Shocks in the Chain: How Exchange Rate Volatility Disrupts Value-Added Trade *

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Abstract

Exchange-rate volatility poses well-documented risks to international trade, yet its effects on the distinct components of global value chain (GVC) participation remain largely unexplored. This paper fills that gap. We are the first to pair GARCH-based volatility measures with a Panel VAR framework applied to GVC-disaggregated trade flows, using the Koopman-Wang decomposition to track foreign value-added (FVA), directly-absorbed domestic value-added (DV), intermediate value-added re-exported to third countries (IV), and re-imported domestic value-added (RDV) across 24 countries and 13 manufacturing industries from 2001 to 2020. Industry-specific real effective exchange rates from Sato et al. (2013) feed a GARCH(1,1) model that provides our primary volatility metric, with rolling-window measures used for robustness. Sector-specific Panel VARs, evaluated through orthogonalized impulse-response functions and forecast-error variance decompositions, show that volatility shocks reduce FVA and RDV more sharply and more persistently than other GVC components. Because FVA and RDV cross borders more frequently than directly-absorbed value-added, exchange-rate uncertainty disproportionately disrupts these links, which is a prediction that our results confirm. Impacts vary sharply across sectors, underscoring heterogeneous exposure along the value chain. Alternative rolling and moving-average volatility measures yield weaker and less consistent results, reinforcing the case for GARCH-based estimation. The findings imply that macro-stabilization policies and wider access to hedging instruments are especially critical for economies whose GVC integration is deepest.

Keywords: global value chains, exchange rate volatility, panel VAR, GARCH model, value-added trade. JEL Codes: F14, F31, C33.

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1 Introduction

International economists have long viewed volatile exchange rates as a potential tax on international trade. Unexpected fluctuations in exchange rates lead to unexpected fluctuations in revenue streams for sellers and unexpected fluctuations in costs for buyers, which may deter either party from committing to a trade contract. Thus, early theoretical work in this area said that, when firms had to invoice in foreign currencies and could not hedge against exchange rate risk, there would be a negative relationship between exchange rate volatility and international trade volumes. However, several decades of empirical investigations have yet to unambiguously confirm this prediction. Many studies do find a negative relationship, but others find positive relationships, insignificant relationships, or threshold-dependent relationships. Many of these results seem to be dependent on a firm's risk attitudes, cost structures, and invoicing choices. However, an increasing amount of literature focuses on a firm's participation in global value chains (GVCs).

Internationally fragmented production has changed the way that we think about international trade. Whereas classical trade theory assumed that goods were produced largely in one country and then traded as finished products, a modern smartphone might cross an international boundary multiple times before reaching consumers. Each one of these border crossings, while allowing for specialization along the value chain, exposes a producer to exchange rate risk. Consequently, a growing literature has focused on how participation in GVCs has affected the elasticity of bilateral trade volumes with respect to the levels of exchange rates. The consensus is that GVC participation tends to dampen this elasticity.

However, virtually all of this literature focuses on the levels of exchange rates rather than their volatility. As a result, we lack a clear picture about how exchange rate uncertainty affects distinct types of GVC participation, such as those that we examine in this study: foreign value-added in exports (FVA), aggregate domestic value-added (DVA), domestic value-added directly absorbed by importers (DV), domestic value-added reimported from overseas (RDV), and domestic value-added absorbed by third countries (IV).

This study fills this gap in the literature. We are the first to apply GARCH-based volatility measures within a PVAR framework to GVC-disaggregated trade flows. We show that the Koopman-Wang decomposition reveals heterogeneity in volatility exposure that aggregate measures conceal. For instance, because FVA and RDV cross borders more frequently than directly-absorbed domestic value-added, exchange-rate uncertainty should disproportionately affect those components, which is a prediction our results confirm. We also demonstrate that GARCH dominates rolling-window measures on both statistical and economic grounds.

To justify these contributions, our empirical analysis combines high frequency data on real effective exchange rates by sectors from (Sato et al. 2013) with a decomposition of trade in GVCs from the Trade in Value-Added (TiVA) dataset. From these data, we can analyze exports from 24 countries in 13 sectors from 2001-2020. We use the high-frequency exchange-rate data to create GARCH models of exchange rate uncertainty. While we use other measures of volatility as a robustness check, rolling and moving-average volatility measures rely on arbitrary windows and smooth away high-frequency shocks, introducing time-aggregation bias and potential endogeneity when trade and policy respond within the window (Wang and Barrett 2007). We therefore use GARCH(1,1) conditional variances from industry-specific REER measures, which captures volatility clustering and better matches firms' contracting horizons (Hall et al. 2010; Serenis and Tsounis 2012; Sugiharti, Esquivias, and Setyorani 2020). We also report rolling/moving-average volatility measures for robustness checks. We then incorporate these measures into sectoral-level vector autoregressions that treat exchange rate level, volatility, and GVC components as jointly determined. Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs) allow us to trace both the magnitude and persistence of volatility shocks across the value chain.

Our analysis reveals four main facts:

1. A one-standard-deviation volatility shock based on GARCH model reduces FVA by approximately 4.1% in the first period, with effects lasting for two periods, and are roughly twice as large as those on aggregate domestic value-added.
2. The part of the GVC most affected by GARCH based volatility measure is re-imported domestic value-added embedded in previous exports (RDV), which falls by about 12.4% in the first period and effects lasting for up to three years. The "round trip" made by these components are doubly affected by foreign exchange volatility. To a lesser extent, re-exported intermediate value-added (IV) is also highly affected by exchange rate volatility.
3. The effect from GARCH based volatility measure varies substantially across sectors. Some industries, such as metals and machinery, have large negative responses to foreign exchange rate volatility, whereas other sectors like textiles and food processing are not highly affected.
4. The measures based on rolling and moving average standard deviation yield smaller results quantitatively, with some changes in the qualitative conclusions.

Because exchange-rate uncertainty disproportionately disrupts multi-stage production links, macrostabilization tools (e.g., inflation-targeting frameworks) and wider access to hedging instruments become even more important for economies embedded in GVCs. Sector-targeted support may be warranted where value chains are deepest and shocks most severe.

The rest of this study is organized as follows: Section 2 reviews the existing literature on exchange-rate volatility, global value chains, and international trade. Section 3 describes our data and variable construction. Section 4 outlines our empirical strategy. Section 5 presents our results, robustness checks, and discussion. Section 6 concludes with some policy implications and directions for future research.

2 Literature Review

2.1 Exchange Rate Volatility and Trade

Early theoretical work established a presumption that exchange rate uncertainty can inhibit international trade. Seminal models by Ethier (1973) and Clark (1973) showed that when exporters are risk-averse and future exchange rates are unpredictable, the volatility acts like a risk premium on export revenues, leading firms to curtail their export commitments. In Clark's model of a competitive firm paid in foreign currency, greater variance in the exchange rate lowers the certainty-equivalent of export earnings, inducing the firm to scale back output and overseas sales. Hooper and Kohlhagen (1978) later refined this framework by allowing for lags between contracting and delivery, similarly concluding that unanticipated exchange-rate swings during the contract period erode traders' profits and thus discourage trade. These early studies assumed conditions like perfect competition, pricing in the exporter's currency, no imported inputs, high risk aversion, and limited hedging instruments. Under such restrictive assumptions, exchange-rate volatility unambiguously reduces trade volumes.

Subsequent theories relaxed these assumptions and found that the volatility–trade relationship is not necessarily one-sided. For instance, if firms can source imported inputs more cheaply after a partner's currency depreciates, the cost savings can offset the revenue loss from a weaker export price, dampening the net effect on trade. Firms may also hedge exchange risks by invoicing in multiple currencies or using forward contracts, though in practice hedging is often imperfect due to coordination challenges and added costs. The degree of risk aversion plays a crucial role: highly risk-averse exporters might actually increase exports under greater exchange-rate uncertainty to secure a higher expected marginal utility of revenue (an "income effect"), whereas less risk-averse firms react by retrenching (the standard "substitution effect"). As De Grauwe (1988) and others have shown, the net outcome of these opposing effects can be positive, negative, or nil depending on firms' risk preferences. Likewise, if producers can flexibly adjust their production across markets or rely on a large home market buffer, they may not reduce exports when facing volatile exchange rates (and might even exploit favorable rate swings). Thus, theory ultimately yields ambiguous predictions: while early models predicted a uniformly negative impact of exchange-rate volatility on trade, later work established conditions under which this impact could be neutral or even positive.

Empirically, the evidence on exchange rate volatility and trade is mixed, reflecting the theoretical ambiguities. Many studies – spanning different countries, periods, and methodologies – have found that higher exchange-rate volatility is associated with lower bilateral trade volumes. For example, Akhtar and Hilton (1984) documented a significant negative effect of volatility on trade between major economies in the early floating era, and many subsequent studies through the 1990s and 2000s reported similar findings across both developed and developing countries. An IMF analysis (Clark et al. 2004) using a multi-country gravity model likewise found a negative volatility–trade relationship on average. However, the IMF study noted that this result was not robust across all model specifications – the inclusion of different product types or country samples sometimes weakened the effect. Notably, the same study found that entering a currency union (thereby eliminating bilateral exchange-rate fluctuations) yielded much larger gains in trade among members than merely reducing volatility under separate currencies. In another influential study, Wei (1999) observed a negative association between exchange-rate volatility and bilateral trade among countries with high trading potential, yet found no evidence that greater financial hedging activity lessened this trade-deterring effect. Such findings suggest that, in many cases, exchange-rate uncertainty has some dampening influence on trade, but the magnitude can depend on countries' ability to hedge or other institutional factors.

On the other hand, a considerable body of work finds little or no impact of exchange-rate volatility on trade, or even a positive impact in certain contexts. Several studies have failed to uncover any significant link between volatility and trade flows. For instance, using gravity models with improved controls, Tenreyro (2007) concluded that exchange-rate variability has no robust effect on trade once endogeneity and country characteristics are accounted for. At the same time, some researchers have reported positive correlations whereby higher volatility coincides with greater trade. Early examples include Asseery and Peel (1991) and McKenzie and Brooks (1997) for specific markets, and more recently Bahmani-Oskooee, Harvey, and Hegerty (2013) found cases where exchange rate uncertainty appeared to boost export volumes. These divergent results across studies likely reflect differences in data and modeling. Research designs vary in their country samples and time periods, the choice between real vs. nominal exchange rates, how volatility is measured (e.g.

simple standard deviations, moving averages, or GARCH-based estimates), and the estimation techniques employed. Such heterogeneity makes it difficult to directly compare results and helps explain why consensus on the overall effect of exchange-rate volatility on trade has remained elusive. Overall, the empirical literature paints a nuanced picture: exchange-rate volatility can hamper international trade under many conditions, but this outcome is not universal.

Several recent contributions have added further nuance to this debate. One important consideration is reverse causality – the idea that trade flows themselves can stabilize exchange rates. Indeed, as posited by Mundell's classic optimum currency area theory, countries that trade intensively tend to have more correlated economic conditions and potentially more stable bilateral exchange rates. Broda and Romalis (2011) provide empirical support for this, showing that country-pairs with larger trade shares (for example, geographically closer partners) exhibit lower exchange-rate volatility, whereas pairs that trade less have more volatile exchange rates. This implies that failing to control for the endogeneity of volatility (i.e. that more trade can lead to less volatility), may cause one to overstate the harmful effect of volatility on trade. Another extension is to account for third-country effects. Volatility in the exchange rate between a country and a third partner can indirectly affect bilateral trade with a given partner, a factor first highlighted by Cushman (1986). Studies incorporating such multilateral exchange-rate volatility (e.g. Dell'Ariccia (1999); Bahmani-Oskooee and Fariditavana (2016); Lee, Li, and Lee (2022)) often find improved explanatory power for trade flows, underscoring that a bilateral exchange rate does not tell the whole story when firms compete in a multi-currency global market. Researchers have also explored asymmetric effects of volatility, asking whether uncertainty arising from currency depreciations has a different impact than volatility during appreciations. Some evidence suggests asymmetry matters: for instance, volatility accompanying a sharp depreciation might hurt exports more than an equivalent degree of fluctuation during appreciation. However, results on such asymmetries are mixed, with different studies reporting positive, negative, or insignificant effects depending on the context. Finally, the currency of invoicing in trade transactions plays a crucial role. If exports are predominantly invoiced in a vehicle currency (like the US dollar) or in the importer's currency rather than the exporter's, then the direct bilateral exchange-rate volatility faced by the exporter may have a muted effect on trade volumes in the short run. In such cases, traditional models based on producer-currency pricing may mis-predict outcomes, and it becomes necessary to consider third-currency exchange rates or invoicing-adjusted measures of volatility (as emphasized by Iqbal, Nosheen, and Wohar (2023)). Each of these extensions highlights that the impact of exchange-rate volatility on trade is contingent on a host of mitigating factors.

In summary, decades of research have not yielded a definitive consensus on this issue. While many studies support the conventional view that exchange-rate volatility tends to suppress international trade, plenty of others find weak or even opposite effects under certain conditions. The overall relationship appears to depend on country characteristics, time horizons, and modeling assumptions, warranting a cautious and context-specific interpretation of results. One important question that arises – and which has only recently begun to attract attention – is how this volatility–trade nexus might be altered by the rise of global value chains. Modern production networks often involve inputs crossing borders multiple times, which could amplify or attenuate the cost of exchange-rate fluctuations as firms are more deeply intertwined across currencies. Indeed, if suppliers and buyers are spread across different countries in a production chain, exchange-rate risk may propagate in complex ways (potentially increasing uncertainty costs). To date, relatively few studies have examined how GVC integration might change the trade response to exchange-rate volatility. The following subsections therefore turn to this emerging literature, exploring how participation in global value chains could modify the effect of exchange rate volatility on trade.

2.2 Global Value Chains and Exchange Rates

The rise of GVCs – internationally fragmented production networks – has introduced new considerations for the exchange rate–trade nexus. When intermediate goods cross borders multiple times, exchange rate fluctuations can accumulate costs along the supply chain. In fact, a currency depreciation may not always boost a country's exports in the short run if its exporters rely heavily on imported inputs, since their input costs rise with a weaker home currency. Conversely, a depreciation can improve the competitiveness of foreign downstream firms that use cheaper imported inputs to produce exports. Considering these effects, a growing empirical literature asks how GVC participation alters the trade responsiveness to exchange rates. Ahmed, Appendino, and Ruta (2017) find that greater involvement in GVCs is associated with significantly lower export elasticity to exchange rate changes. Similarly, Bang and Park (2018) report that deeper GVC integration dampens the impact of exchange rate movements on export volumes, with the effect most pronounced in highly integrated economies. These findings suggest that when production is internationally integrated, exchange rate changes are transmitted less straightforwardly to export competitiveness.

Researchers have also explored the mechanisms behind this dampening. For example, Soyres et al. (2021) show that the effect of an exchange rate shift differs by a firm's position in the production chain. By separately examining FVA in exports (upstream inputs) and various categories of DVA (such as inputs re-exported or final goods), they demonstrate that aggregating GVC involvement into a single backward or forward linkage measure can obscure important heterogeneity. In another study, Adler, Meleshchuk, and Buitron (2023) assess how GVCs influence external adjustment. They find that, for a given level of overall trade openness, greater GVC integration tends to reduce the trade-balance response to exchange rate changes. In other words, supply-chain linkages can cushion the impact of currency swings on a country's trade balance. At the same time, Adler, Meleshchuk, and Buitron (2023) note an offsetting force: GVC integration increases total trade exposure, which can amplify the responsiveness of the trade balance to exchange rates. Due to these countervailing effects, they conclude that GVC participation, on net, does not radically alter the benefits of exchange rate flexibility. Overall, the literature on GVCs indicates that global production sharing tends to weaken the traditional exchange rate–trade relationship, although the magnitude and channels of this modification vary across studies.

2.3 Exchange Rate Volatility in Global Value Chains

Only recently have researchers explicitly analyzed exchange rate volatility in the context of GVCs. Early evidence suggests that GVC integration may buffer, or even reverse, the adverse trade impact of currency volatility. Tan, Trieu Duong, and Chuah (2019) examine eight ASEAN economies and find that higher exchange rate volatility generally correlates with lower gross exports, but this negative effect is statistically significant only after accounting for firms' use of imported inputs. Moreover, when Tan and colleagues include an interaction term for GVC participation (measured by the foreign-value-added share of exports), they find that volatility is associated with an increase in exports at high levels of GVC involvement. In a broader cross-country study, Sato and Zhang (2019) reach a similar conclusion. They show that while exchange rate volatility on average reduces bilateral exports, greater GVC participation weakens this negative effect, and beyond a certain integration threshold the effect of volatility on exports becomes positive. These results imply that extensive GVC linkages can provide firms with diversification or flexibility that insulates them from exchange rate risk – for example, by allowing producers to source inputs or redirect sales across markets in response to currency fluctuations.

Despite these advances, two important gaps remain. First, no existing study examines how exchange-rate volatility affects the components of GVC-linked trade separately. Soyres et al. (2021) decompose exports into domestic and foreign value-added in the context of exchange-rate levels, but do not examine volatility. Tan, Trieu Duong, and Chuah (2019) and Sato and Zhang (2019) incorporate volatility, but treat GVC participation as a modifier of aggregate export responses rather than disaggregating trade flows by value-added type. This matters because FVA and RDV cross international borders more frequently than directly-absorbed domestic value-added, so they face qualitatively different, and plausibly larger, exposure to exchange-rate uncertainty. A composite GVC participation index obscures this heterogeneity. Second, the volatility measures used in prior GVC studies rely on rolling-window or moving-average standard deviations, which are sensitive to arbitrary window-length choices, smooth away high-frequency clustering and shorten the effective time series, reducing efficiency and potentially introducing measurement error (Wang and Barrett (2007) and Bahmani-Oskooee, Harvey, and Hegerty (2013)). They are also backward-looking and do not incorporate the persistence of shocks. A GARCH based measure can explicitly address these loopholes. To our knowledge, no study has applied GARCH-based volatility within a Panel VAR framework to GVC-disaggregated trade flows. We address both gaps simultaneously.

3 Data

Our empirical analysis combines value-added trade data from the OECD Trade in Value Added (TiVA) database with industry-specific exchange rate indices from the Research Institute of Economy, Trade and Industry (RIETI).

Value-added trade data: From the TiVA 2023 edition, we obtain annual measures of gross exports decomposed into various value-added components. TiVA provides these indicators for 76 OECD and non-OECD economies across 45 industries classified under ISIC Revision 4, covering 1995–2020. For consistency with the exchange rate dataset, we focus on 24 countries and 13 manufacturing sectors (12 manufacturing industries and aggregate manufactures) over 2001–2020.

Exchange rate data: Industry-specific real effective exchange rates (REERs) are drawn from Sato et al. (2013, 2020), which provide daily and monthly REER indices for 25 economies across 13 manufacturing industries on the basis of ISIC Revision 3. These series capture competitiveness at the sectoral level by weighting bilateral exchange rates with trade shares and adjusting for producer price indices. Because TiVA is based on ISIC Revision 4, we concord the classifications using the OECD Bilateral Trade Database by Industry and End-Use Category (BTDIxE).

Macroeconomic controls: Country-level GDP and gross national expenditure (GNE) in constant USD are taken from the World Bank's World Development Indicators (WDI). These serve as proxies for domestic and foreign demand in the VAR system.

Panel structure: After concording and harmonizing the sources, we construct a balanced panel of 24 countries and 13 manufacturing sectors for 2001–2020. All trade variables are measured in millions of USD, while REER indices and volatility measures are unit-free. Following the literature, variables (other than volatility) are log-transformed prior to estimation. Volatility is constructed from the daily REER data using GARCH(1,1) models, with rolling-window and moving-average measures used for robustness checks.

4 Methodology

Our empirical approach links industry-level exchange rate volatility to GVC trade using a panel VAR framework.

4.1 GVC Decomposition

Following Koopman, Wang, and Wei (2014) and Wang, Wei, and Zhu (2013), gross exports are decomposed into foreign value-added (FVA) and domestic value-added (DVA). DVA is further split into three components:

1. Direct domestic value-added (DV): absorbed directly abroad.
2. Intermediate value-added (IV): re-exported to third countries.
3. Re-imported value-added (RDV): returning home after processing abroad.

This structure allows us to assess how volatility affects both upstream (FVA) and downstream (DV, IV, RDV) linkages in GVCs.

4.2 Measuring Exchange Rate Volatility

We construct sectoral measures of exchange rate volatility from industry-specific real effective exchange rates (REERs). Several conventional approaches are common in the literature:

1. Rolling standard deviations of the REER, computed over short (12-month) or long (5-year) windows (SD_REER_12, SD_REER_5).
2. Rolling standard deviations of first differences in log REERs, over short and long horizons (SD_ΔlnREER_12, SD_ΔlnREER_5).
3. Moving-average standard deviations of REERs or their logs over short and long horizons (MASD_REER_12, MASD_REER_5, MASD_lnREER_12, MASD_lnREER_5).

These measures capture recent fluctuations but have important limitations as outlined in Section 2. To address these shortcomings, our preferred measure of volatility is obtained from a GARCH(1,1) model estimated on daily REER data from Sato et al. (2013, 2020). The GARCH framework explicitly models conditional heteroskedasticity, allowing today's volatility to depend on both past shocks and past volatility. This is important because exchange rates display volatility clustering: periods of calm are followed by periods of turbulence. GARCH captures this persistence, producing a conditional variance that evolves with new information rather than relying on a fixed historical window (Engle (1982) and Bollerslev (1986)).

In addition, GARCH measures provide a more efficient use of high-frequency data. Whereas rolling-window approaches may fail to capture the impact of large shocks that affect expectations about future volatility, the GARCH conditional variance directly incorporates this information. Previous applications in international economics have shown that GARCH-based measures yield lower standard errors and more stable estimates compared with moving-average alternatives (Hall et al. (2010) and Sugiharti, Esquivias, and Setyorani (2020)).

The GARCH procedure assumes that the log return of REER can be modeled by the following equation:

$$r_{it} = \mu + \epsilon_{it} \tag{1}$$

where μ is the average returns, $\epsilon_{it} \sim N(0, \sigma_{it})$ and σ_{it} is the conditional variance of return. While a GARCH specification can take many forms, the GARCH(1,1) specification assumes that the conditional variance can be modeled as:

$$\sigma_{it} = \omega + \alpha\epsilon_{it-1}^2 + \beta\sigma_{it-1} \tag{2}$$

That is, the expected variance in any given period t will be a function of the long-term variance over the period studied (ω), squared new shocks to the system from previous period (ϵ), and the expected variance of the previous period. This specification allows for clustering of shocks in the exchange rate over time, which is observed empirically. We can then use the estimated value of σ_{it}, as our measure of volatility for the country at a given point in time.

For robustness, we also report results using rolling and moving-average measures of REER volatility. These comparisons highlight that the GARCH(1,1) specification consistently delivers the most persistent and economically interpretable dynamics. We therefore emphasize the GARCH results in our main discussion.

4.3 Estimation Strategy

The regression equations to be estimated take the following forms:

$$\begin{aligned}
DVA_{it}^h &= \alpha_1 + \beta_{11} GDP_t^h + \beta_{12} GNE_t^{\mathrm{ROW}} + \beta_{13} REER_{it}^h + \beta_{14} \sum_{c \neq h} REER_{it}^c + \beta_{15} VOL_{it}^h \\
&\quad + \beta_{16} \sum_{c \neq h} VOL_{it}^c + \epsilon_{1it}^h && (3) \\
FVA_{it}^h &= \alpha_2 + \beta_{21} GDP_t^h + \beta_{22} GNE_t^{\mathrm{ROW}} + \beta_{23} REER_{it}^h + \beta_{24} VOL_{it}^h + \epsilon_{2it}^h && (4) \\
DV_{it}^h &= \alpha_3 + \beta_{31} GNE_t^{\mathrm{ROW}} + \beta_{32} REER_{it}^h + \beta_{33} VOL_{it}^h + \epsilon_{3it}^h && (5) \\
IV_{it}^h &= \alpha_4 + \beta_{41} GNE_t^{\mathrm{ROW}} + \beta_{42} REER_{it}^h + \beta_{43} \sum_{c \neq h} REER_{it}^c + \beta_{44} VOL_{it}^h + \beta_{45} \sum_{c \neq h} VOL_{it}^c + \epsilon_{4it}^h && (6) \\
RDV_{it}^h &= \alpha_5 + \beta_{51} GDP_t^h + \beta_{52} GNE_t^{\mathrm{ROW}} + \beta_{53} REER_{it}^h + \beta_{54} VOL_{it}^h + \epsilon_{5it}^h \quad . && (7)
\end{aligned}$$

According to equation (3), the domestic value-added from sector i in country h at time t is a function of the GDP in country h, the GNE in the rest of the world (ROW), the real-effective exchange rate level with respect to sector i in country h and ROW, as well as the associated exchange rate volatility in country h and ROW. The other equations similarly represent the determinants of upstream and other downstream linkages.

The above system of equations is estimated within a panel VAR framework, which treats country specific GVC components, REER levels, and associated volatility as jointly endogenous. Exogenous controls include GDP (home demand), GNE (foreign demand) and REER levels and volatility for rest of the world.

We estimate the PVAR using system GMM with forward orthogonal deviations (Arellano–Bover / Blundell–Bond style) to address dynamic panel bias. Variables are tested for stationarity using the Harris and Tzavalis (1999) panel unit root test. Optimal lag length and moment conditions are selected using the Andrews and Lu (2001) information criteria. The estimated PVAR models report heteroskedasticity and autocorrelation consistent (HAC) variance-covariance matrix evaluated using the bartlett kernel with Newey and West (1994) optimal lag order specification.

Orthogonalised IRFs trace the dynamic effects of a one-standard-deviation volatility shock on each GVC component, while FEVDs quantify the share of variability explained by volatility shocks. Cholesky ordering places volatility after the GVC components and REER, consistent with the view that uncertainty shocks affect trade and REER with a lag but can be contemporaneously influenced by trade flows and REER changes.

5 Results

We present the results in two steps. Subsection 5.1 reports the main findings using our preferred volatility measure from the GARCH(1,1) specification. Subsection 5.2 compares these results with alternative rolling and moving-window volatility measures for aggregate manufactures.

5.1 Results from the GARCH-Based Volatility Measure

Panel VAR estimates at the sectoral level yield coefficients that are difficult to interpret directly (Table 1), so we turn to Granger causality tests to assess whether past volatility significantly predicts GVC components (Table 2). Several clear patterns emerge from Table 2.

First, volatility significantly affects both foreign value-added (FVA) and domestic value-added (DVA), but with asymmetries across sectors. In 11 out of 12 manufacturing sectors, either FVA or some component of DVA responds to volatility shocks. Within DVA, the directly absorbed component (DV)is most frequently Granger-caused, followed by re-imported value-added (RDV) and intermediate exports (IV). Only in textiles and apparel (Sector 2) do we find no significant effect of volatility on any component.

Second, sectoral heterogeneity is pronounced. In industries such as food and beverages (Sector 1), paper and printing (Sector 4), and chemicals (Sector 6), volatility Granger-causes virtually all GVC components, while in others the impact is more selective. This underscores that volatility exposure depends heavily on production structure and import intensity.

Third, when all manufacturing is aggregated (Sector 13), volatility shocks impact FVA, DVA, IV, and RDV. Aggregate DV does not respond significantly, highlighting how volatility primarily reshapes the border-intensive links of the chain.

Impulse response functions (see Figures A4, A5, and A6 in the Appendix) confirm these dynamics. At the aggregate level, volatility shocks lead to statistically significant negative responses in FVA and RDV

Table 1: Panel VAR Regression Coefficients with GARCH Measure

Sector	Lags	FVA	IV	RDV	DV	DVA
1	L1	2.144**	3.309**	5.143***	6.276***	2.870***
		(0.044)	(0.022)	(0.003)	(<0.001)	(<0.001)
2	L1	-6.663	1.953	-0.566	-0.790	-0.018
		(0.338)	(0.122)	(0.873)	(0.301)	(0.994)
3	L1	0.677	-0.103	-3.026***	-1.015**	-0.692*
		(0.672)	(0.977)	(<0.001)	(0.023)	(0.076)
4	L1	-2.640***	-3.838***	-5.651***	-7.111***	-9.734***
		(0.006)	(<0.001)	(<0.001)	(0.003)	(0.001)
5	L1	6.574***	-4.223	1.794	-1.228	-1.186
		(<0.001)	(0.386)	(0.683)	(0.714)	(0.719)
	L2	-4.939**	-1.489	0.657	-0.682	-0.812
		(0.023)	(0.741)	(0.770)	(0.810)	(0.778)
6	L1	-3.694***	-4.613***	-9.115***	-2.197***	-3.097***
		(0.001)	(<0.001)	(<0.001)	(0.008)	(<0.001)
	L2	-	-	-	0.912	-
					(0.569)	
7	L1	-2.012	-4.557***	-1.364	-1.816***	-0.752
		(0.171)	(<0.001)	(0.563)	(<0.001)	(0.329)
8	L1	-1.360***	0.124	2.256	0.435	0.674*
		(<0.001)	(0.719)	(0.507)	(0.333)	(0.069)
9	L1	-20.714	28.358***	-9.493	-12.274***	1.507
		(<0.001)	(<0.001)	(0.117)	(<0.001)	(0.338)
10	L1	-0.758	-1.975***	-2.284***	0.698**	-0.523*
		(0.171)	(0.003)	(<0.001)	(0.029)	(0.068)
11	L1	-9.354***	0.326	-11.889***	-0.774	1.534*
		(<0.001)	(0.916)	(<0.001)	(0.133)	(0.059)
12	L1	-0.540**	-1.064***	-0.395	-0.631***	-0.861***
		(0.033)	(<0.001)	(0.869)	(<0.001)	(<0.001)
13	L1	-3.249***	-8.227***	-8.255***	-0.905	-1.774**
		(<0.001)	(<0.001)	(<0.001)	(0.362)	(0.029)

Note: Figures in parentheses denote p values. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 2: Granger Causality Tests with GARCH Measure

Sector	FVA	IV	RDV	DV	DVA
1	4.054**	5.245**	8.628***	28.748***	15.243***
	(0.044)	(0.022)	(0.003)	(<0.001)	(<0.001)
2	0.919	2.389	0.025	1.069	<0.001
	(0.338)	(0.122)	(0.873)	(0.301)	(0.994)
3	0.179	0.001	25.719***	5.191**	3.141*
	(0.672)	(0.977)	(<0.001)	(0.023)	(0.076)
4	7.640***	25.919***	32.914***	8.987***	10.153***
	(0.006)	(<0.001)	(<0.001)	(0.003)	(0.001)
5	17.412***	0.856	0.642	0.151	0.159
	(<0.001)	(0.652)	(0.725)	(0.927)	(0.924)
6	11.263***	15.624***	54.348***	7.301**	15.375***
	(0.001)	(<0.001)	(<0.001)	(0.026)	(<0.001)
7	1.876	20.720***	0.334	12.765***	0.952
	(0.171)	(<0.001)	(0.563)	(<0.001)	(0.329)
8	12.244***	0.130	0.440	0.937	3.300*
	(<0.001)	(0.719)	(0.507)	(0.333)	(0.069)
9	163.988***	24.432***	2.453	26.136***	0.919
	(<0.001)	(<0.001)	(0.117)	(<0.001)	(0.338)
10	1.873	8.560***	17.424***	4.746**	3.339*
	(0.171)	(0.003)	(<0.001)	(0.029)	(0.068)
11	88.676***	0.011	70.640***	2.261	3.555*
	(<0.001)	(0.916)	(<0.001)	(0.133)	(0.059)
12	4.522**	36.986***	0.027	13.051***	12.242***
	(0.033)	(<0.001)	(0.869)	(<0.001)	(<0.001)
13	92.881***	16.297***	146.898***	0.832	4.770**
	(<0.001)	(<0.001)	(<0.001)	(0.362)	(0.029)

Note: Figures in parenthesis denote p values from chi-squared tests. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

for up to three years, while IV and DVA exhibit briefer effects. The magnitude of the impact on FVA is roughly twice that on DVA, consistent with the idea that foreign-sourced inputs bear the brunt of exchange risk. Notably, RDV absorbs the sharpest and most persistent declines, consistent with its double exposure to border crossings. At the sectoral level, however, positive short-run effects occasionally appear (e.g., IV in paper/printing, FVA in metals), echoing theoretical predictions that risk-averse exporters may sometimes expand activity under volatility if expected utility rises (De Grauwe (1988) and Broil and Eckwert (1999)). Still, these positive responses are short-lived, and negative effects dominate beyond the first year.

Forecast error variance decompositions (FEVDs; Table 3) provide additional perspective. For aggregate manufacturing, volatility shocks explain a larger share of forecast error in DVA than FVA, with the bulk of this effect coming from RDV. Sectoral FEVDs suggest that in many industries DV is most sensitive, but once aggregated, RDV emerges as the dominant margin through which volatility shapes value-added trade.[1]

The stability of all the estimated models can be confirmed from Figures A1, A2, and A3 in the Appendix.

5.2 Results with Alternative Volatility Measures

We next assess whether rolling and moving-window volatility measures yield similar conclusions for manufacturing sector in aggregate. Results are more mixed. In Table 4, for total manufacturing, none of the alternative volatility measures are observed to Granger-cause both FVA and DVA, thus contradicting the results from the GARCH measure. The ability of these alternative measures to pick up FVA responses more reliably than DVA, suggests a bias towards upstream exposure. Unlike the GARCH measure, some of these alternative measures are also observed to Granger-cause DV.

Impulse Response Functions (see Figure A8 in the Appendix) reveal some measures to generate positive short-run effects on IV, RDV or DV, in contrast with the consistent negative responses under GARCH. The measure based on the moving average of log(REER) over 12 months, captures the sharpest decline in FVA revealing the vulnerability of foreign sourced inputs to volatility shocks. The measure has marginally less impact on RDV.

Moreover, model stability checks (Figure A7) reveal that few alternative specifications produce unstable VARs, limiting the interpretability of the results. Even where significant, their impulse responses generally dissipate after one to two years, whereas GARCH-based shocks persist longer and display cleaner dynamics. FEVDs with alternatives based on moving averages of log(REER) over 12 months (Table 5), confirm FVA as the most volatile subcomponent with stronger explanatory power than under GARCH. The measure's explanatory power with respect to RDV now falls.[2]

Taken together, these comparisons reinforce our choice of the GARCH(1,1) measure as the baseline. The conditional variance approach better captures clustering and transmission of shocks through GVCs, yielding results that are economically and statistically more robust.

1. The orthogonalised IRFs and FEVDs in Figures A4, A5, and A6 and Table A2 (Appendix) respectively are reported only in cases where currency volatility is found to Granger-cause the GVC components. Table 3 contains a representative sample of the FEVDs in periods 2, 6, and 10, after the shock.

2. The FEVDs for all periods are presented in Table A3 in the Appendix.

Table 3: FEVDs Corresponding to Currency Volatility Shocks for 13 Industrial Categories with GARCH Measure

Sector Code	**Forecast Horizon**	**FVA**	**IV**	**RDV**	**DV**	**DVA**
1	2	0.071	0.079	0.179	0.308	0.238
	6	0.118	0.126	0.207	0.291	0.380
	10	0.118	0.126	0.207	0.291	0.381
2	2	-	-	-	-	-
	6	-	-	-	-	-
	10	-	-	-	-	-
3	2	-	-	0.062	0.010	0.005
	6	-	-	0.085	0.010	0.005
	10	-	-	0.085	0.010	0.005
4	2	0.101	0.075	0.189	0.361	0.358
	6	0.104	0.119	0.192	0.354	0.381
	10	0.104	0.119	0.192	0.354	0.385
5	2	0.152	-	-	-	-
	6	0.256	-	-	-	-
	10	0.282	-	-	-	-
6	2	0.131	0.160	0.275	0.322	0.174
	6	0.133	0.184	0.275	0.355	0.180
	10	0.133	0.184	0.275	0.354	0.180
7	2	-	0.235	-	0.100	-
	6	-	0.268	-	0.124	-
	10	-	0.268	-	0.126	-
8	2	0.028	-	-	-	0.013
	6	0.029	-	-	-	0.014
	10	0.029	-	-	-	0.014
9	2	0.272	0.329	-	0.319	-
	6	0.429	0.356	-	0.496	-
	10	0.427	0.356	-	0.508	-
10	2	-	0.036	0.024	0.009	0.004
	6	-	0.036	0.024	0.009	0.004
	10	-	0.036	0.024	0.009	0.004
11	2	0.383	-	0.337	-	0.021
	6	0.405	-	0.337	-	0.021
	10	0.405	-	0.337	-	0.021
12	2	0.003	0.009	-	0.005	0.008
	6	0.003	0.010	-	0.005	0.008
	10	0.003	0.010	-	0.005	0.008
13	2	0.164	0.289	0.327	-	0.194
	6	0.178	0.240	0.348	-	0.230
	10	0.178	0.233	0.348	-	0.230

Table 4: Granger Causality Test Results with Alternative Measures of Volatility

Volatility Measure	FVA	IV	RDV	DV	DVA
SD_REER_12	1.604	20.160***	0.532	11.286***	1.899
	(0.205)	(<0.001)	(0.466)	(0.004)	(0.387)
SD_REER_5	2.063	7.615**	1.220	2.570	0.942
	(0.356)	(0.022)	(0.269)	(0.277)	(0.624)
SD_ΔlnREER_12	<0.001	10.961***	0.524	0.002	1.993
	(0.999)	(0.001)	(0.469)	(0.968)	(0.158)
SD_ΔlnREER_5	8.915**	20.723***	8.258***	1.915	1.848
	(0.012)	(<0.001)	(0.004)	(0.384)	(0.397)
MASD_REER_12	12.079***	3.994**	0.533	1.477	0.530
	(0.002)	(0.046)	(0.465)	(0.224)	(0.467)
MASD_REER_5	0.209	7.430**	0.002	2.200	1.328
	(0.901)	(0.024)	(0.965)	(0.138)	(0.723)
MASD_lnREER_12	16.830***	7.493***	53.937***	6.233**	2.425
	(<0.001)	(0.006)	(<0.001)	(0.013)	(0.119)
MASD_lnREER_5	3.854**	17.603***	0.154	11.772***	1.205
	(0.050)	(<0.001)	(0.694)	(0.001)	(0.272)

Note: Figures in parenthesis denote p values. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 5: FEVDs with Alternate Measures of Currency Volatility Shocks

Volatility Measure	Forecast Horizon	FVA	IV	RDV	DV	DVA
	2	-	0.026	-	0.196	-
SD_REER_12	6	-	0.042	-	0.248	-
	10	-	0.043	-	0.248	-
	2	-	0.005	-	-	-
SD_REER_5	6	-	0.047	-	-	-
	10	-	0.060	-	-	-
	2	-	0.171	-	-	-
SD_ΔlnREER_12	6	-	0.151	-	-	-
	10	-	0.151	-	-	-
	2	0.014	0.320	0.126	-	-
SD_ΔlnREER_5	6	0.134	0.359	0.170	-	-
	10	0.155	0.360	0.170	-	-
	2	0.010	0.085	-	-	-
MASD_REER_12	6	0.017	0.113	-	-	-
	10	0.017	0.113	-	-	-
	2	-	0.070	-	-	-
MASD_REER_5	6	-	0.095	-	-	-
	10	-	0.101	-	-	-
	2	0.208	0.074	0.070	0.039	-
MASD_lnREER_12	6	0.285	0.069	0.072	0.039	-
	10	0.286	0.069	0.072	0.039	-
	2	0.067	0.121	-	0.222	-
MASD_lnREER_5	6	0.150	0.144	-	0.314	-
	10	0.155	0.144	-	0.324	-

6 Conclusion

This study shows that exchange-rate volatility reshapes how countries trade by disrupting the most border-intensive segments of global value chains. Using industry-specific REERs and a GARCH-based volatility measure embedded in sectoral panel VARs for 24 economies in the years 2001–2020, we find that a volatility shock reduces foreign value-added (FVA) and re-imported domestic value-added (RDV) more, earlier, and more persistently than other components. Effects are front-loaded within the first year and attenuate by roughly the third, consistent with clustering in volatility and short-run adjustment frictions. Alternative volatility constructions occasionally weaken or flip responses, but the GARCH formulation delivers the most consistent and persistent pattern, which we treat as our preferred specification.

Exposure to exchange rate volatility along multi-stage chains magnifies risk as due to "round-trips" of intermediate goods across borders. Sectoral heterogeneity is meaningful: heavy manufacturing and machinery/basic metals appear more exposed than lighter, less import-intensive industries, implying limited mileage for one-size-fits-all policy.

Policy should therefore target FX-risk intermediation where GVC depth is greatest: deepen affordable hedging markets, encourage stable invoicing conventions, and integrate RDV/FVA exposure into trade-policy and macroprudential assessments. For firms, the actionable margin is operational: prioritize hedging and supplier/lead-time diversification at stages with high foreign content or likely "round-trip" flows; revisit contract clauses and pricing lags in those nodes where our results attribute the largest volatility share.

Limitations of our study include reduced form identification in PVARs and aggregation in the TiVA dataset that may smooth firm-level exposure. Possible avenues for future work could (i) pair these dynamics with correlated-random-effects or Mundliak-type specifications to absorb time-invariant heterogeneity to better understand cross-country risk exposures, and (ii) validate with local and firm level data to better understand firm-level margins. Overall, volatility matters for which links of the chain contract first, and policy that cushions those links could materially stabilize trade.

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A Appendix

Table A1: Sector Codes

Sector Description	**Sector Code**
Food, beverages and tobacco	1
Textiles, Leather and Footwear	2
Wood and Products of Wood and Cork	3
Paper and Printing	4
Coke and refined petroleum products	5
Chemical and pharmaceutical products	6
Rubber and plastic products	7
Other non-metallic mineral products	8
Basic metals and fabricated metal products	9
Computer, electronic and optical products	10
Machinery and equipment not elsewhere classified	11
Transport equipment	12
Total manufacturing	13

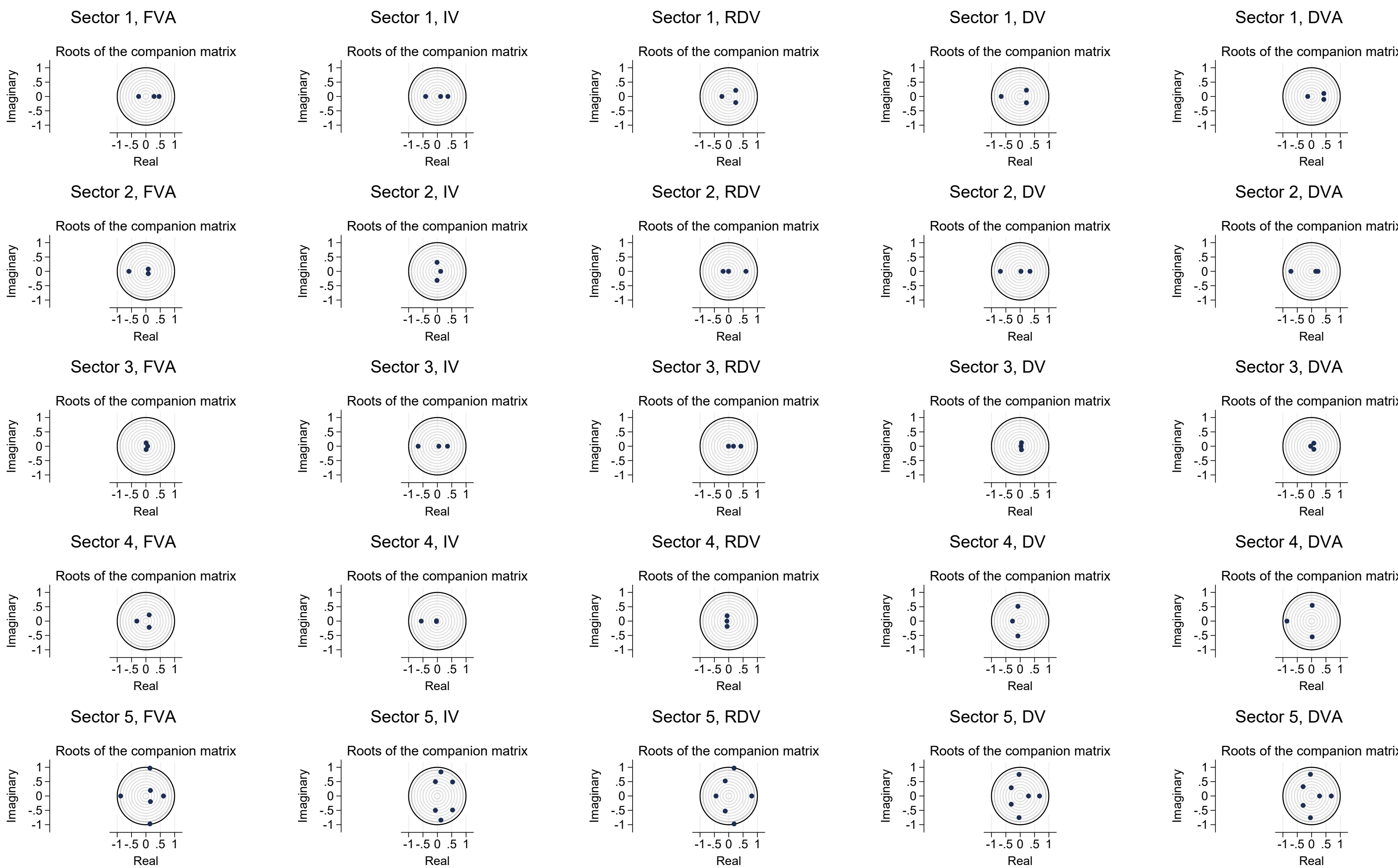

Figure A1: Model Stability Results for 13 Industrial Categories with GARCH Measure (Sectors 1-5)

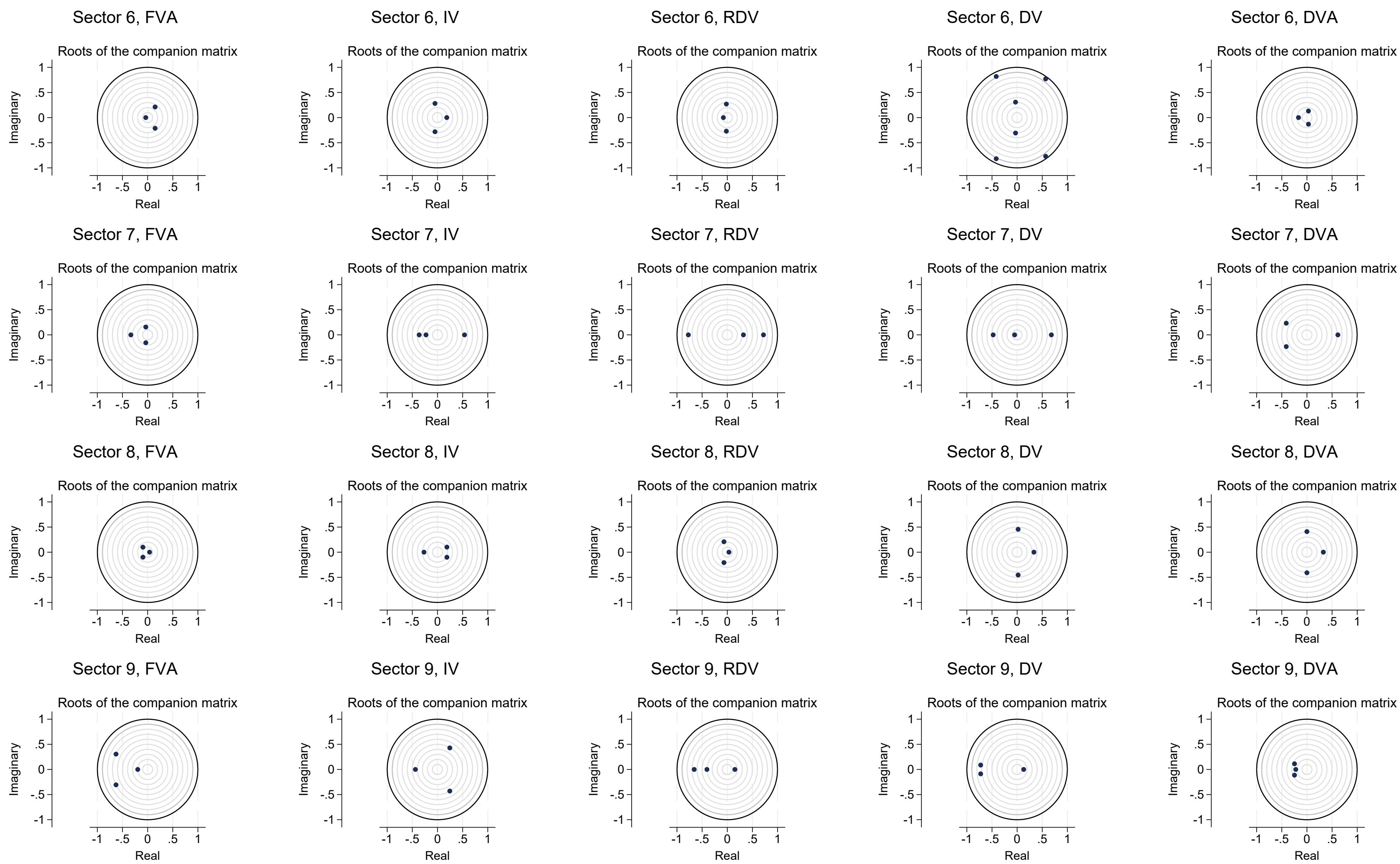

Figure A2: Model Stability Results for 13 Industrial Categories with GARCH Measure (Sectors 6-9)

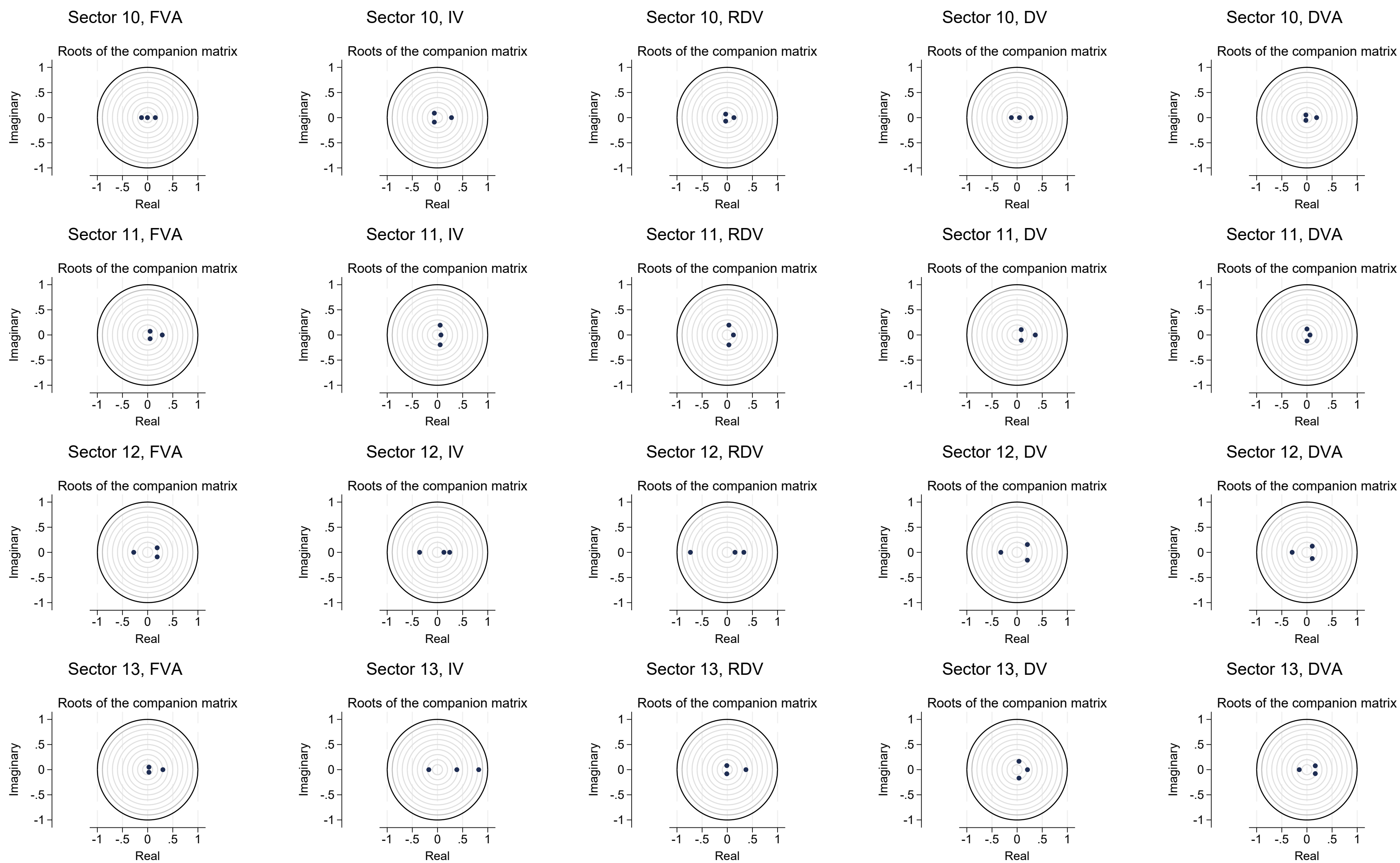

Figure A3: Model Stability Results for 13 Industrial Categories with GARCH Measure (Sectors 10-13)

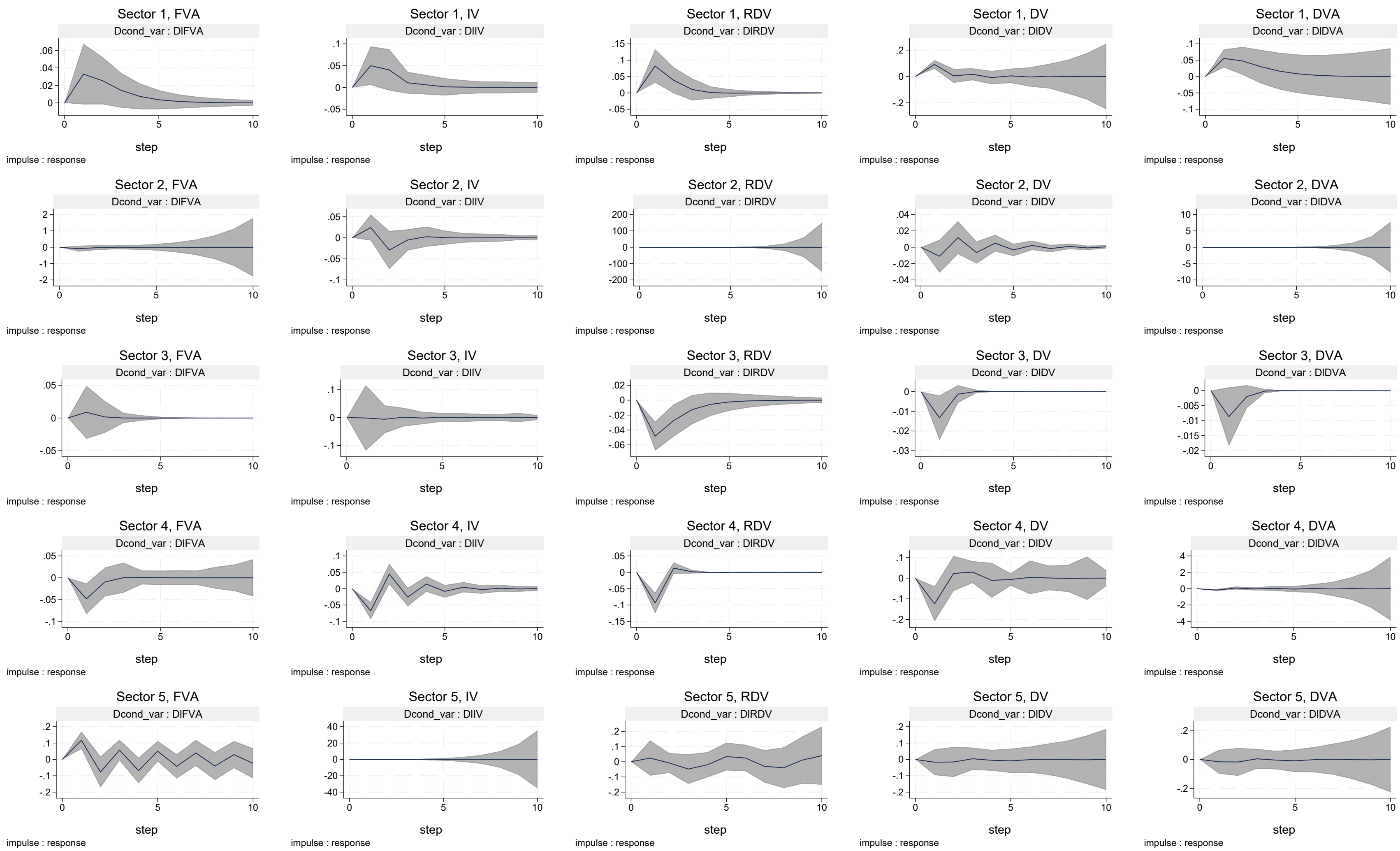

Figure A4: Orthogonalised IRF Plots From Shocks to Currency Volatility with GARCH Measure (Sectors 1-5)

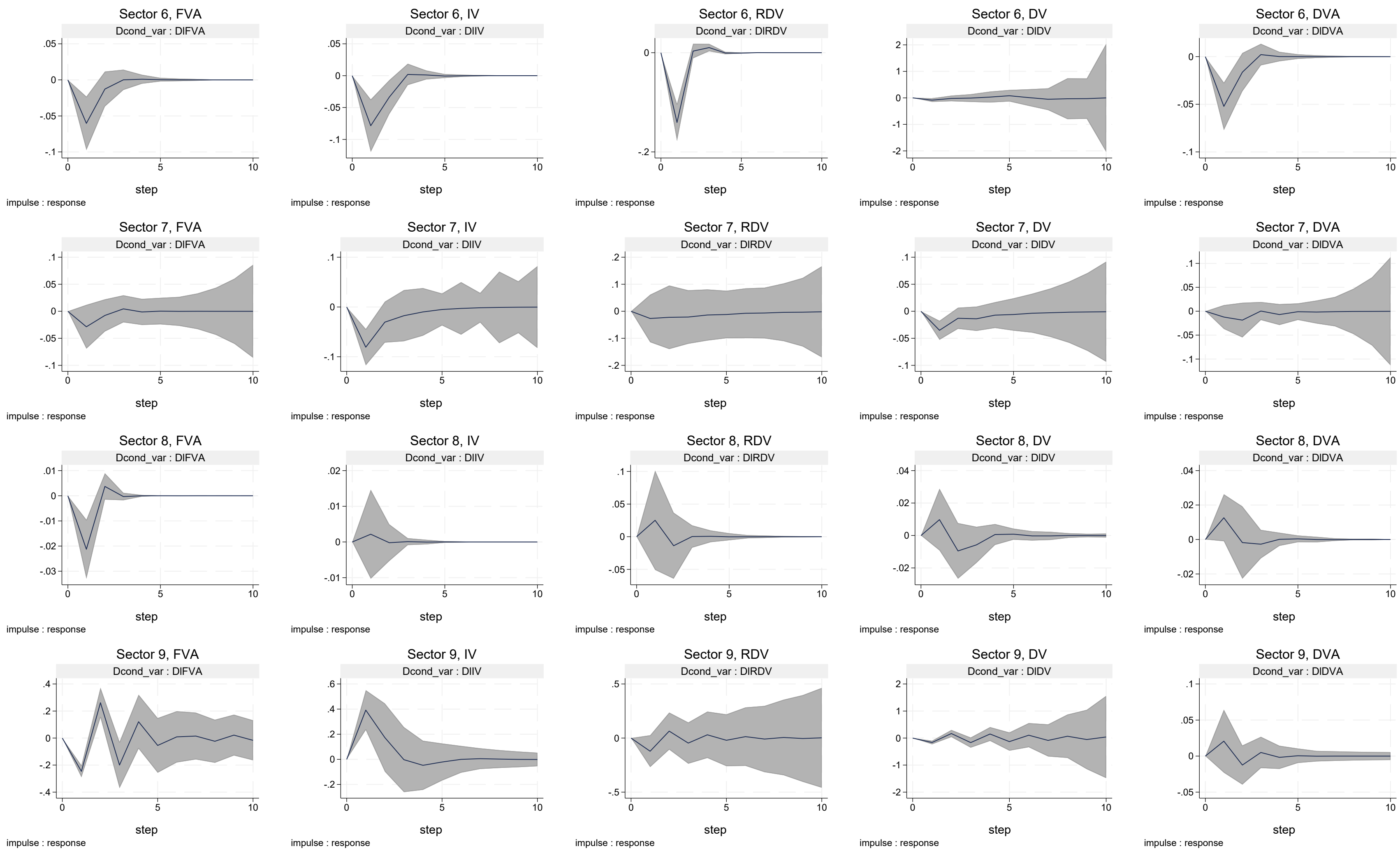

Figure A5: Orthogonalised IRF Plots From Shocks to Currency Volatility with GARCH Measure (Sectors 6-9)

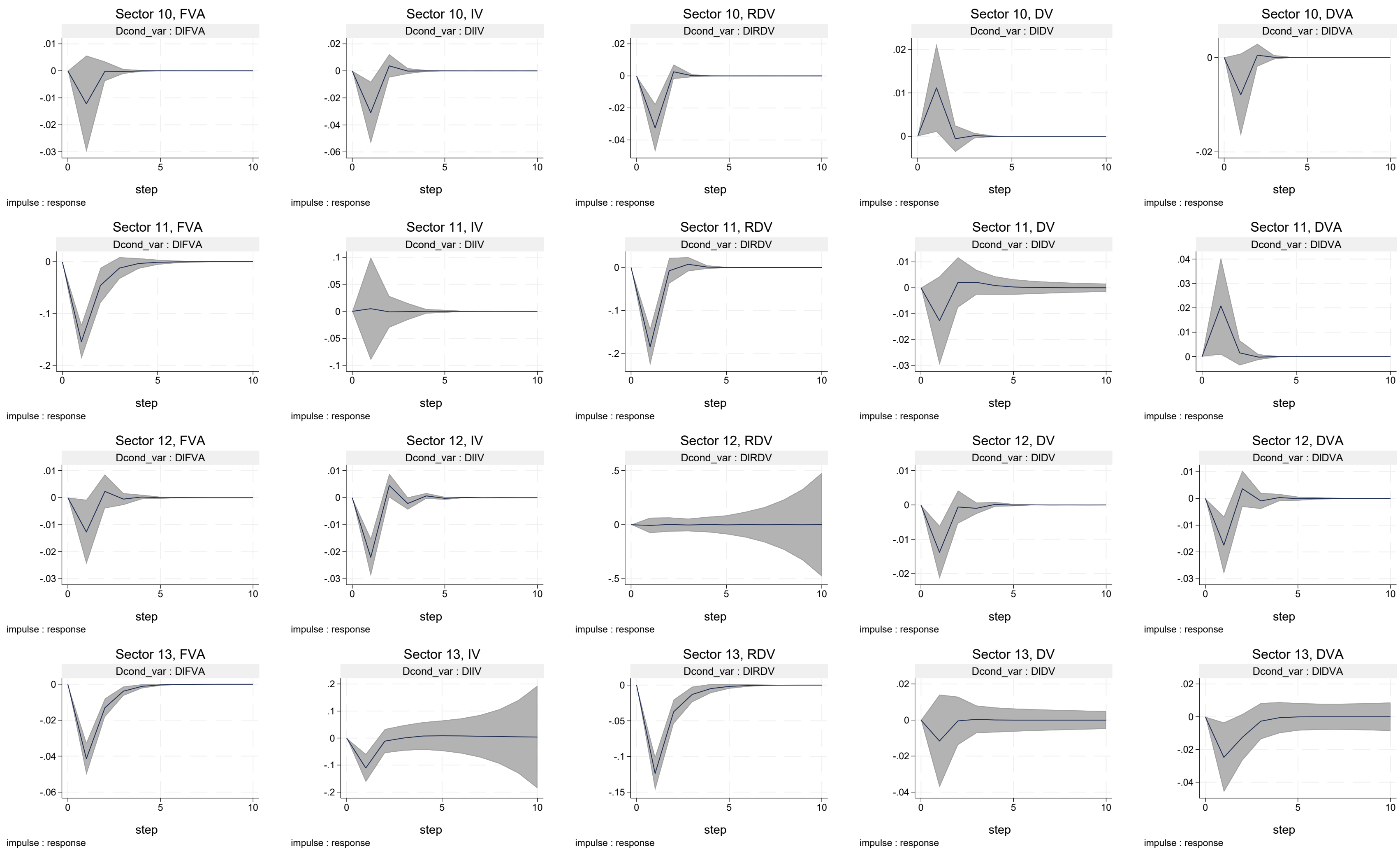

Figure A6: Orthogonalised IRF Plots From Shocks to Currency Volatility with GARCH Measure (Sectors 10-13)

Table A2: FEVDs Corresponding to Currency Volatility Shocks for 13 Industrial Categories with GARCH Measure

Sector Code	Forecast Horizon	FVA	IV	RDV	DV	DVA
1	0	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.000	0.000
	2	0.071	0.079	0.179	0.308	0.238
	3	0.105	0.123	0.205	0.283	0.338
	4	0.115	0.125	0.207	0.289	0.369
	5	0.117	0.126	0.207	0.290	0.378
	6	0.118	0.126	0.207	0.291	0.380
	7	0.118	0.126	0.207	0.291	0.380
	8	0.118	0.126	0.207	0.291	0.381
	9	0.118	0.126	0.207	0.291	0.381
	10	0.118	0.126	0.207	0.291	0.381
2	0	-	-	-	-	-
	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-	-	-	-	-
	4	-	-	-	-	-
	5	-	-	-	-	-
	6	-	-	-	-	-
	7	-	-	-	-	-
	8	-	-	-	-	-
	9	-	-	-	-	-
	10	-	-	-	-	-
3	0	-	-	0.000	0.000	0.000
	1	-	-	0.000	0.000	0.000
	2	-	-	0.062	0.010	0.005
	3	-	-	0.080	0.010	0.005
	4	-	-	0.084	0.010	0.005
	5	-	-	0.084	0.010	0.005
	6	-	-	0.085	0.010	0.005
	7	-	-	0.085	0.010	0.005
	8	-	-	0.085	0.010	0.005
	9	-	-	0.085	0.010	0.005
	10	-	-	0.085	0.010	0.005

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Table continued from previous page

Sector Code	**Forecast Horizon**	**FVA**	**IV**	**RDV**	**DV**	**DVA**
	0	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.000	0.000
	2	0.101	0.075	0.189	0.361	0.358
	3	0.104	0.105	0.192	0.344	0.392
	4	0.104	0.115	0.192	0.353	0.375
4	5	0.104	0.118	0.192	0.354	0.373
	6	0.104	0.119	0.192	0.354	0.381
	7	0.104	0.119	0.192	0.354	0.383
	8	0.104	0.119	0.192	0.354	0.383
	9	0.104	0.119	0.192	0.354	0.384
	10	0.104	0.119	0.192	0.354	0.385
	0	0.000	-	-	-	-
	1	0.000	-	-	-	-
	2	0.152	-	-	-	-
	3	0.191	-	-	-	-
	4	0.213	-	-	-	-
5	5	0.242	-	-	-	-
	6	0.256	-	-	-	-
	7	0.264	-	-	-	-
	8	0.271	-	-	-	-
	9	0.280	-	-	-	-
	10	0.282	-	-	-	-
	0	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.000	0.000
	2	0.131	0.160	0.275	0.322	0.174
	3	0.134	0.184	0.274	0.321	0.180
	4	0.133	0.184	0.275	0.253	0.180
6	5	0.133	0.184	0.275	0.276	0.180
	6	0.133	0.184	0.275	0.355	0.180
	7	0.133	0.184	0.275	0.334	0.180
	8	0.133	0.184	0.275	0.361	0.180
	9	0.133	0.184	0.275	0.366	0.180
	10	0.133	0.184	0.275	0.354	0.180

Continued on next page

Table continued from previous page

Sector Code	Forecast Horizon	FVA	IV	RDV	DV	DVA
7	0	-	0.000	-	0.000	-
	1	-	0.000	-	0.000	-
	2	-	0.235	-	0.100	-
	3	-	0.258	-	0.107	-
	4	-	0.265	-	0.119	-
	5	-	0.267	-	0.122	-
	6	-	0.268	-	0.124	-
	7	-	0.268	-	0.125	-
	8	-	0.268	-	0.126	-
	9	-	0.268	-	0.126	-
	10	-	0.268	-	0.126	-
8	0	0.000	-	-	-	0.000
	1	0.000	-	-	-	0.000
	2	0.028	-	-	-	0.013
	3	0.029	-	-	-	0.013
	4	0.029	-	-	-	0.014
	5	0.029	-	-	-	0.014
	6	0.029	-	-	-	0.014
	7	0.029	-	-	-	0.014
	8	0.029	-	-	-	0.014
	9	0.029	-	-	-	0.014
	10	0.029	-	-	-	0.014
9	0	0.000	0.000	-	0.000	-
	1	0.000	0.000	-	0.000	-
	2	0.272	0.329	-	0.319	-
	3	0.392	0.355	-	0.415	-
	4	0.427	0.353	-	0.462	-
	5	0.431	0.355	-	0.484	-
	6	0.429	0.356	-	0.496	-
	7	0.427	0.356	-	0.502	-
	8	0.426	0.356	-	0.505	-
	9	0.427	0.356	-	0.507	-
	10	0.427	0.356	-	0.508	-

Continued on next page

Table continued from previous page

Sector Code	Forecast Horizon	FVA	IV	RDV	DV	DVA
10	0	-	0.000	0.000	0.000	0.000
	1	-	0.000	0.000	0.000	0.000
	2	-	0.036	0.024	0.009	0.004
	3	-	0.036	0.024	0.009	0.004
	4	-	0.036	0.024	0.009	0.004
	5	-	0.036	0.024	0.009	0.004
	6	-	0.036	0.024	0.009	0.004
	7	-	0.036	0.024	0.009	0.004
	8	-	0.036	0.024	0.009	0.004
	9	-	0.036	0.024	0.009	0.004
	10	-	0.036	0.024	0.009	0.004
11	0	0.000	-	0.000	-	0.000
	1	0.000	-	0.000	-	0.000
	2	0.383	-	0.337	-	0.021
	3	0.383	-	0.337	-	0.021
	4	0.405	-	0.337	-	0.021
	5	0.405	-	0.337	-	0.021
	6	0.405	-	0.337	-	0.021
	7	0.405	-	0.337	-	0.021
	8	0.405	-	0.337	-	0.021
	9	0.405	-	0.337	-	0.021
	10	0.405	-	0.337	-	0.021
12	0	0.000	0.000	-	0.000	0.000
	1	0.000	0.000	-	0.000	0.000
	2	0.003	0.009	-	0.005	0.008
	3	0.003	0.009	-	0.005	0.008
	4	0.003	0.010	-	0.005	0.008
	5	0.003	0.010	-	0.005	0.008
	6	0.003	0.010	-	0.005	0.008
	7	0.003	0.010	-	0.005	0.008
	8	0.003	0.010	-	0.005	0.008
	9	0.003	0.010	-	0.005	0.008
	10	0.003	0.010	-	0.005	0.008

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Sector Code	**Forecast Horizon**	**FVA**	**IV**	**RDV**	**DV**	**DVA**
13	0	0.000	0.000	0.000	-	0.000
	1	0.000	0.000	0.000	-	0.000
	2	0.164	0.289	0.327	-	0.194
	3	0.176	0.268	0.346	-	0.228
	4	0.177	0.253	0.348	-	0.230
	5	0.178	0.245	0.348	-	0.230
	6	0.178	0.240	0.348	-	0.230
	7	0.178	0.237	0.348	-	0.230
	8	0.178	0.235	0.348	-	0.230
	9	0.178	0.234	0.348	-	0.230
	10	0.178	0.233	0.348	-	0.230

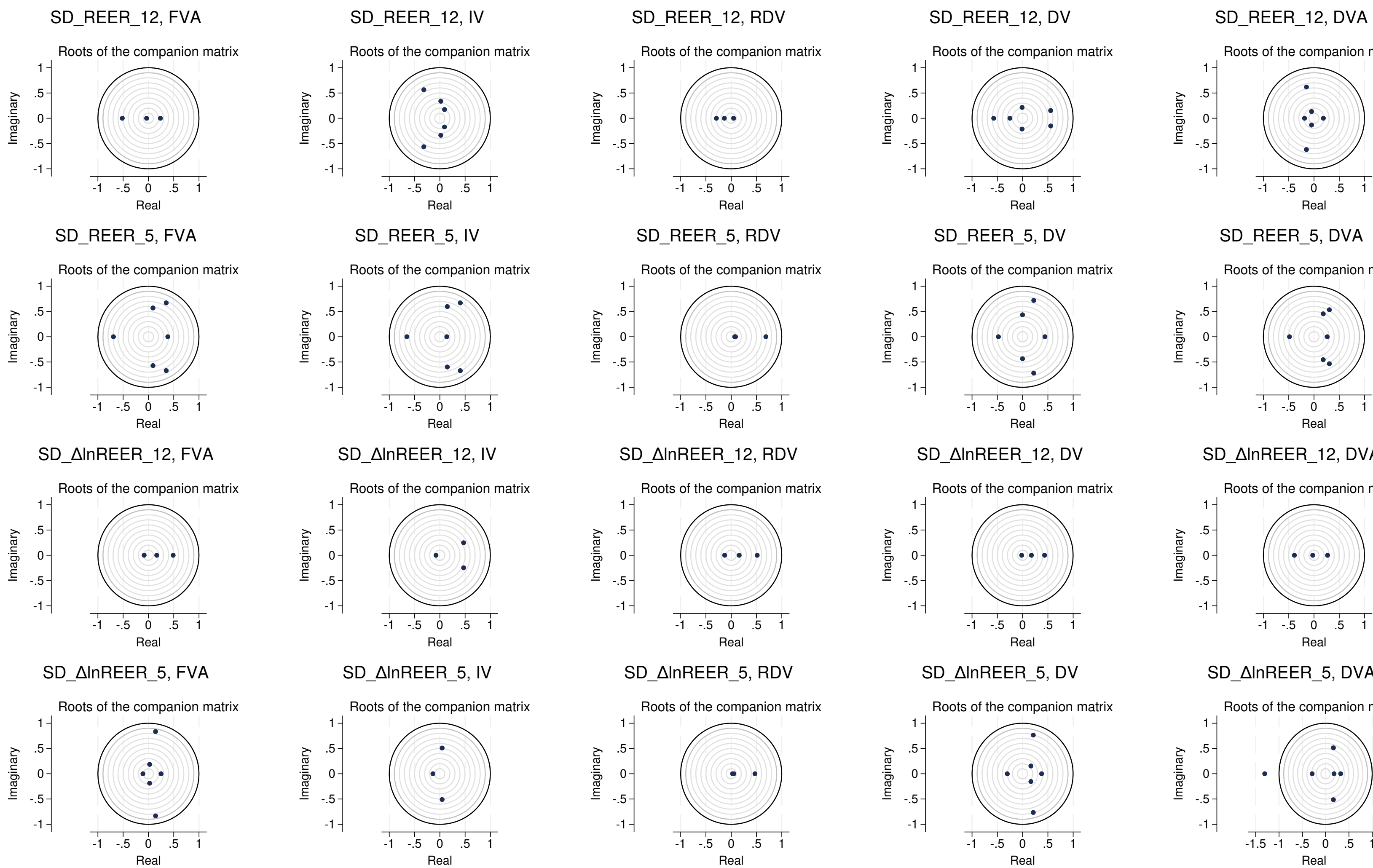

Figure A7: Model Stability Test Results for Total Manufacturing with Alternative Measures (Sector 13)

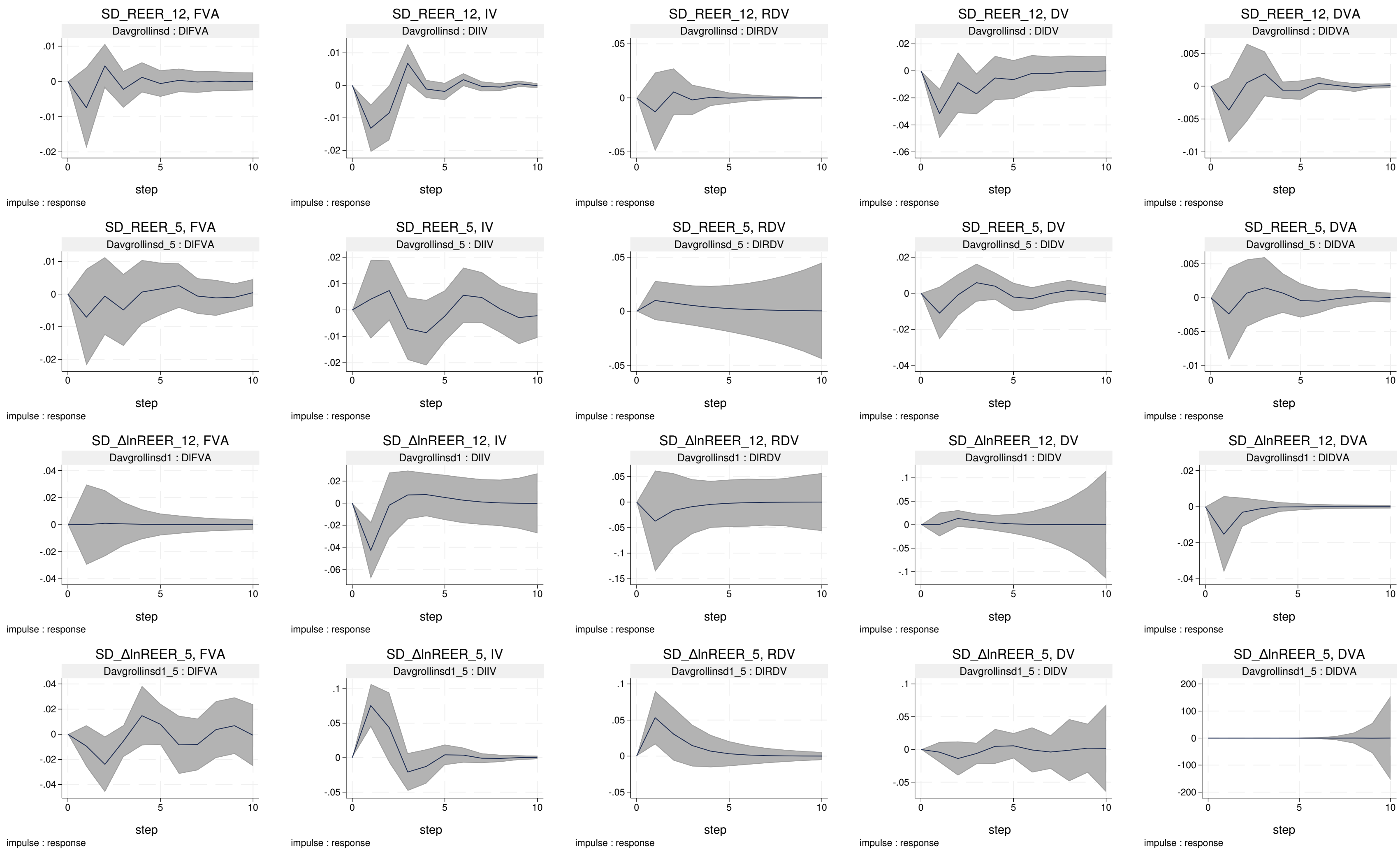

Figure A8: Orthogonalised IRF Plots from Shocks to Currency Volatility with Alternative Measures (Sector 13)

Table A3: FEVDs with Alternate Measures of Currency Volatility Shocks

Volatility Measure	Forecast Horizon	FVA	IV	RDV	DV	DVA
	0	-	0.000	-	0.000	-
	1	-	0.000	-	0.000	-
	2	-	0.026	-	0.196	-
	3	-	0.036	-	0.199	-
	4	-	0.042	-	0.239	-
SD_REER_12	5	-	0.042	-	0.242	-
	6	-	0.042	-	0.248	-
	7	-	0.043	-	0.248	-
	8	-	0.043	-	0.248	-
	9	-	0.043	-	0.248	-
	10	-	0.043	-	0.248	-
	0	-	0.000	-	-	-
	1	-	0.000	-	-	-
	2	-	0.005	-	-	-
	3	-	0.018	-	-	-
	4	-	0.029	-	-	-
SD_REER_5	5	-	0.046	-	-	-
	6	-	0.047	-	-	-
	7	-	0.054	-	-	-
	8	-	0.058	-	-	-
	9	-	0.058	-	-	-
	10	-	0.060	-	-	-
	0	-	0.000	-	-	-
	1	-	0.000	-	-	-
	2	-	0.171	-	-	-
	3	-	0.150	-	-	-
	4	-	0.147	-	-	-
SD_ΔlnREER_12	5	-	0.149	-	-	-
	6	-	0.151	-	-	-
	7	-	0.151	-	-	-
	8	-	0.151	-	-	-
	9	-	0.151	-	-	-
	10	-	0.151	-	-	-

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Volatility Measure	**Forecast Horizon**	**FVA**	**IV**	**RDV**	**DV**	**DVA**
SD_ΔlnREER_5	0	0.000	0.000	0.000	-	-
	1	0.000	0.000	0.000	-	-
	2	0.014	0.320	0.126	-	-
	3	0.097	0.347	0.160	-	-
	4	0.100	0.356	0.168	-	-
	5	0.127	0.359	0.169	-	-
	6	0.134	0.359	0.170	-	-
	7	0.142	0.360	0.170	-	-
	8	0.149	0.360	0.170	-	-
	9	0.150	0.360	0.170	-	-
	10	0.155	0.360	0.170	-	-
MASD_REER_12	0	0.000	0.000	-	-	-
	1	0.000	0.000	-	-	-
	2	0.010	0.085	-	-	-
	3	0.014	0.106	-	-	-
	4	0.017	0.111	-	-	-
	5	0.017	0.112	-	-	-
	6	0.017	0.113	-	-	-
	7	0.017	0.113	-	-	-
	8	0.017	0.113	-	-	-
	9	0.017	0.113	-	-	-
	10	0.017	0.113	-	-	-
MASD_REER_5	0	-	0.000	-	-	-
	1	-	0.000	-	-	-
	2	-	0.070	-	-	-
	3	-	0.082	-	-	-
	4	-	0.086	-	-	-
	5	-	0.096	-	-	-
	6	-	0.095	-	-	-
	7	-	0.099	-	-	-
	8	-	0.099	-	-	-
	9	-	0.100	-	-	-
	10	-	0.101	-	-	-

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Volatility Measure	Forecast Horizon	FVA	IV	RDV	DV	DVA
MASD_lnREER_12	0	0.000	0.000	0.000	0.000	-
	1	0.000	0.000	0.000	0.000	-
	2	0.208	0.074	0.070	0.039	-
	3	0.270	0.070	0.072	0.039	-
	4	0.283	0.069	0.072	0.039	-
	5	0.285	0.069	0.072	0.039	-
	6	0.285	0.069	0.072	0.039	-
	7	0.286	0.069	0.072	0.039	-
	8	0.286	0.069	0.072	0.039	-
	9	0.286	0.069	0.072	0.039	-
	10	0.286	0.069	0.072	0.039	-
MASD_lnREER_5	0	0.000	0.000	-	0.000	-
	1	0.000	0.000	-	0.000	-
	2	0.067	0.121	-	0.222	-
	3	0.110	0.147	-	0.356	-
	4	0.133	0.141	-	0.322	-
	5	0.144	0.144	-	0.293	-
	6	0.150	0.144	-	0.314	-
	7	0.152	0.144	-	0.333	-
	8	0.154	0.144	-	0.326	-
	9	0.154	0.144	-	0.319	-
	10	0.155	0.144	-	0.324	-