Dual Engines of Global Uncertainty: Divergent Spillovers from U.S. and China to Emerging Asia

Jongrim Ha Haiqin Liu*

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Preliminary and incomplete, comments welcome.

Abstract

We investigate how global economic policy uncertainty—particularly originating from the United States and China—affects emerging Asian economies in heterogeneous ways. Using novel data spanning 2000 to 2024 for the U.S., China, and eight emerging Asian economies, we integrate macroeconomic, firm-level, and network-based approaches to quantify both the magnitude and transmission mechanisms of these uncertainty shocks. Panel structural VAR estimates indicate that a one-standard-deviation increase in U.S. or Chinese uncertainty reduces output in emerging Asia by approximately 1 percent within a year. U.S.-originated shocks tend to have stronger financial effects, while Chinese shocks generate more persistent impacts, primarily through trade channels. Firm-level analysis shows that heightened uncertainty significantly dampens investment and employment, consistent with a wait-and-see response by firms—particularly in reaction to uncertainty stemming from China. Furthermore, spatial-econometric decompositions based on input-output linkages reveal that 80–90 percent of global uncertainty transmission occurs via trade and production networks: upstream for U.S. demand shocks and downstream for Chinese supply shocks. Overall, the findings highlight the asymmetric nature of global uncertainty spillovers and the heightened vulnerability of highly interconnected Asian economies to external policy volatility.

JEL code: E32, F20, F42

Keywords: Uncertainty; Emerging Asia; SVAR; Firm-level Response; Spatial Autoregressive

*J. Ha: World Bank; email: jongrimha@worldbank.org. H. Liu: Fudan University and World Bank; email: liuhq21@m.fudan.edu.cn. The findings, interpretations and conclusions expressed in this paper are entirely those of the authors and should not be attributed to the World Bank.

1 Introduction

Asia's two principal trading partners are the United States and China—often collectively termed "Chimerica" (Ferguson and Schularick, 2009). For decades, many Asian economies have consequently sought to maintain relatively stable exchange rates against the currencies of these two powers. The deepening of cross-border production networks has reinforced this pattern: raw cotton produced in the Philippines may be spun into cloth in Thailand, dyed in Vietnam, assembled in China, and ultimately exported to the United States (as illustrated in Figure A5). Each stage of this process is embedded within international trade and finance, making stability around the Chimerica nexus increasingly self-reinforcing. Policymakers have adapted to these network dynamics rather than consciously designing them (Rogoff, 2025).

This paper examines how *global economic policy uncertainty*—originating from the United States and China—is transmitted to emerging Asian (EA) economies, which are small, highly open, and deeply embedded in global value chains. The 1997–98 Asian Financial Crisis revealed the region's exposure to external shocks and the resulting policy trade-offs among monetary autonomy, exchange-rate stability, and financial openness. While previous research has extensively studied the cross-border transmission of first-moment shocks (e.g., to output, interest rates, or asset prices), the propagation of second-moment shocks—such as policy uncertainty—remains much less understood, particularly for shocks emanating from China.

We view the global system through an asymmetric, multipolar lens: China functions as a downstream production hub, transmitting supply-side disturbances through input–output linkages, whereas the United States acts as an upstream financial center and final-goods market. The coexistence of high trade openness, dense regional networks, and financial fragility makes Emerging Asia a natural laboratory for analyzing heterogeneous spillovers of both real and uncertainty shocks (Huidrom et al., 2020).[1] Recent surveys underscore this gap: Cascaldi-Garcia et al. (2023) catalog the growing range of uncertainty measures and their macroeconomic implications, while Castelnuovo et al. (2025) review evolving evidence on uncertainty spillovers before and after COVID-19.

Our analytical framework integrates *macroeconomic*, *micro-level*, and *network-based* approaches. This multi-layered strategy captures both the *magnitude* and *persistence* of global uncertainty spillovers.

[1] More specifically, the analysis covers eight emerging and developing Asian economies—four in East Asia and the Pacific (Thailand, the Philippines, Malaysia, Indonesia) and four in South Asia (Bangladesh, India, Sri Lanka, Nepal)—with China treated as both a source and a recipient of shocks.

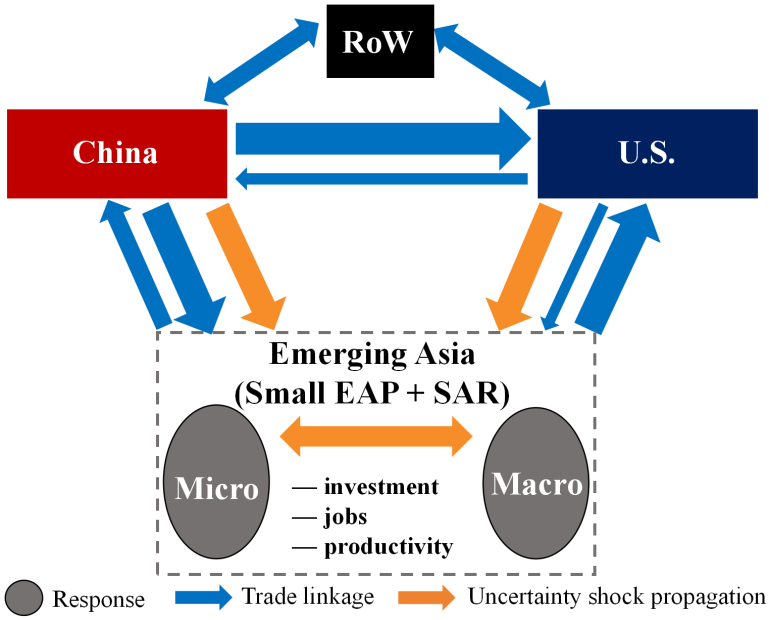


Figure 1: **Schematic Flow of Analyses**

1. At the **macro level**, we estimate panel structural vector autoregressions (SVARs) to quantify how U.S. and China uncertainty shocks affect output, inflation, exchange rates, and asset prices in EA economies.

2. At the **micro level**, we examine firm-specific responses—revenues, investment, employment, and stock performance—to identify the behavioral mechanisms underlying aggregate effects.

3. At the **network level**, we apply spatial-econometric models to decompose spillovers into *direct*, *upstream*, and *downstream* components, revealing how production and trade linkages amplify or dampen uncertainty transmission.

Our key findings are threefold. **First**, global uncertainty shocks exert large and statistically significant macro-financial effects on EA economies, with important asymmetries between the U.S. and China. A one-standard-deviation increase in either U.S. or China uncertainty lowers regional output by roughly 1 percent within a year. U.S. shocks primarily affect financial variables—equity, bond, and currency prices—whereas Chinese shocks have more persistent real effects, mainly through trade. **Second**, firm-level analysis shows that uncertainty dampens investment and employment, consistent with precautionary *wait-and-see* behavior. A one-standard-deviation rise in Chinese uncertainty reduces firm investment and employment by about 3 percent over six quarters, compared with smaller but faster-acting declines after U.S. shocks. **Third**, network decompositions reveal that about two-thirds

of total spillovers occur through trade linkages: U.S. uncertainty transmits primarily via *upstream* (demand-side) channels, while Chinese uncertainty propagates *downstream* (supply-side). These structural asymmetries explain the differing macro patterns—financial dominance for U.S. shocks and trade rebalancing for Chinese shocks.

Related literature. A growing body of research underscores that fluctuations in macroeconomic conditions across both emerging and developed economies are significantly influenced by global uncertainty shocks. Empirical studies have documented that indicators such as the VIX index, global inflation uncertainty, geopolitical fragmentation, oil price volatility, and trade policy uncertainty account for substantial portions of output and financial volatility in emerging markets (e.g., Carrière-Swallow and Céspedes (2013); Bhattarai et al. (2020); Fernández-Villaverde et al. (2024); Li et al. (2025); Ha and So (2024); Abiad and Qureshi (2023); Caldara et al. (2019)). At the microeconomic level, theories concerning heterogeneous agents and firm-level evidence reveal that global uncertainty affects portfolio choices, investment timing, and managerial decisions (see, for instance, Fiori and Scoccianti (2023); Handley and Li (2020); Bachmann et al. (2021)), as well as influencing the structure of production networks (Kopytov et al., 2024).

Jurado et al. (2015) formalizes the notion of macroeconomic uncertainty as the squared error of macroeconomic variable conditional forecasts. The measurement of uncertainty has evolved substantially since Jurado et al. (2015) formalized macroeconomic uncertainty as the conditional forecast errors of economic variables. Alternative approaches include survey-based dispersion metrics (Bachmann et al., 2013; D'Amico and Orphanides, 2008) and text-analytic indices such as the news-derived Economic Policy Uncertainty (EPU) index (Baker et al., 2016). Conceptually different these measures are, they have been shown to consistently correlate with macroeconomic contractions in output, investment, and consumption. Recent extensions have produced cross-country uncertainty indices, including China-specific measures (Baker et al., 2013; Davis et al., 2019) and the World Uncertainty Index (Ahir et al., 2022). An even more straightforward measure is time-varying volatility. Many studies adopt the VIX index Carrière-Swallow and Céspedes (2013); Leduc and Liu (2016) as a standard measure of global uncertainty essentially sourced from the US. Baker et al. (2023) computes country-wise measures of volatilities for a panel of 58 countries.

Several researches have pushed forward the agenda of global spillovers of uncertainties from core economies. Multiple channels are investigated, while we mainly call for two directions. One is real economy and business cycle spillover (Carrière-Swallow and Céspedes, 2013). Another is financial

spillover (Akinci et al., 2022). Bhattarai et al. (2020) explores how U.S. uncertainty propagates to emerging market asset prices. Whereas we study U.S.- and China-origin shocks as they transmit to Emerging Asia, Handley and Limão (2017), instead, identify how policy-uncertainty reduction associated with China's WTO accession drove firm entry and export growth to the U.S., with sizable U.S. price and welfare effects.

Regionally, while EA-focused analyses remain sparse, extant work includes country-level examinations of South Korea (Cheng, 2017), China (Fontaine et al., 2018), Japan (Arbatli et al., 2017), Thailand (Apaitan et al., 2020), Malaysia (Shah et al., 2019), and Indonesia-Philippines inflation dynamics (Kuncoro, 2024).

Our Contributions. Our analysis contributes to the literature in four dimensions. First, we shift the empirical focus from advanced economies (Bloom, 2009; Leduc and Liu, 2016) to the EA region—a dual periphery simultaneously anchored to U.S. financial hegemony and China's trade centrality (Miranda-Agrippino et al., 2020; Cerutti et al., 2019). Second, we bridge macro-financial and firm-level perspectives, unifying aggregate spillovers with microeconomic heterogeneity (Barrero, 2022). Third, ours is among the first to investigate the global production network channel of uncertainty transmission, extending Diebold and Yilmaz (2008, 2023)'s volatility spillover paradigm to emerging Asia. Fourth, although a vast literature has investigated transmissions of US uncertainty shocks (Carrière-Swallow and Céspedes, 2013; Firooz et al., 2025), the global transmissions of China uncertainty is still under-explored; our research fills this gap. These innovations provide a roadmap for modeling uncertainty in fragmented production ecosystems, particularly amid escalating fragmentation (Fernández-Villaverde et al., 2024).

The remainder of this paper is organized as follows. Section 2 reviews theoretical channels of uncertainty shock transmission to motivate our empirical frameworks. Section 3 presents macroeconomic responses estimated from panel SVAR. Section 4 presents micro firm-level results from panel OLS and local projection. Section 5 explores the production network channel. In Section 6, we present additional results on macro, firm-level, and networking analyses. Section 7 concludes.

2 Theoretical Channels of International Uncertainty Shock Propagation

This section outlines the main theoretical mechanisms through which global uncertainty shocks are transmitted across economies Global uncertainty shocks transmit through three interlocking mechanisms. *The real channel* suppresses investment and consumption; *the financial channel* alters capital flows and asset prices; and the *trade-rebalancing channel* reshapes external balances through demand- or supply-side effects. For Emerging Asia, high trade openness, intricate production linkages, and partial financial integration make these channels mutually reinforcing, creating asymmetric spillovers from U.S. versus Chinese uncertainty. These channels are empirically examined in the sections that follow.

2.1 The real channel

The real channel captures how uncertainty shocks influence the real economy through firms' and households' decisions about production, investment, and consumption. When uncertainty about future economic policy or global conditions rises, firms face an increase in the option value of waiting (Bloom, 2009). Rather than committing to irreversible investments, they postpone capital expenditures and hiring until uncertainty resolves. Similarly, households facing ambiguous income prospects or higher perceived macroeconomic risk raise precautionary savings and reduce discretionary consumption (Basu and Bundick, 2017). Together, these behaviors depress aggregate demand, slow capital accumulation, and weaken output growth.

Theoretically, this mechanism can be expressed as a standard investment under uncertainty framework where the marginal q of investment falls as the variance of expected profits rises. In this setting, the expected value of waiting exceeds the immediate value of investing, leading to temporary declines in investment growth. On the household side, an analogous rise in precautionary savings shifts the intertemporal consumption path downward, generating short-run disinflationary pressure. Consequently, the real channel serves as the foundational pathway through which uncertainty shocks propagate to macroeconomic activity—complementing the financial and trade channels discussed in the following sections.

In Emerging Asia, the real channel tends to be especially potent. The region's heavy reliance on export-oriented manufacturing and intermediate-goods production means that global demand

uncertainty quickly transmits to factory orders, capacity utilization, and employment. The prevalence of small and medium-sized enterprises—typically more credit-constrained and risk-averse—amplifies these real-sector responses.

2.2 The financial channel

The financial channel of international uncertainty transmission captures how global uncertainty shocks affect cross-border asset prices, interest-rate differentials, and credit conditions through portfolio rebalancing, exchange-rate dynamics, and shifts in risk appetite. When uncertainty rises in core economies such as the United States or China, global investors reassess their exposure to risky assets, triggering reallocations across sovereign bonds, equities, and currencies in emerging markets.

Under the uncovered interest parity (UIP) condition:

$$i_{k,t}^{\text{EA}} - i_{k,t}^{\text{US}} = \mathbb{E}_t\left[\Delta^k s_{\$,t+k}^{\text{EA}}\right] + \rho_t^{(k)}, \quad k = 0, 1, ... \tag{1}$$

where, $i_{k,t}$ stands for the interest rate at maturity k, and $\mathbb{E}_t\left[\Delta^k s_{\$,t+k}^{\text{EA}}\right]$ is $k-$period expected depreciation of Emerging Asia (EA) currency against the dollar. $\rho_t^{(k)}$ is the excess returns investors demand for holding assets denominated in EA currency over the horizon k, or less generally, the EA exchange rate risk premiums.[2]

The expected exchange-rate depreciation ($\mathbb{E}_t\left[\Delta^k s_{\$,t+k}^{\text{EA}}\right]$) and the time-varying risk premium ($\rho_t^{(k)}$) jointly determine returns on emerging-market assets. In tranquil periods, low global uncertainty compresses, encouraging capital inflows and currency appreciation. When uncertainty surges, however, investors demand higher compensation for bearing risk—raising bond yields, widening credit spreads, and inducing "flight-to-safety" flows toward advanced-economy assets (Duffie (2023); Alfaro et al. (2024a)).

Three interrelated transmission subchannels link uncertainty to financial asset prices:

1. **Bond and credit markets**. Heightened global uncertainty increases sovereign and corporate risk premia, raising bond yields and widening spreads (Gilchrist and Zakrajšek (2012)). Empirically, U.S. uncertainty shocks are followed by higher credit spreads and lower long-term yields in Emerging Asia, reflecting both rising risk aversion and expectations of monetary easing.

[2]The deviation from the uncovered interest parity results from various forces, such as liquidity premium, private information, irrational expectations, and the "peso problem" (mismeasurements in exchange rate expectations). See Engel (2014) for a comprehensive review.

2. **Equity markets**. Equity prices decline following hightened global unceratiny as the required rate of return rises and future cash flows are discounted more heavily (Bloom (2009)). In addition, the "finance uncertainty multiplier" (Alfaro et al. (2024a)) implies that uncertainty amplifies equity volatility and tightens financial conditions through balance-sheet effects.

3. **Exchange rates and risk premia**. In global "risk-off" episodes, safe-haven currencies (notably the U.S. dollar) appreciate, while emerging-market currencies depreciate. This response reflects both higher expected depreciation and rising exchange-rate risk premiums (Engel (2014)). Conversely, uncertainty originating in China often leads to localized or sector-specific effects, with less pronounced capital outflows and, at times, regional currency appreciation via trade balance adjustments.

2.3 The trade re-balancing channel

Uncertainty can move exchange rates through trade, not only through finance. In particular, higher trade-policy uncertainty (tariffs, export controls, supply-chain frictions) depresses cross-border trade volumes and tilts demand toward home goods, putting upward pressure on the real exchange rate of countries that become relatively "safer" suppliers, or downward pressure when external demand for their exports falls. While financial uncertainty disrupts capital flows and risk premiums, trade (policy) uncertainty disrupts supply chains, producing synchronized movements of exchange rates and trade balances (Bodenstein et al., 2024).

For Emerging Asia—deeply integrated with both the United States (as a final-demand and financial hub) and China (as an upstream production hub)—the sign of the spillover depends on where the shock originates. A U.S. uncertainty shock that cuts U.S. absorption tends to shrink demand for Asian exports, worsening Asian trade balances and pushing toward depreciation (via trade re-balancing). A China uncertainty shock that cuts Chinese investment and intermediate-goods imports can raise some neighbors' trade balances (via supply-chain rerouting), tending toward appreciation—to the extent the trade channel dominates the financial channel. Hence, U.S. shocks are expected to act primarily through demand-side contraction, while Chinese shocks reflect supply-side disruptions within the regional production network.

Accounting backbone Let TB_t be the (real) trade balance (exports–imports), NFA_t net foreign assets, and r the (constant) world real interest rate. Using the intertemporal approach to the current

account (Obstfeld and Rogoff, 1995), the intertemporal budget constraint is

$$NFA_t = (1+r)NFA_{t-1} + TB_t, \quad NFA_t = -\sum_{k=0}^{\infty} \frac{1}{(1+r)^{k+1}} \mathbb{E}_t \left[TB_{t+k}\right].$$

Thus, any shock that lowers the expected present value of future trade balances requires either financing (a fall in NFA_t) or relative-price adjustment—i.e., a movement in the real exchange rate that improves TB_t. This is the core of the intertemporal approach to the current account.

A reduced form representation:

$$TB_t = \alpha\, q_t + \underbrace{\beta\, y_t^* - \gamma\, y_t + \lambda\, \tau_t + \chi \mathrm{ToT}_t}_{\text{income/trade cost/terms-of-trade terms}} + \varepsilon_t, \quad \alpha > 0,$$

where,

- q_t is the real exchange rate (an increase = real depreciation). With Marshall–Lerner elasticities, a real depreciation improves $TB_t (\alpha > 0)$.
- y_t^* and y_t are foreign and domestic real activities (income) that shift external and internal absorption.
- τ_t captures trade costs (e.g., tariffs, non-tariff barriers, logistics frictions)—think an iceberg/tariff wedge that raises import prices or reduces effective export prices; higher τ_t typically worsens TB_t for a small open economy reliant on imported intermediates (sign of λ is context-specific).
- ToT_t is the terms of trade (export-price/import-price). A positive ToT shock improves purchasing power and can raise TB_t if income effects dominate substitution.

In addition, two classical mechanisms shape empirical responses:

1. **Marshall–Lerner/J-curve**. Even if long-run trade elasticities satisfy Marshall–Lerner, the J-curve implies that a real depreciation can initially worsen TB_t (contractual prices/quantities adjust slowly) before improving it. Hence, high-frequency responses of TB_t and q_t to uncertainty shocks may look muted or even perverse on impact.
2. **Valuation effects**. Changes in q_t also revalue foreign-currency assets and liabilities (the "valuation channel"), which interacts with current-account adjustment and can dampen or amplify the trade re-balancing need.

Putting these together, the trade re-balancing channel implies the following for U.S. versus China uncertainty. First, A negative foreign-demand shock (e.g., U.S. uncertainty reducing y_t^*) lowers expected TB_{t+k}; by the intertemporal logic, the home currency must depreciate ($q_t \uparrow$) until the improved price-competitiveness term αq_t offsets the weaker income term βy_t^*. Second, A supply chain shock in China that raises effective trade costs τ_t for China and reduces its import demand for intermediates can raise some neighbors' TB_t (via redirected trade and relative-price shifts), allowing appreciation (lower q_t) if the trade channel dominates financial stresses. Structural models with production networks deliver precisely this "trade-rebalancing" exchange rate logic.

3 Macroeconomic Evidence (Baseline)

3.1 Panel SVAR model

We model the international transmission of uncertainty shocks using an open-economy panel structural vector autoregression (SVAR):

$$A_c Y_{c,t} = \sum_{i=1}^{p} B_{c,i} Y_{c,t-i} + \varepsilon_{c,t}. \tag{2}$$

where $Y_{c,t}$ is an $n \times 1$ vector of endogenous macroeconomic and financial variables for country c. A_c and $B_i(\forall i \geq 1)$ are nonsingular coefficient matrices. We assume homogeneous coefficients for all countries (so that A and Bs do not vary across countries), while we test the model with heterogeneous coefficients as a robustness check. $\varepsilon_{c,t}$ is $n \times 1$ vector of serially uncorrelated structural disturbances. A lag length of $p = 4$ is selected based on the panel BIC criterion.

Model specification and identification. Our baseline specification treats the global economy as a three-country system—the U.S., China, and Emerging Asia—and identifies shocks through a recursive (Cholesky) structure. We combine the small-open-economy assumption—appropriate for Emerging Asia—with the conservative assumption that the uncertainty index is ordered last within each country block.

- **US**: output (y_t^{US}), inflation (π_t^{US}), uncertainty measure (u_t^{US});
- **China:** output (y_t^{CN}), inflation (π_t^{CN}), Renminbi per USD ($s_{\$,t}^{\text{CN}}$), uncertainty measure ($u_t^{\text{CN}}$);
- **Emerging Asia:** domestic output (y_t^{EA}), inflation (π_t^{EA}), equity prices ($stock_t$), nominal

exchange rate per US dollar ($s^{EA}_{\$,t}$).

All variables are expressed in logarithms or percentage changes. China is allowed to affect the U.S. with a lag but influences Emerging Asia contemporaneously, reflecting the region's close real-sector linkages with China. We follow the convention that the exchange rate of a country is the price of the foreign currency in units of the domestic currency, so an increase in the exchange rate is a depreciation in the home currency (Engel, 2014).[3] We use lowercase notations as all variables are either in logs or in percentage growth rates.

Extended Specifications. To investigate detailed transmission mechanisms, we sequentially augment the baseline model (as explained above) with additional variables such as interest rates, risk premia, and GDP expenditure components (investment, consumption, exports, and imports). Each auxiliary variable is added last in the Cholesky ordering to preserve causal interpretability.[4]

Data. The balanced panel covers eight Emerging Asian economies—Indonesia, Malaysia, the Philippines, Thailand (East Asia); and India, Sri Lanka, Nepal, Bangladesh (South Asia)—over 2000M1 to 2024M12. Industrial production proxies for real activity; inflation is the year-over-year change in the core CPI, following Ha et al. (2023). Other macro-financial series (interest rates, credit spreads, equity prices, exchange rates) are obtained from Havers Analytics and OECDstat. Monthly data are used whereever available; quarterly data supplement missing series such as investment, consumption, and trade volumes.

Uncertainty measures. We use the news-based Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016) as our primary measure of policy uncertainty. This index offers several advantages over survey- and market-based alternatives: (i) high frequency and timeliness, as it is available monthly and updated in real time; (ii) cross-country comparability, since it is constructed using standardized keyword algorithms that enable direct comparisons across the U.S., China, and the Euro Area; (iii) flexibility of sub-components, allowing for separate analysis of monetary, fiscal, and trade policy uncertainty; and (iv) empirical relevance, as media mentions of "uncertainty" are strongly associated with macroeconomic downturns. For the United States, we use the overall EPU index along with its sub-components—monetary policy uncertainty (MPU), fiscal policy uncertainty

[3] Alternative identification schemes—including reversing the uncertainty ordering and factor-augmented SVARs—are reported as robustness checks.

[4] For instance, interest rates or risk premia affect real activity and inflation with a lag (Gilchrist and Zakrajšek (2012)), while net exports or domestic expenditure components are inserted immediately after output and before inflation, consistent with the slower adjustment of quantities relative to prices.

(FPU), and trade policy uncertainty (TPU)—from Baker et al. (2016). For China, we rely on the EPU and TPU indices developed by Davis et al. (2019).[5]

3.2 Empirical Results

In this section, we present the dynamic responses of key variables in Emerging Asia, as reflected in Section 2 to U.S. and Chinese uncertainty shocks, as estimated from the panel SVAR model. The baseline results are organized into three categories: (i) macroeconomic variables—output, investment, consumption, and inflation; (ii) financial market variables—equity prices, bond yields, exchange rates, and credit spreads; and (iii) trade-related variables—exports, imports, and net exports. (iv) exchange rates are particularly important for open economies as they are critical to macroeconomic, financial, and trade activities. For clarity, we report the responses to U.S. and Chinese shocks side by side. The discussion primarily focuses on the aggregate results derived from the eight-country Emerging Asia panel, while country-specific responses are analyzed separately in Section F.3 of the Appendix.[6]

Macroeconomic variables. Figure 2 presents the impulse responses to one–standard-deviation innovations in U.S. and Chinese economic policy uncertainty. Output (industrial production) in the Emerging Asia panel declines on impact, reaching a peak contraction of approximately 1.0% (based on mean responses) a few months after a U.S. uncertainty shock. Following a comparable Chinese uncertainty shock, the peak output decline is somewhat smaller—around 0.7%—but notably more persistent, with the trough occurring roughly three quarters after the initial disturbance.

The response of inflation is similar across two types of uncertainty shocks, with more significant impacts following U.S. uncertainty shocks. Following the uncertainty shocks in U.S. and China, inflation in Emerging Asia falls modestly by about 0.1% and the effects persist in the medium run, consistent with the view that uncertainty shocks resemble aggregate demand disturbances under nominal rigidities (Leduc and Liu, 2016; Bloom, 2009).[7]

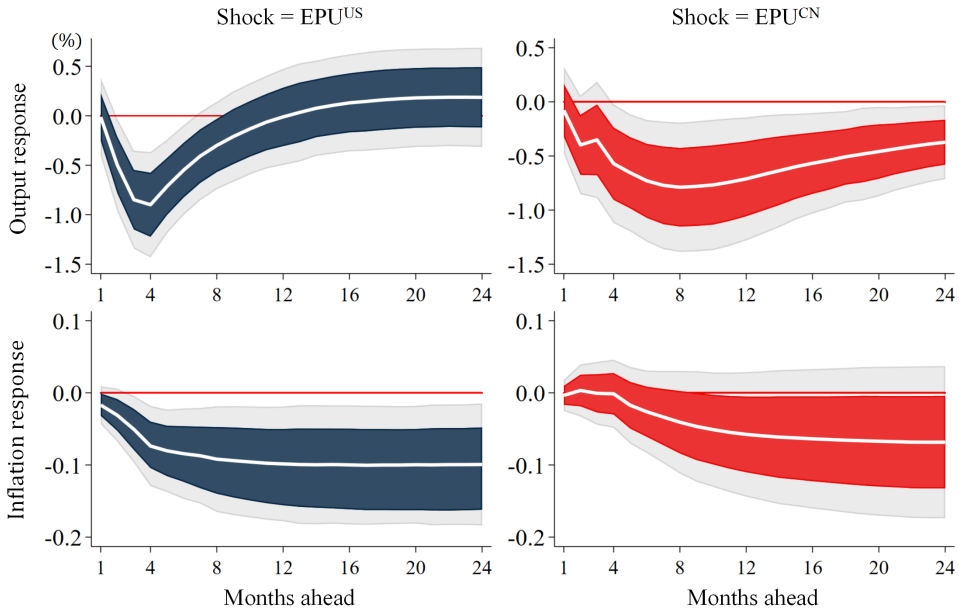
[5]Admittedly, multiple types of uncertainty measures are available in the literature. Prevalent ones include the forecast-based measure of Jurado et al. (2015), the survey-based (disagreement) measures from professional forecasts, dispersions across micro units (Schaab, 2020), and the option-implied volatilities (e.g. VIX index). Conceptually different in nature, these uncertainty indices identify distinctive sources of uncertainty, which potentially exert distinctive economic impacts (Kozeniauskas et al., 2018). In robustness checks, we experiment with survey-based and forecast-dispersion measures (Jurado et al. (2015)) and option-implied volatilities (VIX).In our baseline, however, newspaper-based uncertainty exerts the largest and most consistent effects on Emerging Asia.

[6]Robustness results are found in Appendix A and include alternative modeling [factor-augmented vector autoregressive (FAVAR); stochastic-volatility modeling], different orderings of the endogenous variables, the inclusion of exogenous controls, sub-period tests, and exclusion of post-pandemic data, among others.

[7]Aggregate demand–type disinflation after uncertainty shocks is well documented in models with sticky prices and search frictions and in U.S. data (Leduc and Liu, 2016). Emerging-market responses to global uncertainty are typically larger in activity variables but not uniformly in inflation (Carrière-Swallow and Céspedes, 2013).

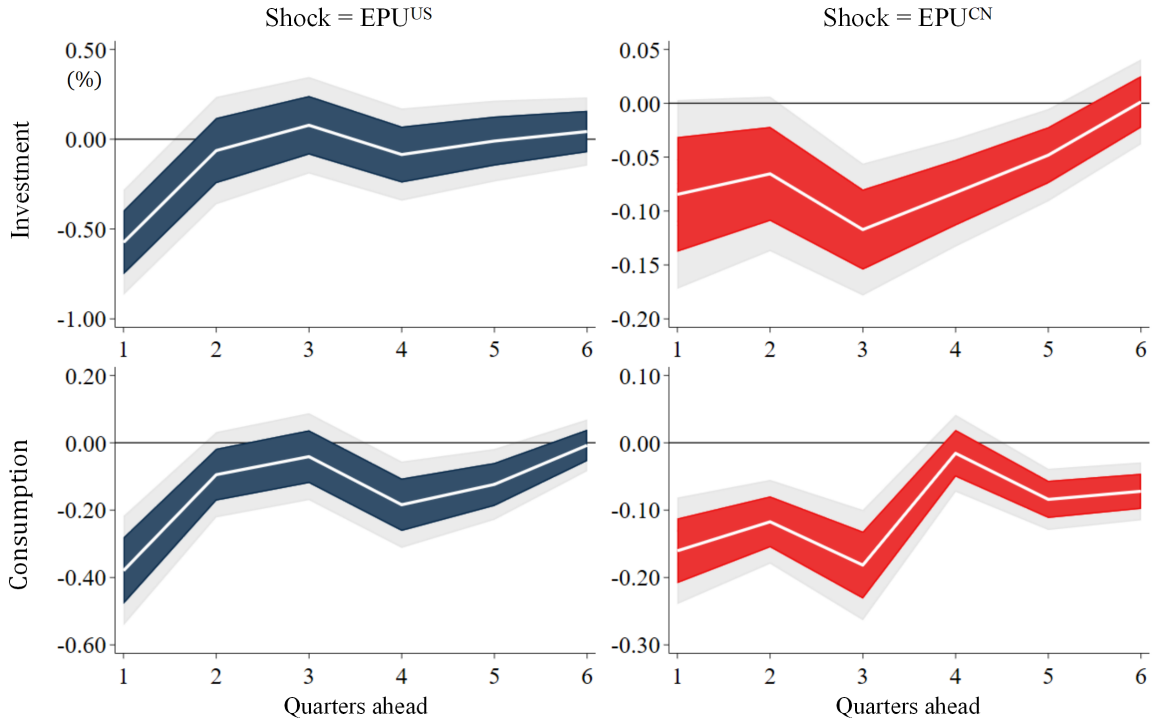
Figure 3 further illustrates the corresponding responses of aggregate investment (gross fixed capital formation) and real consumption (private consumption), based on extended specification with quarterly GDP data. Following a one–standard-deviation U.S. uncertainty shock, Emerging Asia's investment declines by approximately 0.5%, and consumption by 0.4%, with both effects dissipating within a few quarters. In response to a one–standard-deviation Chinese uncertainty shock, the initial declines in investment and consumption are smaller—around 0.2% each—but more persistent, mirroring the longer-lasting contraction observed in output.

Figure 2: **Emerging Asia Output and Inflation Responses to U.S. and China Uncertainty Shocks**



Notes: Based on the estimates from monthly panel SVAR. Left (right) column: responses to a one–standard-deviation U.S. (China) EPU shock. Row 1: EA output (y^{EA}); Row 2: EA inflation (π^{EA}), both in percent. Shaded bands are 68% and 90% confidence intervals.

Figure 3: **Emerging Asia Investment and Consumption Responses to U.S. and China Uncertainty Shocks**

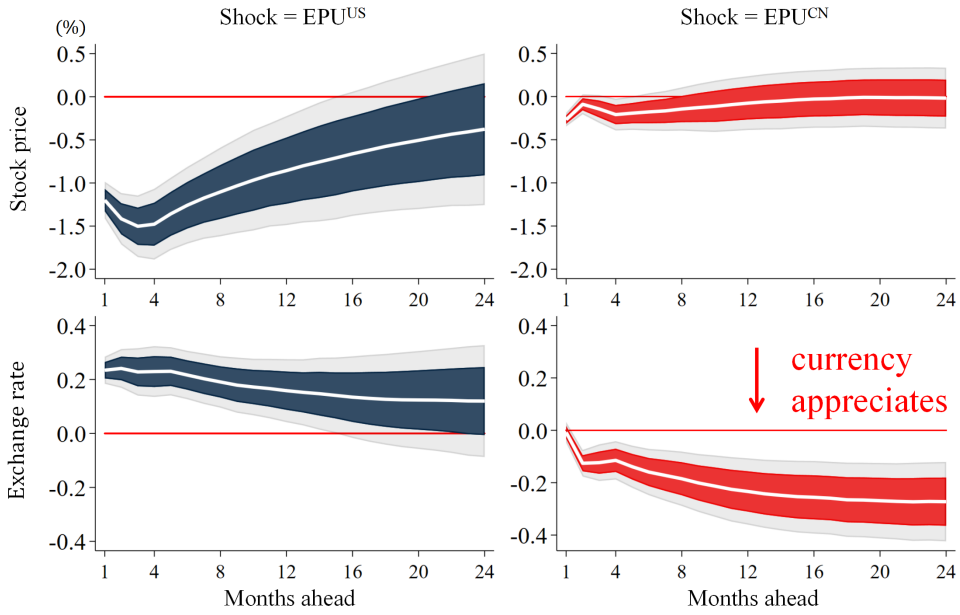


Notes: Based on quarterly panel SVAR in Cholesky order of (US IP, inflation, EPU; China IP, inflation, EPU; Emerging Asia IP, real investment, real consumption, inflation, stock price, exchange rate per USD). Left (right) column: responses to a one–standard-deviation U.S. (China) EPU shock. Row 1: investment responses, Row 2: consumption responses (%). Shaded bands are 68% and 90% confidence intervals.

Financial variables. Figure 4 illustrates the responses of Emerging Asia's financial variables to U.S. and Chinese EPU shocks. Equity prices decline by up to 2% within a few months following a U.S. shock, whereas the corresponding fall after a Chinese shock is considerably smaller.

The exchange rate responses display a striking asymmetry. Following a surge in U.S. uncertainty, Emerging Asia's currencies depreciate by about 0.2% on impact and continue to weaken persistently over a two-year horizon. In contrast, a Chinese uncertainty shock generates no immediate effect on regional exchange rates but is followed by a gradual appreciation over time. To ensure that these patterns are not merely driven by U.S. dollar–specific factors, Section C.1 re-estimates the exchange rate responses using effective (trade-weighted) exchange rates. The results remain qualitatively similar—and, if anything, the asymmetry becomes even more pronounced. We interpret this divergence as an important empirical regularity in our sample, highlighting the fragmented nature of uncertainty spillovers across global and regional sources.

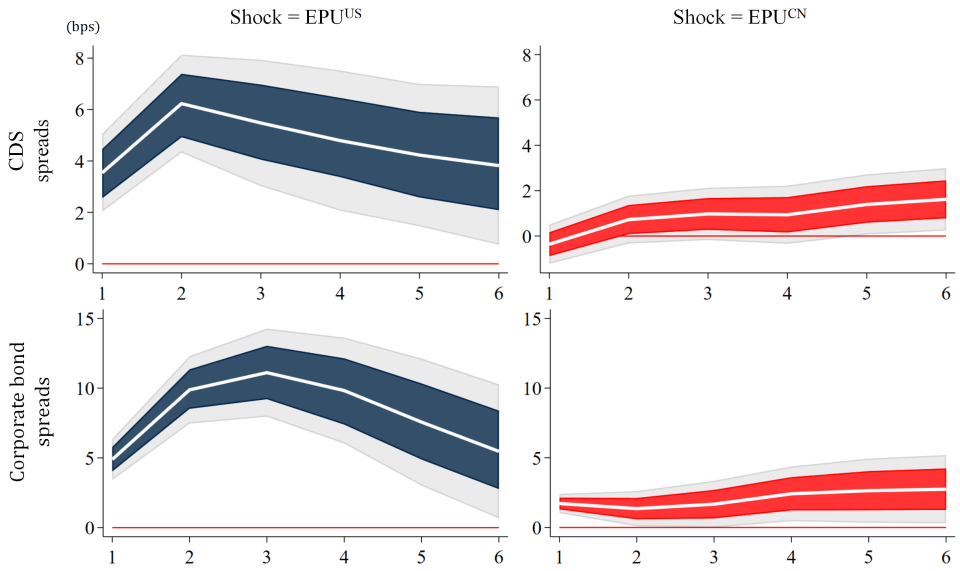
Figure 4: **Emerging Asia Equity and Exchange Rate Responses to U.S. and China Uncertainty Shocks**



Notes: Based on monthly panel SVAR model. Left (right) column: responses to a one–standard-deviation U.S. (China) EPU shock. Row 1: responses of equity price index, Row 2: bilateral Emerging Asia currency vs USD (+ ↑ = depreciation). Shaded bands are 68% and 90% confidence intervals.

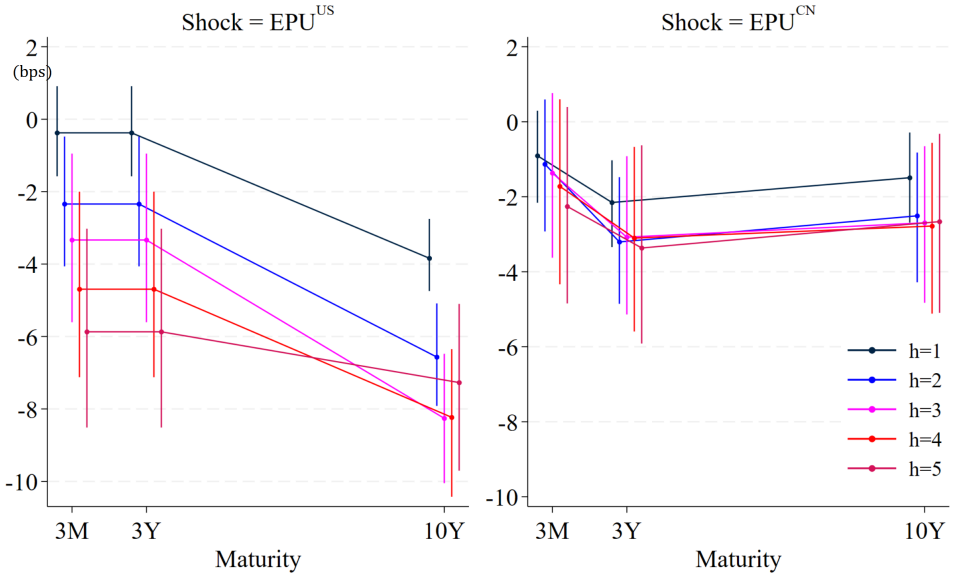
The declines in equity prices and the depreciation of emerging Asian currencies following U.S. uncertainty shocks—as shown in Figure 5—reflect a rise in the region's risk premium, consistent with the financial transmission mechanism discussed in Section 2.2. In response to these shocks, credit spreads, both sovereign and corporate, widen by approximately 6–12 basis points within a few months, indicating tighter financial conditions. By contrast, Chinese uncertainty shocks elicit much milder increases in risk premia, underscoring their more limited financial spillovers. Finally, Figure 6 compares the responses of the yield curves in emerging Asia to these uncertainty shocks. Consistent with expectations of weaker output and accommodative monetary policy, interest rates decline across both short- and long-term maturities. However, the magnitude of these declines is considerably larger following U.S. uncertainty shocks, in line with the broader and more pronounced reactions observed across other financial market variables.

Figure 5: **Emerging Asia Risk Premium Responses to US and China EPU**



Notes: Based on monthly panel SVAR model identified by Cholesky ordering following (US IP, inflation, EPU; China IP, inflation, EPU; Emerging Asia IP, inflation, stock price, exchange rate per USD, **financial spread**), where the financial spread measure is as indicated in the first column. The left (right) shows EA financial spread responses to one-standard-deviation US (China) EPU shock (unit: basis points). Shaded areas are 68% and 90% confidence intervals.

Figure 6: **EA Yield Curve Responses to US and China EPU**



Notes: The sets of vertical dots are estimated from a panel SVAR model identified by Cholesky ordering following (US IP, US CPI, US EPU; China IP, China CPI, China EPU; EA IP, EA CPI, EA stock price, EA FX rate, **EA interest rate**), where the EA interest rate measure is bond yields of the maturity as labeled in x-axis, and each line shows the response of indicated horizon. The left (right) panel shows responses to one-standard-deviation US (China) EPU shock (unit: basis points). The spikes are 68% confidence intervals.

Trade. Figure 7 presents the impulse responses of *logged exports*, *logged imports*, and the *trade balance* for Emerging Asia. Two main empirical findings stand out. First, both exports and imports decline significantly in response to U.S. and Chinese uncertainty shocks. However, the magnitude and statistical significance of these declines are considerably larger following Chinese shocks than after U.S. shocks—a pattern that contrasts with the output, consumption, and investment responses discussed earlier. This asymmetry highlights Emerging Asia's stronger trade exposure to China.

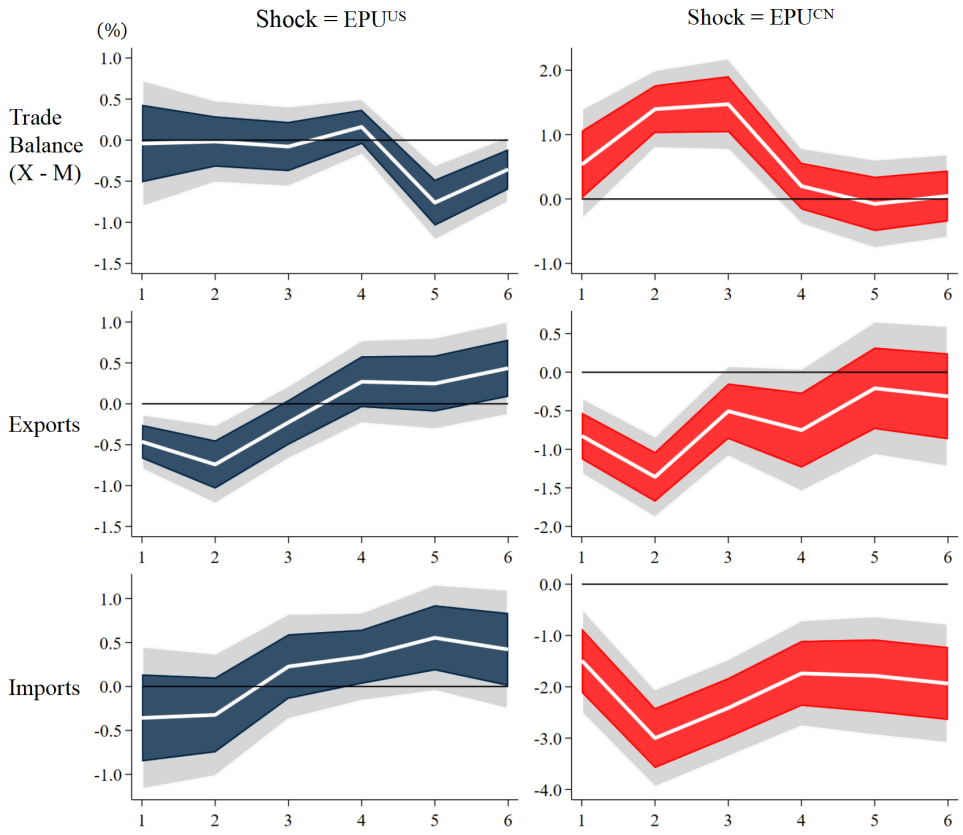
Second, the responses of the trade balance differ sharply across the two types of shocks. Following a U.S. uncertainty shock, Emerging Asia's trade deficits do not widen; if anything, they narrow modestly. This suggests that the contemporaneous U.S. dollar appreciation observed after such shocks cannot be explained by trade imbalances, implying that financial or exchange-rate channels dominate the transmission mechanism.[8] In contrast, a Chinese uncertainty shock leads to a persistent improvement in Emerging Asia's trade balance, with surpluses rising by about 1%. This occurs because imports decline more sharply than exports, reflecting weaker domestic demand and trade rebalancing within the region. The accompanying appreciation of regional currencies further supports the view that, in this case, trade adjustment rather than financial revaluation drives the exchange-rate dynamics.

Finally, in Figure D19, we further decompose the responses of trade volumes by commodity.[9] We find that, in general, commodities more heavily exported to the United States tend to see larger trade deficits following U.S. uncertainty shocks, while those more heavily imported from China tend to exhibit larger trade balance surpluses following Chinese uncertainty.

[8] This is consistent with the "reserve-currency paradox," wherein the center country's currency appreciates in risk-off episodes and valuation effects generate wealth transfers without concomitant U.S. trade deficits; see Maggiori (2017) and Gourinchas and Rey (2022).

[9] Goods trade data are sourced from UN Comtrade.

Figure 7: **Emerging Asia: Trade Flows under US and China Uncertainty Shocks (Balance of Payments)**



Notes: Responses are estimated from a quarterly panel SVAR model, identified by Cholesky ordering in the sequence (US IP, inflation, EPU; China IP, inflation, EPU; Emerging Asia IP, trade volumes (BOP), inflation, stock price, exchange rate per USD). Confidence bands are 90% and 68%.

4 Firm-Level Evidence

The macro-level results presented in hte previous section reveal that uncertainty shocks originating from the U.S. and China exert heterogeneous effects across Emerging Asian economies. Both types of shocks significantly affect real activity, yet their transmission channels differ: U.S. shocks operate mainly through financial markets and credit conditions, whereas Chinese uncertainty exerts more persistent effects on output via trade (and possibly production and employment). To unpack these mechanisms, this section investigates firm-level responses—focusing on investment and employment in individual firms—using a novel panel dataset of firms across Emerging Asia. The micro data allow us to explore the rich cross-sectional heterogeneity that shapes how uncertainty propagates through the economy (Kim, 2020).

4.1 Panel Local Projections

Specifications To trace the overall dynamic effects of uncertainty on firm decisions, panel local projection (LP) à la Jordà (2005) is estimated using quarterly firm data:

$$\Delta_h y_{i,c,t+h} = \alpha_{ih} + \beta_h \hat{u}_t + X_{i,t} + \Pi(L) Y_{c,t} + \varepsilon_{i,c,t+h}, \quad h = 1, \ldots, H \tag{3}$$

where y denotes log revenues, log investment, or log employment; Δ_h represents long-difference operator such that $\Delta_h y_{t+h} = y_{t+h} - y_t$. $\hat{u}_t$ stands for the standardized (z-scored) uncertainty index of u_t. β_h, the main coefficient of interest, captures the cumulative effect of a one–standard-deviation change in the uncertainty index u_t after h quarters. Like our analysis using SVAR models in the previous section, the cumulative impulse responses of firm-level activities are expected to deliver useful information on how much impact the uncertainty shocks influence on Emerging Asia. Firm fixed effects α_{ih} control for unobserved heterogeneity, while X_{it} includes firm-level covariates (log market capitalization, total assets, leverage, age, and Tobin's Q; precise definitions in Appendix B.1).[10]

In estimating the models, four lags of both the dependent variable and uncertainty shock are included to ensure robustness (Driscoll and Kraay, 1998). Besides these covariates in (6), country-level macroeconomic controls, $\Pi(L)\ Y_{ct}$, are drawn from the SVAR specification in Section 3. Standard errors are computed using Driscoll and Kraay (1998) correction to account for cross-sectional dependence.

4.2 Dynamic Responses of Firm Activities

Figure 8 presents the estimated firm-level impulse responses following uncertainty shocks. Investment (as shown in the second row) contracts sharply after both U.S. and China uncertainty shocks, but the magnitude of the China shock is roughly twice as large. Specifically, a one–standard-deviation rise in Chinese economic policy uncertainty reduces firm investment by approximately 3% cumulatively over six quarters, compared with about 1.5% following a US uncertainty shock. Employment responses (in the third row) mirror these dynamics: both types of uncertainty increases lead to job losses,

[10] We use local projections (LPs) for the firm panel because they (i) accommodate large, unbalanced panels with missing observations and fixed effects via horizon-by-horizon OLS; (ii) allow flexible inclusion of interactions and state dependence without re-solving a high-dimensional system; and (iii) are numerically close to VARs under correct specification but empirically more robust to misspecification. See Jordà (2005) for the LP method, Teulings and Zubanov (2014) for panel LPs, and Plagborg-Møller and Wolf (2021); Montiel Olea et al. (2025) and Stock and Watson (2018) for LP–VAR comparisons and identification.

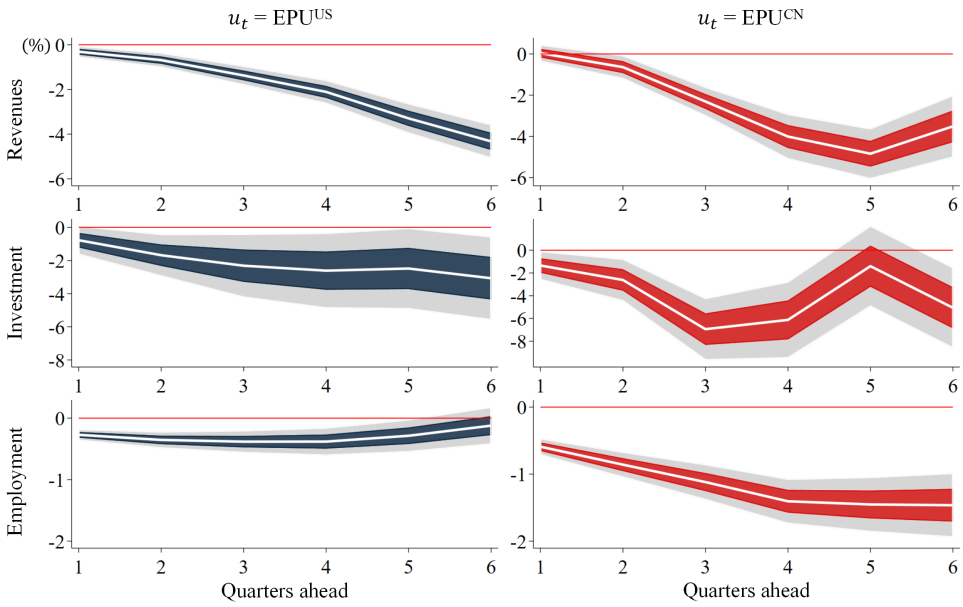
but effects of Chinese uncertainty are more persistent, indicating deeper and longer-lasting real-side adjustments.

The declines in firm-level investment and employment appear to stem from reductions in firm-level income. As illustrated in the figure (first row), firm revenues fall sharply following both U.S. and China uncertainty shocks—by as much as 5% within roughly a year, which finding is quite consistent with the comparable declines in output following U.s. and China uncertainty shocks, as shown in the previous section.

This pattern is further supported by firm equity prices: supplementary regressions (see Appendix E.1) analyzing firm-level stock return responses indicate that uncertainty shocks not only depress stock returns (reflecting lower expected future income and sales, which drive real investment and employment) but also increase stock return volatility, thereby strengthening the connection between real and financial outcomes.

Finally, Figure C13 further decomposes the effects by uncertainty type—monetary, fiscal, and trade policy (depending on the the data availability for US and China EPU index). Heightened trade policy uncertainty (TPU) in either the U.S. or China, or monetary policy uncertainty in the U.S. significantly depresses firm investment across the region, consistent with the macro findings. Employment declines are smaller in magnitude but last longer, persisting for up to one year after the shock. The results imply that trade- and monetary-related uncertainty is a key channel through which global economic policy uncertainty transmits to the firm sector in Emerging Asia.

Figure 8: **EA firm response to US versus China economic policy uncertainty**



Notes: This figure shows Emerging Asia (EA) firm impulse responses to one standard deviation increase of US (China) economic policy uncertainty on the left (right) column. Row 1 shows firm revenue growth responses (%), row 2 shows investment growth responses, row 3 shows employment growth responses. Shaded areas are 68% (navy or red) and 90% (gray) confidence intervals.

5 Uncertainty Transmission via Trade Linkages

The preceding two sections established that uncertainty shocks from the United States and China propagate through Emerging Asia (EA) via asymmetric channels. This section formalizes and quantifies how those shocks spread through international production networks, beyond direct bilateral trade. Specifically, we analyze both direct and indirect spillovers using a spatial-autoregressive (SAR) framework that captures higher-order linkages embedded in global value chains.

5.1 Conceptual Background

While the United States serves as EA's largest final-goods market, China remains its dominant supplier of intermediate inputs, shocks originating in these two major economies transmit along different network directions. Hence, a U.S. uncertainty shock primarily reduces final demand for EA exports and thus propagates upstream from the United States to EA (buyers → suppliers). By contrast, a China uncertainty shock constrains the supply of inputs to EA and therefore propagates

downstream from China to EA (suppliers → buyers). These forces are not confined to immediate bilateral links: goods and inputs traverse multi-stage global chains—for example, cotton from Xinjiang processed in Indonesia, finished in Mexico, and then re-entering EA production.[11] Such interdependencies imply that an initial uncertainty shock can reverberate through multiple layers of the global production network, magnifying its ultimate macroeconomic impact. This motivates an explicit treatment of global linkages.

We model this mechanism using a spatial econometric structure that explicitly represents network propagation, building on LeSage and Pace (2009) and Acemoglu et al. (2016).

5.2 Heterogeneous Dynamic Spatial Autoregression Framework

Model Setup. Our global economy is characterized by a production network of NS country-sector nodes. Let $R_t \in \mathbb{R}^{NS}$ collect quarter-t growth rates (investment, employment, or revenues) for all $N \times S$ country–sector nodes. We study how a common uncertainty shock propagates across the production network using a heterogeneous spatial autoregressive (SAR) mapping following Di Giovanni and Hale (2022):

$$R_t = (I - \text{diag}(\rho)\,\Phi)^{-1}\beta\hat{u}_t + \varepsilon_t, \tag{4}$$

where (i) u_t is a scalar uncertainty shock (U.S. or China EPU), (ii) $\beta \in \mathbb{R}^{NS}$ captures the *direct* shock sensitivity at each node, (iii) $\rho \in \mathbb{R}^{NS}$ measures the *intensity of network propagation* (stacked into $\text{diag}(\rho)$), (iv) Φ is a row-normalized *network weight matrix* inferred from global input–output linkages, and (v) ε_t is an idiosyncratic disturbance.[12]

Network construction. To distinguish propagation along supplier vs. customer links, we construct two empirical weight matrices from the Asian Development Bank multiregional input–output (MRIO) tables (35 sectors × 62 economies; base year 2000). Let $Z_{m_i \to n_j}$ denote intermediate sales from node m_i to node n_j, and let $\text{Sales}_{n_j} := \sum_{m,i} Z_{n_j \to m_i} + \text{FinalConsumption}_{n_j}$. We define:

$$\text{(Upstream / supplier exposure)} \quad W(m_i, n_j) := \frac{Z_{m_i \to n_j}}{\text{Sales}_{n_j}}$$

$$\text{(Downstream / customer exposure)} \quad H(m_i, n_j) := \frac{Z_{n_j \to m_i}}{\text{Sales}_{m_i}}.$$

[11] Figure A5 provides a stylized illustration based on the narrative in Chapter 15 of Rogoff (2025).

[12] With node-specific β and ρ, (4) nests the standard homogeneous SAR model $R_t = (I - \lambda W)^{-1}(\alpha\mathbf{1} + \beta u_t) + \varepsilon_t$ used in LeSage and Pace (2009).

Both W and H are row-normalized before excluding final consumption sectors (row sums < 1), so that they can be used as spatial weight matrices. In the empirical implementation, we set $\Phi \in \{W, H\}$ depending on whether the focus is supplier-side (upstream) or customer-side (downstream) transmission. Although the MRIO is static, it provides a reasonable approximation for short-run propagation.[13]

Dynamic Extension. Next, to incorporate temporal dynamics, we extend the static SAR model following the local-projection (LP) approach:[14]

$$R_{t+h} = (I - \text{diag}(\rho_h)\,\Phi)^{-1}\beta_h u_t, \quad h = 1, 2, \ldots, H. \tag{5}$$

where (β_h, ρ_h) vary by horizon. This specification allows estimation of *direct* and *network* effects at each forecast horizon h. Parameters β_h and ρ_h are estimated via maximum likelihood, with clustered wild-bootstrap standard errors at the country–sector level.

Interpretation and Decomposition. When $\rho_h = 0,\ \forall h = 0, 1, \ldots, H$, (5) collapses to a standard panel LP regression with impulse coefficient β_h on the common shock. (as in Section 4). When $\|\text{diag}(\rho)\,\Phi\| < 1$, the spatial multiplier admits the Neumann expansion:

$$\big(I - \text{diag}(\rho_h)\Phi\big)^{-1} \;=\; I \;+\; \text{diag}(\rho_h)\Phi \;+\; \big(\text{diag}(\rho_h)\Phi\big)^2 \;+\; \cdots,$$

so that

$$R_{t+h} \;=\; \underbrace{\beta_h u_t}_{\text{direct effect}} \;+\; \underbrace{\text{diag}(\rho_h)\Phi\,\beta_h u_t \;+\; \big(\text{diag}(\rho_h)\Phi\big)^2\beta_h u_t \;+\; \cdots}_{\text{network propagation via } \Phi}.$$

The first term reflects the impact on each node abstracting from network feedbacks. The higher-order terms capture first-round, second-round, ... spillovers that travel along the edges of Φ (supplier links if $\Phi = W$; customer links if $\Phi = H$). [15]

[13] We acknowledge possible time variation and endogeneity in the network matrices (e.g. Qu et al. (2021)); a comprehensive treatment is left for future work.

[14] The original form of SAR model in LeSage and Pace (2009) has a spatial (cross-sectional network spillover) dimension, but has no time dimension.

[15] Existence of the generalized Leontief inverse $(I - \text{diag}(\rho)\,\mathbf{\Phi})^{-1}$ is ensured because (i) $Sales_{nj} = \sum_m \sum_i Sales_{nj\to mi} + \text{FinalConsumption}_{nj}$, where $\text{FinalConsumption}_{nj} > 0$, and (ii) the resistance parameter has $|\rho| < 1$, which guarantee the spectral radius $\text{diag}(\rho)\Phi < 1$. See Figure A7 for the distribution of these parameters across country-sector nodes.

For reporting, we follow the spatial econometrics convention of decomposing impacts at each horizon h:

$$\begin{aligned}\text{Direct Effect} &= \beta_h,\\ \text{Total Effect} &= (I - \text{diag}(\rho_h)\Phi)^{-1}\beta_h,\\ \text{Network Effect} &= (I - \text{diag}(\rho_h)\Phi)^{-1}\beta_h - \beta_h.\end{aligned}$$

When $\Phi = W$ we label the network effect "upstream (supplier) propagation," and when $\Phi = H$ we label it "downstream (customer) propagation." This decomposition follows Acemoglu et al. (2016) and makes transparent how a common uncertainty shock splits into (i) a direct node-specific sensitivity and (ii) amplification through higher-order paths in the production network.

Estimation. Parameters β_h and ρ_h are estimated by maximum likelihood, enforcing $|\rho| < 1$ for numerical stability. Standard errors are computed using clustered wild-bootstrap at the country–sector level to account for spatial and serial correlation. Appendix E.2 reports decomposition results for $h = 0$, while Appendix Section D.2 extends the model to sector-specific uncertainty shocks where u_t is an $NS \times 1$ vector.[16]

5.3 Empirical Results: Direct and Indirect Effects of Uncertainty

Figure 9 summarizes firm-level responses to a **U.S.** uncertainty shock, based on (5). A one-standard-deviation increase in U.S. EPU reduces EA investment, employment, and revenues by 0.5–3 percent, with effects more concentrated in sectors most exposed to upstream customers—consistent with the U.S. acting as an external demand source.[17] In Figure 10, we further quantify the relative share of uncertainty propagation directly and via production linkages within the international input-output network. As seen clearly, a sizable share of U.S. uncertainty shock transmission is from the upstream linkages, explaining up to 36% of total investment declines (and over 64% on South Asian economies), consistent with a demand-driven narratives of uncertainty shocks (Leduc and Liu, 2016).[18] For

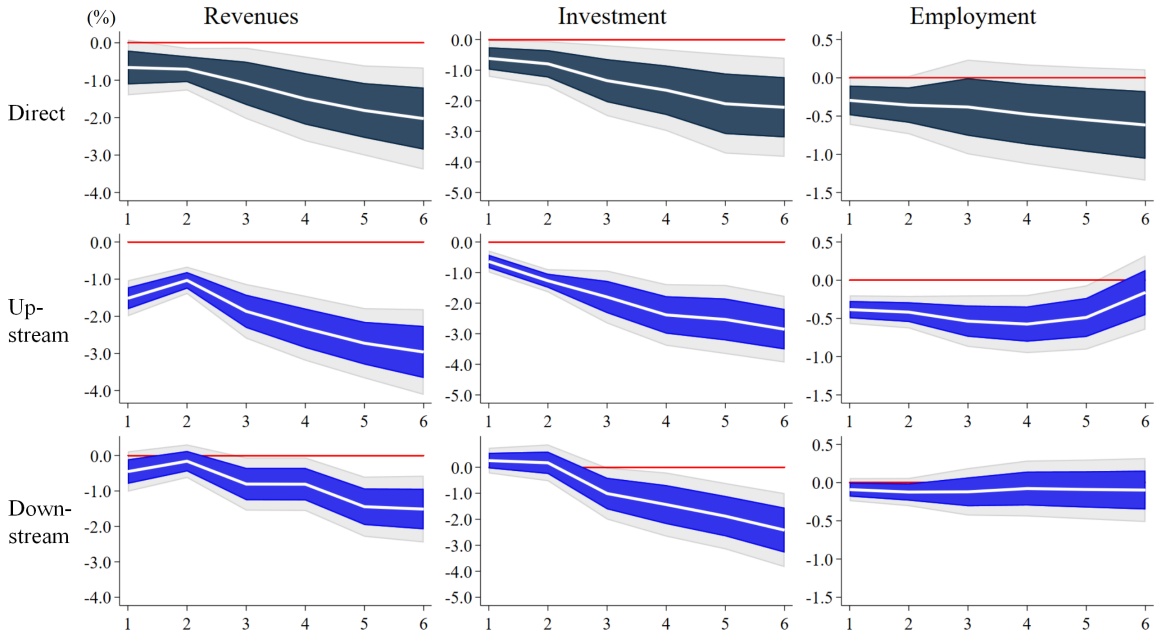
[16]This is potentially an important extension, due to multiple reasons on the importance of production network in idiosyncratic uncertainty shock propagation (e.g. Kopytov et al. (2024); Cacciatore and Candian (2025); Chodorow-Reich et al. (2025)).

[17]Quantitatively, about 60 percent of total transmission occurs through upstream propagation, while direct effects account for about 40 percent.

[18]Although now shown here, the negative investment responses are the strongest for Indonesia, which has a magnitude of -2.2% at peak, of which over 50% comes from downstream propagation, around 25% is from the upstream, and 25% is direct responses.

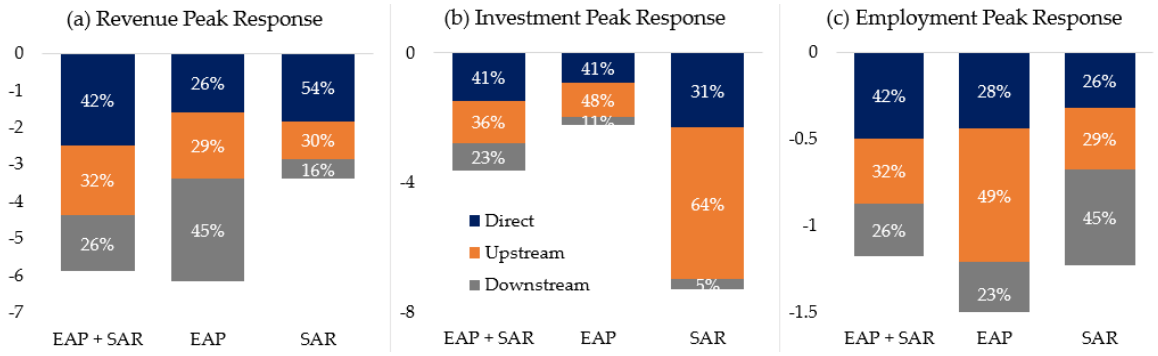
employment responses, the upstream networks explain 32% of the declines due to US uncertainty.[19]

Figure 9: **EA Firm Responses to U.S. Economic Policy Uncertainty Shocks and Network Propagation**



Notes: This charts presents the the estimates spillover effects of US uncertainty based on (5), with firm revenue growth (%, left column),investment growth (%, middle), and employment growth (%, right). The uncertainty shock is one-standard-deviation increase in US EPU. Shaded areas are 68% (blue) and 90% (grey) confidence intervals respectively.

Figure 10: **EA Firm Peak Responses to US Uncertainty Shocks: Direct and Network Effects**

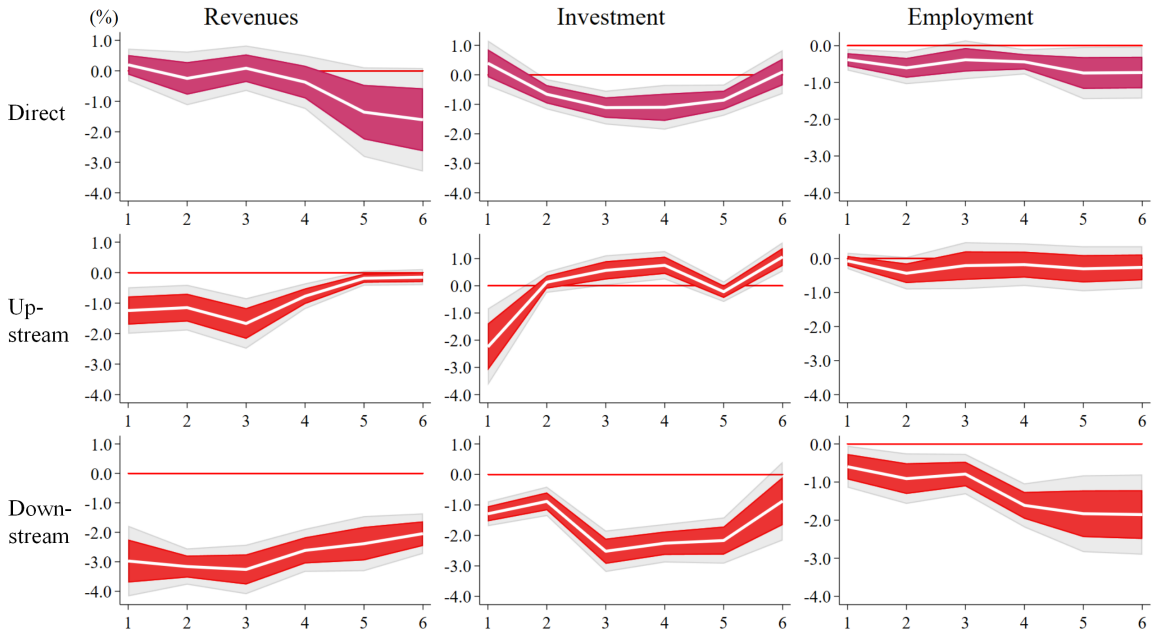


Notes: The chart shows peak responses of Direct effect (navy), Upstream Propagation (orange) and Downstream Propagation (gray) estimated from (5) for the EA sector-quarter panel (first bar in each panel) or decomposed by EAP or SAR subsamples as indicated on the x-axis, to one-standard-deviation increase of US EPU. Panel (a) shows for firm revenue responses, (b) for investment responses, and Panel (c) for employment responses.

[19]Both Indonesia and Thailand firms have negative responses close to 1% at peak, among which over 80% comes from upstream linkages.

Next, Figure 11 displays the corresponding responses of firm-level revenue, investment, and employment to a **China** uncertainty shock. The figure clearly suggests that propagation is dominated by downstream linkages, reflecting China's role as a critical input supplier. While revenue and investment declines by 3 percent through the downstream network, employment contracts by about 2 percent. The decompositions in Figure 12 again suggest that China uncertainty is a supplier shock, with the giant share propagating through downstream network. Figure C15-Figure C16 report the quantification for each EA country and document similar patterns.

Figure 11: **EA Firm Responses to China Economic Policy Uncertainty Shocks and Network Propagation**



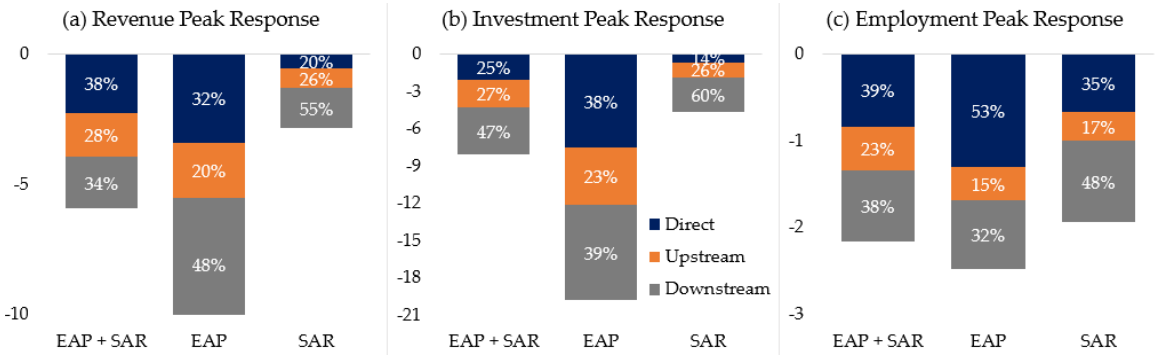
Notes: Column 1 shows estimates of (5), with firm revenue growth (%) on the right hand side, column 2 shows those for investment growth (%), and column 3 shows employment growth (%). The uncertainty shock is one-standard-deviation increase in China EPU. Shaded areas are 68% and 90% confidence intervals respectively.

6 Further Considerations

6.1 Sub-sector Analysis

An important element of our supply chain narrative is sectoral heterogeneity, arising along two dimensions: (i) the origin of volatility across sectors and (ii) the heterogeneous responses of agents specialized in different sectors.

Figure 12: **EA Firm Peak Responses to China Uncertainty Shocks: Direct and Network Effects**



Notes: The chart shows peak responses of Direct effect (navy), Upstream Propagation (orange) and Downstream Propagation (gray) estimated from (5) for the EA sector-quarter panel (first bar in each panel) or decomposed by EAP or SAR subsamples as indicated on the x-axis, to one-standard-deviation increase of China EPU. Panel (a) shows for firm revenue responses, (b) for investment responses, and Panel (c) for employment responses.

For the first dimension, we compute, for each SIC 1-digit sector, the market-capitalization-weighted average of stock return volatility (within-month standard deviation). We then re-estimate the baseline specification, replacing EPU^{US} and EPU^{CN} with each sector-specific uncertainty measure in turn. The results are reported in Figure D20–Figure D21. Sectoral uncertainty shocks are strongly synchronized in their transmission to the aggregate economy. Uncertainty originating in the U.S. agriculture sector has a muted effect on EA inflation, whereas shocks from other sectors are significantly deflationary and of similar magnitude (about –0.2%). Output and equity responses resemble those under aggregate EPU, and the depreciating effect on EA currencies persists across all sectors. The China sectoral exercises deliver similar messages with the baseline results as discussed before: the EA currency appreciates by 0.3–0.4% across all Chinese sectors, while the RMB depreciates.

For the second dimension, Figure A3–Figure A4 show that firms specialized in different sectors respond differently to U.S. and China uncertainty shocks. U.S. construction-sector uncertainty generates the largest negative impact on EA firm investment (about –4%), while manufacturing-sector uncertainty from the United States has the strongest effect on EA firm employment (about –1.5%). For China, uncertainty in both manufacturing and services transmits to EA firm employment at roughly –3%. The most adverse impact on EA firm investment arises from China retail trade uncertainty, with an effect of about –10%.

6.2 Different types of Uncertainty

This section distinguishes the effects of different categories of policy uncertainty—monetary, fiscal, and trade—originating from the United States and China. Figure C11–Figure C12 summarize the corresponding macroeconomic and firm-level responses.

At the macroeconomic level, U.S. monetary and fiscal policy uncertainty exert the most pronounced and persistent effects on Emerging Asia's aggregate activity. A one–standard-deviation rise in either component leads to an average 1 percent decline in regional output, with effects lasting for several quarters. These results are consistent with the narratives that monetary and fiscal uncertainty elevate financing costs and depress aggregate demand through precautionary saving and deferred investment.

In contrast, China's trade-policy uncertainty appears to primarily transmit through the real economy and supply chains, rather than through financial channels. A comparable one–standard-deviation shock to China's trade policy uncertainty reduces Emerging Asia's output by over 0.5 percent, presumably driven mainly by contractions in trade volumes and intermediate-goods production (based on the results in the preceding sections).

Turning to financial markets, U.S. trade-policy uncertainty produces the largest and most persistent declines in regional equity prices—typically between 1 and 2 percent—reflecting investors' heightened sensitivity to global demand and tariff risks. Across uncertainty types, our baseline exchange-rate results remain robust: U.S.-originated uncertainty depreciates Emerging Asia's currencies, while China-originated uncertainty tends to appreciate them, consistent with the asymmetric demand- and supply-side channels identified earlier.

At the firm level (as show in Figure C13), these asymmetries are even more pronounced. Firms respond most strongly to U.S. monetary and fiscal policy uncertainty through declines in investment and employment, whereas China's trade-policy uncertainty generates more persistent effects on production and sales (as reflected in revenues). Together, these findings confirm our earlier findings that not all uncertainty is alike: U.S. shocks primarily operate through financial tightening, whereas Chinese shocks propagate through trade and production disruptions within the regional network.

6.3 Country-specific Results

We further present firm-level local-projection responses in each Emerging Asia country to a one-standard-deviation increase in U.S. Economic Policy Uncertainty (EPU) in Figure A1, and to a comparable shock in China's EPU in Figure A2. The country-specific patterns are broadly consistent with the panel estimates presented in Section 4. However, the South Asia sub-region exhibits a markedly higher sensitivity to the U.S. uncertainty shock. For instance, Indian firms' investment responses to a one-SD U.S. uncertainty shock are approximately –15 % cumulatively after four quarters—about five times the magnitude of the panel estimate (about –3 %). Meanwhile, both the EAP and South Asia regions include countries that experience very large negative responses to a China uncertainty shock. For example, in the East Asian sub-region group, Malaysia and Thailand exhibit cumulative responses of roughly –6 % to a one-standard-deviation China-uncertainty shock; in South Asia, firms in Bangladesh and Sri Lanka show responses of approximately –15 %.

6.4 Extended Firm-level Results based on Stock Prices

In Appendix E, we study firm-level stock-return responses to uncertainty at a daily frequency.

First, we document that firm-level daily stock returns decline following increases in both U.S. and China economic policy uncertainty. In contrast to the stronger real-activity responses (investment, sales, and employment) to China-specific uncertainty, equity markets react more strongly to U.S. uncertainty. In pooled OLS estimates for the eight Emerging Asia (EA) economies, a one-standard-deviation U.S. uncertainty shock is associated with about a 5% decline in daily returns, compared with roughly 2% for a comparable China uncertainty shock.

Second, we find meaningful heterogeneity across countries and sectors. Within EA, Agriculture firms exhibit the strongest sensitivity to U.S. EPU, whereas Retail trade, Agriculture, and Manufacturing are the most responsive to China EPU.

Finally, decomposing transmission into direct, upstream, and downstream network channels shows distinct patterns by source. For China EPU, the downstream channel dominates (ranging from about 21% in Thailand to 62% for Chinese firms). For U.S. EPU, the upstream channel dominates (from roughly 26% in Thailand and the Philippines up to 90% for Sri Lanka).

7 Conclusion

This paper provides new evidence on how global economic policy uncertainty—especially from the United States and China—shapes macroeconomic and microeconomic dynamics in Emerging Asia. By combining structural VAR analysis, firm-level regressions, and spatial-econometric modeling, we uncover a consistent pattern of asymmetric and network-amplified spillovers. U.S. uncertainty shocks predominantly transmit through financial markets, tightening credit conditions and depressing asset prices, while Chinese uncertainty propagates mainly through trade and production linkages, leading to prolonged effects on output and employment. Firm-level data confirm that uncertainty induces significant investment and hiring slowdowns, reflecting precautionary behavior and heightened risk aversion.

Overall, our results highlight the crucial role of production networks in magnifying global uncertainty shocks—accounting for up to 80–90 percent of total transmission. The findings underscore the vulnerability of highly interconnected Asian economies to external volatility, particularly amid rising geopolitical and trade tensions. Strengthening macroprudential frameworks, diversifying supply chains, and enhancing policy coordination can help mitigate these vulnerabilities and build resilience against future waves of global uncertainty.

References

Abiad, Abdul and Irfan A. Qureshi, "The macroeconomic effects of oil price uncertainty," *Energy Economics*, 2023, *125*, 106839.

Acemoglu, Daron, Ufuk Akcigit, and William Kerr, "Networks and the Macroeconomy: An Empirical Exploration," *NBER Macroeconomics Annual*, 2016, *30*, 273–335.

Ahir, Hites, Nicholas Bloom, and Davide Furceri, "The World Uncertainty Index," Working Paper 29763, National Bureau of Economic Research February 2022.

Akinci, Ozge, S̄ebnem Kalemli-Özcan, and Albert Queralto, "Uncertainty Shocks, Capital Flows, and International Risk Spillovers," Working Paper 30026, National Bureau of Economic Research May 2022.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin, "The finance uncertainty multiplier," *Journal of Political Economy*, 2024, *132* (2), 577–615.

Alfaro, Iván, Nicholas Bloom, and Xiaoji Lin, "The Finance Uncertainty Multiplier," *Journal of Political Economy*, 2024, *132* (2), 577–615.

Apaitan, Tosapol, Pongsak Luangaram, and Pym Manopimoke, "Uncertainty and Economic Activity: Does it Matter for Thailand?," *PIER Discussion Papers*, 2020, *130*, 1–43.

Arbatli, Elif C, Steven J Davis, Arata Ito, and Naoko Miake, "Policy uncertainty in Japan," Technical Report, National Bureau of Economic Research 2017.

Bachmann, Rüdiger, Steffen Elstner, and Eric R Sims, "Uncertainty and economic activity: Evidence from business survey data," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 217–249.

Bachmann, Ruediger, Kai Carstensen, Stefan Lautenbacher, and Martin Schneider, "Uncertainty and Change: Survey Evidence of Firms' Subjective Beliefs," Working Paper 29430, National Bureau of Economic Research October 2021.

Baker, Scott R, Nicholas Bloom, and Stephen J Terry, "Using Disasters to Estimate the Impact of Uncertainty," *The Review of Economic Studies*, 03 2023. rdad036.

_ , _ , and Steven J Davis, "Measuring economic policy uncertainty," *Quarterly Journal of Economics*, 2016, *131* (4), 1593–1636.

Baker, S.R., N. Bloom, S.J. Davis, and Xiaoxi Wang, "Economic Policy Uncertainty in China," 2013. Unpublished paper, University of Chicago.

Barrero, Jose Maria, "The micro and macro of managerial beliefs," *Journal of Financial Economics*, 2022, *143* (2), 640–667.

Basu, Susanto and Brent Bundick, "Uncertainty shocks in a model of effective demand," *Econometrica*, 2017, *85* (3), 937–958.

Bhattarai, Saroj, Arpita Chatterjee, and Woong Yong Park, "Global spillover effects of US uncertainty," *Journal of Monetary Economics*, 2020, *114*, 71–89.

Bloom, Nicholas, "The impact of uncertainty shocks," *Econometrica*, 2009, *77* (3), 623–685.

Bodenstein, Martin, Pablo Cuba-Borda, Nils Gornemann, and Ignacio Presno, "Exchange rate disconnect and the trade balance," *International Finance Discussion Paper*, 2024.

Cacciatore, Matteo and Giacomo Candian, "Uncertainty through the Production Network: Sectoral Origins and Macroeconomic Implications," Working Paper 33953, National Bureau of Economic Research June 2025.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo, "Does Trade Policy Uncertainty Affect Global Economic Activity?," *FEDS Notes*, September 2019. Last Update: September 04, 2019.

Carrière-Swallow, Yan and Luis Felipe Céspedes, "The impact of uncertainty shocks in emerging economies," *Journal of International Economics*, 2013, *90* (2), 316–325.

Cascaldi-Garcia, Danilo, Cisil Sarisoy, Juan M Londono, Bo Sun, Deepa D Datta, Thiago Ferreira, Olesya Grishchenko, Mohammad R Jahan-Parvar, Francesca Loria, Sai Ma et al., "What is certain about uncertainty?," *Journal of Economic Literature*, 2023, *61* (2), 624–654.

Castelnuovo, Efrem, Giovanni Pellegrino, and Laust Særkjær, "The Inflation Uncertainty Amplifier," *CESifo Working Paper*, 2025.

Cerutti, Eugenio, Stijn Claessens, and Damien Puy, "Push factors and capital flows to emerging markets: why knowing your lender matters more than fundamentals," *Journal of International Economics*, 2019, *119*, 133–149.

Cheng, Chak Hung Jack, "Effects of foreign and domestic economic policy uncertainty shocks on South Korea," *Journal of Asian Economics*, 2017, *51*, 1–11.

Chodorow-Reich, Gabriel, Xavier Gabaix, and Davide Viviano, "Propagation of Shocks in Networks: Identification and Applications," *Available at SSRN 4885984*, 2025.

D'Amico, Stefania and Athanasios Orphanides, "Uncertainty and disagreement in economic forecasting," Finance and Economics Discussion Series 2008-56, Board of Governors of the Federal Reserve System (U.S.) 2008.

Davis, S.J., Dingqian Liu, and Xugang S. Sheng, "Economic Policy Uncertainty in China Since 1949: The View from Mainland Newspapers," 8 2019. Working Paper.

Diebold, Francis X and Kamil Yilmaz, "Macroeconomic Volatility and Stock Market Volatility, Worldwide," Working Paper 14269, National Bureau of Economic Research August 2008.

Diebold, Francis X. and Kamil Yilmaz, "On the past, present, and future of the Diebold–Yilmaz approach to dynamic network connectedness," *Journal of Econometrics*, 2023, *234*, 115–120. Jubilee Issue - Celebrating our Fiftieth Anniversary: 1973–2023.

Driscoll, John C and Aart C Kraay, "Consistent covariance matrix estimation with spatially dependent panel data," *Review of economics and statistics*, 1998, *80* (4), 549–560.

Duffie, Darrell, "Resilience redux in the US Treasury market," in "Jackson Hole Symposium, Federal Reserve Bank of Kansas City, August" 2023.

Engel, Charles, "Exchange rates and interest parity," *Handbook of international economics*, 2014, *4*, 453–522.

_ , "Exchange rates, interest rates, and the risk premium," *American Economic Review*, 2016, *106* (2), 436–474.

Fama, Eugene F., "Forward and spot exchange rates," *Journal of Monetary Economics*, 1984, *14* (3), 319–338.

Ferguson, Niall and Moritz Schularick, "The end of Chimerica," *Harvard Business School BGIE Unit Working Paper*, 2009.

Fernández-Villaverde, Jesús, Pablo Guerrón-Quintana, Juan F Rubio-Ramirez, and Martin Uribe, "Risk matters: The real effects of volatility shocks," *American Economic Review*, 2011, *101* (6), 2530–2561.

Fernández-Villaverde, Jesús, Tomohide Mineyama, and Dongho Song, "Are We Fragmented Yet? Measuring Geopolitical Fragmentation and Its Causal Effect," Working Paper 32638, National Bureau of Economic Research June 2024.

Fiori, Giuseppe and Filippo Scoccianti, "The economic effects of firm-level uncertainty: Evidence using subjective expectations," *Journal of Monetary Economics*, 2023, *140*, 92–105.

Firooz, Hamid, Sylvain Leduc, and Zheng Liu, "Reshoring, automation, and labor markets under trade uncertainty," *Journal of International Economics*, 2025, p. 104091.

Fontaine, Idriss, Justinien Razafindravaosolonirina, and Laurent Didier, "Chinese policy uncertainty shocks and the world macroeconomy: Evidence from STVAR," *China Economic Review*, 2018, *51*, 1–19.

Gilchrist, Simon and Egon Zakrajšek, "Credit spreads and business cycle fluctuations," *American economic review*, 2012, *102* (4), 1692–1720.

Giovanni, Julian Di and Galina Hale, "Stock market spillovers via the global production network: Transmission of US monetary policy," *The Journal of Finance*, 2022, *77* (6), 3373–3421.

_ and John Rogers, "The impact of US monetary policy on foreign firms," *IMF Economic Review*, 2024, *72* (1), 58–115.

Gourinchas, Pierre-Olivier and Helene Rey, "Exorbitant privilege and exorbitant duty," *CEPR Discussion Paper No. DP16944*, 2022.

Ha, Jongrim and Inhwan So, "The Economic Effects of Global Inflation Uncertainty," *International Journal of Central Banking*, April 2024, *20* (2), 69–150.

_ , M Ayhan Kose, and Franziska Ohnsorge, "One-stop source: A global database of inflation," *Journal of International Money and Finance*, 2023, *137*, 102896.

Handley, Kyle and J. Frank Li, "Measuring the Effects of Firm Uncertainty on Economic Activity: New Evidence from One Million Documents," NBER Working Papers 27896, National Bureau of Economic Research, Inc October 2020.

_ and Nuno Limão, "Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States," *American economic review*, 2017, *107* (9), 2731–2783.

Huidrom, Raju, M Ayhan Kose, Hideaki Matsuoka, and Franziska L Ohnsorge, "How important are spillovers from major emerging markets?," *International Finance*, 2020, *23* (1), 47–63.

Husted, Lucas, John Rogers, and Bo Sun, "Monetary policy uncertainty," *Journal of Monetary Economics*, 2020, *115*, 20–36.

Jarociński, Marek and Peter Karadi, "Deconstructing monetary policy surprises—the role of information shocks," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 1–43.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American economic review*, 2005, *95* (1), 161–182.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng, "Measuring uncertainty," *American Economic Review*, 2015, *105* (3), 1177–1216.

Kim, Junhyong, "The Impact of Uncertainty Shocks on the Investment of Small and Large Firms: Micro Evidence and Macro Implications," *Available at SSRN 3943024*, 2020.

Kopytov, Alexandr, Bineet Mishra, Kristoffer Nimark, and Mathieu Taschereau-Dumouchel, "Endogenous Production Networks Under Supply Chain Uncertainty," *Econometrica*, 2024, *92* (5), 1621–1659.

Kozeniauskas, Nicholas, Anna Orlik, and Laura Veldkamp, "What are uncertainty shocks?," *Journal of Monetary Economics*, 2018, *100*, 1–15.

Kuncoro, Haryo, "Inflation and its uncertainty: Evidence from Indonesia and the Philippines," *Global Journal of Emerging Market Economies*, 2024, *16* (2), 231–247.

Leduc, Sylvain and Zheng Liu, "Uncertainty shocks are aggregate demand shocks," *Journal of Monetary Economics*, 2016, *82*, 20–35.

LeSage, James and Robert Kelley Pace, *Introduction to spatial econometrics*, Chapman and Hall/CRC, 2009.

Li, Thomas H., Juan M. Londono, and Sai Ma, "The Global Transmission of Inflation Uncertainty," *FEDS Notes*, January 2025. Available at SSRN: https://ssrn.com/abstract=5148621.

Maggiori, Matteo, "Financial Intermediation, International Risk Sharing, and Reserve Currencies," *American Economic Review*, October 2017, *107* (10), 3038–71.

Miranda-Agrippino, Silvia, Tsvetelina Nenova, and Helene Rey, "Global Footprints of Monetary Policy," Discussion Papers 2004, Centre for Macroeconomics (CFM) January 2020.

Obstfeld, Maurice and Kenneth Rogoff, "The intertemporal approach to the current account," *Handbook of International Economics*, 1995, *3*, 1731–1799.

Olea, José Luis Montiel, Mikkel Plagborg-Moller, Eric Qian, and Christian Wolf, "Local Projections or VARs? A Primer for Macroeconomists," *NBER Working Paper*, 2025.

Plagborg-Møller, Mikkel and Christian K Wolf, "Local projections and VARs estimate the same impulse responses," *Econometrica*, 2021, *89* (2), 955–980.

Qu, Xi, Lung fei Lee, and Chao Yang, "Estimation of a SAR model with endogenous spatial weights constructed by bilateral variables," *Journal of Econometrics*, 2021, *221* (1), 180–197.

Rogoff, Kenneth, *Our dollar, your problem: an insider's view of seven turbulent decades of global finance, and the road ahead*, Yale University Press, 2025.

Schaab, Andreas, "Micro and macro uncertainty," *Available at SSRN 4099000*, 2020.

Shah, Said Zamin, Ahmad Zubaidi Baharumshah, Rusmawati Said, and Rafiqa Murdipi, "The international transmission of volatility shocks on an emerging economy: The case of Malaysia," *Malaysian Journal of Economic Studies*, 2019, *56* (2), 243–265.

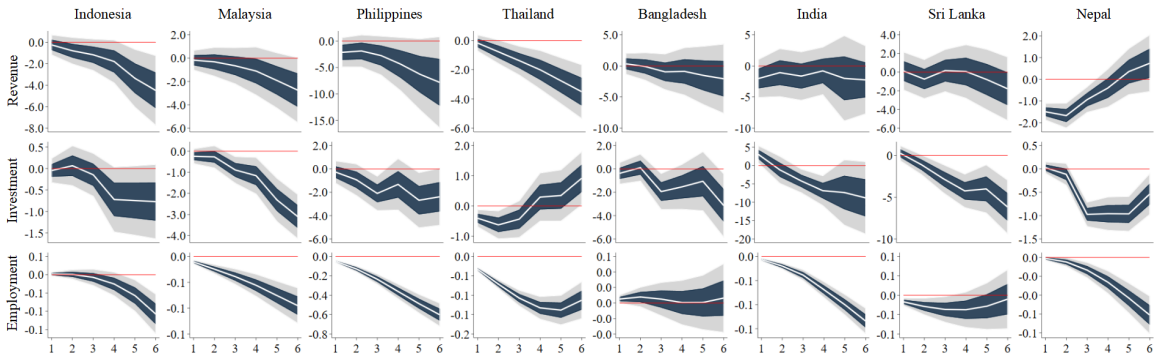
Stock, James H. and Mark W. Watson, "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments," *The Economic Journal*, 05 2018, *128* (610), 917–948.

Teulings, Coen N and Nikolay Zubanov, "Is economic recovery a myth? Robust estimation of impulse responses," *Journal of Applied Econometrics*, 2014, *29* (3), 497–514.

Appendix: For Online Publication Only

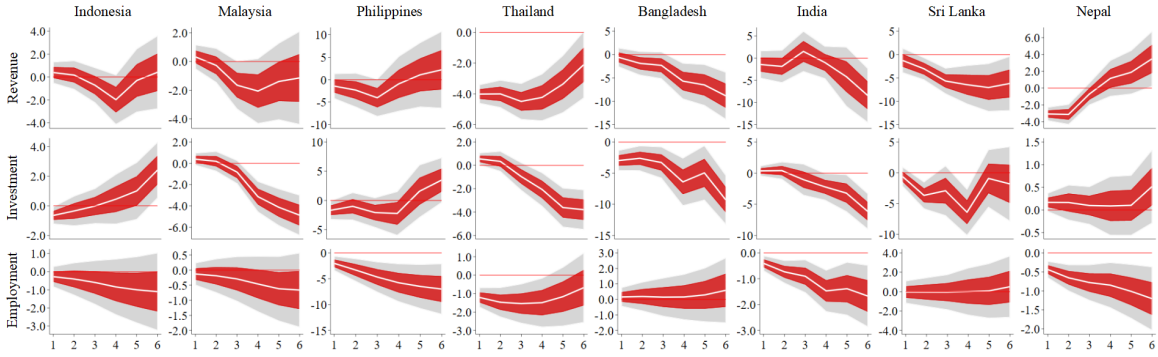
A Additional Figures

Figure A1: **EA firm-level responses to US economic policy uncertainty: by country**



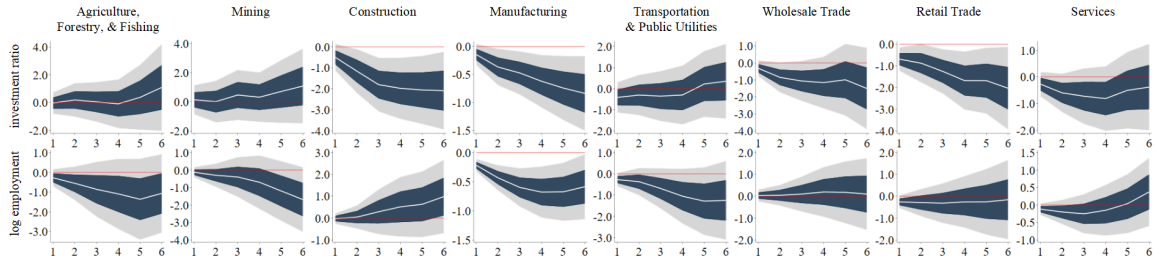
Notes. This figure shows firm-level impulse responses—based on local projections—to one standard deviation increase of US economic policy uncertainty in individual EA country (indicated in column titles). Row 1 shows revenue growth responses, row 2 shows investment growth responses, row 2 shows employment growth responses. Shaded areas are 68% (navy) and 90% (gray) confidence intervals.

Figure A2: **EA firm-level responses to China economic policy uncertainty: by country**



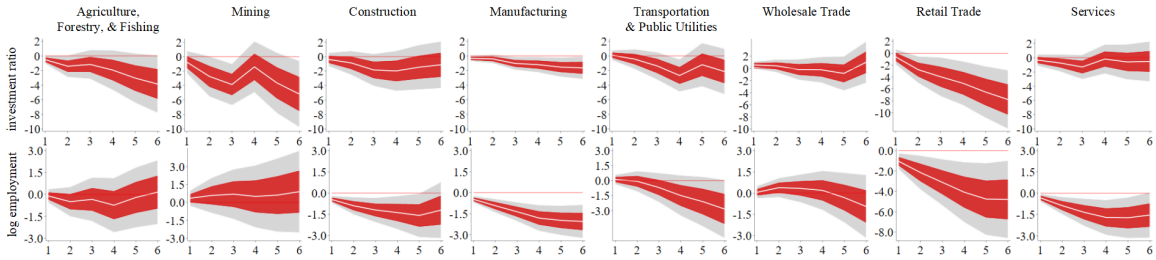
Notes. This figure shows firm-level impulse responses—based on local projections—to one standard deviation increase of China economic policy uncertainty, for individual EA countries (indicated in column titles). Row 1 shows revenue growth responses, row 2 shows investment growth responses, row 2 shows employment growth responses. Shaded areas are 68% (red) and 90% (gray) confidence intervals.

Figure A3: **EA firm local projection response to US economic policy uncertainty: by sector**



Notes. This figure shows EA firm impulse responses to one standard deviation increase of US economic policy uncertainty, for each sector (indicated in column titles). Row 1 shows investment growth responses, row 2 shows employment growth responses. Shaded areas are 68% (navy) and 90% (gray) confidence intervals.

Figure A4: **EA firm local projection response to China economic policy uncertainty: by sector**



Notes. This figure shows EA firm impulse responses to one standard deviation increase of China economic policy uncertainty, for each sector (indicated in column titles). Row 1 shows investment growth responses, row 2 shows employment growth responses. Shaded areas are 68% (red) and 90% (red) confidence intervals.

B Data Appendix

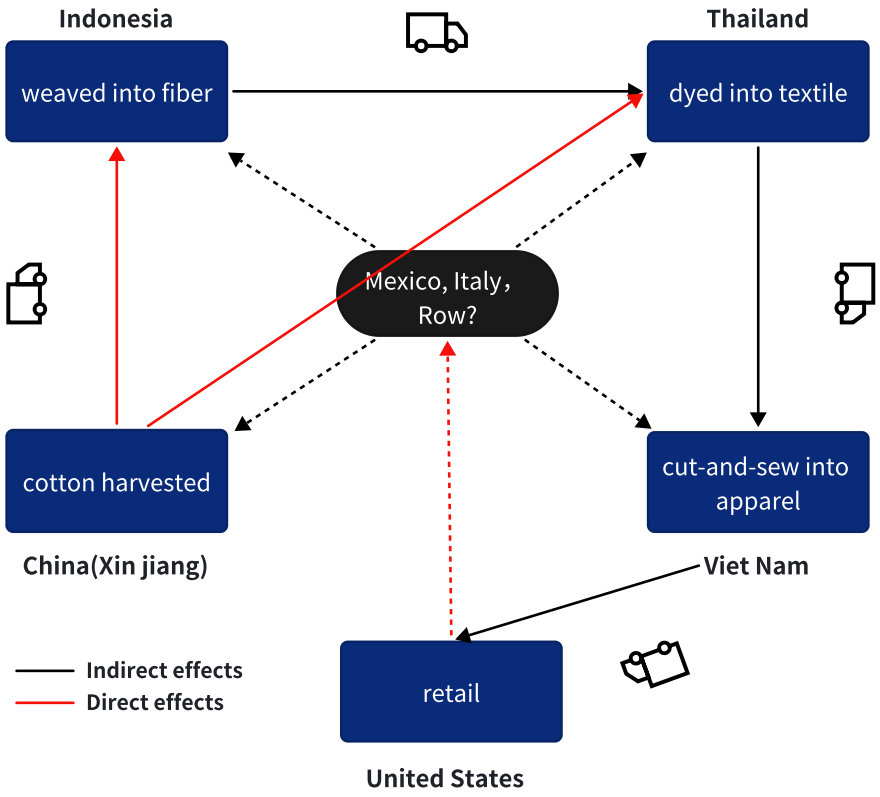
B.1 Firm-level Data

The firm-level analyses integrate two harmonized data sources: daily stock price quotes from Datastream and quarterly financial statements from Worldscope, linked through consistent firm identifiers and standardized regional/industry classifications. The final sample includes 4,328 firms with 7,111,993 daily observations and 421,634 quarterly observations. Daily stock returns, $r_{i,c,t}$, are the close-to-close annualized log returns, based on USD-denominated closing prices, winsorized at 1% and 99%, respectively.[20] Investment is defined as changes in fixed capital (`PPENT`) scaled by lagged fixed capital. Employment is quarterly headcount interpolated from annual Q4 reports. Revenue is Gross sales and other operating revenue less discounts, returns and allowances (ITEM1001). Size is the logarithm of total assets (`AT`), age is the number of quarters since the firm's foundation date.[21]

[20] The price denominated in domestic currency is also checked for robustness.

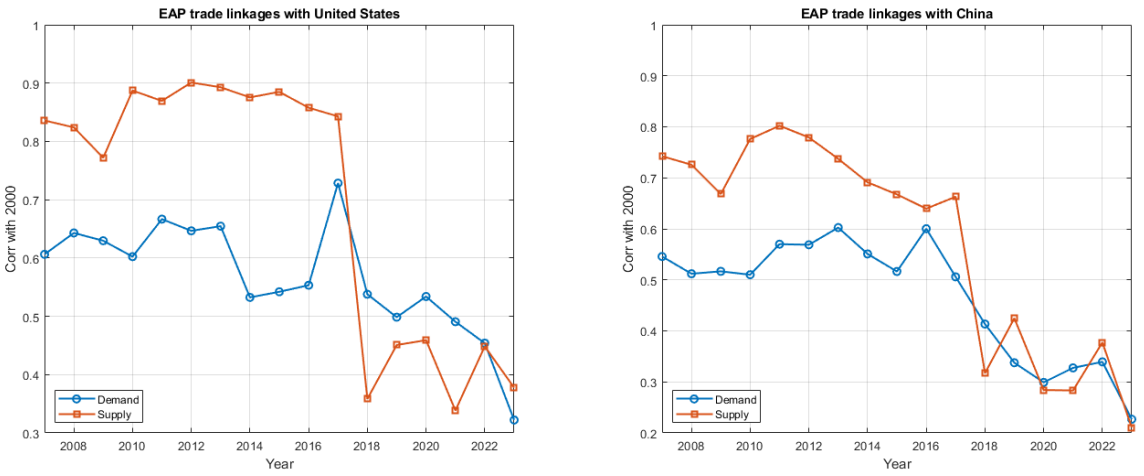
[21] Wherever the foundation date is missing, we use the minimum of the firm's initial public offering date and first observation date with non-missing `AT`.

Figure A5: **An Illustration on the "Asian Supply Chain"**



Leverage is total debt over assets (`(DLTT+DLC)/AT`), and Tobin's Q is `(PRCC*CSHO+DLTT+DLC)/AT`. Age is quarters since incorporation; whenever the incorporation date is missing, it is the time span since the first entry with non-missing total assets. As in Di Giovanni and Rogers (2024), each of these controls is normalized around its mean for each country-year, to avoid confounding the estimates by the cross-country difference in firm distributions.

Figure A6: **Correlations of Demand and Supply Closeness to U.S. and China in MRIO of year after 2000**



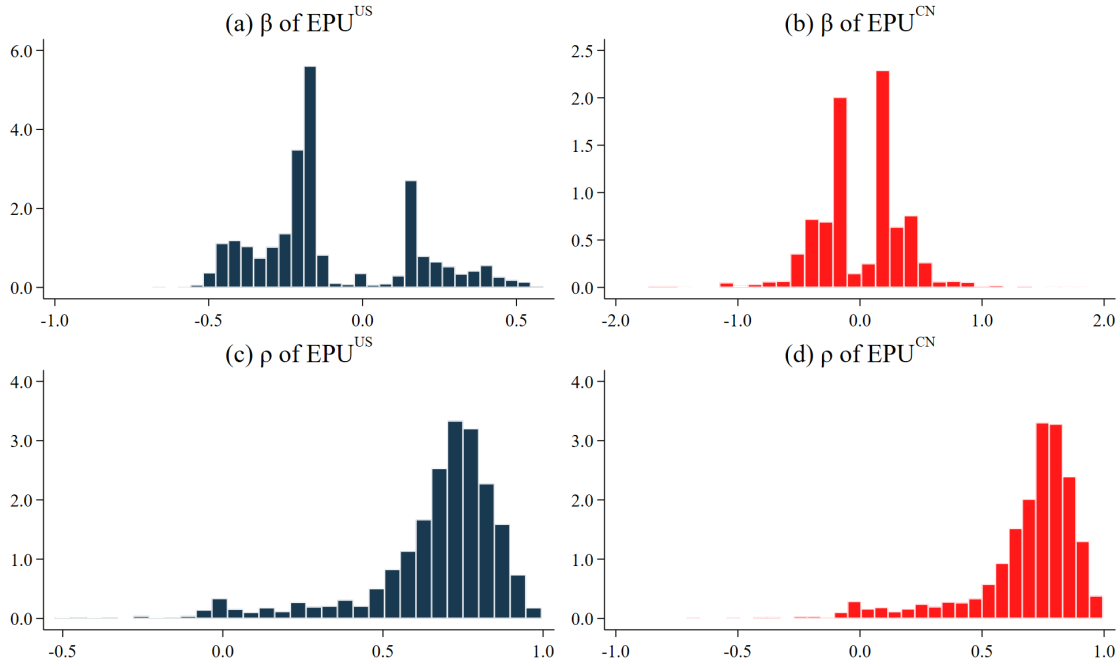
Notes. The charts show correlations of demand or supply closeness to each of the subsequent MRIO table with the MRIO table in 2000. The demand closeness are defined as the share of intermediate + final consumption imports of the four EA economies in our sample from the U.S. (left) or China (right). The supply closeness are defined as the share of intermediate + final consumption imports of the U.S. (left) or China (right) from the four EA economies in our sample.

Table A1: **Emerging Asia, China and U.S. Trade Shares**

Flow	**Exports**			**Imports**		
Country	**→ China**	**→ US**	**→ RoW**	**← China**	**← US**	**← RoW**
Indonesia	22.58	9.67	67.75	28.52	4.94	66.54
Malaysia	13.58	10.80	75.62	21.32	7.77	70.91
Philippines	13.89	15.81	70.30	20.43	6.64	72.93
Thailand	11.98	16.58	71.44	23.51	5.93	70.56
India	3.33	17.72	78.95	13.86	7.07	79.07
Sri Lanka	2.22	25.51	72.27	20.04	3.00	76.96
Bangladesh	2.00	19.35	78.65	21.53	3.00	75.47
Nepal	1.50	11.32	87.18	13.49	2.14	84.37
Emerging Asia	**2.26**	**18.48**	**78.94**	**17.73**	**3.80**	**78.97**
Country	**→ EA**	**→ US**	**→ RoW**	**← EA**	**← US**	**← RoW**
China (Mainland)	**8.00**	**16.22**	**75.78**	**7.00**	**7.50**	**85.50**
Country	**→ EA**	**→ China**	**→ RoW**	**← EA**	**← China**	**← RoW**
United States	**2.90**	**7.50**	**89.60**	**16.40**	**3.90**	**79.70**

Notes: WITS, 2022 snapshots.

Figure A7: **Correlations of Demand and Supply Closeness to U.S. and China in MRIO of year after 2000**



Notes. The charts show distributions of MLE estimates for β and ρ in the model as noted in Section 5.2, for $u_t = \text{EPU}^{\text{US}}$ on the left column, $u_t = \text{EPU}^{\text{CN}}$ on the right column.

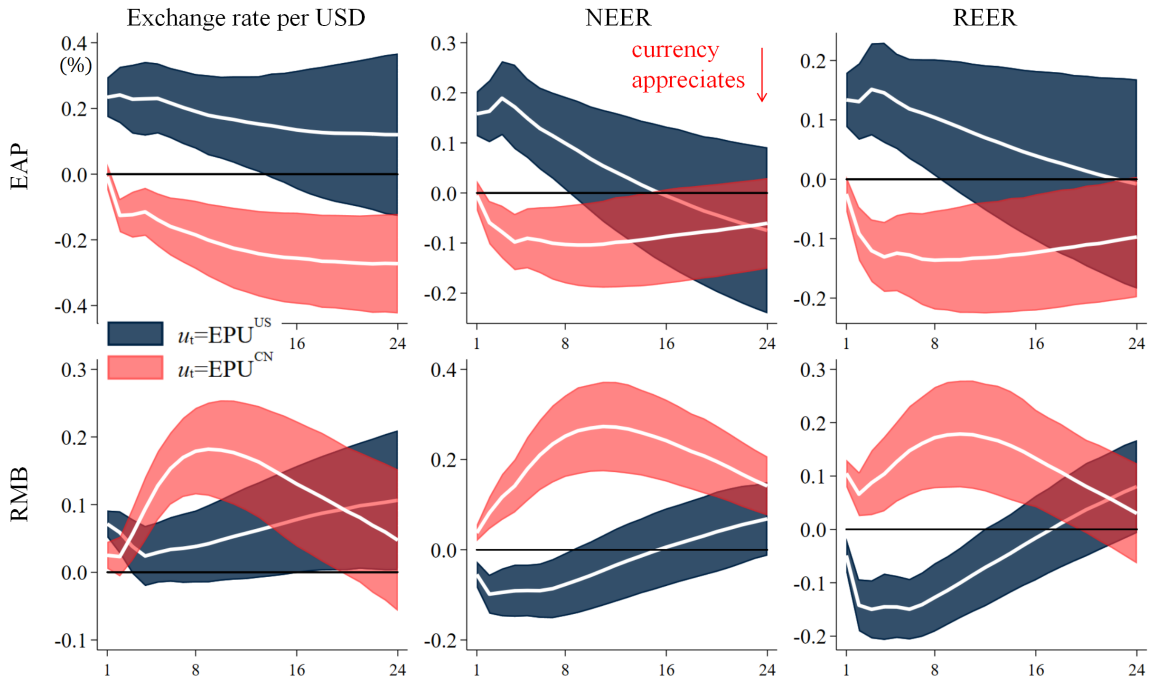
C Extended Robustness Analyses on the Macro Responses

C.1 Robustness of exchange rate responses

To verify whether our bilateral USD results are driven solely by a dollar-specific factor, we replace bilateral rates with nominal and real *effective* exchange rates (NEER, REER) for the EA country and for the RMB. For interpretability, NEER/REER are inverted so that an increase indicates depreciation. Figure C8 shows that the same pattern holds while evaluating on an effective basis, with slightly less persistency. We find that U.S. uncertainty shock induces strong depreciation in EA effective exchange rates. This effect dies out after 16 months. China uncertainty, on the other hand, induces appreciation, with a more persistent effect. These results indicate that our bilateral findings in Figure 4 are not an artifact of measurement and warrant further analysis.

In the second row of Figure C8, we additionally look at responses of RMB exchange rates. On an effective basis, RMB exchange rate responses to China uncertainty are more persistent. The response of RMB NEER is 0.3% at peak. The responses of RMB to US uncertainty shock are slightly different among bilateral rate against dollar and effective rates. We find that RMB bilateral rate against dollar depreciates, while RMB effective rates appreciate, following a US uncertainty shock.

Figure C8: **Bilateral vs. Effective Exchange Rates: Responses to U.S. and China Policy Uncertainty**



Notes: This chart presents the impulse responses of different measures of exchange rates based on SVAR model in Section 3. Row 1: EA currencies; Row 2: Chinese RMB. Column 1: bilateral USD rates (+ ↑ = depreciation); Column 2: inverted NEER; Column 3: inverted REER. Shocks are one–standard-deviation innovations in U.S. (navy) or China (red) EPU. Bands: 90% confidence intervals.

C.2 Details of the Financial Channel of Uncertainty Spillovers

Financial frictions and balance sheet constraints are important multipliers of uncertainty shock transmission, as documented in the seminal work of Alfaro et al. (2024b). In this section, we provide a complete analysis on this well-documented channel in our sample, to connect with existing literature.

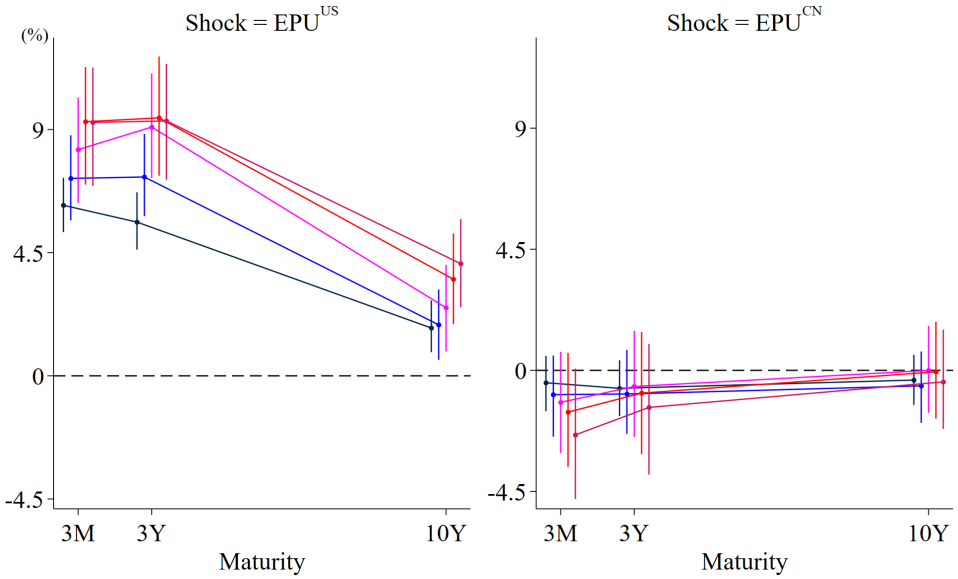
We start from macro-level analyses, by adding each of the following variables to the end of the baseline VAR, one at each time:

- *Yield curve*: government bond yields at 3-month, 3-year and 10-year maturities retrieved from Haver.
- *Risk premiums*: 5-year tenor modified restructuring terms credit default swap (CDS) spreads from Markit, and emerging market corporate bond index in the international financial markets from FRED.
- *Interest rate differentials*: EA government bond yields minus U.S. treasury yields at 3-month, 3-year and 10-year maturities.

Although the yield curve response is an interesting piece of finding, what is more at the center of our focus is the interest rate differentials of EA economies versus the U.S. Figure C9 shows the result. We find that interest rate differentials comove with risk premiums following a US uncertainty shock—higher interest rate EA currencies earn excess returns—consistent with the forward premium puzzle (Fama, 1984). While following a China uncertainty shock, they do not. Risk premiums significantly increase while interest rate differentials decrease. This must suggest a strong appreciation of EA both contemporaneously and in expectations (Engel, 2016). A heightened risk premium can be either compensated by a weaker domestic currency or a wider interest rate differential. Here, we find that the interest rate differentials rise much more than risk premiums – one sd. U.S. uncertainty shock leads to 9 pp. widening in interest rate differentials in the short end, and 4.5 pps in the long end – whereas the risk premium responses are in the magnitude of 1.5 pp. This means, in expectation, EA currencies depreciate more against the U.S. dollar, which thus explains the persistent depreciation following U.S. uncertainty spikes. Meanwhile, the reactions of interest rate differentials to 1 sd. China uncertainty shock is significantly negative at around -2-4 pp. Although this is in support of EA appreciation, it is much larger than the 0.2% appreciation following a China uncertainty spike in Figure C8. Meanwhile, as documented above, the risk premiums are non-reactive to a China uncertainty shock. It must either because future appreciation of the EA currency in expectation is strong, or the enhancements of current accounts against China is significant. The excess returns of EA currencies following China uncertainty hike call for an alternative channel, which we turn to international trade.

In Figure 5 in the main text, we document that U.S. uncertainty shock transmission is overall consistent with the "flight-to-safety" narratives. However, during tranquil episodes of "searching-for-yields", the results could be reversed. In particular, following Engel (2016), we look at 2005-2008 August and the 2009-2010 subperiods. We find that the depreciation effects of U.S. uncertainty shocks during these periods are indeed much smaller than the full sample, however, the appreciating effects of China still persist.

Figure C9: **EA Interest Rate Differential versus U.S. and US and China Uncertainty Shocks**



Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (US IP, US CPI, US EPU; China IP, China CPI, China EPU; EA IP, EA CPI, EA stock price, EA FX rate, **EA interest rate differential**), where the EA interest rate differential is at the maturity as labeled in x-axis, and each line shows the response of indicated horizon. The left (right) panel shows responses to one-standard-deviation US (China) EPU shock (unit: basis points). The spikes are 68% confidence intervals.

Figure C10: **U.S. and US and China Uncertainty Shocks Transmissions During Searching-for-Yields**

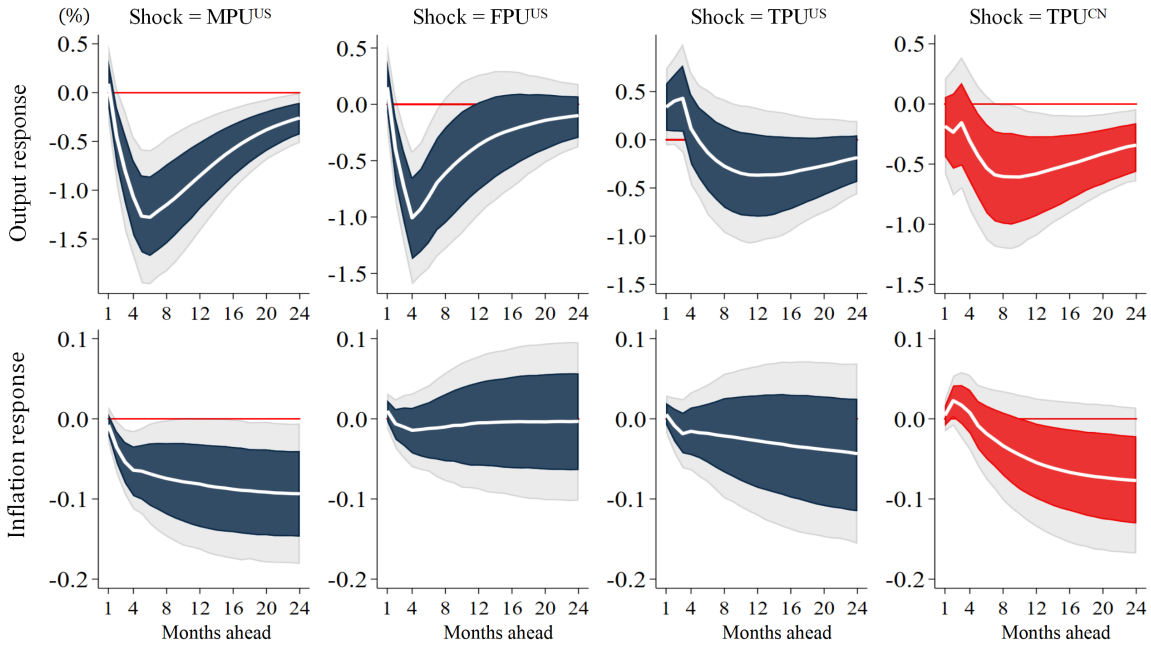
Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (US IP, US CPI, US EPU; China IP, China CPI, China EPU; EA IP, EA CPI, EA stock price, EA FX rate), for 2005M1-2008M8 (top) and 2009M1-2010M12 (bottom). The left (right) panel shows responses to one-standard-deviation US (China) EPU shock (unit: basis points). Shaded areas are 68% and 90% confidence intervals.

C.3 Analysis based on sub-component EPU

Subcomponents of policy uncertainty. Next, we turn our attention to the different effects of different components of economic policy uncertainty. We emphasize that changing the proxy measure per se does not necessarily change the uncertainty *structural shock* identified. The true process of uncertainty *shock* remains agnostic to us. Whereas by peaking at (Cholesky-identified) responses to uncertainty shock replacing the type of uncertainty indicator, as in Figure C14, is still suggestive. We observe that the general US uncertainty shock is most strongly captured by the US monetary policy uncertainty indicator. The fiscal policy uncertainty is effective at mimicking the output and stock price responses, while the inflation responses are more or less muted. In both cases for US and China, we find the TPU index is not a quite refined measure in capturing general uncertainty shock, generating largely correctly-signed while imprecise response estimates. However, if focusing on financial market responses, we find a shock to a US trade policy uncertainty significantly depresses EA stock market while keeping the EA exchange rates largely unchanged; whereas a shock to a China

trade policy uncertainty significantly *appreciates* EA currencies, leaving the stock market unaffected. This supplements our findings on general uncertainty shock, providing a potential angle to unpack the sources of uncertainty shocks.

Figure C11: **EA Output and Inflation Responses to US and China Economic Policy Uncertainty: Sub-components**



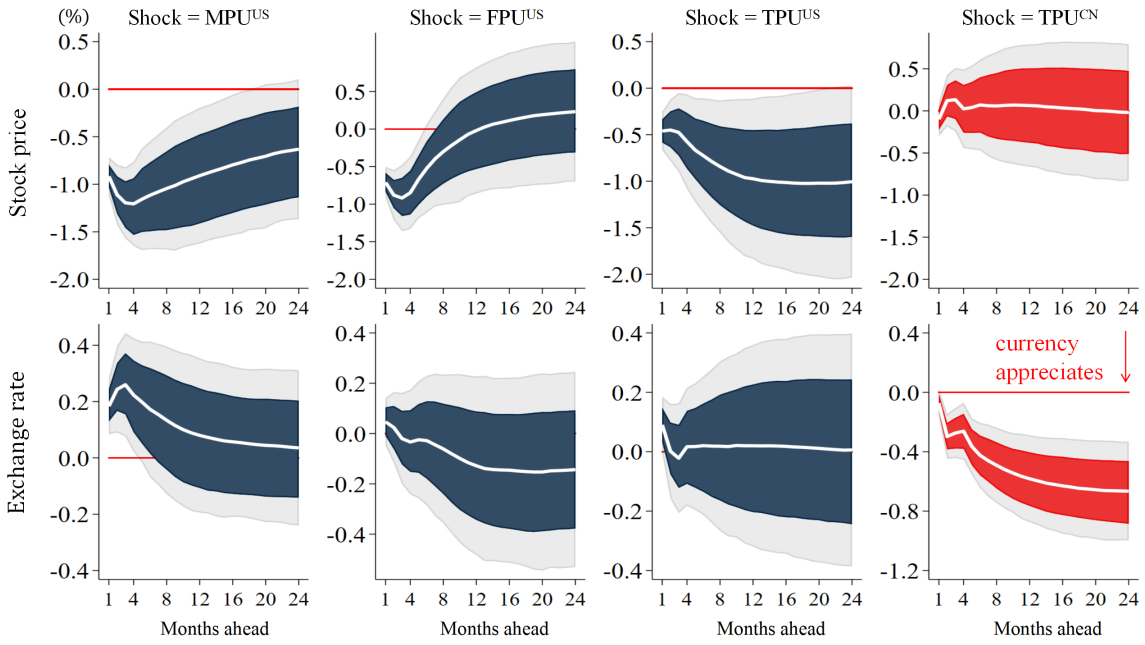
Notes: Each column reports responses to a one–standard-deviation U.S. uncertainty component (MPU, FPU, TPU) or China TPU. Row 1 (2) shows y (π) responses (unit: %). Bands: 68% and 90% CIs.

Heterogeneity across EA economies. Finally, we take a look at country-specific responses, in Figure C14, focusing on shock to US EPU (in navy), and China EPU (red). The patterns mirror the panel results: The two shocks registered comparable impacts on EA outputs, except for Thailand, who is more responsive to US uncertainty shock. The US shock has stronger impacts on stock prices; it depreciates EA currencies against the dollar. The China shock appreciates EA currencies against the dollar. The China uncertainty appreciation effects are the strongest for Malaysia and the Philippines, while the US depreciation effect is the strongest for Indonesia.

C.4 Level vs. Uncertainty Shocks

Core citations in the uncertainty literature have emphasized the importance of separating first-moment (level) and second-moment (uncertainty/volatility) shocks in causal inference (Alfaro et al., 2024b; Jurado et al., 2015; Baker et al., 2023). In models with time-varying volatility, uncertainty can move endogenously with the cycle, so identifying its causal effects requires comparing innovations in levels (productivity, markups, financial prices, policy instruments) with innovations in measures of uncertainty itself (Fernández-Villaverde et al., 2011; Basu and Bundick, 2017). Our baseline already

Figure C12: **EA Equity and Exchange Rate Responses to US and China Economic Policy Uncertainty: Sub-components**



Notes: Each column reports responses to a one–standard-deviation U.S. uncertainty component (MPU, FPU, TPU) or China TPU. Row 1 (2) shows *stock* (s) responses (unit: %). Bands: 68% and 90% CIs.

conditions on observed real and nominal aggregates, but in this section we explicitly juxtapose first- and second-moment shocks for activity, prices, financial markets, and monetary policy.

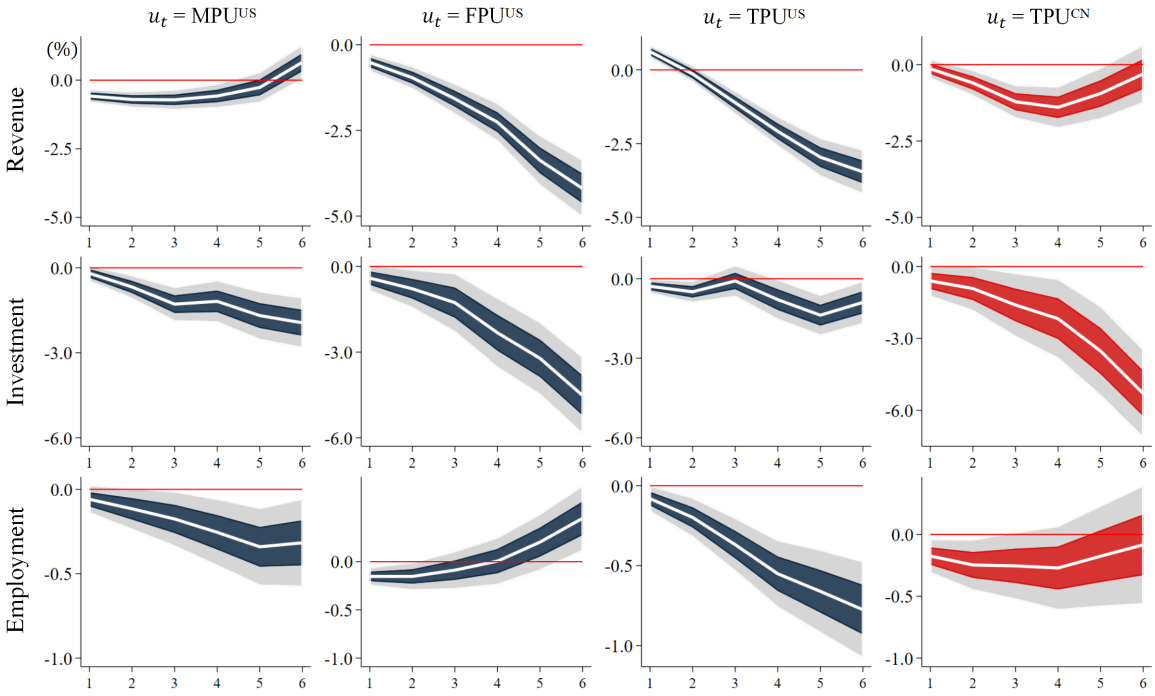
Design. We implement two types of comparisons in the responses of variables:

(i) Financial markets. We compare a *negative U.S. equity shock* (S&P 500) to a *financial uncertainty* shock using the VIX, the option-implied 30-day volatility of the S&P 500. For China we use the CBOE China ETF volatility index (CVIX) as a parallel proxy and compare it with an equity-level shock (CSI 300). In the Cholesky ordering we place the volatility index before equities to allow volatility to move first and prices to react within the period.

(ii) Monetary policy. We compare a *U.S. monetary tightening* (the "pure" high-frequency monetary policy shock of Jarociński and Karadi 2020, JKMP) with *monetary policy uncertainty* (MPU) of Husted et al. 2020. Because JKMP is identified from high-frequency surprises, we order it first in the U.S. block; other variables follow the baseline ordering.

Results. Figure C17-Figure C18 summarize the EA responses. We highlight three patterns. First, for the real economy, a one–s.d. negative U.S. output shock reduces EA output by about 3% at four quarters, whereas a U.S. macro-uncertainty (MacroUNC) shock yields much smaller and less precisely estimated declines. This accords with evidence that uncertainty shocks typically generate shallower but quicker "real options" slowdowns than level shocks (Bloom, 2009; Baker et al., 2023). By contrast,

Figure C13: **EA firm response to US versus China policy uncertainty: sub-components**



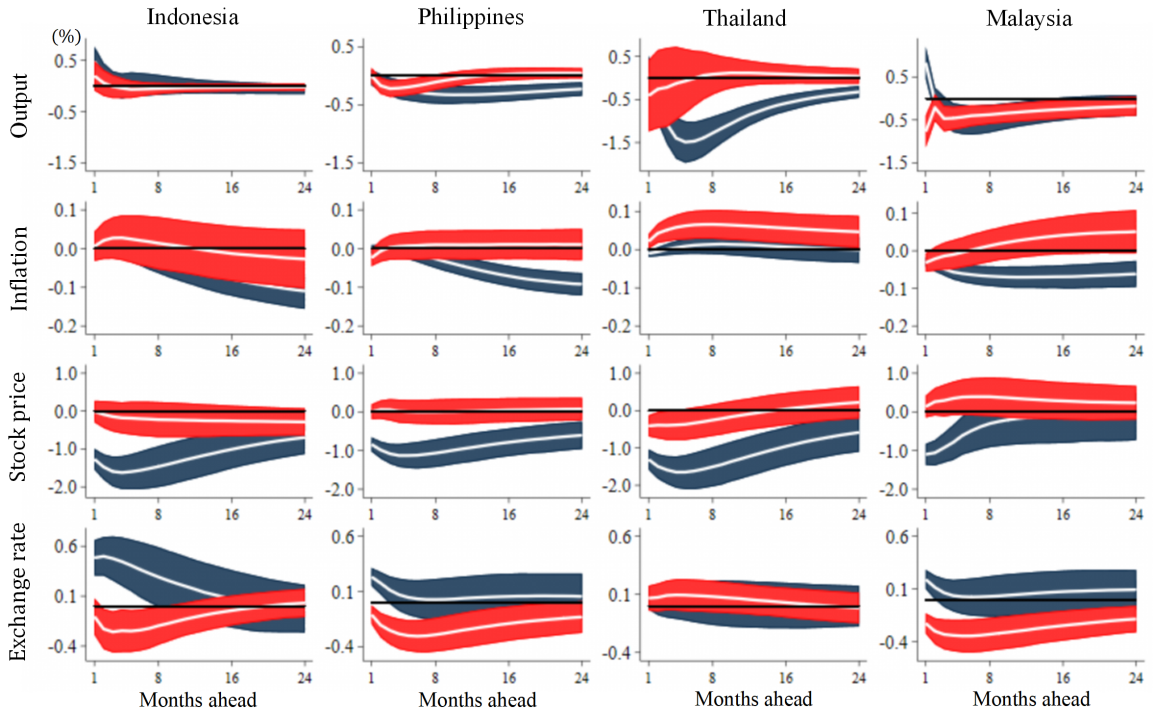
Notes: This figure shows EA firm impulse responses to one standard deviation increase of components of US or China economic policy uncertainty (indicated in column title). Row 1 shows revenue growth responses, row 2 shows investment growth responses, row 3 shows employment growth responses. Shaded areas are 68% (navy or red) and 90% (gray) confidence intervals.

China's output uncertainty (CN GDPUNC) produces EA output declines comparable to those from a China level shock (roughly 1.5–2%), consistent with the region's tight production-network exposure to China.

Second, for financial markets, U.S. financial uncertainty (VIX) robustly depreciates EA currencies and lowers EA equity prices, matching a classic risk-off/safe-haven response. China financial uncertainty (CVIX), in contrast, is associated with *appreciation* of EA currencies and, in our estimates, rises in EA equity prices. This pattern is consistent with intra-regional portfolio/trade reallocation when the shock is China-specific rather than global.

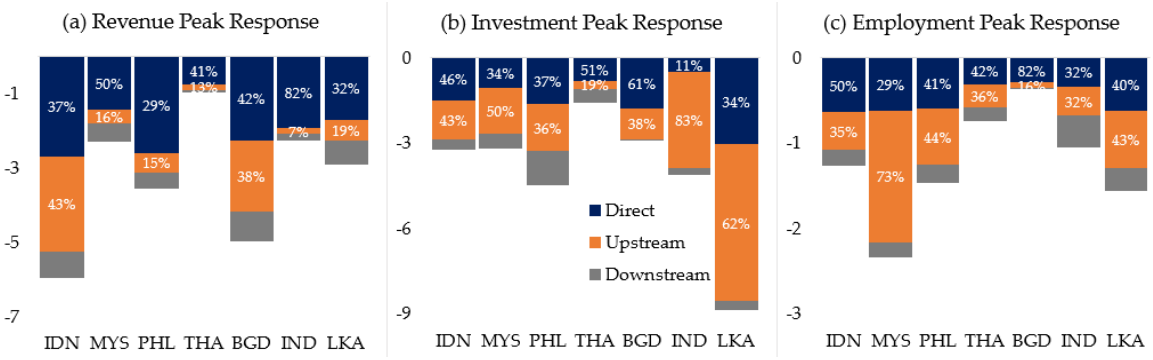
Third, for monetary policy, we document second-moment dominance for policy uncertainty. The U.S. MPU shock yields larger EA output and equity responses than a canonical U.S. monetary tightening (JKMP): MPU lowers EA output by about 2% (vs. 1.5% for JKMP) and generates sharper equity declines. In our sample, MPU is disinflationary for EA, while U.S. tightening is inflationary and depreciating for EA—consistent with depreciation-led pass-through in small open economies even when U.S. policy is a demand contraction at the source.

Figure C14: **Country-Specific Macro Responses to U.S. and China Policy Uncertainty**



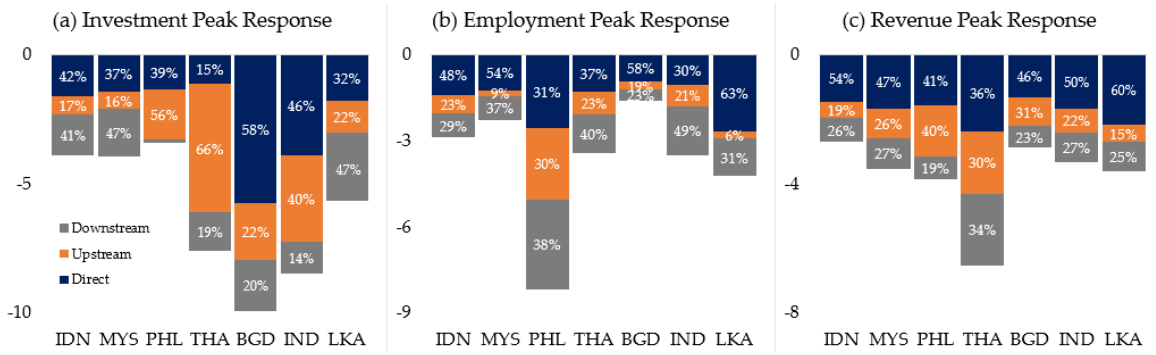
Notes: Each column shows impulse responses to one-standard-deviation US policy uncertainty shock, of the country named in the header. Row 1: equity (percent). Row 2: bilateral EA/USD (+ ↑ = depreciation). Bands: 90% CIs.

Figure C15: **EA Firm Peak Responses to US Uncertainty Shocks: By Country**



Notes: The chart shows peak responses of Direct effect (navy), Upstream Propagation (orange) and Downstream Propagation (gray) estimated based on models as explained in 5.2, to one-standard-deviation increase of US EPU. Panel (a) shows for firm revenue responses, (b) for investment responses, and Panel (c) for employment responses.

Figure C16: **EA Firm Responses to China Uncertainty Shocks: By Country**



Notes: The chart shows peak responses of Direct effect (navy), Upstream Propagation (orange) and Downstream Propagation (gray) estimated from (5) for Chinese sectors (first bar) or each of the EA country sector-quarter panel (first bar in each panel), to one-standard-deviation increase of China EPU. Panel (a) shows for firm revenue responses, (b) for investment responses, and Panel (c) for employment responses.

D Details on Sectoral Results

D.1 Trade Volume Responses by Commodties

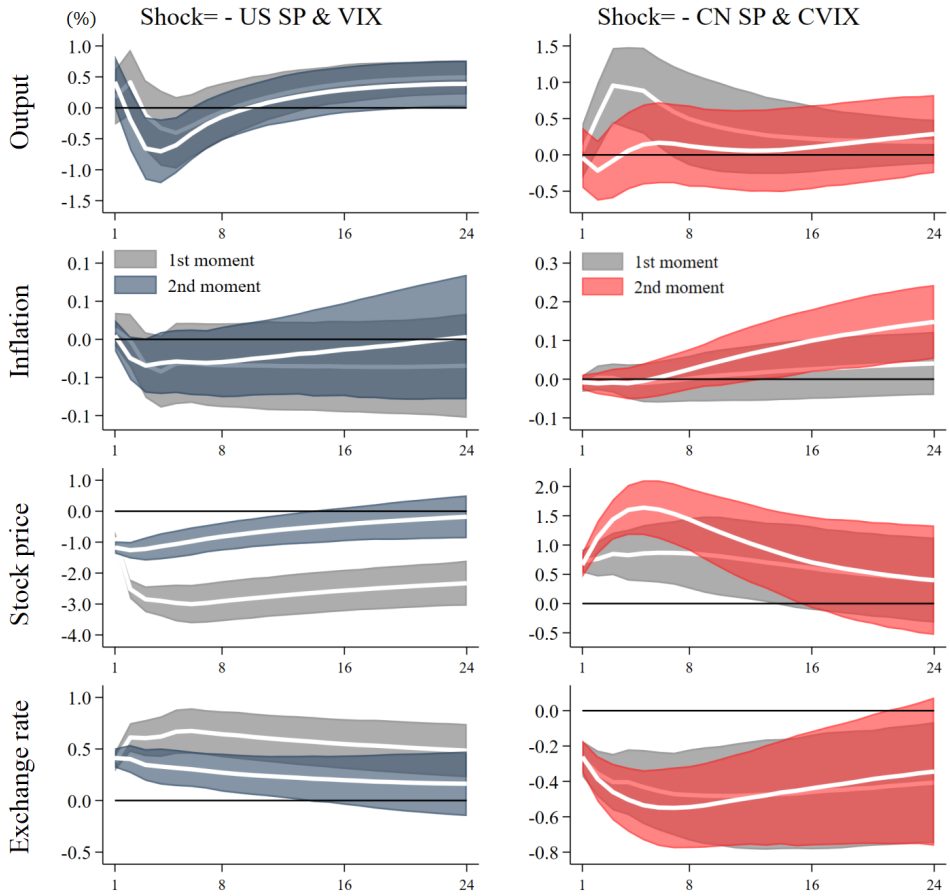
Figure D19 further examines the trade balance responses across major commodity categories in Emerging Asia (EA). Specifically, we focus on bilateral trade with the United States, China, and the world total for five key product groups: Mineral fuels (HS 27), Apparel (HS 61–62), Textiles (HS 63), Machinery (HS 84–85), and Vehicles (HS 87). We document that:

- (1) Machinery (HS 84–85). EA countries such as Indonesia and Malaysia predominantly import machinery and electrical equipment from China, while the Philippines exports certain electronics and components to the United States. This pattern supports our interpretation that a China uncertainty shock acts as an upstream disturbance, primarily reducing EA's imports of intermediate goods rather than exports—thereby improving trade balances. In contrast, a U.S. uncertainty shock acts as a downstream disturbance, reducing EA exports of final goods and consequently deteriorating trade balances in the region.

- (2) Textiles and apparel (HS 61–63). EA economies are typically net importers of textiles and fabrics but net exporters of finished garments. Accordingly, following a China uncertainty shock, EA's trade balance in textiles improves (reflecting lower import demand or cheaper inputs), whereas a U.S. uncertainty shock leads to a sharp deterioration in the apparel trade balance, consistent with weaker external demand for EA garment exports. The China shock response is muted for apparel, while the U.S. shock response is muted for textiles—consistent with their respective trade linkages.

- (3) Vehicles (HS 87). EA economies are generally importers of vehicle parts and finished cars from both China and the U.S., yielding a positive trade balance response to a China uncertainty shock, as imports decline. The response to a U.S. uncertainty shock is also slightly positive but

Figure C17: **EA Responses to US and China Financial Uncertainty**

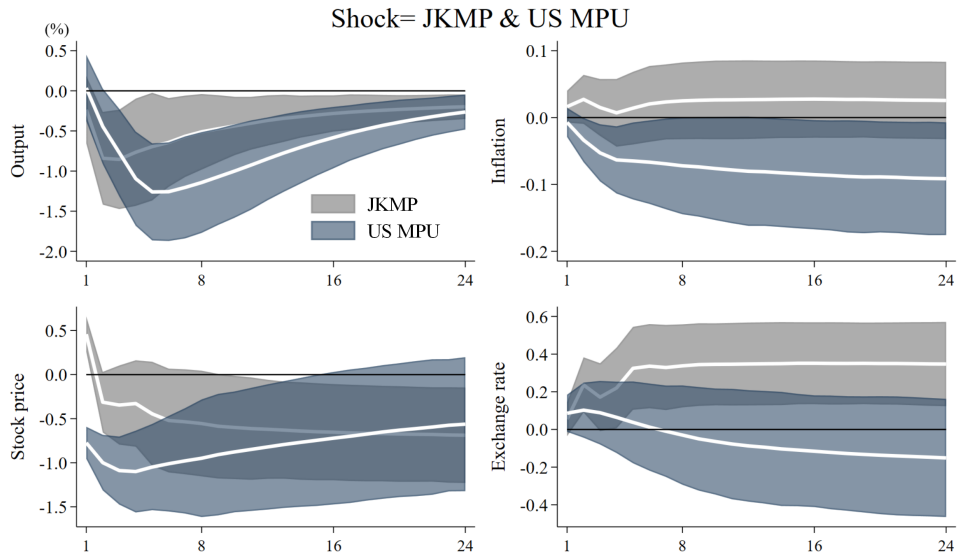


Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (y^{US}, π^{US}, VIX, SP500; y^{CN}, π^{CN}, VIX, CSI; y, π, *stock*, $s_{\$}$). The left (right) shows y, π, *stock*, $s_{\$}$ responses to one-standard-deviation US (China) first or second moment shock, where the first moment shock hikes the negative of SP500 (CSI), and the second moment shock hikes VIX (CVIX). Bands are 90% confidence intervals.

insignificant, reflecting smaller bilateral vehicle trade volumes. A key exception is Thailand, a major net exporter of vehicles ("Detroit of Asia"). Since its exports are directed primarily to ASEAN and Middle Eastern markets, regional risk sharing dampens its response to a U.S. shock, whereas its vehicle trade balance with China shows a mild deterioration.

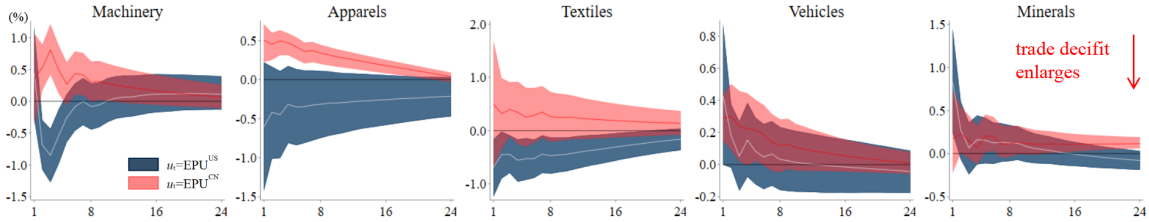
- (4) Mineral fuels and products (HS 27). Indonesia and Malaysia are net exporters of coal, LNG, and crude to China, whereas Thailand and the Philippines are net importers. In contrast, all four economies are predominantly importers from the U.S., which serves as a key supplier of crude oil, LPG, and refined products to the region (with Malaysia occasionally exporting LNG or crude). Consequently, the EA region exhibits a positive trade balance response to a U.S. uncertainty shock, while the response to a China uncertainty shock is more ambiguous, given the mix of exporter and importer roles within the region.

Figure C18: **EA Responses to US Monetary Policy Tightening and Uncertainty Shocks**



Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (JKMP, y^{US}, π^{US}, MPU^{US}; y^{CN}, π^{CN}, EPU^{CN}; y, π, *stock*, $s_{\$}$). The left (right) shows y, π, *stock*, $s_{\$}$ responses to one-standard-deviation JKMP (in gray) or MPU^{US} (in navy) shock. Bands are 90% confidence intervals.

Figure D19: **Emerging Asia Trade Balance and US and China Uncertainty Shocks: By Commodities**



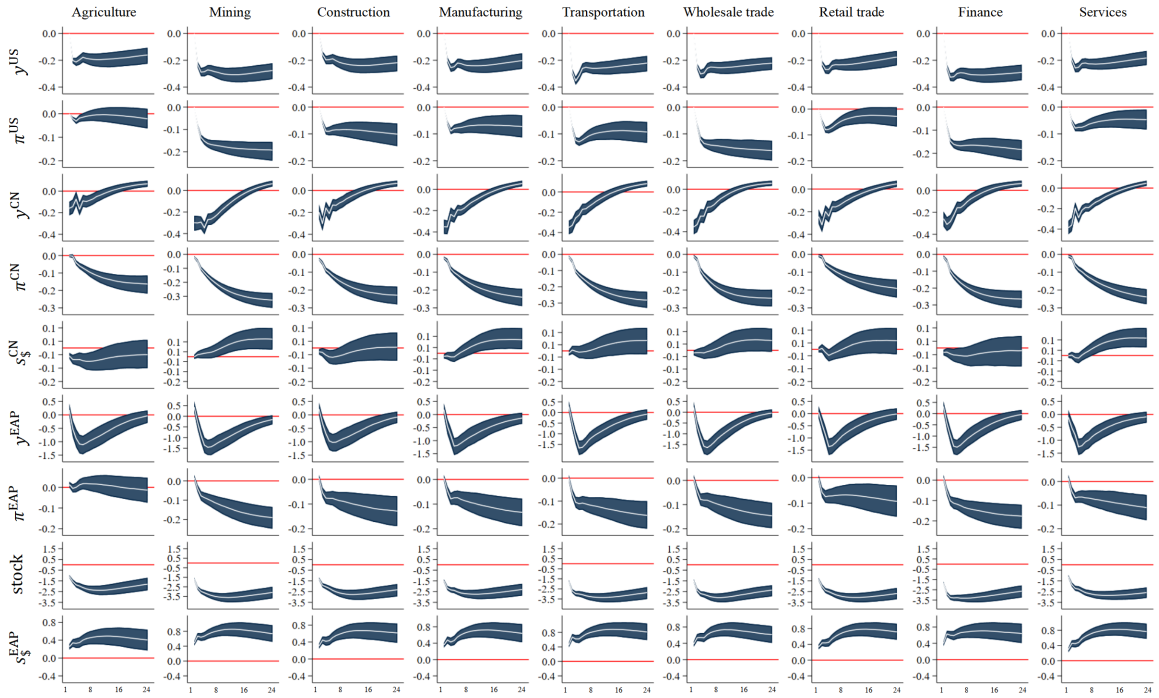
Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (US IP, inflation, EPU; China IP, inflation, EPU; Emerging Asia IP, **trade balances of HS product indicated in the column title**, inflation, stock price, exchange rate per USD). Bands are 90% confidence intervals.

D.2 Sectoral Uncertainty Transmission to Firms and Network Channel

In this subsection, we extend the framework of (5) to allow for heterogeneous uncertainty shocks originating from different country–sector pairs. Using rich firm-level data, we follow Cacciatore and Candian (2025) and compute sectoral uncertainty as the weighted average of within-quarter standard deviations of firm stock returns within each country–sector pair. For each one-digit Standard Industry Classification (SIC) sector, we compute the market-capitalization weighted average of firm stock volatility within each month.

Figure D22 shows estimates of (5) with uncertainty shocks varying across country–sector pairs, which allows us to assess how shocks from different sectors propagate. We focus in particular on shocks originating in U.S. and Chinese sectors. Two patterns stand out. First, a large share of

Figure D20: **Baseline Model: Sectoral Uncertainty in the U.S.**



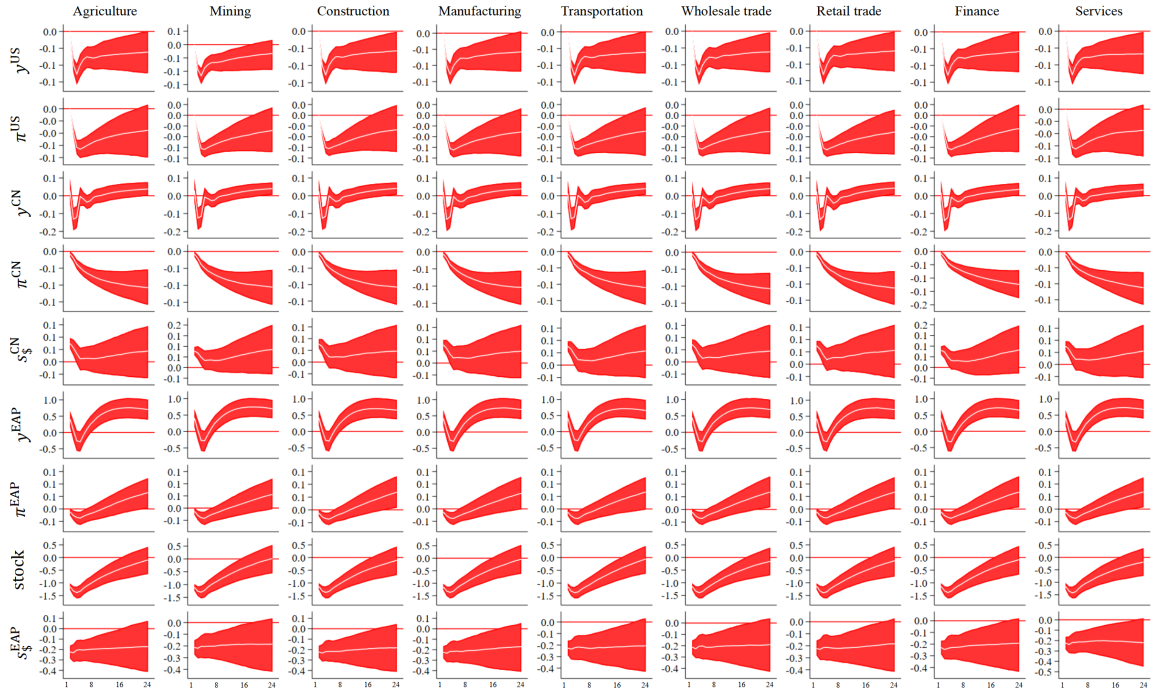
Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (y_t^{US}, π_t^{US}, u_{jt}^{US}; y_t^{CN}, π_t^{CN}, u_t^{CN}, $s_{\$,t}^{\text{CN}}$; y_t^{EA}, π_t^{EA}, $stock_t$, $s_{\$,t}^{\text{EA}}$), where u_{jt}^{US} is firm stock returns volatility within sector j in the US, and u_t^{CN} is China EPU.

sectoral uncertainty is transmitted through downstream links in the production network, pointing to a global supply-side channel. Second, uncertainty shocks originating in China dominate firms' investment responses in EA economies, whereas globally originating uncertainty shocks have the largest effects on employment.

Figure D23 further decomposes the results by EA sectors. For investment responses, the Transportation sector has the strongest network effects. The wholesale trade sector is mostly affected via downstream linkages. For employment responses, the agriculture sector has a relatively large response to upstream propagated uncertainty shock, while retail trade sector has the most pronounced downstream responses.

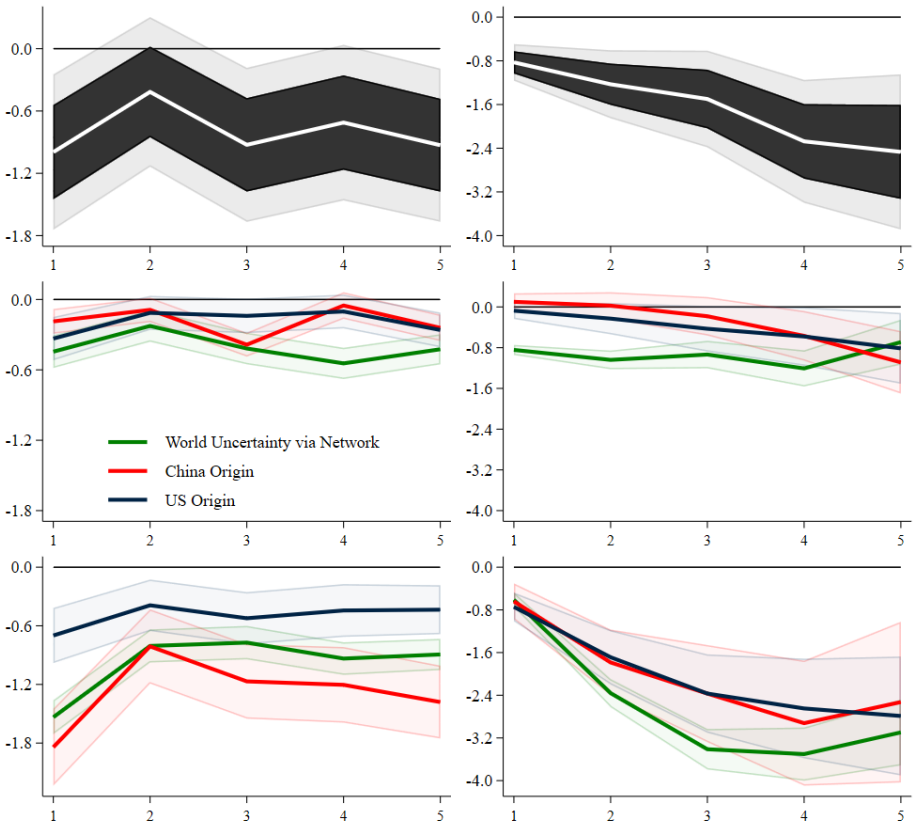
Moving on to China responses (Figure D24), we found the service sector has the most pronounced downstream propagation effects to investment, mostly subject to reactions of downstream customers. While for employment responses, the service and manufacturing sectors have the largest upstream responses, mostly subject to reactions of upstream suppliers.

Figure D21: **Baseline Model: Sectoral Uncertainty in China**



Notes: Responses are estimated from a panel SVAR model identified by Cholesky ordering following (y_t^{US}, π_t^{US}, u_t^{US}; y_t^{CN}, π_t^{CN}, u_{jt}^{CN}, $s_{\$,t}^{\text{CN}}$; y_t^{EA}, π_t^{EA}, $stock_t$, $s_{\$,t}^{\text{EA}}$), where u_{jt}^{CN} is firm stock returns volatility within sector j in China, and u_t^{US} is US EPU.

Figure D22: **Direct and Network Effects For Global Sectoral Uncertainty to EA**



Note: Dark and light areas are 68% and 90% bands respectively.

Figure D23: **Upstream and Downstream Network Propagation For US EPU to EA: Sectoral Heterogeneity**



Notes: Each chart plots peak responses of Upstream propagation against Downstream propagation computed from (5), when the left hand side variable is sectoral stock returns, for each SIC 1-digit sector, to one-standard-deviation increase of US EPU. The size of each node represents the relative magnitude of Direct effects.

Figure D24: **Upstream and Downstream Network Propagation For China EPU to EA: Sectoral Heterogeneity**



Notes: Each chart plots peak responses of Upstream propagation against Downstream propagation computed from (5), when the left hand side variable is sectoral stock returns, for each SIC 1-digit sector, to one-standard-deviation increase of China EPU. The size of each node represents the relative magnitude of Direct effects.

E Analyses on Firm-Level Stock Prices

E.1 Linear Regression Results: Stock Return Responses to Uncertainty

In this section, We analyze firm-level stock returns with a static firm–date panel regression with granular fixed effects:

$$r_{i,c,s,t} = \alpha_i + \sum_{j \in \mathcal{S}} \beta_j \, \mathbb{1}_{s=j} \, u_t + \sum_{k \in \mathcal{H}} \beta_k \, \mathbb{1}_{c=k} \, u_t + \Gamma X_{it} + \Pi(L) \, Y_{ct} + \delta_{y(t)} + \varepsilon_{it}. \tag{6}$$

Here, $r_{i,c,s,t}$ is the stock return of firm i in country c and sector s at time t, and α_i are firm fixed effects. The shock u_t is an uncertainty index observed monthly: (i) U.S. economic policy uncertainty (EPU^{US}) of Baker et al. (2016) and its three categorical components—monetary (MPU^{US}), fiscal (FPU^{US}), and trade policy uncertainty (TPU^{US}); and (ii) China's economic policy uncertainty (EPU^{CN}) and trade policy uncertainty (TPU^{CN}) based on mainland newspapers. For ease of interpretation, each uncertainty series is standardized to zero mean and unit variance. $\delta_{y(t)}$ is a year fixed effect.

The generic form in (6) allows heterogeneous coefficients across countries and industries ($\mathcal{S}$ and $\mathcal{H}$ are the sets of sectors and countries in our sample, and $\mathbb{1}_{\cdot}$ is the indicator function). In what follows, however, we report the version with homogeneous β as baseline, and versions allowing β to vary across country-industry pairs as complementary results.

Baseline results: US and China EPU transmission. We firstly present the estimates of (6) for the pooled panel of all eight EA countries, in Panel A of Table E2. As expected, heightened economic policy uncertainty in the U.S. or China has led to lower stock returns of EA firms. One standard-deviation increase in US EPU declines EA stock returns by 4-5% annualized on average (column 1), and one standard-deviation increase in China EPU declines EA stock returns by 2% annualized on average (column 5).

Decompositions of US EPU effects. Based on this first piece of micro evidence, we delve into various decompositions. First, we look at sub-components of US and China EPU, expressed in Panel (a) of Table E2, column 2-5 for sub-components of US EPU, and column 6 for China EPU. Second, we look at cross-country heterogeneity, in Panel (b). Third, we look at distribution of coefficients across industries, in Figure E25. Evidently, monetary policy uncertainty in the US exerts the greatest impact on EA firms stock prices, suggesting, potentially, a dominant discount rate channel. Meanwhile, the heterogeneity across the four EA countries is huge. To a bit of our surprise, we found Indonesia and Philippines firms lose the most when economic policy uncertainty the US heightens (close to 7% drops on impact), while Malaysia is the least affected (1.8% drops on impact). The estimates on sector-specific coefficients are precise and suggestive. We find Agriculture and Mining sectors are the most exposed to US economic policy uncertainty shocks. The response of Mining sector is noisy, potentially due to the including to safe-heaven metals such as Gold, whose performance could be enhanced when uncertainty is high.

Table E2: **Stock Return Responses to US Policy Uncertainties, Decomposed**

Panel A. Components of US and China EPU						
u_t =	US EPU	US MPU	US FPU	US TPU	CN EPU	CN TPU
β	-4.716^a	-6.374^a	-3.290^a	-3.155^a	-2.341^a	-2.220^a
	-0.433	-0.317	(0.264)	(0.195)	(0.341)	
within-R^2	0.005	0.004	0.004	0.004	0.004	
Obs.			9,087,794			
Panel B. Country-wise coefficients						
c =	Indonesia	Malaysia	Philippines	Thailand	India	Sri Lanka
US EPU	-7.350^a	-1.843^a	-7.207^a	-4.405^a	-8.229^b	-6.881^a
	(1.588)	(0.672)	(1.695)	(0.581)	(3.987)	(2.643)
CN EPU	-2.248	-0.866	-17.109^a	-2.415^a	-0.253	-2.359^a
	(1.531)	(0.709)	(1.337)	(0.387)	(0.500)	(0.251)
Obs.	1,252,138	1,455,980	693,692	1,685,960	1,303,340	720,883
Fixed effects			Firm			
Standard errors			Cluster on Firm			

Notes: Panel A shows estimates of homogeneous β, using the pooled panel of EA firms as in Table E2 while replacing u_t with the measure indicated in the second row. Panel B shows β_k in (6), row 1 in Panel B shows the regression results on US EPU, and row 2 shows the results on China EPU. Standard errors are clustered on firms and shown in parentheses. Significance: ^{a} 1%, ^{b} 5%, ^{c} 10%.

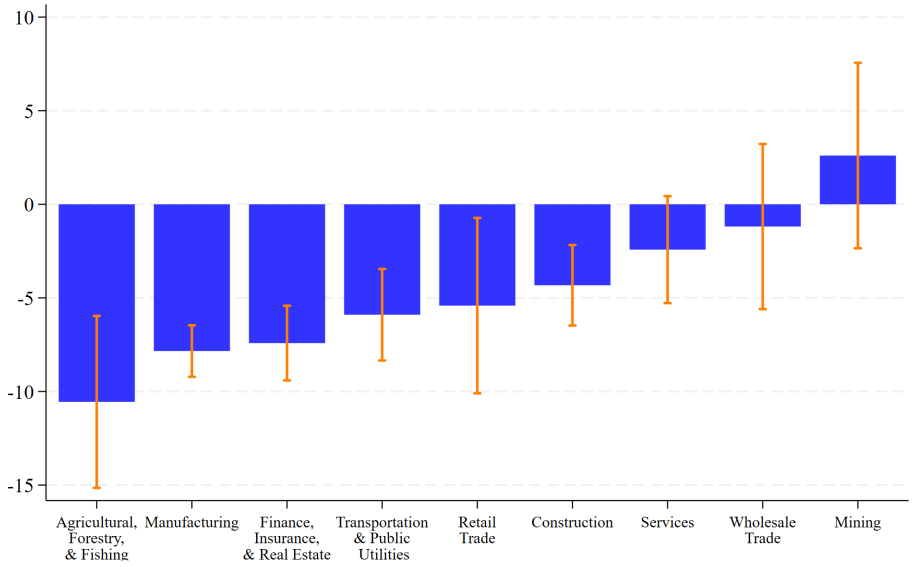


Figure E25: **Impacts of US EPU on EA Firm Stock Returns, by Sector**

Notes: The chart shows estimates of β_j in (6), with u_t = US EPU. Capped bars are 90% confidence bands. The categories of sectors are 1-digit Standard Industry Classification (SIC) level. "Public Administration" and "Nonclassifiable Establishments" are dropped due to lack of data.

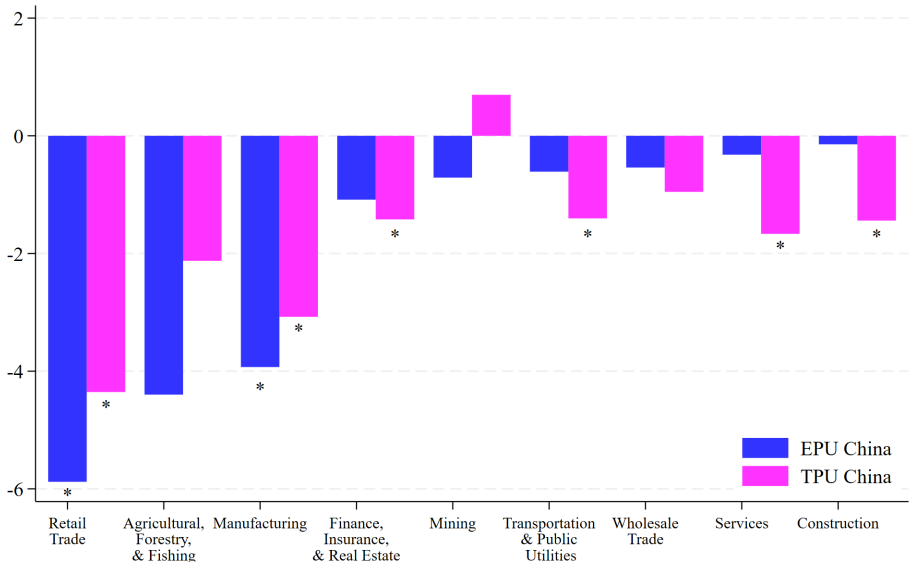


Figure E26: **Impacts of China EPU and TPU on EA Firm Stock Returns, by Sector**

Notes: The chart shows estimates of β_j in (6), with u_t = China EPU (blue bars) or China TPU (pink bars). Capped bars are 90% confidence bands. The categories of sectors are 1-digit Standard Industry Classification (SIC) level. "Public Administration" and "Nonclassifiable Establishments" are dropped due to lack of data.

E.2 Spatial Autoregression Results for Stock Returns

The LP framework flexibly captures dynamic responses but does not decompose how much of the total effect arises from . To quantify first-, second- and higher-order network connections of stock returns, we also estimate the SAR model described in Section 5, by aggregating the firm-daily stock return data to sector-by-month observations.

Table E3 summarizes the SAR estimates for five EA economies. Two main findings stand out. First, the magnitude of total impacts aligns closely with those in Table E2, and they are predominantly negative. Second, production network effects account for 80–90% of the overall impact, underscoring their central role in transmitting global uncertainty.

Table E3: **Heterogeneous Spatial Autoregression Estimates: EA Average**

	Direct	Network	Net%	Direct	Network	Net%	Direct	Network	Net%
u_t:		EPU^{US}			EPU^{CN}			TPU^{CN}	
Mean	-0.057	-0.440	88.55	-0.151	-0.725	82.76	-0.073	-0.335	82.14
SE	0.335	0.316		0.291	0.317		0.278	0.223	
u_t:		MPU^{US}			FPU^{US}			TPU^{US}	
Mean	-0.112	-0.519	82.24	-0.013	-0.117	89.91	-0.127	-0.361	73.91
SE	0.279	0.275		0.271	0.237		0.292	0.214	

Note: Estimates report direct and network-mediated effects of six global uncertainty measures on five EA economies (China, Indonesia, Malaysia, the Philippines, Thailand), embedded within a global input-output structure fixed in 2000. Standard errors are based on 3,000 wild bootstrap replications. All uncertainty indicators are normalized as z-scores.

As shown in Figure E27-Figure E28, and consistent with the main text, we find the US shock is a customer shock, predominantly propagating via upstream networks (direct effect takes $\sim 40\%$, upstream propagation takes up the other 60%), while the China shock is a supplier shock, predominantly propagating via downstream networks (direct effect takes $\sim 60\%$, downstream propagation takes up the other 40%). This pattern holds across countries in our sample, with a certain degree of heterogeneity.

Figure E27: **Direct and Network Effects For US Uncertainty to EA Firm Stock Returns**

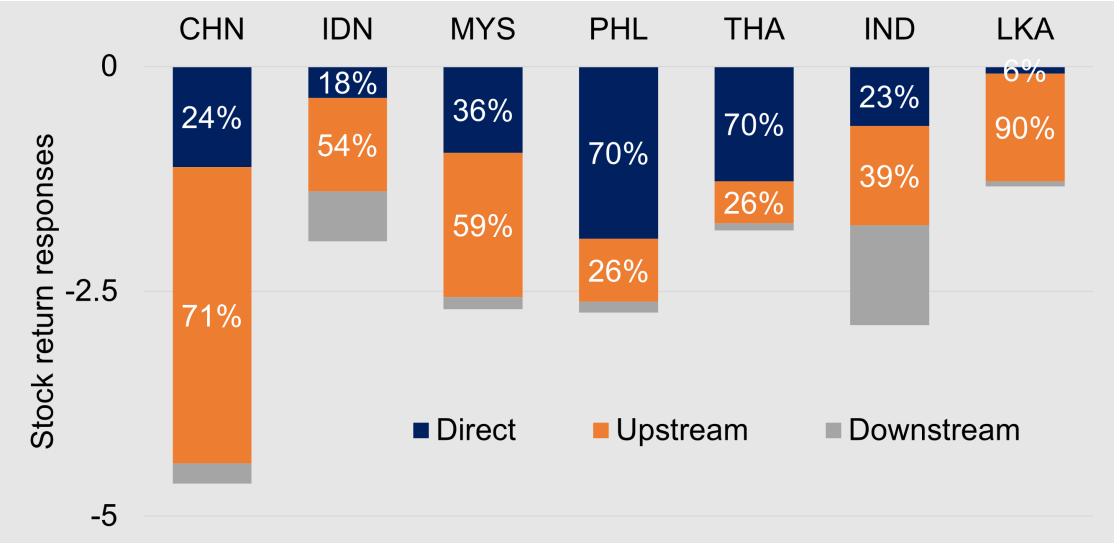


Figure E28: **Direct and Network Effects For China Uncertainty to EA Firm Stock Returns**

