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Shocks and income dynamics

Oleg Gurshev and Lucas van der Velde

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Oleg Gurshev
FAME|GRAPE

Lucas van der Velde
FAME|GRAPE and Warsaw School of Economics

Abstract

This article examines the contribution of supply and demand shocks to income dynamics in an international panel setting. Leveraging the newly created Global Repository of Income Dynamics and an alternative identification of structural shocks, we study how unanticipated disturbances affect the distribution of innovations to income processes. We distinguish between permanent versus transitory structural shocks, as well as global (U.S.) versus local (domestic) shocks. Our results show that structural shocks originating in the U.S. exert larger and more persistent effects on innovations than domestic shocks. These changes are procyclical for skewness, suggesting greater income risk in downturns. In contrast to previous findings, we also document a countercyclical behavior of dispersion of innovations in response to structural shocks originating in the U.S. Finally, we consider the role of different transmission channels. Domestic shocks mainly affect skewness and decrease income volatility. Trade and financial channels drive the transmission of U.S. demand and supply shocks, respectively, whereas expectations play a limited role.

Keywords:
Income dynamics; Macroeconomic shocks; Administrative data; Spillovers of shocks

JEL Classification:
J31, E24, E32, F44

Corresponding author: :
Oleg Gurshev, o.gurshev@grape.org.pl.

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1 Introduction

For most individuals, wages represent the most important (perhaps the only) source of income. Fluctuations in income have been associated with negative outcomes, not only for the recipient but also of their household(s). Recent literature highlights that even if households can raise precautionary savings to shield against exposure to income fluctuations, there is a welfare loss for even moderate levels of risk aversion (Busch & Ludwig, 2024). Moreover, the presence of income risk correlates with suboptimal investment in risky assets (Catherine et al., 2024). The literature on demographics shows that children exposed to higher volatility tended to complete fewer years of education, leading to disadvantages later in life (Hardy, 2014; Hardy & Marcotte, 2020). Evidence also suggests that policy can help reduce income risk (Busch et al., 2018). To date, research on income dynamics has paid little attention to how broader economic fluctuations affect these patterns. This is an important gap that we aim to fill. In particular, we consider the role of international shocks, which have become an important source of income uncertainty, including disruptions caused by the pandemic and related policy responses, the war in Ukraine and associated trade sanctions, and trade wars initiated by the United States (U.S.).

While international shocks affect economies broadly, U.S. shocks are especially influential, shaping global asset markets, trade flows, and, ultimately, household income dynamics. For example, changes in U.S. monetary policy have been found to affect the valuation of risky assets around the world (Di Giovanni et al., 2022; Miranda-Agrippino & Rey, 2020; Miranda-Agrippino & Rey, 2022; Rey, 2016), and have been linked to greater income inequality (Amberg et al., 2022; Andersen et al., 2023; Coibion et al., 2017; Furceri et al., 2018). There is also a growing strand of studies focused on the international spillovers of U.S. shocks — monetary, technological, financial, fiscal — on a variety of economic measures, such as output, prices, interest rates, consumption (Canova, 2005; Fink & Schüler, 2015; Lakdawala et al., 2021; Lastauskas & Nguyen, 2023; Levchenko & Pandalai-Nayar, 2020).

This paper studies how income processes react to structural shocks. Given the growing importance of international linkages, we consider both domestic shocks and shocks originating in the U.S. For income, we draw on a rich cross-country database: the Global Repository of Income Dynamics (GRID) by Guvenen et al. (2022). This database contains comparable international data on income dynamics of unparalleled quality derived from administrative data. Our study analyzes data from countries that participated in the first phase of GRID and meet the data requirements needed for the estimation of shocks: Canada, Denmark, France, Germany, Italy, Mexico, Norway, Spain, and Sweden. This is a relatively broad set of developed countries, whose exposure to U.S. shocks has remained understudied since previous comparative analyses have either focused on Latin American countries (see Canova, 2005, for example) or bilateral relations between the U.S. and a closely linked economy (see Carrillo et al., 2020; Levchenko & Pandalai-Nayar, 2020).

Our analysis proceeds as follows. First, we estimate supply and demand shocks using long-run restrictions as proposed by Blanchard and Quah (1989). This standard approach allows us to disentangle two conceptually distinct sources of macroeconomic fluctuations. Permanent (supply) shocks are identified as innovations that have lasting effects on output, while demand shocks are assumed to exert only transitory effects. This identification scheme provides a theoretically grounded distinction between structural forces that shape the long-run productive capacity of the economy (wage differentials, capital-labor shares) and cyclical fluctuations that mainly operate through aggregate demand (redistributive policies, labor market changes). An additional advantage of this method is its relatively minimal data requirements, which makes it particularly suited for our broad international setting.

The second step involves estimating the responses to U.S. and country-specific (domestic) shocks using cumulative impulse response functions (IRFs) estimated directly from local projections (Jordà, 2005; Jordà & Taylor, 2024). In this step, we study how the distribution of one-year (log) earnings growth reacts to shocks. We focus on four different statistics: mean, median, standard deviation, and Kelley skewness. These statistics capture different elements of the earnings growth distribution. The mean earnings growth reflects changes in the central tendency of the earnings distribution. The median reflects shifts in the location. A higher value of the median suggests that a typical worker experienced higher growth in earnings. The standard deviation captures income volatility. Higher dispersion suggests that individuals earning growth is less predictable, and makes median changes less characteristic. Finally, Kelley skewness is a measure of shock asymmetry. Positive values of skewness indicate longer tails to the right, which one would associate with the presence of higher dispersion of shocks above the median (when compared to the dispersion below the median). In principle, one can derive these measures using moments of the distribution or from percentiles. We opted for percentiles, as these are less sensitive to extreme observations.

Interest in the distribution of earnings growth has intensified following the influential work of Guvenen et al. (2014). In that article, the authors use administrative records from the U.S. to explore the behavior of earnings growth in expansions and recessions. They show that volatility and dispersion are relatively stable, but asymmetry becomes more negative during recessions. They refer to this phenomenon as income risk. Hoffmann and Malacrino (2019) replicates this finding using Italian data, but shows that income risk is more closely related to employment than wages. Busch et al. (2018) shows that income risk is countercyclical in three countries. When this heightened risk materializes into an actual decline in gross income during economic downturns, governmental insurance (through taxes and transfers) cushions part of the decline in gross income. Yet, systematic evidence is still lacking.

Our study offers three contributions. First, we study how the distribution of income changes reacts to permanent and transitory shocks. We consider both domestic and global shocks, i.e., shocks originating in the U.S. We find that the response to permanent (supply) shocks depends on the shock's origin, varying in both direction (sign) and size (magnitude). Specifically, the reaction to U.S. shocks appears heterogeneous: some countries react strongly, while others react weakly or even in the opposite direction. Our second contribution seeks to better understand this heterogeneity. We consider three potential transmission channels: trade exposure (as in Corsetti & Müller, 2011), financial exposure (as in Faccini et al., 2016; Kalemli-Ozcan et al., 2013), and expectations (as in Klein & Linnemann, 2021). We evaluate the role of these channels using state-dependent local projections in the spirit of Auerbach and Gorodnichenko (2013). Third, to test the sensitivity of our results, we apply a novel data-driven method of structural shock identification based on their statistical properties. The identification is achieved by rotating the reduced-form errors and minimizing the Cramér – von Mises dependence criterion for joint distributions (Herwartz, 2018). Application of this method produces structural shocks that satisfy economic intuition seen in other studies that have used modifications of the original BQ decomposition (see Bashar, 2011, 2012; W. Chen & Netunajev, 2016; Cover et al., 2006; Hwang et al., 2025; Shapiro, 2024). This serves as a powerful external validation for both our baseline results and the broader set of studies that identify supply and demand shocks.

We find that U.S. shocks induce larger responses in the distribution of earnings growth than domestic shocks. Positive shock in the U.S. (i.e., an expansion) induces mild effects on the location the distribution. In contrast, the dispersion reacts more strongly during a negative demand shock (i.e. a recession) in the U.S. This result is new, as previous literature showed these measures to be unrelated to recessions. The analysis of skewness shows some hints of procyclicality. A positive shock is linked to larger skewness. The different channels serve to explain part of the reactions. When trade links to the U.S. are stronger, so is the reaction of mean and Kelley skewness to demand shocks. The reaction to demand shocks does not appear to be different based on the degree of financial integration with the U.S., nor based on business confidence. When considering the effects of U.S. supply shocks on mean, median, and standard deviation, we observe that the degree of financial integration with the U.S. differentiates countries after the impact of this shock.

There are several implications of our findings. Domestic policy should anticipate and mitigate the transmission of global shocks originating in the U.S., particularly in economies with strong trade and financial links to the U.S. Because these shocks primarily alter the asymmetry of income changes, targeted measures aimed at lower- and middle-income groups are particularly important to limit distributional imbalances. Moreover, because domestic supply shocks can act as a stabilizing force, policies that foster capacity and resilience may help counteract external volatility. Finally, the differing roles of supply and demand shocks underscore the importance of distinguishing them when designing policy responses.

The rest of the paper is organized as follows. Section 2 provides background on the innovations of income processes. Section 3 describes data and empirical methodology. Section 4 reports the results. Section 5 concludes.

2 Innovations to income processes

The income of an individual is defined by the following equation:

$$y_{i,c,t} = \mu_{i,c,t} + e_{i,c,t} \tag{1}$$

where $y_{i,c,t}$ denotes the log-income accrued to individual i, of cohort c in year t. The income consists of two components. The first $\mu_{i,c,t}$ is the expected wage given the characteristics of the individual. In a Mincerian wage regression, this component would include returns on education, experience, and also attributes such as gender or age. This component also accounts for year-specific shocks that are common across individuals. The second component $e_{i,c,t}$ represents income shocks, i.e., stochastic innovations.

It is common to characterize these innovations as a stochastic process with an autoregressive component, i.e. $e_{i,c,t} = \rho e_{i,c,t-1} + v_{i,c,t}$, where the latter term represents a random variable with a normal distribution. Previous findings suggest that ρ is substantially lower than one, suggesting a moderate persistence of these shocks, though this depends on the specification. Gustavsson and Österholm (2014) estimates ρ using time series data for Swedish workers, and concludes that the median ρ_i is around 0.6. Analyses by Guvenen (Guvenen, 2007, 2009) place ρ at around 0.8.

Recent literature began to inquire about the distribution of these shocks. In the AR(1) specification, the shocks are assumed to follow a normal distribution. Guvenen et al. (2014) shows that in the U.S., a normal distribution fails to capture important features of these shocks, particularly the fact that they exhibit left-skewness during recessions and excess kurtosis. More recently, the research compiled in Guvenen et al. (2022) shows that this feature is shared by income processes around the globe.

We follow the steps of Guvenen et al. (2022) to study the distribution of income shocks. The first step consists of obtaining residuals $e_{i,c,t}$, which are obtained via OLS that incorporates age, gender, and year fixed effects. We do not study these residuals, but the innovations, that is $\Delta e_{i,c,t} = e_{i,c,t+1} - e_{i,c,t}$ (the shock is forward-looking).

Hence, we study the distribution of innovations through the lens of four statistics. First, as measures of location, we consider the mean and the median. The mean captures the average direction and magnitude of income innovations, while the median reflects the representative shock less affected by extreme values. Next, we measure dispersion using the standard deviation, which summarizes how widely innovations are spread around the mean. Finally, we assess asymmetry using Kelleys statistic, defined as $Kelley = ((p90 - p50) - (p50 - p10))/(p90 - p10)$. A positive value indicates that the distribution of innovations is more spread at the top, whereas a negative value indicates the reverse.

These distributional statistics summarize key aspects of the income processits central tendency, dispersion, and asymmetryand serve as the dependent variables in the next stage of our analysis. In particular, we study how these features respond to domestic and U.S. structural supply and demand shocks.

3 Methodology

3.1 Data

The Global Repository of Income Dynamics (GRID) is a concerted effort by researchers from across the world inspired by Guvenen et al. (2014). The GRID database includes several measures of income inequality and income dynamics computed on administrative records. These include conditional and unconditional percentiles of income, and income changes, as well as measures of earnings mobility over long horizons. Importantly, these statistics were computed using consistent definitions for sample and income, and they employed identical scripts. Both measures ensure comparability of the estimated statistics. The entire process is documented in Guvenen et al. (2022).

Statistics in GRID are computed from individuals who are expected to be active in the labor market. To ensure this condition, they restrict the sample based on two criteria. First, individuals should be between ages 25-55, to exclude students and early retirees. Second, individuals should earn yearly income above a minimum threshold (which is set at one fourth of the minimum monthly wage); this condition excludes individuals who are marginally attached to the labor markets. All measures are based on gross earnings[1] deflated to 2018 price levels.

This research focuses on the growth of residual earnings. Residual earnings are computed by fitting a linear regression of income on indicator variables for age, gender and year. Then residual earnings growth represents the difference in the residuals for the same individual between two subsequent periods. In GRID this difference is forward-looking: the growth in year t is computed as the difference in residuals between years t and $t + 1$.

Working with GRID statistics has numerous advantages. First, the statistics are based on

[1]Each country has its own specific approach to measuring gross earnings. However, the resulting measures are comparable as they include all forms of compensation subject to taxation and social security contributions (i.e., base salary, overtime compensation, performance and seasonal bonuses, paid vacations, paid sick leaves, and severance payments).

administrative data, as such income is less subject to errors that affect survey-based measures, such as reporting errors (rounding, misreporting) or attrition. These errors could affect the measurement of income change, and the direction of the bias is difficult to sign. Moreover, as statistics are computed over millions of observations, one could expect them to be more precise than those in the available longitudinal surveys. Finally, administrative data are likely to better capture changes in income among top earners, which is not guaranteed in alternative surveys.

For all its positive features, the database has some limitations, namely: i) income refers to labor income at the individual level, ii) since it is based on tax records, envelope payments are not included. The first limitation means that GRID provides only a partial picture of income changes and risk. Within these data, a sudden decline in earnings can represent a proper shock or a reaction to changes in other forms of household income (e.g., a promotion for a partner or assets). As records are annual, it is also not possible to disentangle the role of changes in wage rates from changes in hours worked (Hoffmann & Malacrino, 2019). Finally, the lack of information on envelope wages could lead to an underestimation of dispersion of income growth, as one could expect this component to be more volatile. However, since the sample contains mostly developed countries, the bias introduced by the second limitation is likely to be relatively small.

Table 1 presents descriptive statistics for the moments of one-year log earnings growth as collected from GRID. A number of points are worth noting. First, average annual earnings growth is positive in all countries, with France exhibiting the highest mean growth (0.07) and Italy and Germany the lowest (0.01-0.02). Second, median growth generally exceeds the mean in France, Norway, and Spain, suggesting slight left-skew in these distributions. Third, income volatility, as measured by standard deviation, is lowest in Germany (0.40) and highest in Mexico (0.65), indicating more variable earnings growth in the latter. Fourth, Kelley skewness values are mostly close to zero, with Germany displaying a positive skew (0.18) and France and Spain a slight negative skewness. Finally, countries such as Sweden and Denmark exhibit relatively balanced growth distributions with modest income volatility and near-zero skewness, whereas Italy, Spain, and Mexico show higher variability or more pronounced tails.

Table 1: Availability and descriptive statistics of moments collected from GRID.

Country	Scope	Mean			Median			Std			Kelley skewness			N
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	
Canada	1990–2015	0.05	0.03	0.07	0.061	0.05	0.08	0.53	0.51	0.56	0.02	-0.17	0.11	26
Denmark	1990–2015	0.04	0.01	0.06	0.043	0.02	0.06	0.42	0.41	0.45	0.03	-0.17	0.12	26
France	1991–2015	0.07	0.04	0.10	0.084	0.07	0.14	0.47	0.44	0.51	-0.03	-0.22	0.18	25
Germany	2001–2015	0.02	-0.00	0.04	-0.002	-0.01	0.01	0.40	0.39	0.41	0.18	-0.04	0.31	15
Italy	1990–2015	0.01	-0.04	0.06	0.001	-0.02	0.04	0.48	0.44	0.52	0.03	-0.27	0.23	26
Mexico	2005–2018	0.04	-0.02	0.06	0.042	0.03	0.06	0.65	0.64	0.67	-0.01	-0.18	0.03	14
Norway	1993–2016	0.04	0.01	0.05	0.059	0.04	0.08	0.59	0.54	0.66	-0.01	-0.14	0.10	24
Spain	2005–2017	0.05	0.00	0.09	0.062	0.03	0.11	0.50	0.45	0.55	0.02	-0.35	0.24	13
Sweden	1990–2015	0.04	0.02	0.06	0.049	0.03	0.06	0.49	0.47	0.51	0.04	-0.20	0.18	26

Note: reported moments are based on one-year log earnings growth. Panel size: $N = 195$.

3.2 Structural shocks

The Blanchard and Quah (1989) (BQ) decomposition and its later modifications (i.e., Cover et al. (2006) or Bayoumi and Eichengreen (1992)) remain a popular choice for international studies with broad geographic coverage. In recent years, it has been applied to investigate the responses of markups to demand and supply disturbances (Afonso & Jalles, 2015), and to identify structural shocks in the context of G-7 (Bashar, 2011), ASEAN (Bashar, 2012), the Eurozone (Bk & Maciejewski, 2017), Australia (Enders & Hurn, 2007), and China (A. Chen & Groenewold, 2019).

The identification of shocks begins with a reduced-form VAR of order p:

$$X_t = \sum_{i=1}^{p} A_i X_{t-i} + e_t \tag{2}$$

where $X_t = [\Delta y_t, u_t]'$ is the vector of endogenous variables (growth rate of real output and the unemployment rate), A_i are coefficient matrices, and e_t is a vector of serially uncorrelated reduced-form residuals with covariance matrix Ω.

These reduced-form residuals are linear combinations of the underlying structural shocks, $\epsilon_t = [\epsilon_t^s, \epsilon_t^d]'$, which represent supply and demand shocks, respectively. The relationship is given by:

$$e_t = S\epsilon_t \tag{3}$$

where we assume the structural shocks are orthonormal, i.e., $E[\epsilon_t \epsilon_t'] = I$. To identify the matrix S, we consider the moving-average representation of the VAR, $X_t = C(L)e_t = C(L)S\epsilon_t$. The long-run impact of the structural shocks on the variables is given by the matrix $C(1)S$.

The key identifying assumption is that the demand shock (ϵ_t^d) has no long-run effect on the level of output because output in the long run is defined by supply-side factors such as technology, labor, and capital (Blanchard & Quah, 1989). This economic restriction implies that the cumulative effect of a demand shock on the output growth, Δy_t, must sum to zero. This restriction imposes the matrix $C(1)S$ to be lower triangular. Hence, when combined with the condition from the covariance matrix ($SS' = \Omega$), allows to uniquely identify the structural shocks.

While popular, the assumption of long-run neutrality of demand shocks might be too restrictive, and it was called into question by a number of papers, which suggest persistent or even permanent effects of demand shocks on output [see][](Bashar, 2011; W. Chen & Netunajev, 2016; Cover et al., 2006; Keating, 2013). The consequences of this misspecification are substantial: imposing invalid long-run restrictions may lead to misidentified structural shocks, biased impulse responses, and misguided policy conclusions. To address this critique, in Section 4.4.2, we test whether shocks estimated using different identification strategies produce similar patterns of changes in the distribution of earnings growth.

Following the original framework, we estimate a bivariate VAR for each country in our sample using quarterly rates of unemployment and real output growth[2] We collect the necessary data from the Federal Bank of St. Louis (FRED) and the OECD databases.[3]. All series were de-meaned prior to VAR input. Detailed description of the data used for the estimation of the bivariate models is available in Tables A1 and A2 (Appendix A). Finally, given that GRID data are available at the yearly level, we annualize (average within each year) and standardize (mean-center and scale to unit variance) the obtained shocks before using them in panel estimation. This transformation ensures comparability across countries, prevents scale effects from biasing the estimates, and facilitates interpretation of the impulse responses in standard deviation units.

3.3 Local projections

To study the responses of moments to supply and demand shocks, we compute cumulative IRFs directly from local projections. Specifically, we estimate the following regression at the country level:

$$y_{c,t+h} - y_{c,t-1} = \beta^h z_{c,t} + \gamma_c^h + \gamma_t^h + \pi^h X_{c,t} + e_{c,t+h}^h \tag{4}$$

where $y_{c,t+h}$ are the dependent variables in our estimation: scale, dispersion, and asymmetry of earnings growth for country c measured at time $t+h$, $z_{c,t}$ is the exogenous shock, and β^h are the

[2] Lag length is selected using Schwartz Criterion separately for each country: one lag (Canada, Italy, Mexico, Norway), two lags (Denmark, France, Germany, Spain, Sweden). Impulse response functions for each country (demand and supply shocks) are available in Figures B9 and B10 (Appendix B). While demand shocks are temporary, they decay at a slow rate. In some countries, the responses are different from zero even 20 quarters after the initial shock (see Figure B9).

[3] Even if data requirements are minimal, they are not satisfied by every country. Argentina and Brazil lack data on unemployment rates for the early years of the sample. Therefore, we excluded these countries from further analysis.

estimated responses for $h = 0, .., 3$ periods after the shock. The term γ_c^h accounts for country-specific fixed effects, while γ_t^h control for period-specific differences. For domestic shocks, γ_t^h corresponds to time fixed effects. For shocks originating in the U.S. (which affect all countries), γ_t^h captures NBER-identified recessions (including the level and two lags).

Our baseline set of controls ($X_{c,t}$) includes two lags of: changes in the moment ($\Delta y_{c,t-i}$, for $i = 1, 2$) and exogenous shock used ($z_{c,t-i}$, for $i = 1, 2$), i.e. supply or demand. As a robustness check, we expand the set of control variables to include two lags of i) share of exports to the U.S. to total exports (trade exposure), ii) share of U.S. bank claims to GDP (financial exposure), iii) changes in *de facto* economic openness (proxied by the *de facto* component of the KOF index), iv) expectations (proxied by the OECD's business confidence index), and v) changes in domestic labor market policies (proxied by the Economic Freedom of the World's indicator of labor market regulation), see Table A3 for details (Appendix A).

Finally, all estimations of local projections use Driscoll-Kraay standard errors to construct confidence bands. These standard errors accommodate different forms of autocorrelation and heteroskedasticity.

4 Results

We report our results as follows. First, we describe the baseline cumulative responses of moments to unanticipated, one-standard-deviation change in a U.S. or domestic shock. Second, we present the results for the transmission channels of U.S. shocks. We motivate our investigation into channels by first examining whether positive and negative U.S. shocks generate asymmetric responses, and then interpret the results from the state-dependent local projections. Finally, we assess the robustness as well as sensitivity of our findings to an alternative U.S. demand shock. We compare our original responses with added controls to the responses obtained using an alternative approach of Bayoumi and Eichengreen (1993) that uses inflation as a proxy for a U.S. demand shock. Finally, we run a SVAR identification procedure that delivers the expected matrix S used to identify structural supply and demand shocks under relaxed long-run restrictions. Specifically, it imposes the conventional relationship between shocks: supply shocks positively affect output but negatively affect prices, while demand shocks positively affect both variables.

4.1 The reaction of income processes to structural shocks

The top row of Figure 1 displays the responses of the mean to demand and supply shocks originating from the U.S. A U.S. demand shock leads to a significant and long-lasting decrease (up to -80 basis points) in cumulative earnings growth that is delayed by 1 year. Next, the impact of a U.S. supply shock is more immediate (+60 basis points), but largely transient. In contrast, the effects of domestic shocks (bottom row) are considerably more modest. A domestic demand shock generates a small and delayed negative response (up to 15 basis points) that is mostly insignificant, while a domestic supply shock leads to a gradually accumulating positive impact that reaches 30 basis points by $t+3$. Overall, U.S. shocks have a substantially larger impact on the mean of earnings growth abroad than domestic shocks. The peak effect of a U.S. demand shock is more than five times larger than that of a domestic demand shock.

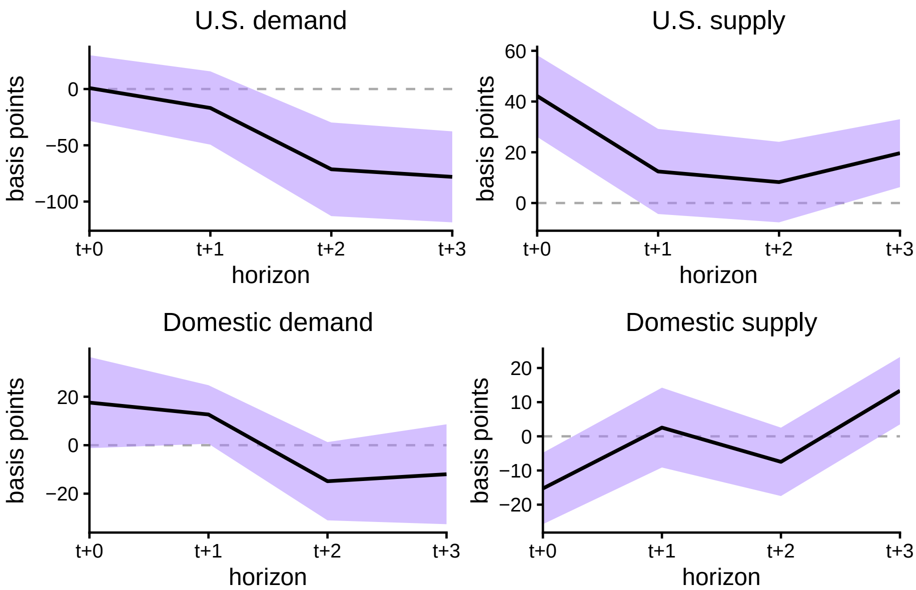
We now turn to the responses of the median (Figure 2), which is less sensitive to extreme values than the mean. Indeed, unlike the previous set of responses, the median shows no significant response to a U.S. demand shock. Further, a U.S. supply shock leads to an immediate and significant decrease of around 25 basis points that gradually diminishes over the horizon. A domestic demand shock induces a quick positive response that is followed by a more sustained and significant decline, while a domestic supply shock generates a persistently negative effect. Taken together, these results reveal a stark difference: economic shocks arising from the U.S. that decrease mean earnings growth bypass the median, indicating that the gains are driven by outliers and unevenly shared.

Figure 3 illustrates the impact of four shocks on the standard deviation. Both U.S. shocks eventually increase the volatility of earnings growth, but they propagate differently. The response to the U.S. demand shock is statistically significant and positive for the first two periods, suggesting that the inequality effects of U.S. demand propagate fairly quickly. The U.S. supply shock causes a statistically significant compression that leads to a persistent increase in the standard deviation from period $t+2$ onward. In contrast, domestic shocks generate substantially different responses. Specifically, we observe an insignificant reaction to a domestic demand shock, whereas a domestic supply shock tends to significantly narrow the distribution (up to -50 basis points), reducing income volatility.

Next, Figure 4 shows the responses of Kelley skewness to various shocks. A U.S. demand shock leads to a significant decrease in Kelley skewness, indicating increased left-skewness (i.e., a longer lower tail of the distribution). Conversely, a U.S. supply shock increases Kelley skewness, generating right-skewness, though this effect is transitory and dissipates by period $t+2$. Domestic shocks elicit milder responses. A domestic demand shock causes a brief increase in Kelley skewness, followed by a decrease that mirrors the left-skewed pattern of its U.S. counterpart. A domestic supply shock, however, induces a persistent increase in Kelley skewness, reflecting sustained right-skewness over the entire horizon.

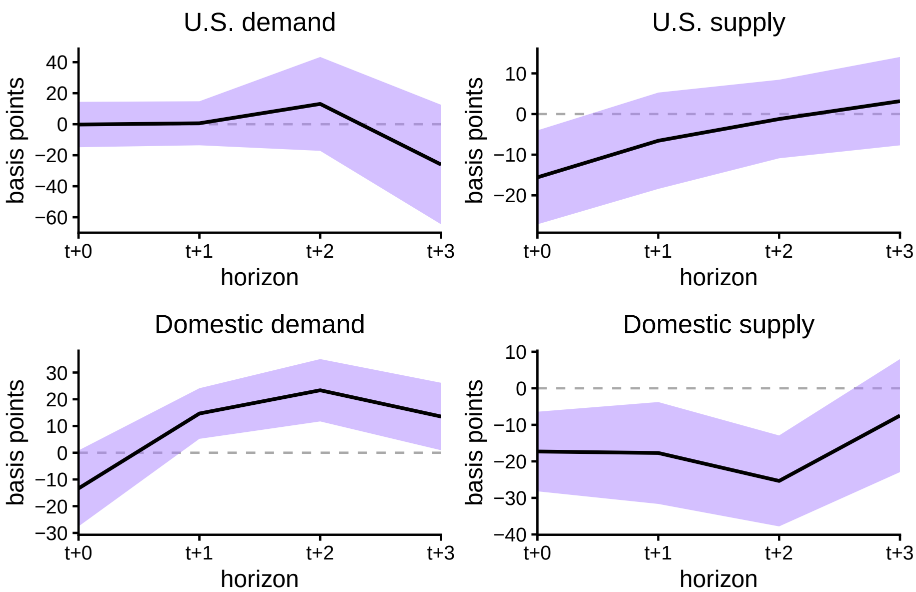
Taken together, these results suggest that U.S. shocks play an important role in shaping domestic income dynamics relative to domestic disturbances observed in our sample. The increased income volatility and left-skewness of earnings growth indicate that U.S. shocks tend to impact those at the lower tail of the distribution. In contrast, domestic shocks have modest aggregate effects but can still alter the distribution through shifts in the skewness or decreased volatility of earnings growth.

Figure 1: Cumulative impulse responses to demand and supply shocks: mean, baseline.



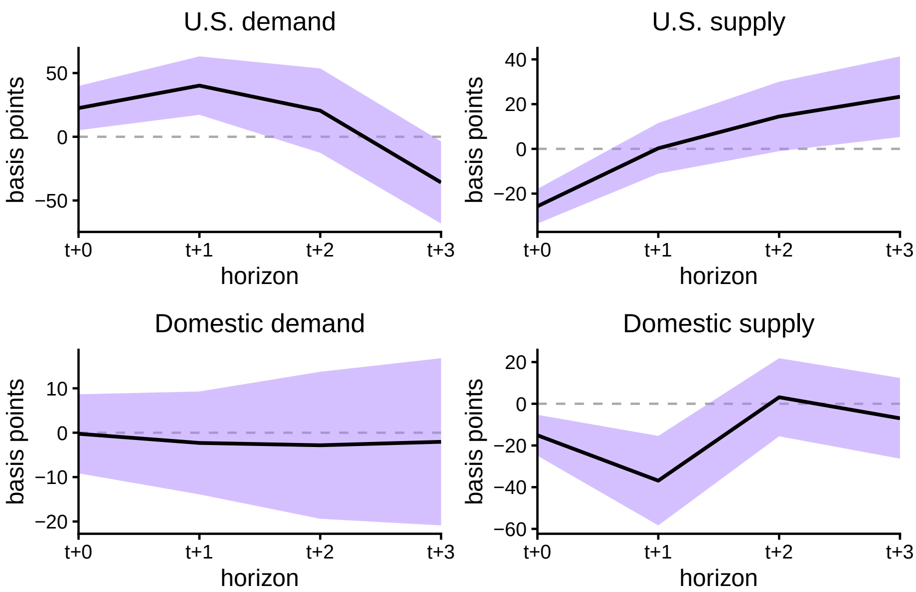
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 2: Cumulative impulse responses to demand and supply shocks: median, baseline.



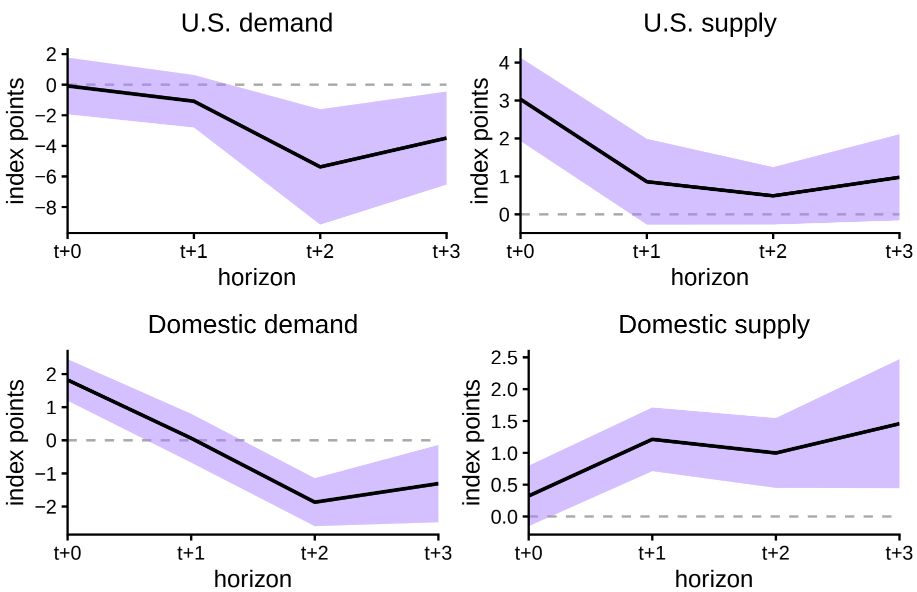
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 3: Cumulative impulse responses to demand and supply shocks: standard deviation, baseline.



Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 4: Cumulative impulse responses to demand and supply shocks: Kelley skewness, baseline.



Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

4.2 Exploring asymmetric responses

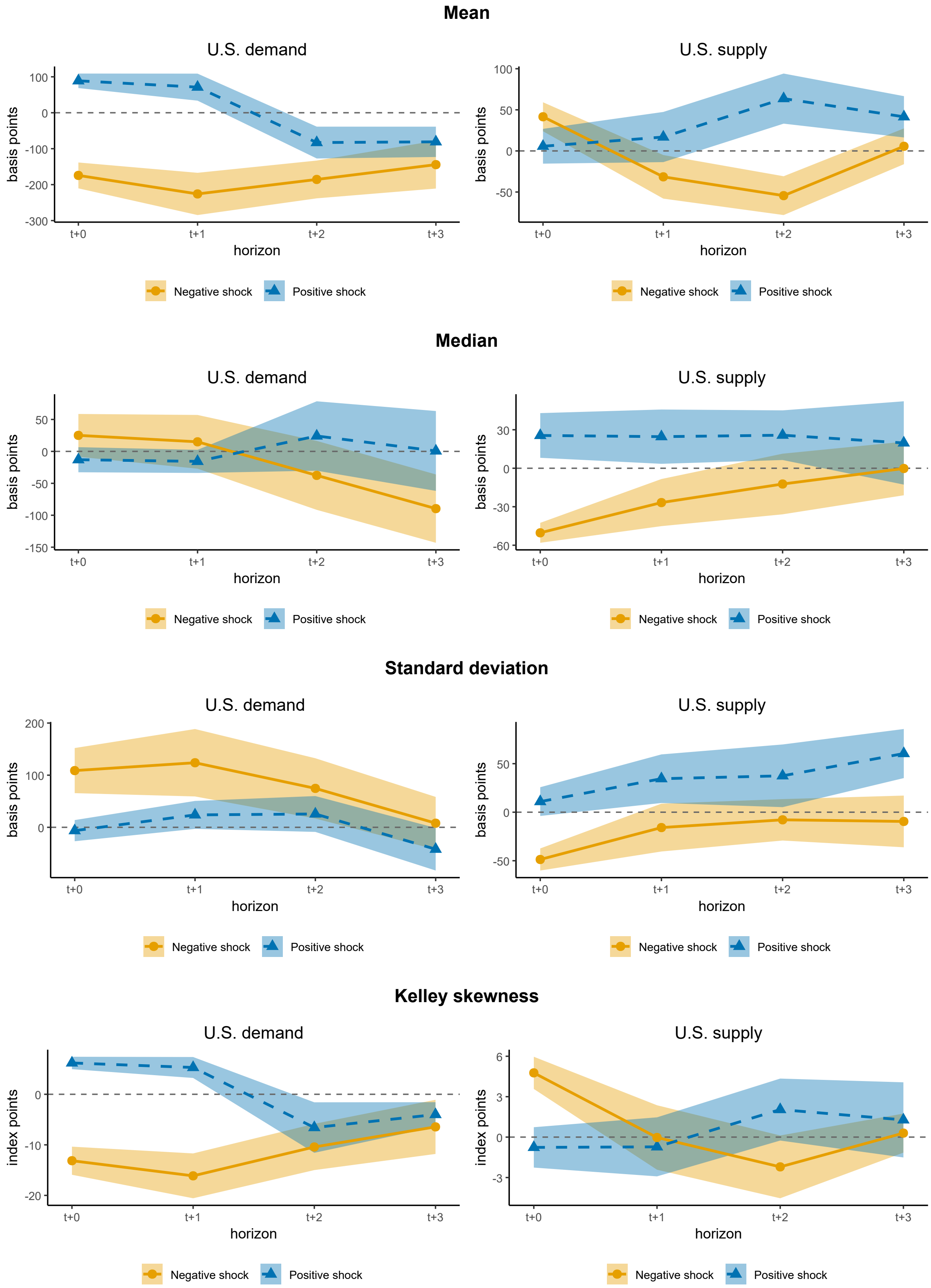
In the previous subsection, we studied the response to domestic and U.S. shocks. The estimated responses represent an average over responses to expansionary and contractionary shocks. In this section, we explore whether the sign of the U.S. shocks matters for those responses. To this end, we modify regression (4) by splitting shocks into two variables representing positive and negative shocks. The resulting regression takes the following form:

$$y_{c,t+h} - y_{c,t-1} = \beta^{h,+} z_t^+ + \beta^{h,-} z_t^- + \pi^h X_{c,t} + \gamma_c^h + e_{c,t+h}^h \tag{5}$$

where z denotes the demand and supply shocks originating in the U.S. We define these variables as $z_t^+ = \max(z_t, 0)$ and $z_t^- = \min(z_t, 0)$. The coefficients $\beta^{h,+}$ and $\beta^{h,-}$ represent the response of the variable y to positive and negative shocks. The regressions also include controls for recession years (γ_c^h) and the first two lag values of changes in the dependent variable and the exogenous shocks used.

Figure 5 displays the estimated response functions. In these plots, blue-shaded areas represent responses to a positive shock (i.e., an expansion), whereas yellow-shaded areas represent responses to negative shocks (i.e., a recession).

Figure 5: Cumulative impulse responses to positive or negative U.S. demand and supply shocks.



Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

The mean responds in a procyclical and asymmetric manner (especially noticeable for a U.S.

supply shock), where increases in output and decreases in unemployment are associated with earnings growth: expansions (higher output, lower unemployment) are associated with higher earnings growth. This finding is consistent with the existing evidence on economic co-movement between booms and busts occurring in the U.S. and the rest of the world (Fink & Schüler, 2015; Kose et al., 2003, 2012).

The median remains largely unresponsive to U.S. demand shocks, as the responses fluctuate at around zero. However, we do observe some signs of asymmetric responses for supply shocks. Positive supply shocks lead to a persistent (within the horizon) increase in the median. The value of around 30 basis points roughly corresponds to between 5% and 10% of the range, depending on the country. In contrast, recessionary supply shocks correspond to even larger declines in income growth that vanish after the third period (up to 60 basis points).

The exploration of dispersion shows that the response to U.S. demand shocks presented in Figure 3 is driven almost exclusively by negative demand shocks. Specifically, demand shocks increase the dispersion of earnings growth by at least 100 basis points. Positive demand shocks barely affect the dispersion, which is in line with previous findings showing a similar spread in expansions and recessions. The response of dispersion to U.S. supply shocks shows large hints of asymmetry, as positive shocks display more persistent effects.

Negative U.S. demand shocks increase variation at the bottom of the distribution (-10 index points on impact), indicating a pronounced increase in left-skewness driven by a disproportionate widening of the lower tail (P50 – P10) relative to the upper tail. In contrast, positive U.S. demand shocks move skewness in the opposite direction for at least the first period. On the other hand, Kelley skewness shows no significant response to either positive or negative U.S. supply shocks. The impulse response functions remain statistically indistinguishable from zero at all horizons and mostly overlap.

In total, this evidence suggests that U.S. supply and demand shocks have asymmetric impacts on the distribution of earnings growth abroad. We interpret this as indicative of the fact that distributional outcomes can potentially be explained by the specific transmission channels.

4.3 Transmission channels of U.S. shocks

To examine the three potential transmission channels of supply and demand shocks originating in the U.S. we apply the state-dependent local projection in the style of Auerbach and Gorodnichenko (2013). Namely, we estimate the following regression:

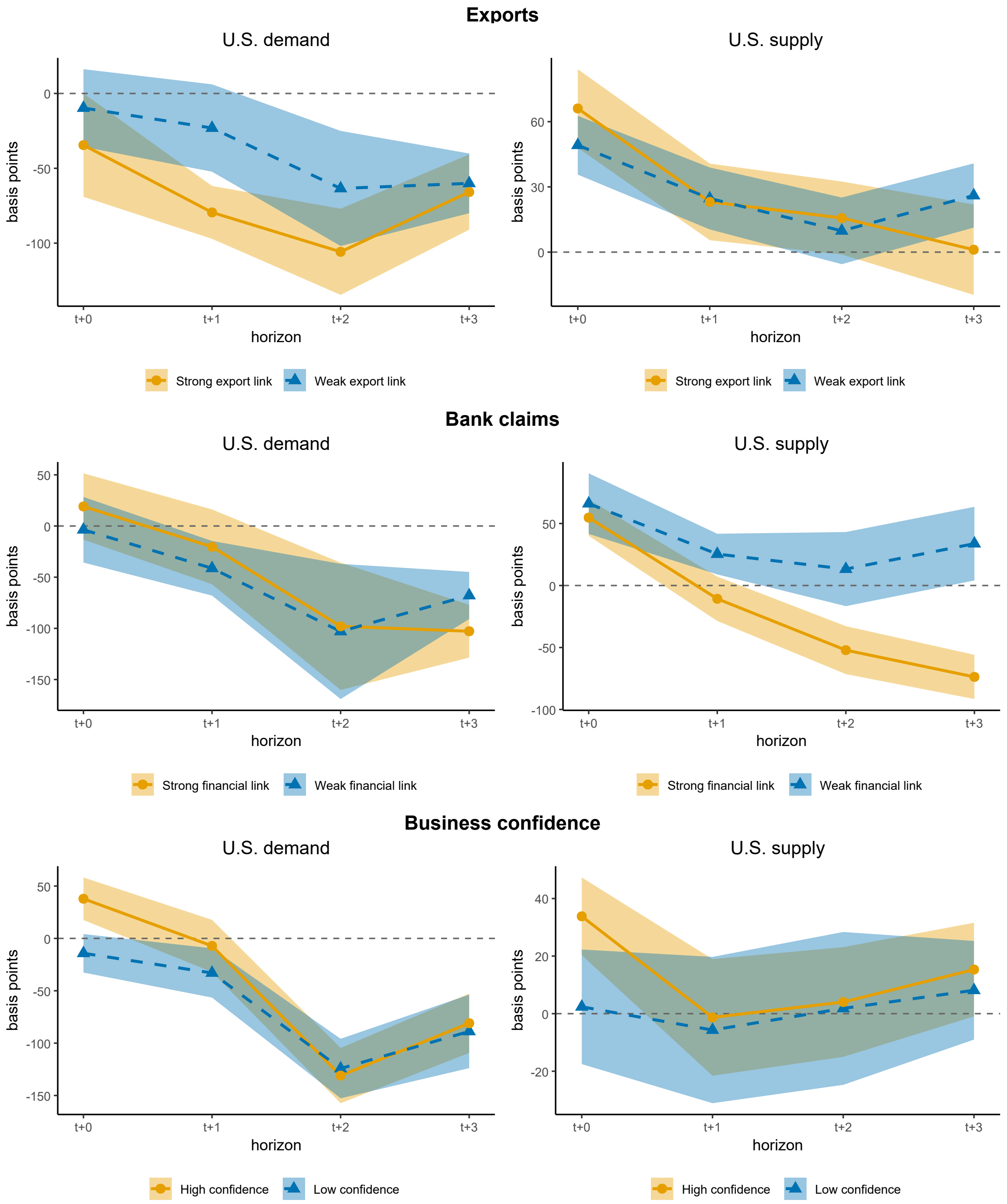
$$y_{c,t+h} - y_{c,t-1} = \beta^h z_t^{US} + \delta^h (z_t^{US} \times s_{c,t-1}) + \pi^h X_{c,t} + \gamma_c^h + e_{c,t+h} \tag{6}$$

where $s_{c,t-1}$ represents the state variable: i) percentage of exports to U.S. in all exports of country c (trade channel), ii) bilateral U.S. bank claims as a proportion of GDP in country c (financial channel), or iii) business confidence in country c (expectations channel). $X_{c,t}$ includes two lags of changes in the moment, exogenous shock being used, interaction term, state variable, and NBER-identified recessions. The state-dependent cumulative impulse response is the linear combination $\beta^h + \delta^h \times s_{c,t-1}$.

Our analysis of the three transmission channels—trade linkages (Corsetti & Müller, 2011), financial market integration (Faccini et al., 2016), and expectations (Klein & Linnemann, 2021)—offers some explanation of the observed asymmetry (see responses in Figures 6, 7, 8, 9). In countries with strong export links to the U.S., the mean responds more strongly to a U.S. demand shock (see top row of Figure 6), whereas the median reacts a bit stronger to a U.S. supply shock through the same channel (see top row of Figure 7). The trade channel is also important for skewness: earnings growth in trade-exposed economies tends to become more left-skewed following a U.S. demand shock. Economies with developed financial links to the U.S. experience a substantially larger increase in income volatility following a U.S. supply shock (middle row of Figure 8); in all other cases, we report that the responses are broadly similar across all three channels.

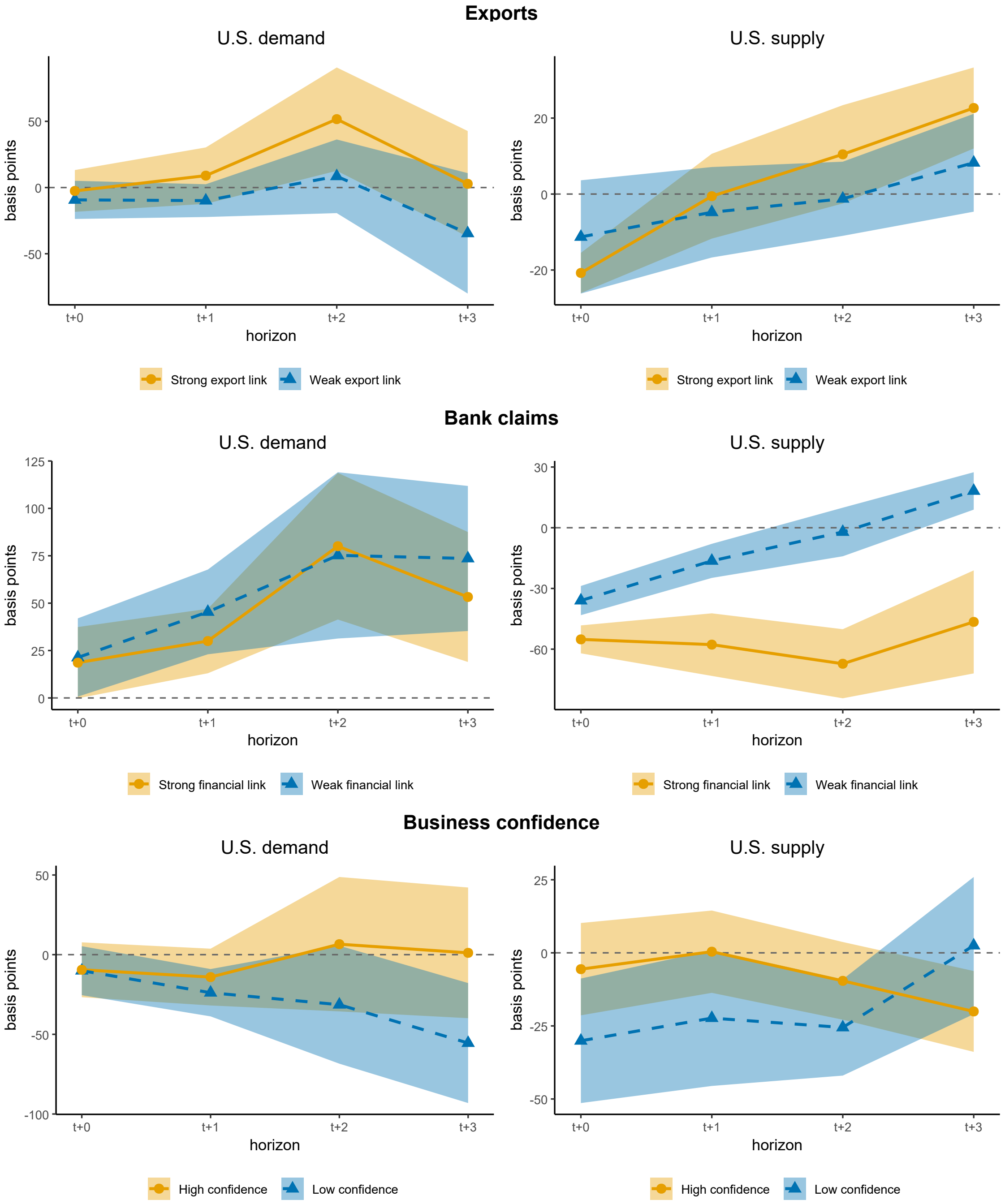
All things considered, the results provide novel evidence that U.S. shocks cause significant channel-specific effects on income dynamics in other economies. Specifically, we report that the trade channel is the primary conduit for U.S. demand shocks, which tend to decrease the mean of earnings growth. In contrast, the financial channel transmits U.S. supply shocks, leading to a substantial increase in volatility and reaction of the median. As for the expectations channel, we note that the responses are quantitatively similar for both states except for the one case of standard deviation (see Figure 8).

Figure 6: Cumulative state-dependent impulse responses to U.S. demand and supply shocks: mean.



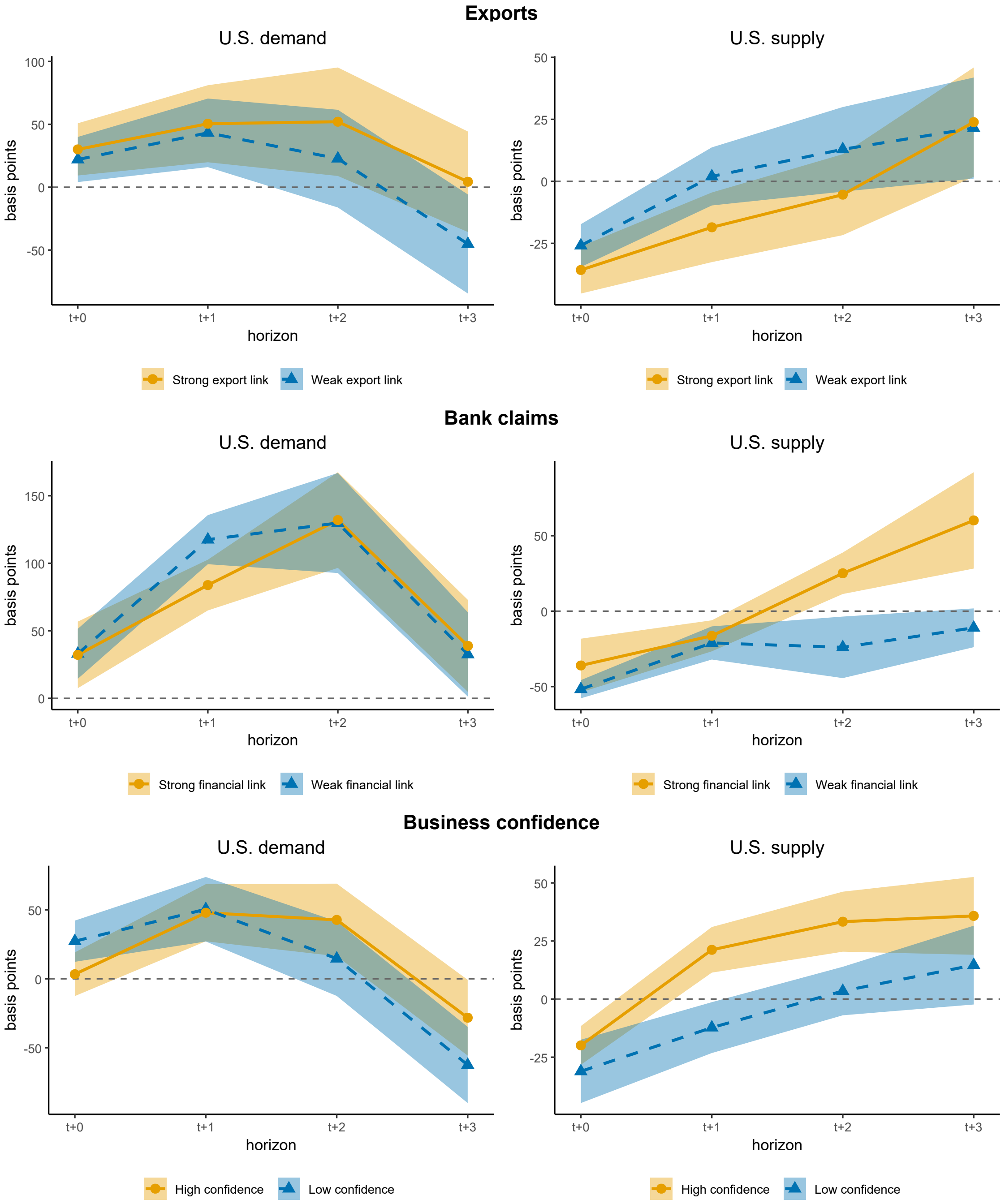
Note: levels are data-driven, i) exports (weak: 50th percentile; strong: 90th percentile), ii) bank claims (weak: 25th percentile, strong: 75th percentile), iii) business confidence (low: 25th percentile, high: 75th percentile). Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 7: Cumulative state-dependent impulse responses to U.S. demand and supply shocks: median.



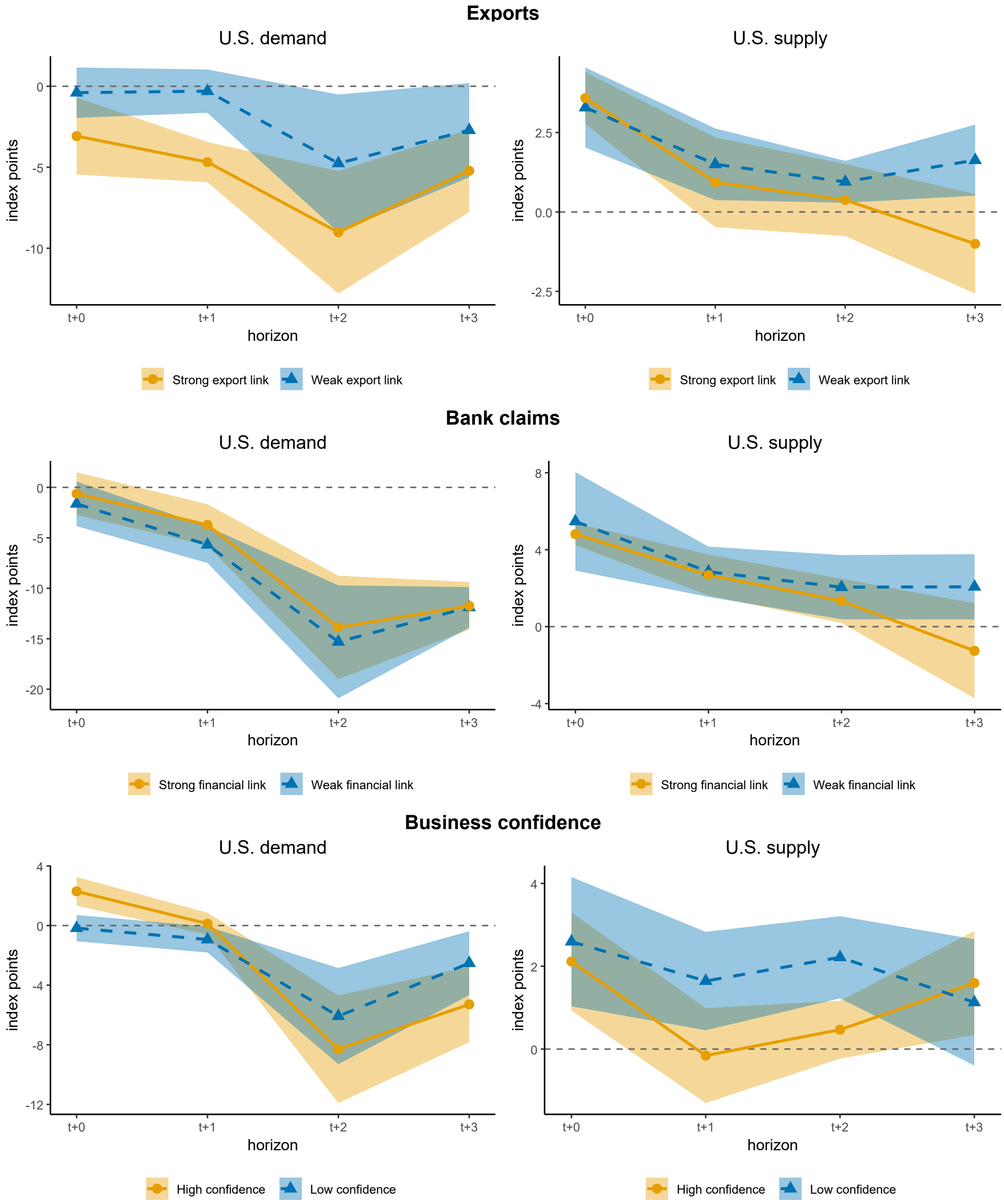
Note: levels are data-driven, i) exports (weak: 50th percentile; strong: 90th percentile), ii) bank claims (weak: 25th percentile, strong: 75th percentile), iii) business confidence (low: 25th percentile, high: 75th percentile). Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 8: Cumulative state-dependent impulse responses to U.S. demand and supply shocks: standard deviation.



Note: levels are data-driven, i) exports (weak: 50th percentile; strong: 90th percentile), ii) bank claims (weak: 25th percentile, strong: 75th percentile), iii) business confidence (low: 25th percentile, high: 75th percentile). Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 9: Cumulative state-dependent impulse responses to U.S. demand and supply shocks: Kelley skewness.



Note: levels are data-driven, i) exports (weak: 50th percentile; strong: 90th percentile), ii) bank claims (weak: 25th percentile, strong: 75th percentile), iii) business confidence (low: 25th percentile, high: 75th percentile). Shaded areas represent 68% Driscoll-Kraay confidence bands.

4.4 Robustness

4.4.1 Additional controls and estimation horizon

We conduct a number of robustness exercises. First, we check whether the inclusion of additional drivers or specific channels affects the estimated responses as mentioned in the equation (4). The resulting IRFs are portrayed in Figures B1, B2, B3, and B4 (Appendix B). The trajectories of responses to shocks are largely robust to the inclusion of these controls. Second, we evaluate the evolution of responses beyond the initial estimation horizon of three years, as shown in Figures B5, B6, B7, and B8 (Appendix B). Given that the panels are short, the obtained estimates are less reliable, which is reflected in the broader confidence bands. To the extent that conclusions are possible, the patterns of the responses remain similar to the ones reported in Section 4.1.

4.4.2 Sensitivity to alternative identification strategies

The structural shocks recovered using the original BQ decomposition rely on two assumptions, orthonormality of structural shocks, and long-run neutrality of the effects of demand shocks on output. Both restrictions have been called into question by recent research. Cover et al. (2006), based on a similar macroeconomic model, imposes sign restrictions on the impact of structural shocks, allowing them to be correlated. Analysis from both the U.S. and the EU (Bashar, 2011) provides evidence of a positive correlation. On the other hand, Keating (2013) and W. Chen and Netunajev (2016) study the long-run non-neutrality of demand shocks. If demand shocks are non-neutral, then the structural shocks in BQ can only be interpreted as transitory and permanent shocks to output, without a clear economic meaning. Keating (2013) reveals the presence of long-run non-neutrality of demand shocks in the preWorld War I period. W. Chen and Netunajev (2016), on the other hand, finds evidence of non-neutrality of demand shocks in more recent years under a different identification strategy. Given this evidence, we derive structural shocks under two alternative procedures.

The first procedure was proposed by Bayoumi (1992) and popularized in Bayoumi and Eichengreen (1993). This approach is based on a similar macroeconomic model, though for open economies. Unlike BQ, the structural shocks are recovered from a bivariate VAR that includes changes in GDP and changes in price levels (CPI) as the endogenous variables. Bayoumi (1992) proceeds under the same assumptions concerning orthonormality of shocks and the long-run output neutrality of demand shocks. The main advantage of using prices to identify shocks comes from the possibility to impose additional overidentifying restrictions, as for example (Campos & Macchiarelli, 2016). It also remains to be a popular choice for the approximation of demand shocks in recent studies (e.g., A. Chen and Groenewold (2019) or Hwang et al. (2025)). As a result, we test the sensitivity of our baseline results by estimating a bivariate VAR for the U.S. using de-meaned quarterly growth rates of real GDP and CPI changes following Bayoumi and Eichengreen (1993) (BE). This new set of U.S. shocks provides us with a systematic way to assess whether the initially taken approximation of U.S. demand using the unemployment rate captures the underlying transitory dynamics with reasonable accuracy. Notably, the two demand shocks are quite different from each other, which shares a correlation of 0.14. Further, we also find using a Granger causality test that the new inflation-based demand shock leads the unemployment-based one, suggesting that this alternative shock reflects quicker demand adjustments. We standardize (mean-center and scale to unit variance) and input the estimated shocks into equation (4) and compare the resulting cumulative IRFs for the four moments with all robustness controls for channels, changes in economic openness, and changes in domestic labor market policies.

The second procedure was proposed by Herwartz (2018). Much like Bayoumi (1992), the procedure requires the estimation of a bivariate VAR of changes in output and prices. Their identification procedure does not require orthonormality or long-run neutrality of demand shocks. Instead, Herwartz proposes to identify shocks based on their statistical properties. The identification is achieved by rotation of the reduced-form errors, and the minimization of the Cramér – von Mises (CvM) dependence criterion for joint distributions. The key statistical prerequisite for the CvM method to achieve unique identification is that at most one of the structural shocks follows a normal distribution. We note, however, that the method does rely on the assumption that the true structural shocks are independent—a condition that, while untestable, produces economically coherent results in our application.

Application of the CvM method results in a matrix S, which transforms structural shocks into reduced-form residuals. We align S to the theoretical sign pattern via an automated permutation and sign-flip routine as outlined in Herwartz (2018) such that it satisfies the expected economic intuition required for shock identification[4]. These differential impacts have been used for identification in the work of Cover et al. (2006), Hwang et al. (2025), and Shapiro (2024) to name a few.

$$\begin{bmatrix} e_t^Y \\ e_t^P \end{bmatrix} = \begin{bmatrix} + & + \\ - & + \end{bmatrix} \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^d \end{bmatrix} \tag{7}$$

where supply shocks (ε_t^s) increase output and decrease prices, while demand shocks (ε_t^d) increase both variables. Prior to using alternative shocks in equation (4), we standardize them (mean-centered and scaled to unit variance).

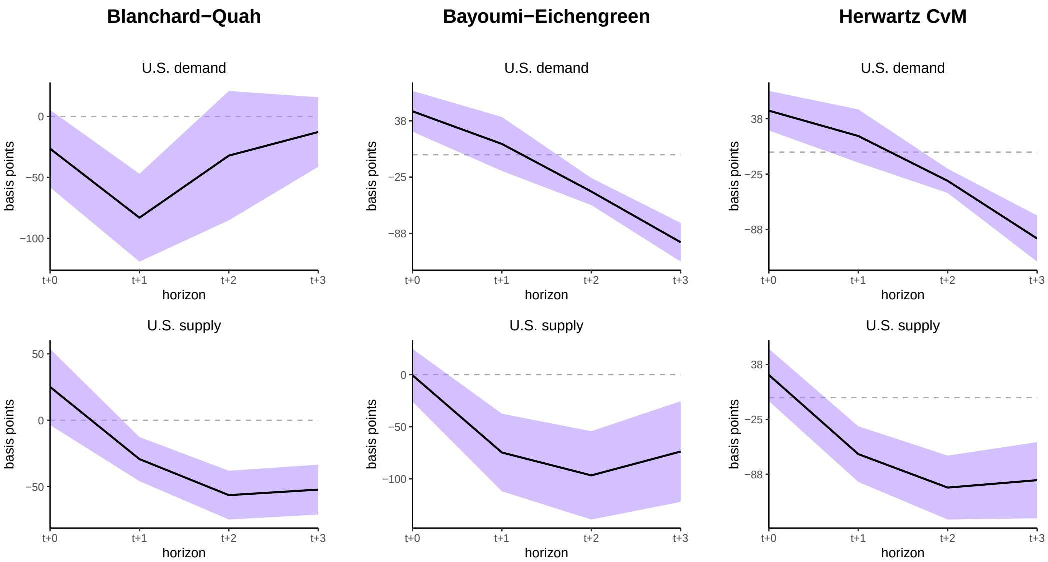
Figures 10 to 13 present how the distribution of earnings growth reacts to the structural shocks estimated using the two methods. For reference, we also include the responses generated in Section 4.4.1. The new IRF deviates from the results obtained under the original approach of BQ, particularly for demand shocks. U.S. demand shock leads to an increase in the median of the distribution

[4]To ensure that the identified decomposition is robust to optimization starting points and invariant to sign indeterminacy, we repeat the estimation over 100 random seeds and pick the best seed, where the CvM is the closest to zero for shock computation. We also retained the CvM independence criterion for each initialization; across all 100 seeds, this criterion remained very close to zero, indicating that the structural shocks are effectively independent in every run.

of earnings shocks, which was not detected earlier. The discrepancy starts at around the second lag. U.S. demand shock also commands a more permanent increase in variation of income growth abroad, and a negative, if potentially delayed effect on the skewness. Structural shocks identified following BQ did not exhibit a permanent effects on either dispersion or skewness.

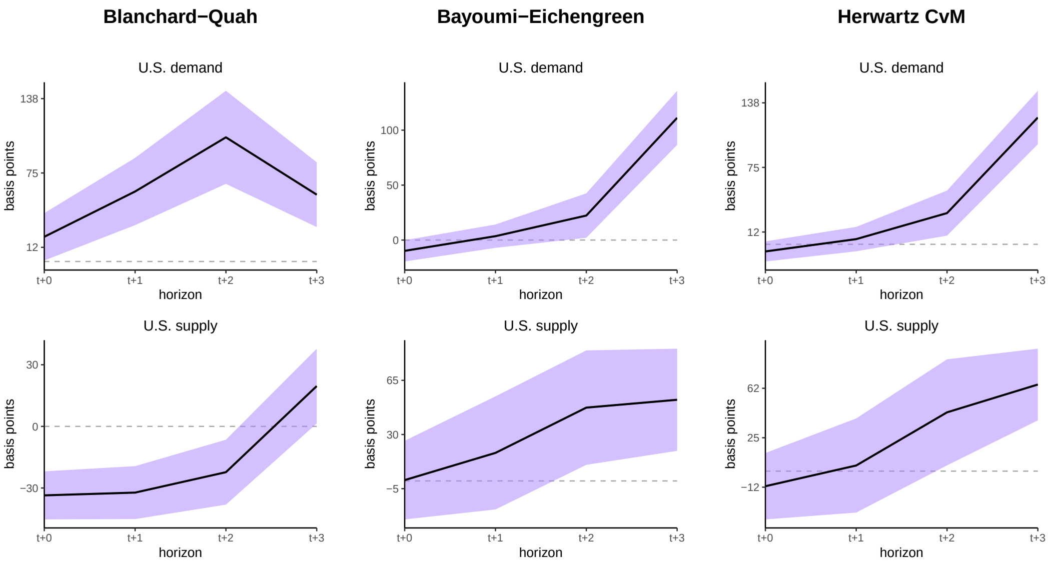
The response functions of earnings growth to U.S. supply shocks do not differ much between shocks estimated using BQ, BE, or CvM. However, the statistical identification leads to some minor deviations from our baseline results. For all statistics, responses have mostly very similar shapes in the first three periods.

Figure 10: Cumulative impulse responses to demand and supply shocks: mean, different identification strategies, all controls.



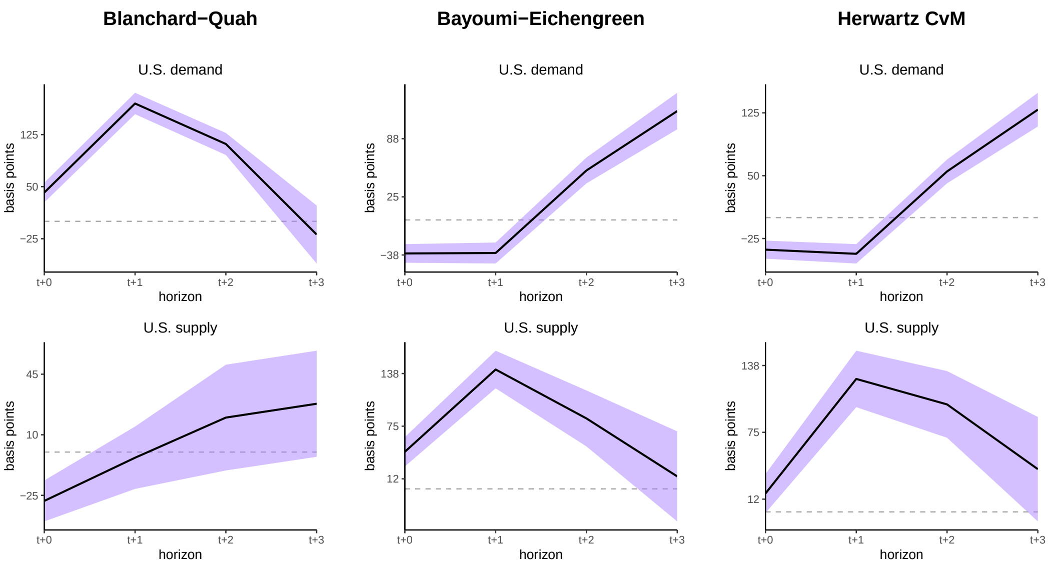
Note: in the BQ column, U.S. demand shock is obtained from unemployment rate, while other columns use CPI. Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 11: Cumulative impulse responses to demand and supply shocks: median, different identification strategies, all controls.



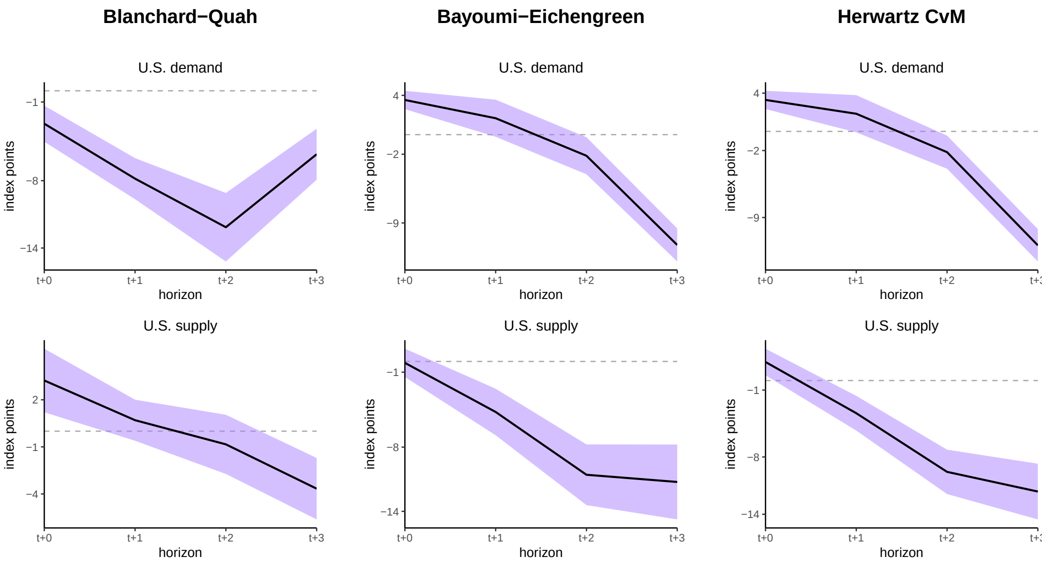
Note: in the BQ column, U.S. demand shock is obtained from unemployment rate, while other columns use CPI. Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 12: Cumulative impulse responses to demand and supply shocks: standard deviation, different identification strategies, all controls.



Note: in the BQ column, U.S. demand shock is obtained from unemployment rate, while other columns use CPI. Shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure 13: Cumulative impulse responses to demand and supply shocks: Kelley skewness, different identification strategies, all controls.



Note: in the BQ column, U.S. demand shock is obtained from unemployment rate, while other columns use CPI. Shaded areas represent 68% Driscoll-Kraay confidence bands.

5 Concluding remarks

This paper investigated the relationship between a broad set of macroeconomic shocks and income dynamics using local projections. In line with the existing empirical studies on international shock spillovers, our results also establish a clear hierarchy — shocks originating in the U.S. are the most potent drivers of income dynamics abroad, with effects that are larger and more persistent than those of domestic shocks.

The core contribution of our analysis is to show how different shocks—distinguishing between permanent versus transitory, and U.S. versus domestic—impact income dynamics. By analyzing the first four moments of earnings growth, we uncover the more nuanced characteristics of each shock. Focusing first on shocks originating in the U.S., we find that changes in the mean and skewness are procyclical, while the standard deviation is countercyclical and largely follows booms and busts occurring in the U.S. The majority of moments also exhibit asymmetries over the business cycle. As to the domestic shocks, though smaller in aggregate impact, they contribute to changes in income dynamics by shifting skewness and decreasing volatility of earnings growth.

To understand the transmission of U.S. shocks, we study the three candidate channels using linear state-dependence. We find that the trade channel is the main conduit for U.S. demand shocks, while the financial channel transmits U.S. supply shocks, leading to a substantial increase in volatility of earnings growth. By contrast, we find little evidence that expectations play a significant role in transmitting these specific U.S. shocks.

The series of robustness tests confirms that U.S. supply and demand shocks exert significant and meaningful influences on the higher-order moments of earnings growth. The fact that these patterns emerge under both theory-based (Blanchard-Quah, Bayoumi-Eichengreen) and statistical (CvM) identification strategies strongly suggests that our conclusions are not an artifact of a specific methodological choice, but reflect a robust feature of the structural shocks originating in the U.S.

Looking ahead, the expansion of detailed administrative data through projects like GRID will be crucial for testing the external validity of these channel-based findings. Future work could also benefit from employing alternative methods for identifying unanticipated shocks across all countries in the sample.

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Appendix

Part A: Data

Table A1: Real output and unemployment series used for estimation of domestic supply and demand shocks using long-run restrictions.

Country	Scope
Canada	1990:Q2-2019:Q4
Denmark	1990:Q2-2019:Q4
France	1990:Q2-2019:Q4
Germany	1991:Q1-2019:Q4
Italy	1990:Q2-2019:Q4
Mexico	1990:Q2-2019:Q4
Norway	1990:Q2-2019:Q4
Spain	1990:Q2-2019:Q4
Sweden	1990:Q2-2019:Q4

Note: own summary, all data are quarterly and obtained from the OECD National Accounts database.

Table A2: Data used for estimation of U.S. supply and demand shocks.

Method	Series	Scope
Blanchard-Quah	GDPC1, UNRATE	1950:Q2-2019:Q4
Bayoumi-Eichengreen	GDPC1, CPIAUCSL	1950:Q2-2019:Q4
Herwartz CvM	GDPC1, CPIAUCSL	1950:Q2-2019:Q4

Note: own summary, all data are quarterly and obtained from the Federal Reserve Bank of St. Louis (FRED) database. VAR lag length used across all three methods: 3 lags as identified by the Schwarz Criterion.

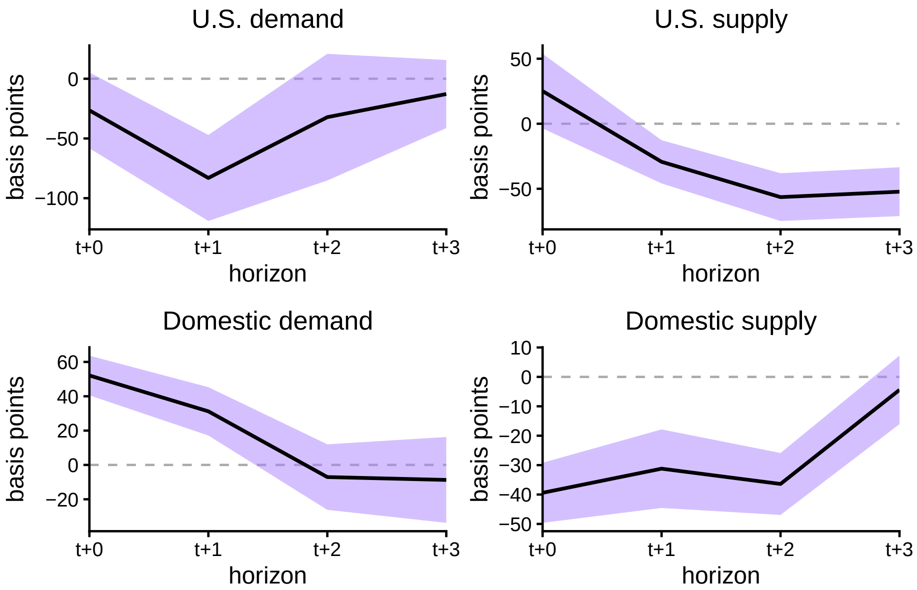
Table A3: Control variables used in the estimation of local projections.

Variable	Source	Availability
NBER identified economic recessions in the US	NBER	1990-2019
De facto component of the KOF Economic Globalization index	Gygli et al. (2019)	1990-2017
Labor market regulations score (Area 5)	Fraser Institute	1990,1995,2000-2019
Share of exports to the US	Own estimation based on UNCTAD	1990-2019, with gaps
Bilateral US bank claims to GDP	Own estimation based on BIS	1990-2019, with gaps
Business confidence index	OECD	1990-2019, with gaps

Note: own summary, all data are annual.

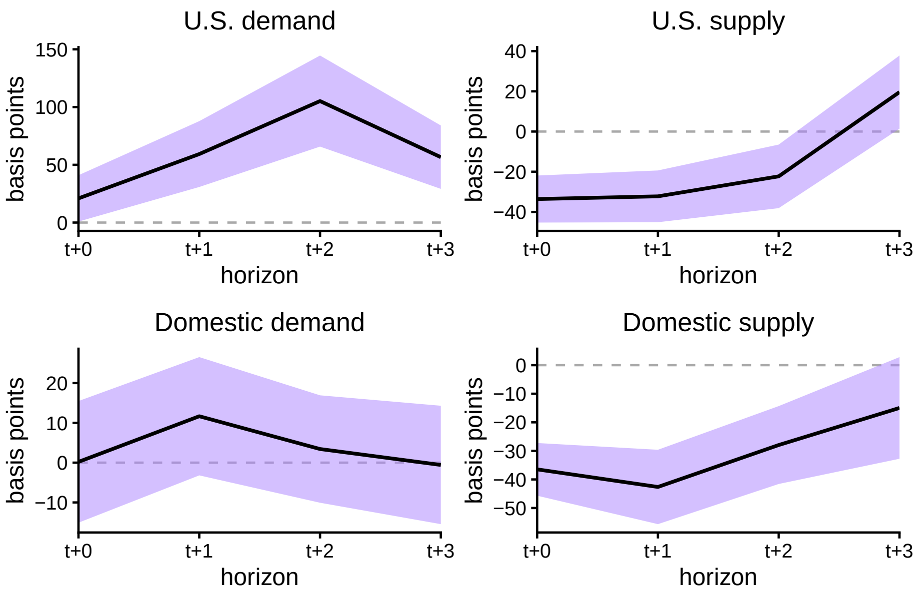
Part B: Additional results

Figure B1: Cumulative impulse responses to demand and supply shocks: mean, all controls.



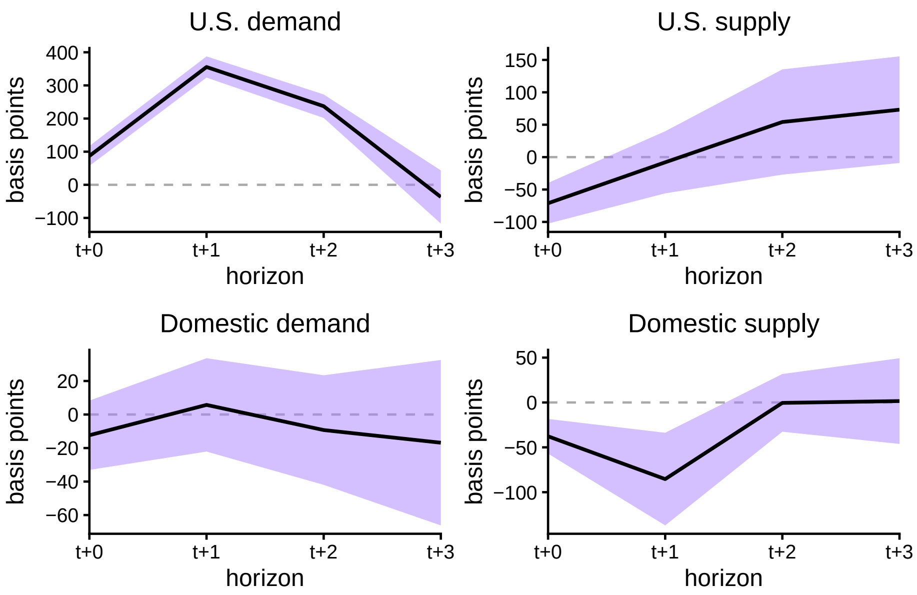
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B2: Cumulative impulse responses to demand and supply shocks: median, all controls.



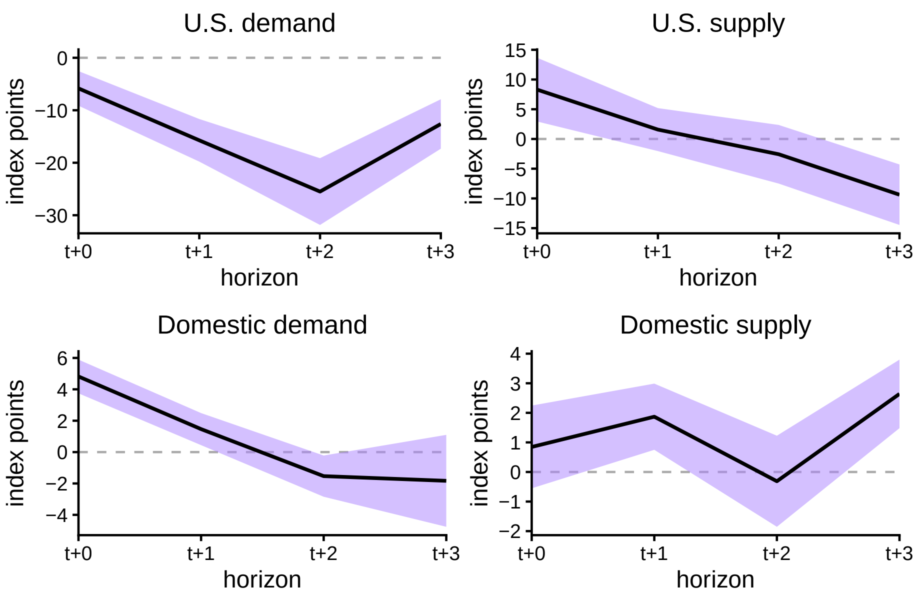
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B3: Cumulative impulse responses to demand and supply shocks: standard deviation, all controls.



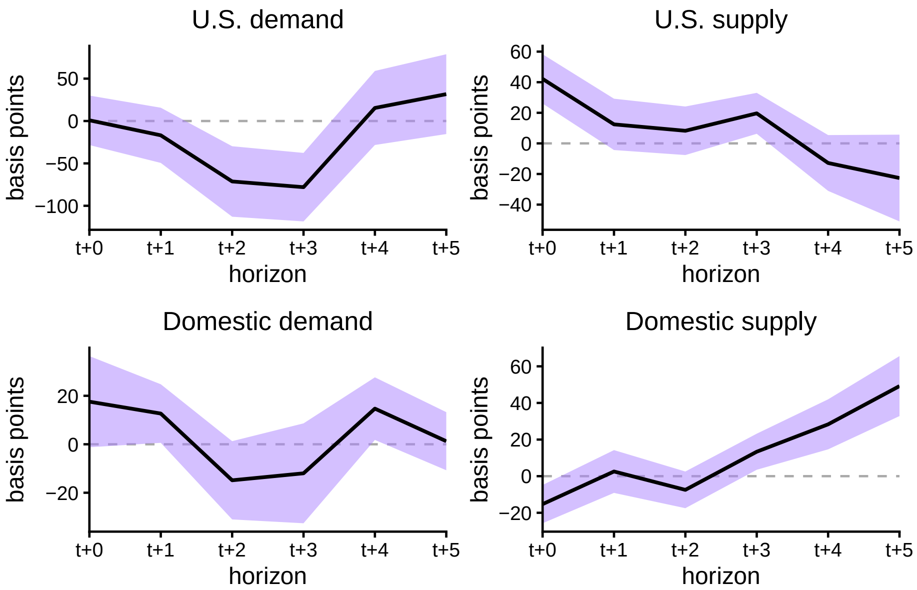
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B4: Cumulative impulse responses to demand and supply shocks: Kelley skewness, all controls.



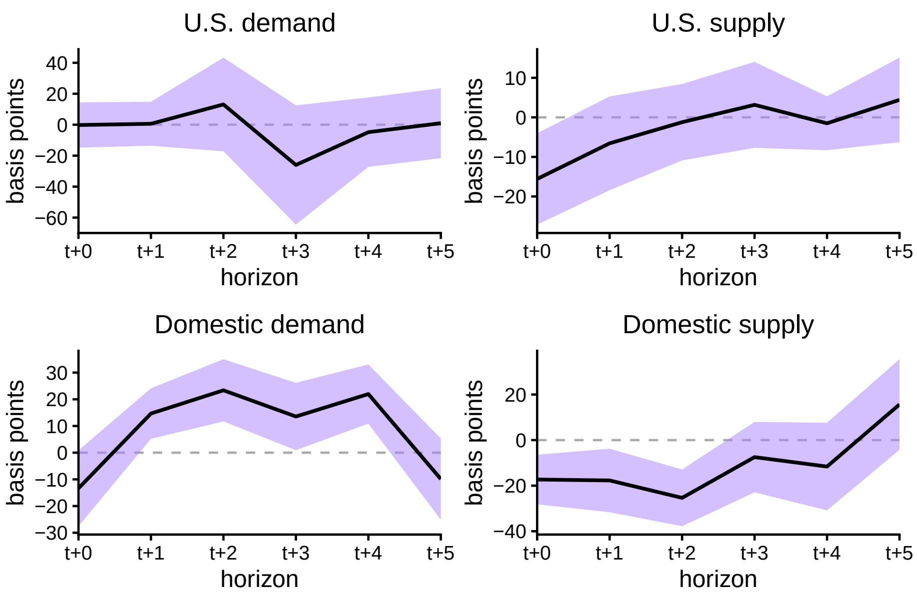
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B5: Cumulative impulse responses to demand and supply shocks: mean, extended horizon.



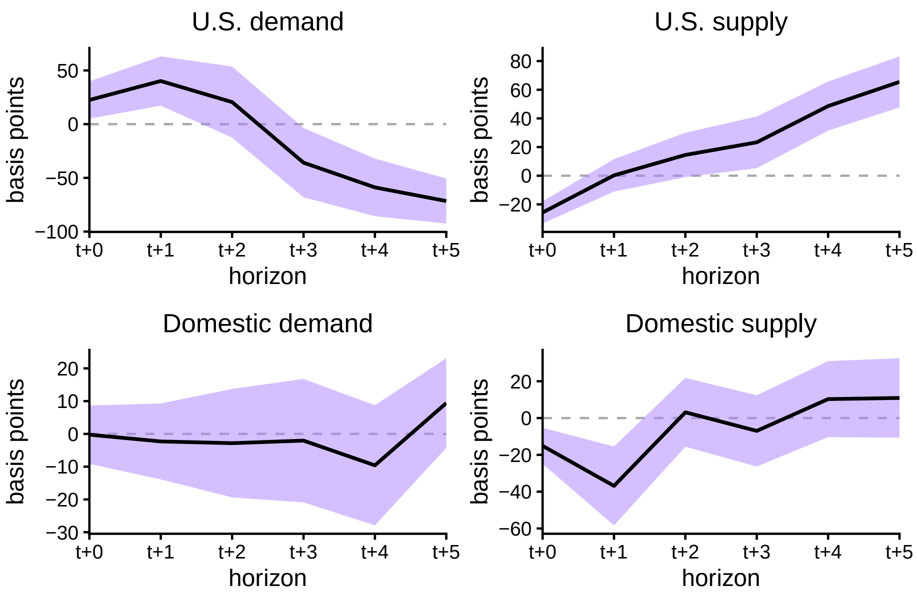
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B6: Cumulative impulse responses to demand and supply shocks: median, extended horizon.



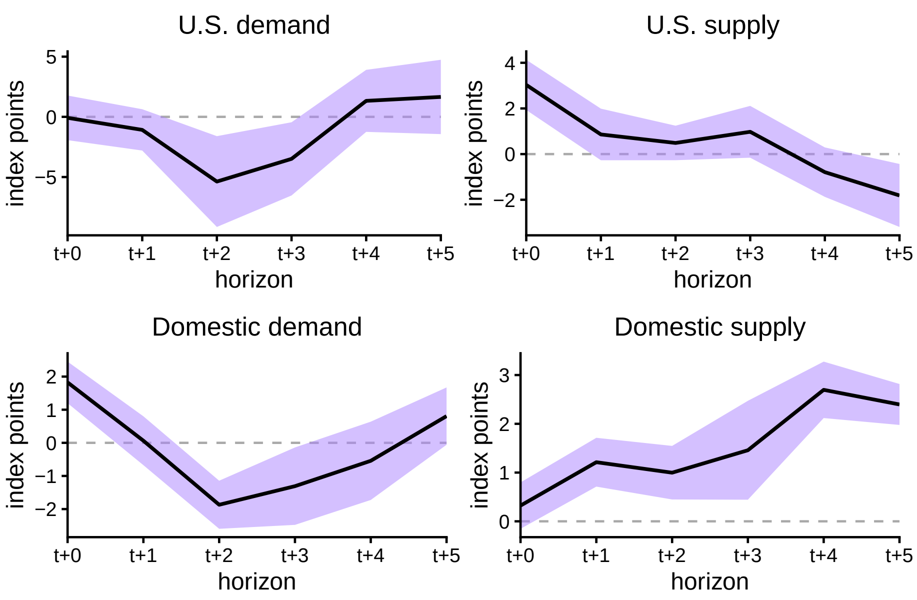
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B7: Cumulative impulse responses to demand and supply shocks: standard deviation, extended horizon.



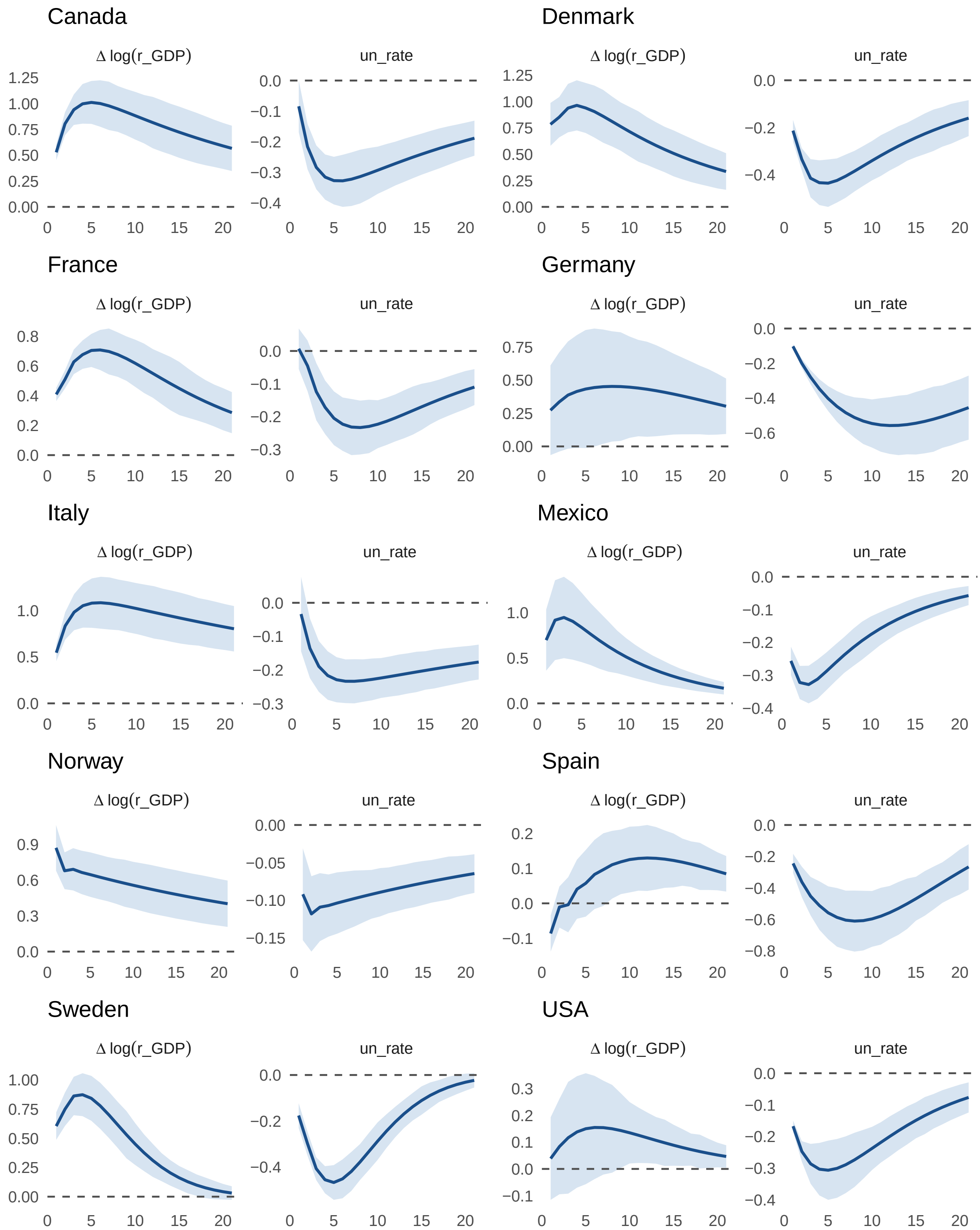
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B8: Cumulative impulse responses to demand and supply shocks: Kelley skewness, extended horizon.



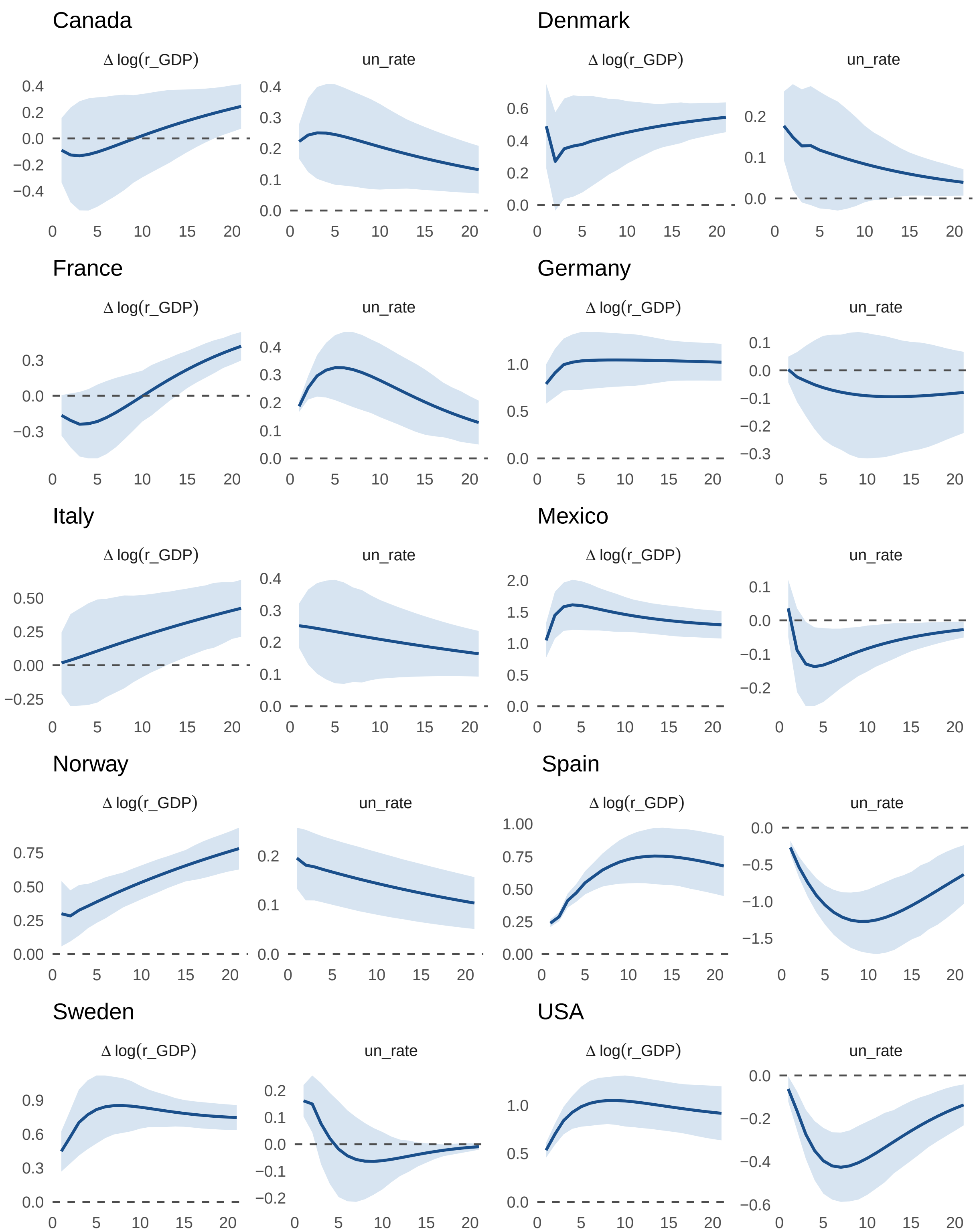
Note: shaded areas represent 68% Driscoll-Kraay confidence bands.

Figure B9: Estimated impulse response functions to a positive demand shock.



Note: 20 quarters, shaded areas represent 68% confidence bands. r_GDP and un_rate stand for real output growth and unemployment rate.

Figure B10: Estimated impulse response functions to a positive supply shock.



Note: 20 quarters, shaded areas represent 68% confidence bands. r_GDP and un_rate stand for real output growth and unemployment rate.