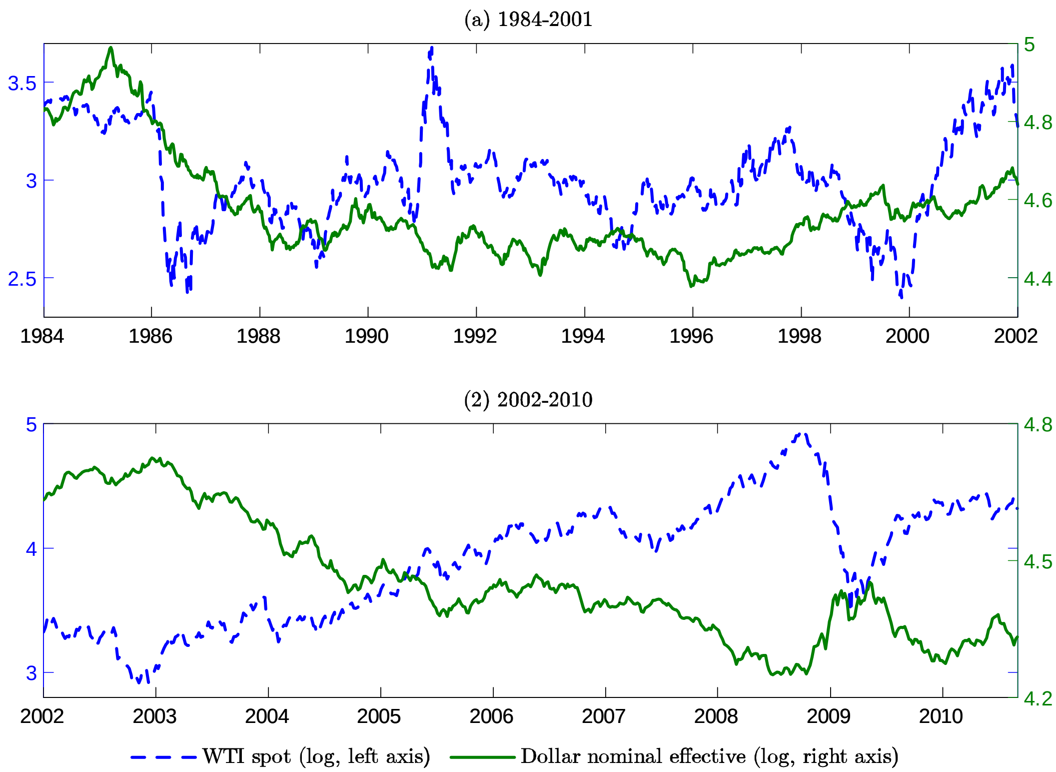


Figure 1: Oil prices and the US Dollar effective exchange rate (against major currencies)

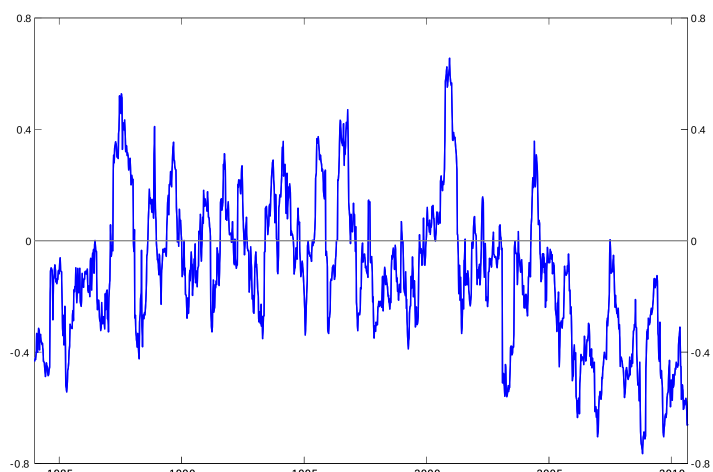

Figure 2: Correlation of oil prices (WTI spot price, weekly log changes) and the US Dollar nominal effective exchange rate (against major currencies, weekly log changes), computed over 6-month moving windows.

have been caused by strong global demand for oil, especially from fast-growing economies in Asia; and the depreciation of the Dollar during much of the recent oil price boom likely reflected both US-specific and global factors.[9] To allow for this possibility, we control for US and global economic developments by including data on the surprise component of economic news releases, captured by the Citi Economic Surprise indices. The availability of this data on news releases limits the start of our sample to the beginning of 2003, so that our analysis focuses on the recent years in which oil prices and the Dollar exchange rate appear to exhibit a clear negative relationship (as seen in Figure 1).

The results indicate that an increase in oil prices is associated with a depreciation of the Dollar both in the short run (within the same week) and over longer horizons. Also, Dollar depreciation leads to higher oil prices within the same week. In the long run, fluctuations in interest rates explain most of the variation in oil prices and exchange rates. The finding that oil prices affect the US Dollar in the long run is consistent with previous studies, although in contrast to much of the previous literature this paper focuses on nominal variables, uses weekly data, and studies the 2003-2010 period. This paper allows for two-way contemporaneous feedback between oil prices and exchange rates in a fully identified structural model; this allows us to identify the short-run effect of changes in the Dollar on oil prices that has not been picked up in the previous literature.

The next section reviews potential reasons why oil prices and the US Dollar exchange rate could be related. The third section discusses the data and the empirical methodology used in this paper. Section four presents benchmark results and discusses robustness. Finally, section five concludes.

## 2 Linkages between oil prices and US Dollar exchange rates

This section provides a brief overview of potential transmission channels which could generate comovement between oil prices and the Dollar.[10] First, changes in the US Dollar exchange rate could have an effect on oil prices because of (1) their effect on the global demand for oil, and (2) their effect on oil producers' price setting behavior. In particular, since oil is priced in Dollar on international financial markets, when the US Dollar depreciates oil becomes less expensive in terms of local currency for consumers in non-Dollar countries. This could increase their demand for oil, which in turn could lead to higher oil prices. This channel provides an intuitive explanation for the negative relationship between oil prices and the Dollar observed in recent years, but there is little empirical evidence that the global demand for oil is in fact responsive to changes in the Dollar. A

[9] Kilian and Hicks (2009) present evidence that revisions of monthly forecasts of one-year ahead real GDP growth in emerging economies and Japan were associated with higher oil prices, and explain much of the surge in oil prices between 2003 and 2008. Kilian and Vega (2010) analyze the impact of the surprise component of US macroeconomic news releases on the daily percent change of oil prices. They find that US data releases have no significant effect on oil prices at the daily and monthly horizon.

[10] See also Breitenfellner and Cuaresma (2008) and Coudert, Mignon and Penot (2008). Golub (1983) and Krugman (1983) build theoretical models of the relationship between oil prices and exchange rates.

related argument is that Dollar depreciation could be associated with monetary easing in countries that peg their exchange rate to the Dollar. Lower interest rates in these countries could in turn stimulate economic activity and lead to a higher demand for commodities.

Since oil is priced in Dollar, the export revenue of oil-producing countries is predominantly denominated in Dollars. However, shipments from the US account for only a small fraction of the imports of oil producers. Also, many oil producing countries peg their exchange rates to the Dollar. This implies that a depreciation of the Dollar is associated with a decline in the purchasing power of oil revenues (the amount of non-Dollar denominated goods and services that oil producers can buy). Therefore oil producers have an incentive to counterbalance the effects of Dollar depreciation by raising oil prices. To the extent that oil producers do indeed have some pricing power (for example, OPEC may be able to affect prices through changing the amount of oil supplied to the market) this could lead to higher oil prices.

Next, consider the reverse effect of oil prices on exchange rates. Changes in oil prices could affect the value of the US Dollar because of (1) the impact of higher oil prices on the US and global growth outlook, and (2) the impact of higher oil prices on the global allocation of capital and trade flows. In particular, higher oil prices could be associated with an appreciation of the US Dollar if markets expect that the US economy will suffer less from increased prices than the rest of the world, for example because it is less energy intensive.[11] Kilian, Rebucci and Spatafora (2009) regress the external balances of oil exporting and importing countries on oil shocks as identified by Kilian (2009). They find that oil price shocks are associated with a deterioration in the oil trade deficit of selected oil importers (US, Euro Area, Japan), although the strength of the effect depends on the type of oil shock considered (shocks to oil supply, aggregate demand and oil-specific demand).

Higher oil prices imply higher revenues for oil producers and lower savings in oil-importing countries. To the extent that oil revenues are used to purchase goods and services disproportionately from the US, or are invested disproportionately in the US, this recycling of petrodollars could be associated with a stronger Dollar. Higgins, Klitgaard and Lerman (2006) document that only a small fraction of payments from the US to oil exporters has been used to purchase goods and services from the US. However, they argue that although limited data availability makes it inherently difficult to track where oil exporters' savings are invested, most of the profits of oil producers during the recent oil price boom directly or indirectly ended up financing the US current account deficit.

[11] For evidence on the effects of oil price shocks on the macroeconomy see Hamilton (1983, 2003) and Kilian (2008a, 2008b, 2009) .

# 3 Data and methodology

## 3.1 The data

Weekly data on oil prices (WTI spot price, Cushing), the US Dollar exchange rate and short-term US interest rates (3-month Treasury bill) is obtained from Haver. As a measure of the exchange value of the Dollar we use the trade-weighted US Dollar exchange rate (against major currencies) computed by the Federal Reserve Board.

To control for US and global economic developments we employ the Citi Economic Surprise indices, which are measures of the surprise component of economic news releases (available from Bloomberg). These indices are computed from weighted historical standard deviations of data surprises (actual releases versus Bloomberg survey median) over the past 3 months, using declining weights for older releases. A positive reading of the index indicates that economic releases have on balance been above the consensus.[12] Surprise indices are available from January 2003 for individual G10 countries (United States, Euro Area, Japan, United Kingdom, Canada and Australia); furthermore, aggregate indices are available for Asia (including data releases from China, South Korea, Hong Kong, India, Taiwan, Singapore, Indonesia, Malaysia, Thailand and the Philippines), Latin America (including data releases from Mexico, Brazil, Chile, Columbia and Peru) and selected other countries (Turkey, Poland, Hungary, South Africa, Czech Republic). Data coverage is most extensive for indices on the US and the euro area (see Table 1), while for some emerging economies only two or three economic data releases are covered.

Using weekly data helps to deal with the issue of the timing of news releases that are captured in the City Economic Surprise indices across different regions and time zones. We include only Friday's value of the Citi indices for each week, which by construction aggregate the news releases over the week and indeed the previous three months with decaying weights.[13]

## 3.2 Methodology

Our empirical model is a structural VAR,

$$\mathbf{A}\mathbf{y}_t = \Sigma_{j=1}^{J}\mathbf{B}_j\mathbf{y}_{t-j} + \mathbf{C}\mathbf{x}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\mathbf{y}_t$ is an $n$x1 vector of endogenous variables, $\mathbf{x}_t$ is a set of exogenous variables and $\boldsymbol{\varepsilon}_t$ is a vector of structural shocks. The $n$x$n$ matrix $\mathbf{A}$ determines the contemporaneous feedback effects among the endogenous variables. The diagonal elements in $\mathbf{A}$ are normalized to one. We assume that $E(\varepsilon_i) = E(\varepsilon_i\varepsilon_{j\neq i}) = 0$.

[12] The weights of economic indicators are derived from relative high-frequency spot FX impacts of 1 standard deviaion data surprises. See James and Kasikov (2008) for details.

[13] The use of news indices that aggregate data releases over the past 3 months may be more appropriate to capture the impact of economic news on the levels of variables, rather than on changes as in this paper. However, the Citi Economic Surprise indices are available from Bloomberg only in aggregated form.

Table 1: Components of the Citi Economic Surprise indices

| United States | Euro Area |
|---|---|
| Change in Non-Farm Payrolls | German IFO Survey |
| Unemployment Rate (sign inverted) | German ZEW Survey |
| Trade Balance | German GDP, QoQ % |
| GDP, QoQ % ann. | Euro-Zone Core CPI, YoY % |
| Retail Sales ex-Autos, MoM % | German Factory Orders, MoM % |
| ISM Non-manufacturing | German Industrial Production, MoM % |
| CB Consumer Confidence | Italy Business Confidence |
| ISM Manufacturing | Euro-Zone Economic Confidence Index |
| TICS Net Portfolio Flows | Euro-Zone M3, YoY % |
| Chicago PMI | France Consumer Spending, MoM % |
| Durable Goods Orders, MoM % | German Retail Sales, YoY % |
| New Home Sales | Euro-Zone Consumer Confidence Index |
| Core CPI, MoM % | France INSEE Business Confidence |
| Empire Manufacturing PMI | Euro-Zone Industrial Confidence Index |
| Industrial Production, MoM % | |
| Philadelphia Fed Business Conditions | |
| UoM Consumer Confidence | |
| Housing Starts | |
| Initial Jobless Claims (sign inverted) | |

*Components ordered with decreasing weights. Source: Citi.

To identify the structural shocks in (1) we use 'identification by heteroskedasticity', following Rigobon (2003) and Ehrmann, Fratzscher and Rigobon (2010).[14] In particular, we allow the variances of the structural shocks to change across the sample. Suppose that $s = 1, ..., S$ volatility periods or 'regimes' can be found such that the shock variances are constant within each regime, but may differ across regimes. We write the variance-covariance matrix of shocks in regime $s$ as

$$E\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'\right) = \boldsymbol{\Omega}_{\varepsilon,s}$$

The estimation strategy is as follows. First we estimate the reduced-form version of equation (1) by OLS,

$$\mathbf{y}_t = \Sigma_{j=1}^{J} \mathbf{A}^{-1}\mathbf{B}_j \mathbf{y}_{t-j} + \mathbf{A}^{-1}\mathbf{C}\mathbf{x}_t + \mathbf{u}_t \tag{2}$$

where we have defined

$$\mathbf{u}_t \equiv \mathbf{A}^{-1}\boldsymbol{\varepsilon}_t \tag{3}$$

[14] See also Sentana and Fiorentini (2001) for the theoretical background and Rigobon and Sack (2003, 2004) and Lanne and Lütkepohl (2008) for applications.

We then use the residuals of the regression in (2), as a proxy for the underlying structural shocks, to find volatility regimes. Suppose we have determined $s = 1, ..., S$ volatility periods, and let $\mathbf{\Omega}_{e,s}$ denote the variance-covariance matrix of the residuals in regime $s$. From equation (3) the variance-covariance matrix of reduced-from shocks in regime $s$ is computed as

$$\mathbf{\Omega}_{u,s} = \mathbf{A}^{-1}\mathbf{\Omega}_{\boldsymbol{\varepsilon},\mathbf{s}}\mathbf{A}^{-1\prime} \tag{4}$$

Using $\mathbf{\Omega}_{e,s}$, the variance-covariance matrix of the residuals, as a proxy for $\mathbf{\Omega}_{u,s}$ in (4) and rearranging leads to a set of GMM moment conditions,

$$\mathbf{A}\mathbf{\Omega}_{e,s}\mathbf{A}' = \mathbf{\Omega}_{\varepsilon,s} \tag{5}$$

for volatility regime $s = 1, ..., S$. With $n$ endogenous variables $\mathbf{\Omega}_{e,s}$ will have $N = n(n+1)/2$ distinct elements, so that equation (5) delivers $N$ moment conditions for each regime which we summarize in the column vector $\mathbf{m}_s$. Therefore, with $S$ regimes, we obtain $N \cdot S$ moment conditions which can be used for GMM estimation. A total of $n\,(n-1) + S\,(n+1)$ structural parameters need to be estimated: $n\,(n-1)$ non-normalized parameters in $\mathbf{A}$, and the variances of the $n+1$ shocks for the $S$ regimes. The model is identified if the number of volatility regimes $S$ is sufficiently large to ensure that there are at least as many moment conditions as unknown parameters.

Let $\boldsymbol{\theta}$ denote a vector containing all unknown structural parameters. We choose $\boldsymbol{\theta}$ to minimize the objective function

$$\min_{\boldsymbol{\theta}} \mathbf{m}'\mathbf{m} \tag{6}$$

with

$$\mathbf{m} = \left[ \begin{array}{cccc} \mathbf{m}_1' \cdot \frac{T_1}{T} & \mathbf{m}_2' \cdot \frac{T_2}{T} & ... & \mathbf{m}_S' \cdot \frac{T_S}{T} \end{array} \right]'$$

where $T_s$ denotes the number of observations in regime $s$ and $T$ denotes the total number of all observations. Note that we multiply the moment conditions of regime $s$ with the relative weight of the regime: in this way more importance is attached to moment conditions that represent a larger number of observations and thus are associated with less uncertainty. This implicitly defines a weighting matrix for GMM estimation.[15]

What then remains is to identify periods in which the volatility of the underlying structural shocks changes. Several studies using 'identification through heteroskedasticity' have used exogenous events to identify volatility regimes. For example, Rigobon and Sack (2004) analyze the effect of US monetary policy on asset prices. They use two regimes, one including periods of FOMC meetings and Fed chairman's testimonies to congress, and another including all other periods. The idea is that monetary policy is more volatile on days when interest rate decisions are taken or when news about interest rate policies emerge. Since no such natural regime choices are available

[15] The estimation is implemented using the built-in Matlab routine `fmincon`.

in our case, we follow Ehrmann, Fratzscher and Rigobon (2010) in using a simple threshold rule to determine volatility regimes. Whenever the volatility of the residual for one variable in a given period – computed over moving windows of a fixed size – is above the chosen threshold, while the volatility of the other residuals is not, we classify the structural shock for this variable in that period as being excessively volatile. In this way, we identify periods in which the residuals, as proxies for the underlying structural shocks, are uniquely volatile, and periods when the volatility of all residuals is below the threshold. With $n$ variables this gives $n$ high volatility regimes and one 'tranquility' regime, which are sufficient to identify the model. Periods in which the volatility of the residuals of more than one variable is above the threshold are not used for the identification procedure: identification works best with large relative changes in volatility, and periods in which the volatility of all or several variables increases would therefore not help much for identification.

To be precise, we compute the standard deviation of the residual of variable $j$ in period $t$, $\sigma_{jt}$, over fixed windows ending in $t$. The threshold used is $E(\sigma_{jt}) + c \cdot Var(\sigma_{jt})$, with $c = 0.5$. Decreasing the threshold level by lowering $c$ increases the number of observations that are classified as reflecting volatility states, but it also increases the number of periods where more than one variable is volatile. Ehrmann, Fratzscher and Rigobon (2010) use moving windows of 20 days to compute $\sigma_{jt}$, which with daily data roughly corresponds to one month (four work weeks). With weekly data, we use a window size of 2 as the benchmark specification. Section 4.2 discusses the robustness of our results to other assumptions about $c$ and $\omega$.

# 4 Empirical analysis

## 4.1 Results

This section presents the benchmark results for the identification of the structural VAR in (1). We focus on weekly returns of oil prices and exchange rates, so that the vector of endogenous variables is given by

$$\mathbf{y}_t = \begin{bmatrix} 100 \cdot \Delta \ln p_t & 100 \cdot \Delta \ln e_t & \Delta r_t \end{bmatrix}'$$

where $p_t$, $e_t$ and $r_t$ denote the oil price, the nominal US Dollar trade-weighted exchange rate (against major currencies) and the nominal US short-term interest rate. The vector $\mathbf{x}_t$ of exogenous variables in (1) includes a set of measures of the surprise component of US and global economic news releases described in section 3.1. We include 2 lags in the VAR, as suggested by the final prediction error, Akaike's information criterion, and the Hannan-Quinn information criterion.[16] The 2003-2010 sample includes 415 observations of weekly data. The structural coefficients in matrix $\mathbf{A}$ are identified using volatility regimes of 252 weekly observations (shocks to all variables

[16] Schwarz's Bayesian information criterion indicates that a model without any lags is optimal, while the Likelihood ratio test suggests 11 lags. Our intuition is that financial markets should respond quickly to new information, so that including 2 lags with weekly data should be sufficient.

Table 2: Identification results

(a) direct contemporaneous effects (matrix $\mathbf{A}$)

| From... ...to | $\varepsilon_{Oil,t}$ | $\varepsilon_{Dollar,t}$ | $\varepsilon_{r,t}$ |
|---|---|---|---|
| $Oil_t$ | 1 | $-0.1674^{**}$ [0.0220] | 0.0359 [0.3240] |
| $Dollar_t$ | $-0.1755^{**}$ [0.0320] | 1 | $-0.0174$ [0.3940] |
| $r_t$ | 0.0518 [0.1040] | 0.0079 [0.4220] | 1 |

(b) overall contemporaneous effects (matrix $\mathbf{A}^{-1}$)

| From... ...to | $\varepsilon_{Oil,t}$ | $\varepsilon_{Dollar,t}$ | $\varepsilon_{r,t}$ |
|---|---|---|---|
| $Oil_t$ | $1.0324^{***}$ [0.0000] | $-0.1725^{**}$ [0.0220] | 0.0400 [0.3180] |
| $Dollar_t$ | $-0.1821^{**}$ [0.0260] | $1.0303^{***}$ [0.0000] | $-0.0244$ [0.3560] |
| $r_t$ | $0.0521^{*}$ [0.1000] | $-0.0008$ [0.4940] | $1.0019^{***}$ [0.0000] |

*Note:* $Oil_t$, $Dollar_t$ and $r_t$ denote, respectively, the WTI spot oil price, the nominal trade-weighted exchange value of USD versus major currencies (both in log changes), and changes in the US 3-month interest rate. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. P-values (in square brackets) are computed from 500 bootstrap replications. Coefficient $(i, j)$ corresponds to the contemporaneous effect of a shock to variable $j$ on variable $i$. Sample includes weekly data from 2003 to 2010.

have low variance), 31 observations (high oil shock volatility), 56 observations (high Dollar shock volatility) and 25 observations (high interest rate shock volatility).[17]

Table 2 presents the results from the identification procedure. Panel (a) shows the coefficients of matrix $\mathbf{A}$ in equation (1), with inverted signs, which capture the *direct* contemporaneous (intra-week) effects of structural shocks. Panel (b) shows the coefficients of matrix $\mathbf{A}^{-1}$, which determine the *overall* contemporaneous effects of structural shocks. Note that the coefficients on the diagonal of matrix $\mathbf{A}^{-1}$ are greater than one, which indicates that the initial impact of the shocks (which is normalized to one in matrix $\mathbf{A}$) are magnified through the various contemporaneous feedback effects with other variables. The results indicate that a depreciation of the US Dollar is associated with a contemporaneous increase in oil prices in the short-run (within the same week), while higher oil prices lead to a depreciation of the trade-weighted US Dollar exchange rate. Both effects are estimated to be roughly equal in magnitude and statistically significant at the 5 percent level. The contemporaneous effects of US short-term interest rates on oil prices and the US Dollar exchange rate are found not to be statistically significant, but oil price shocks are associated with an increase

[17] The distribution of high volatility regime periods is shown in Figure **??** in the appendix.

Table 3: Granger causality Wald tests

| Equation | Excluded | $\chi^2$ | df | Prob > $\chi^2$ |
|---|---|---|---|---|
| Oil | Dollar | 4.3487 | 2 | 0.114 |
| Oil | Interest rate | 8.6866 | 2 | 0.013 |
| Oil | ALL | 11.902 | 4 | 0.018 |
| Dollar | Oil | 7.8781 | 2 | 0.019 |
| Dollar | Interest rate | 22.457 | 2 | 0.000 |
| Dollar | ALL | 27.517 | 4 | 0.000 |
| Interest rate | Oil | 1.7651 | 2 | 0.414 |
| Interest rate | Dollar | 2.2959 | 2 | 0.317 |
| Interest rate | ALL | 2.9709 | 4 | 0.563 |

*Note:* Oil, Dollar and Interest rate denote, respectively, the WTI spot oil price, the nominal trade-weighted USD versus major currencies (both in log changes), and changes in the nominal US 3-month interest rate. Sample includes weekly data from 2003 to 2010.

in US short-term interest rates.

A somewhat different picture emerges over longer horizons. Table 3 presents the results of Granger causality tests. Oil prices Granger-cause the US Dollar exchange rate, but not vice versa, while US interest rates Granger-cause both oil prices and exchange rates. This is in line with the previous literature that studies the long-run relationship between real oil prices and the real Dollar exchange rate, and typically finds that oil prices Granger-cause exchange rates, but not the other way round.[18] In the reduced-form VAR of equation (2), oil prices are increasing in all news variables, with the exception of news from Canada and Australia, although the coefficients are mostly not significant. The surprise component of US data releases is estimated to be associated with both higher US short-term interest rates and an appreciation of the Dollar, but again the coefficients are not statistically significant.

Since all parameters of the structural model have been estimated, impulse responses and variance decompositions do not depend on the ordering of the endogenous variables. This is a major advantage of the identification method used in this paper. Table 4 presents estimates for the one-week ahead forecast error variance decomposition and the long-run variance decomposition. In the short run, the forecast error variance of each variable is almost exclusively explained by its own structural shocks. Shocks to the Dollar explain only less than 3 percent of the short-run variation in oil prices, and similarly oil prices explain only about 3 percent of the variation in

[18] For example, Amano and van Norden (1998a, 1998b).

Table 4: Variance decompositions

One-week ahead variance decomposition

| | $Oil_t$ | $Dollar_t$ | $r_t$ |
|---|---|---|---|
| $\varepsilon_{Oil,t}$ | 0.9725 | 0.0311 | 0.0037 |
| | [0.0289] | [0.0269] | [0.0071] |
| $\varepsilon_{Dollar,t}$ | 0.0264 | 0.9685 | 0.0000 |
| | [0.0285] | [0.0269] | [0.0028] |
| $\varepsilon_{r,t}$ | 0.0011 | 0.0004 | 0.9963 |
| | [0.0043] | [0.0049] | [0.0080] |

Long-run variance decomposition

| | $Oil_t$ | $Dollar_t$ | $r_t$ |
|---|---|---|---|
| $\varepsilon_{Oil,t}$ | 0.0411 | 0.0110 | 0.0037 |
| | [0.0475] | [0.0103] | [0.0071] |
| $\varepsilon_{Dollar,t}$ | 0.0120 | 0.3204 | 0.0001 |
| | [0.0242] | [0.1137] | [0.0029] |
| $\varepsilon_{r,t}$ | 0.9469 | 0.6686 | 0.9962 |
| | [0.0648] | [0.1166] | [0.0080] |

*Note:* Fraction of the forecast error variance of the variables listed in the columns, explained by shocks listed in the rows. $Oil_t$, $Dollar_t$ and $r_t$ denote, respectively, the WTI spot oil price, the nominal trade-weighted exchange value of USD versus major currencies (both in log changes), and changes in the US 3-month interest rate. Standard errors (in square brackets) are computed from 500 bootstrap replications. Sample includes weekly data from 2003 to 2010.

exchange rates. In contrast, in the long-run the variation in both oil prices and exchange rates is predominantly explained by shocks to US-short term interest rates. Figure 3 plots the response of each of the endogenous variables (listed in the columns) to one standard deviation[19] realizations of different shocks (listed in the rows). The comovement of US Dollar exchange rates and oil prices is statistically significant only within the same week.

## 4.2 Robustness

The identification results for the structural parameters are potentially sensitive to the volatility periods used in the GMM estimation. Recall that periods of 'high' volatility for the residual of variable $j$ are defined as periods in which the standard deviation $\sigma_{jt}$ of these residuals, computed over moving windows of size $t \pm \omega/2$, is above the threshold given by $E(\sigma_{jt}) + c \cdot Var(\sigma_{jt})$. Identification is based on periods in which all residuals have low volatility, and on periods in which the residual of only one variable is classified as volatile. The benchmark results used on a specification with $\omega = 2$ and $c = 0.5$. In general, we would like to choose a value for $\omega$ that is low

[19] We use the average standard deviation weighted by the number of observations across volatility periods

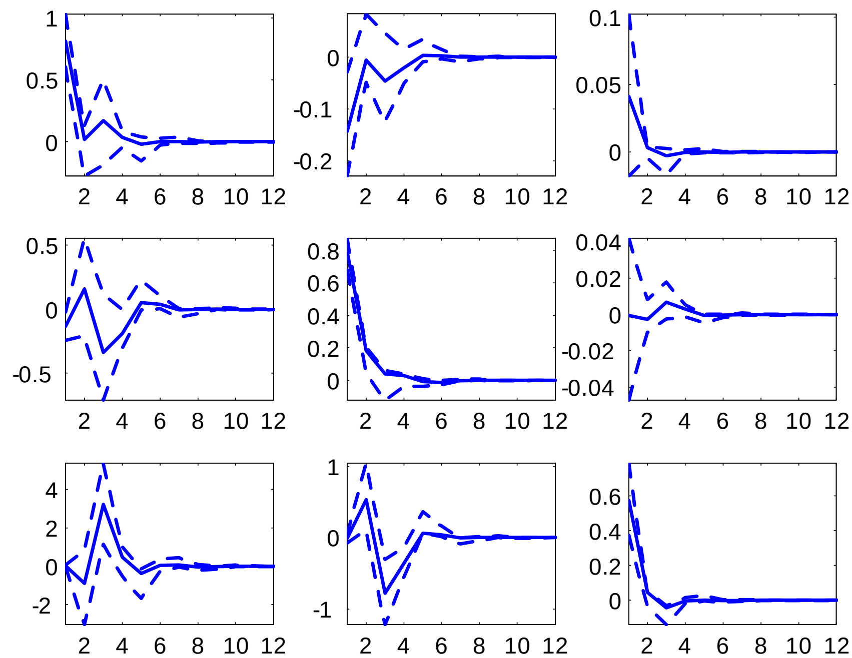

Figure 3: Impulse response functions. Responses of endogenous variables listed in the columns (oil, Dollar, US short-term interest rate) to one-standard deviation shocks listed in the rows ($\varepsilon_{oil,t}$, $\varepsilon_{Dollar,t}$, $\varepsilon_{r,t}$). Dashed lines are 95% confidence bands from 500 bootstrap replications. Sample includes weekly data from 2003 to 2010.

enough to capture the volatility of the shocks in period $t$, rather than several periods away from $t$. Also, the larger $\omega$ the smoother the estimated standard deviations be over time, which makes it more difficult to identify periods of changes in volatility. The threshold $c$ is chosen such that the major spikes in the standard deviation of the residuals are classified as high volatility periods. This section explores the robustness of the identification results to alternative assumptions about the threshold level $c$ and the window size $\omega$.

Panel (a) in Table 5 reports selected identification results for the case where the window size is fixed at $\omega = 2$, as in the benchmark results. As the threshold level $c$ is increased, less periods are classified into the regimes of unique high volatility, making it more difficult to identify the structural parameters based on changes in volatility. The result that higher oil prices are associated with Dollar depreciation and vice versa is robust as long as there are a sufficient number of observations in each high volatility regime to identify statistically significant effects. Panel (b) explores robustness to increasing the window size over which the volatility of the residuals is computed to up to 12 weeks, keeping the threshold level fixed at $c = 0.5$ as in the benchmark results. With a larger window

Table 5: Robustness to choice of volatility regime

(a) Threshold

| | # of obs. in high volatility regime | | | contemporaneous comovement | |
|---|---|---|---|---|---|
| | Oil price | Dollar | Interest rate | Oil→Dollar | Dollar→Oil |
| $c = 0$ | 58 | 70 | 34 | $-0.2029^{**}$ 0.0420 | $-0.1668^{**}$ [0.0440] |
| $c = 0.5$ | 31 | 56 | 25 | $-0.1821^{**}$ [0.0220] | $-0.1725^{**}$ [0.0220] |
| $c = 1$ | 19 | 35 | 21 | $-0.1609^{*}$ [0.0900] | $-0.2284^{**}$ [0.0200] |
| $c = 1.5$ | 22 | 20 | 17 | $-0.1185$ [0.2420] | $-0.2561$ [0.1380] |
| $c = 2$ | 15 | 11 | 16 | 0.0354 [0.2280] | $-0.3590^{*}$ [0.0720] |

(b) Length of window

| | # of obs. in high volatility regime | | | contemporaneous comovement | |
|---|---|---|---|---|---|
| | Oil price | Dollar | Interest rate | Oil→Dollar | Dollar→Oil |
| $\omega = 4$ | 25 | 36 | 33 | $-0.1623$ [0.1600] | $-0.1579$ [0.1300] |
| $\omega = 6$ | 17 | 35 | 34 | $-0.2627$ [0.1440] | $-0.0933$ [0.3000] |
| $\omega = 8$ | 14 | 35 | 40 | 0.1194 [0.3600] | $-0.3550^{*}$ [0.0540] |
| $\omega = 10$ | 11 | 22 | 46 | 0.3583 [0.4540] | $-0.4501$ [0.1860] |
| $\omega = 12$ | 10 | 13 | 51 | $-0.0670$ [0.1780] | $-0.2607$ [0.3200] |

*Note:* High volatility periods for variables $j$ are defined as periods in which the standard deviation $s_{jt}$ computed over moving windows of size $t \pm \omega/2$ is larger than $E(\sigma_{jt}) + c \cdot Var(\sigma_{jt})$. This table presents selected robustness results for different values of window length $\omega$ and threshold level $c$. The reported contemporaneous comovements are the estimated coefficients in matrix $\mathbf{A}^{-1}$. Panel (a) uses $\omega = 2$ as in the benchmark results. Panel (b) uses $c = 0.5$ as in the benchmark results. P-values in square brackets. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

size changes in volatility become less pronounced, making it more difficult to identify the model. Again, the result of negative two-way inter-weekly comovement between oil prices and the US Dollar is robust to different window sizes, as long as the coefficients are statistically significant. The contemporaneous effect of oil prices on the Dollar is estimated to be positive (though not significant) with window sizes $\omega = 8$ and $\omega = 10$, but 14 and 11 observations in the oil shocks high volatility regime are unlikely to be sufficient to correctly identify the contemporaneous feedback effect from oil prices.

## 5 Conclusions

Oil prices and exchange rates tend to move together, and appear to have been negatively related in recent years: during the 2003-2008 oil price boom and during the financial crisis, Dollar depreciation (appreciation) was typically associated with higher (lower) oil prices. This paper investigates the relationship between oil prices and the US Dollar nominal effective exchange rate using a structural model that is fully identified by exploiting the heteroskedasticity in the data, following Rigobon (2003). In contrast to the previous literature this allows us to identify the short-run comovements of oil prices and the Dollar. We control for effects of US and global economic developments on oil prices and exchange rates by including measures of the surprise component of economic news releases.

The results indicate that higher oil prices lead to a depreciation of the Dollar both in the short run – within the same week – and (in line with some of the previous literature) over longer horizons. We also find that Dollar depreciation is associated with higher oil prices within the same week. In the long run, fluctuations in interest rates explain most of the variation of oil prices and exchange rates.

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# Appendix

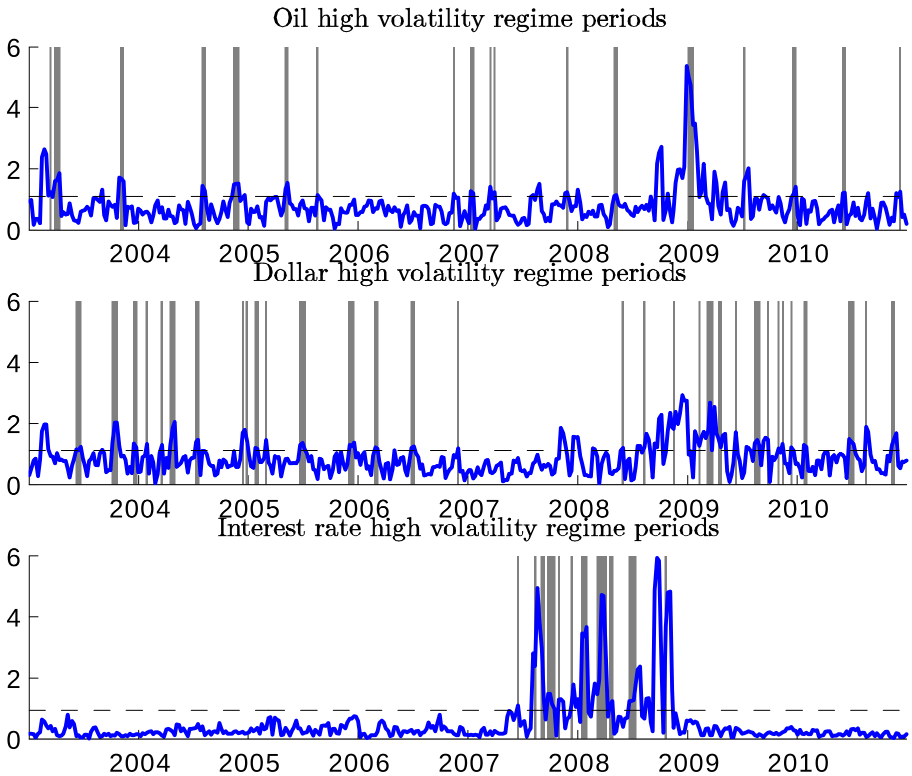


Figure 4: Estimated high volatility regimes. The charts plot the standard deviation of residuals from the reduced-form VAR, $\sigma_{it}$, computed over rolling windows of 2 weeks centered around $t$. Dashed lines represent the threshold used, equal to $E(\sigma_{it}) + c \cdot Var(\sigma_{it})$, where $c = 0.5$. The shaded areas are the chosen high volatility regime periods for each variable.

Table 6: Bootstrap results

**contemporaneous feedback effects (matrix $\mathbf{A}^{-1}$)**

| | | bootstrap | | |
|---|---|---|---|---|
| | **Point estimate** | **mean** | **standard error** | **p-value** |
| $\varepsilon_{oil,t}$ →oil | 1.0324*** | 1.0237 | 0.0151 | 0.0000 |
| $\varepsilon_{oil,t}$ →dollar | -0.1821** | -0.1735 | 0.0877 | 0.0260 |
| $\varepsilon_{oil,t}$ →interest rate | -0.0521* | 0.0517 | 0.0409 | 0.1000 |
| | | | | |
| $\varepsilon_{dollar,t}$ →oil | -0.1725** | -0.1749 | 0.0843 | 0.0220 |
| $\varepsilon_{dollar,t}$ →dollar | 1.0303*** | 1.0224 | 0.0147 | 0.0000 |
| $\varepsilon_{dollar,t}$ →interest rate | -0.0008 | -0.0010 | 0.0366 | 0.4940 |
| | | | | |
| $\varepsilon_{r,t}$ → oil | 0.0400 | 0.0361 | 0.0808 | 0.3180 |
| $\varepsilon_{r,t}$ → dollar | -0.0244 | -0.0203 | 0.0615 | 0.3560 |
| $\varepsilon_{r,t}$ → interest rate | 1.0019*** | 0.9987 | 0.0055 | 0.0000 |

*Note:* ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Results from 500 bootstrap replications. Sample includes weekly data from 2003 to 2010.

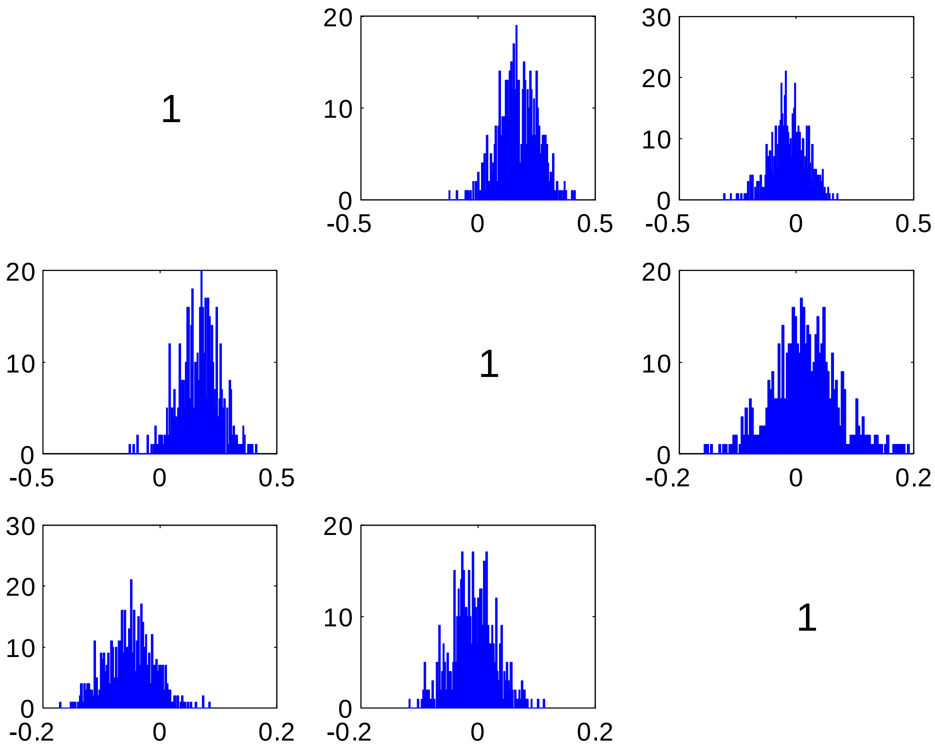


Figure 5: Distribution of estimated coefficients in matrix **A** from 500 bootstrap replications.

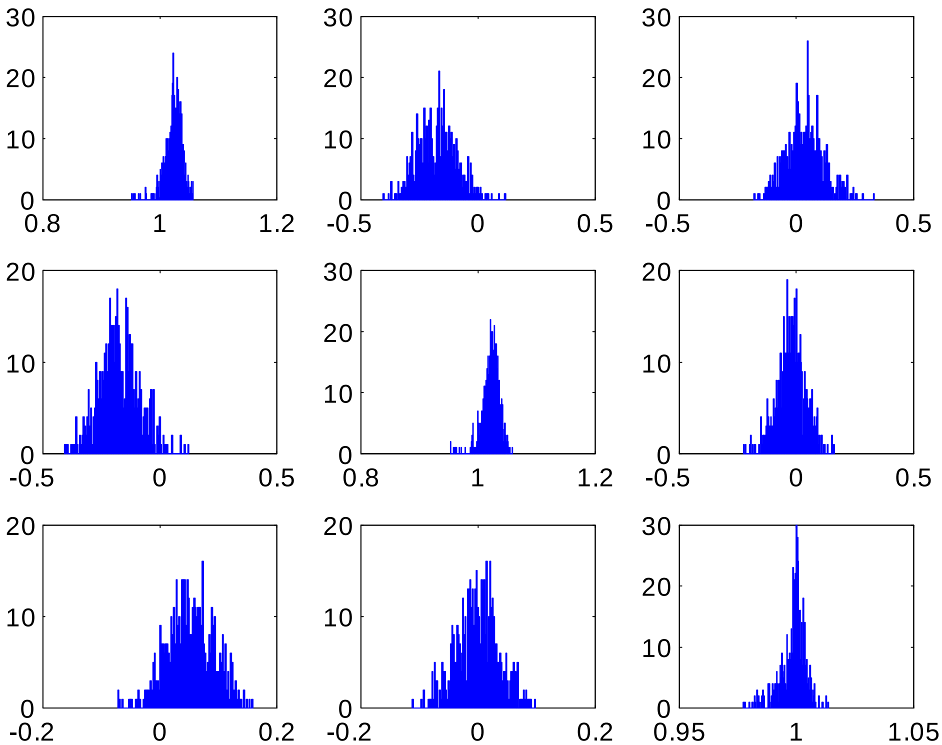


Figure 6: Distribution of estimated coefficients in matrix $\mathbf{A}^{-1}$ from 500 bootstrap replications.