Granularity in the current account *

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Abstract

We present new empirical evidence on the role of granularity in the current account (CA), using a unique and comprehensive firm-level dataset for Switzerland. We show that idiosyncratic shocks to large firms account for almost two thirds of the fluctuations in the headline CA and are the primary source of CA volatility. The granular effect is present across goods, services, and income components, and persists over both short- and medium-term horizons. In addition to their direct impact, idiosyncratic shocks propagate through inter-firm linkages, via input-output relationships and cross-product connections associated with multinational enterprise activity. Our findings challenge standard macroeconomic models that emphasize aggregate fundamentals, highlighting the importance of firm-level heterogeneity in explaining external imbalances and their fluctuations.

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Keywords: current account, firm-level shocks, granular fluctuations, large firms

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1 Introduction

Current account (CA) volatility is a persistent feature of both advanced and emerging market economies. Large swings in the CA often signal underlying economic and financial stress, can exert pressure on exchange rates, and destabilize macroeconomic conditions (Obstfeld, 2012; Gourinchas and Rey, 2014; Boer et al., 2024). Understanding the sources of CA volatility is therefore crucial to assess potential risks from sudden movements in a country's external position.

This paper provides new empirical evidence on the granular origins of CA dynamics. Building on Gabaix (2011)'s granular hypothesis, we show that idiosyncratic shocks to large firms account for nearly two thirds of CA aggregate fluctuations in the headline CA balance and are the primary driver of CA volatility. While previous research has focused on the macroeconomic determinants of CA balances, such as demographics, fiscal policy, and net foreign asset positions (Chinn and Prasad, 2003; Bussière et al., 2006; Gruber and Kamin, 2007; Chinn and Ito, 2008; Behringer and Van Treeck, 2018; Chinn and Ito, 2022; Coutinho et al., 2022; Koomen and Wicht, 2022; Allen et al., 2023; Koomen and Wicht, 2023), it has largely overlooked the microeconomic origins of aggregate external balances. Our findings suggest that this omission may be consequential: in economies with granular external sectors, idiosyncratic shocks to a small number of large firms can shape the evolution of the CA in ways not easily predicted by macro fundamentals.

Central to the analysis is our novel firm-level dataset, which offers the first comprehensive firm-level account of the CA balance. We combine administrative customs records with official surveys of services and income flows for Switzerland. The data spans over 350,000 firms and 70 partner countries at quarterly frequency between 2015 and 2024. It captures the main CA components—goods, services, and income—disaggregated into 27 subcomponents, or products.[1] This richness allows us to quantify granular dynamics across different levels of aggregation, from product-country pairs to main CA components and the headline balance. Our comprehensive dataset allows us to provide evidence for the granular hypothesis in the CA, thus contributing to the literature showing similar findings for a range of macroeconomic outcomes (di Giovanni et al., 2014; Atalay, 2017; Carvalho and Grassi, 2019; Alvarez-Blaser et al., 2025; Grigoli et al., 2023; Eaton et al., 2011; Bernard et al., 2018; Gaubert and Itskhoki, 2021).

We decompose firm-level CA growth into common product-country shocks and idiosyncratic firm-specific shocks. Within a product-country pair, we isolate a common shock, defined as the average firm-level growth rate within that pair. The common shock thus captures factors that affect firms equally given a specific product and partner country. Then, we extract an idiosyncratic shock, defined as the firm-level deviation from the

[1] Our analysis complements recent work that investigates the drivers of the income balance and the implications for the headline CA (e.g., Herkenhoff and Sauré, 2021; Behar and Hassan, 2022; Donato and Tille, 2024).

product-country shock. The idiosyncratic shock thus captures how firm-level outcomes differ from the common shock. Aggregating across firms, we derive the granular residual, the size-weighted sum of idiosyncratic shocks, and examine its contribution to CA fluctuations.

We make two contributions. First, we provide the first empirical assessment of the granular hypothesis in the context of the CA. Using a regression framework, we show that idiosyncratic shocks account for nearly two-thirds of fluctuations in Switzerland's headline CA balance. Granularity in all three main components contributes to fluctuations in the CA, with the income balance showing the strongest effects. Exploiting the richness of the data, we further find that the granular residual explains about 60% of the year-on-year fluctuations at the product-country level, showing the prevalence of granularity in CA dynamics.[2] Notably, the granular effect remains significant when we collapse our panel to the yearly frequency, indicating that firm-level impacts extend beyond business-cycle fluctuations to medium-term dynamics. This result underscores the critical role of large firms in driving aggregate CA dynamics.

Second, performing a variance-covariance decomposition, we identify the granular residual—that is, idiosyncratic volatility—as the dominant source of CA volatility, contributing substantially more to overall CA volatility than the common product-country volatility. Breaking down idiosyncratic volatility further, we show that both individual firm variances (the granular effect) and firm linkages are significant drivers. In particular, the granular effect tends to be larger in more concentrated product-level flows, highlighting the role of market structure in amplifying firm-specific shocks. In addition, firm linkages propagate idiosyncratic shocks through input-output linkages but also through multinationals, which play a key role for the income component. This suggests that shocks to individual large firms have both a direct effect and a spillover effect through firm linkages. These findings highlight the importance of both firm-specific shocks and firm interconnectedness in explaining aggregate CA volatility.

Our results offer a new perspective on the interpretation of CA fluctuations. Large swings in external balances are often interpreted as signals of macroeconomic risk. However, if these swings are instead driven by idiosyncratic firm-level shocks rather than shifts in fundamentals their implications for aggregate risk may differ. Such shocks may be less systemic and easier to absorb, particularly if concentrated in financially resilient firms. However, the outsized influence of a few large firms adds a new dimension of vulnerability: shocks to key players can destabilize aggregate outcomes, even in the absence of macroeconomic imbalances. Recognizing this micro-level channel is thus critical for external surveillance and exchange rate policy, especially in countries with highly granular

[2] We conduct a comprehensive series of robustness tests, as detailed in Section 4 and Appendix B. These include alternative samples, time periods, and redefinitions of the granular residual with different firm size thresholds. Results remain consistent across all specifications, affirming the robustness of our main findings.

external sectors.

The remainder of this paper is structured as follows. Section 2 introduces the empirical framework. Section 3 introduces the data and gives descriptive evidence of granularity in the CA. Then, Section 4 and Section 5 quantify the importance of idiosyncratic shocks for the CA growth rate and CA volatility. Section 6 concludes.

2 Empirical framework

2.1 Modeling the current account

We define the headline CA as the net sum of inflows (receipts) and outflows (expenses) across the main CA components—goods, services, primary and secondary income—between residents and non-residents, consistent with IMF guidelines (IMF, 2009). Formally, let ca_t denote the headline CA balance at time t:

$$ca_t = \sum_{p,c} ca_{pct} = \sum_{p,c} (x_{pct} - m_{pct}), \tag{1}$$

where ca_{pct} denotes the net flow of product p with trading partner country c at time t, and x_{pct} and m_{pct} represent receipts and expenses, respectively, for that product-country pair. We define product p as the type of flows, e.g., net exports of agricultural products, net exports of intellectual property, or net interest payments on debt instruments. Products are thus comprised in one of the main CA component (goods, service, and income).

We disaggregate this framework to the firm level, expressing the CA as the sum of firm-level flows:

$$ca_t = \sum_{i,p,c} ca_{ipct}, \tag{2}$$

where ca_{ipct} denotes firm i's net flow of product p with country c at time t. Our unit of observation is thus the *firm-product-country* flow, allowing us to capture the microeconomic drivers of aggregate CA dynamics.

2.2 Defining CA growth rates

To study CA fluctuations over time, we compute the mid-point CA growth rate g_t, which captures the change in the CA between t and $t-k$ relative to average total flows:

$$g_t = \frac{ca_t - ca_{t-k}}{\frac{1}{4}\left(x_t + m_t + x_{t-k} + m_{t-k}\right)}. \tag{3}$$

This measure is symmetric around zero, bounded—effectively capturing large swings in the CA without extreme values—, and can handle firm entry and exit (Törnqvist et al., 1985; Davis et al., 1998). Unlike log-differences, it does not require strictly positive flows and avoids distortions when values are close to zero. Moreover, it facilitates analysis at multiple levels of aggregation: from the detailed product-country flows to the headline CA balance.[3]

We extend this definition to the firm level and express aggregate the CA growth as a weighted sum of firm-level CA growth rates g_{ipct}:

$$g_t = \sum_{i,p,c} w_{ipct} g_{ipct}, \tag{4}$$

where the firm weights w_{ipct} are calculated as:

$$w_{ipct} = \frac{x_{ipct} + x_{ipct-k} + m_{ipct} + m_{ipct-k}}{x_t + x_{t-k} + m_t + m_{t-k}}. \tag{5}$$

In this framework, firm weights—the share of firm i's transactions relative to total transactions—reflect the relevant measure of firm size. This weighting allows us to capture the contribution of large firms in driving overall CA growth.

2.3 Defining product-country and idiosyncratic shocks

Building on Gabaix (2011), we decompose the firm-level growth rate g_{ipct} into a common product-country component and a firm-specific residual:

$$g_{ipct} = \delta_{pct} + \varepsilon_{ipct}. \tag{6}$$

where δ_{pct} captures product-country shocks shared by all firms trading product p with country c, and ε_{ipct} is the idiosyncratic deviation of firm i.

We compute the common component δ_{pct} as the average growth rate across all firms in the p, c, t triplet:

$$\delta_{pct} = \frac{\sum_i g_{ipct}}{N_{pct}}, \tag{7}$$

where N_{pct} is the number of firms with product p flows to country c at time t.

We thus assume that the product-country shock δ_{pct} depends on the partner country of a transaction and the type of transaction, in a similar vein to di Giovanni et al. (2014). This assumption allows to account for the shared economic conditions that influence flows

[3]Our empirical analysis focuses on growth rates of the CA rather than levels or first differences, following the standard approach in the granularity literature (e.g., Gabaix, 2011; di Giovanni et al., 2014; di Giovanni et al., 2024). While the literature on CA dynamics typically studies CA balances in levels (Chinn and Prasad, 2003, Boer et al., 2024), we opt for growth rates because this allows for clear identification of firm-level idiosyncratic shocks as proportional deviations from common product-country trends. Using levels or first differences would require imposing arbitrary assumptions about a firm-specific baseline or equilibrium CA level, which is conceptually unclear and potentially arbitrary.

across firms engaged in similar types of transactions. For example, fiscal and monetary policies in a partner country can have broad effects on all firms trading with that country, influencing the prices of goods and services or the terms of trade. Similarly, product-specific shocks, such as a boom in demand for specific goods, can affect all firms trading that particular product.

To provide more intuition on the nature of product-country-level shocks, it is useful to consider examples from the literature. For goods trade, common product-country shocks may include shifts in relative demand between domestic and foreign goods due to shifts in consumer preferences or macroeconomic conditions (Boer et al., 2024), or the introduction of sector-wide trade barriers affecting all firms exporting a particular good to a specific country (Alessandria and Choi, 2021). In services trade, relevant macro-level shocks could arise from global events, such as widespread travel restrictions to or from a specific country affecting transportation services, or regulatory changes such as stricter cross-border service provision rules. For the income balance, product-country-level shocks typically reflect monetary policy shocks, shifts in risk premia, or other unexpected financial market developments that affect interest rate differentials between countries. These macroeconomic events influence aggregate cross-border investment returns and income flows at the product-country level (Herkenhoff and Sauré, 2021; Behar and Hassan, 2022; Donato and Tille, 2024).

The idiosyncratic shock ε_{ipct} captures the deviations of individual firms from the product-country shock. Formally, it is derived as the difference between the firm-level growth rate and the product-country shock:

$$\varepsilon_{ipct} = g_{ipct} - \delta_{pct}. \tag{8}$$

This expression isolates the firm-specific deviations that are not explained by broader macroeconomic shocks, reflecting idiosyncratic factors such as firm management, innovation, or unexpected disruptions at the firm level. These shocks can vary widely across firms, especially in markets with large, dominant firms that experience unique supply or demand conditions.

Concerning the nature of idiosyncratic shocks, the granularity literature offers several detailed examples. For instance, di Giovanni and Levchenko (2012) and di Giovanni et al. (2014) identify firm-specific productivity shocks, which alter firms' export competitiveness independently of sector-wide trends; and demand shocks, capturing firm-specific changes in foreign consumers' preferences or perceptions of product quality. In their subsequent work, di Giovanni et al. (2024) further introduce firm-specific cost shifters related to firms' unique sourcing strategies, affecting their costs of imported intermediates, in addition to the aforementioned demand shifters. Similarly, Barrot and Sauvagnat (2016) document firm-specific supply-chain disruptions, such as unique shocks to critical suppliers, affecting individual firms' input costs and imports independently from broader industry conditions. Amiti and Weinstein (2018) provide evidence of unique financial shocks to large firms, such as sudden changes in credit availability or financial distress, impacting their cross-border investment income flows in ways distinct from other firms operating within the same industry. Each of these examples highlights specific types of shocks that could plausibly apply within our empirical framework.

Our measure of idiosyncratic shocks captures deviations in a firm's growth rate from the average growth rate at the product-country level. As such, these shocks reflect the net impact of potentially simultaneous firm-specific shocks affecting receipts and expenses. For example, a positive idiosyncratic shock could result from a firm-specific export demand increase not fully offset by the associated rise in imported intermediate goods, or from a unique, firm-specific improvement in net income flows due to dividend repatriation decisions. Although our methodology does not disentangle these underlying shocks, this net measure aligns closely with the aggregate CA concept, which is the relevant measure from a macroeconomic perspective. Our primary focus is on capturing the aggregate outcomes of these shocks, rather than identifying their individual structural origins.

Moving from the firm-level to the aggregate view, we express the aggregate growth rate g_t as the weighted sum of both product-country and idiosyncratic shocks. This aggregation is performed across all firms, products, and countries. The aggregate growth rate is thus decomposed as follows:

$$g_t = \underbrace{\sum_{p,c} w_{pct}\delta_{pct}}_{\text{product-country shocks}} + \underbrace{\sum_{i,p,c} w_{ipct}\varepsilon_{ipct}}_{\text{idiosyncratic shocks}=\Gamma_t}, \tag{9}$$

where $w_{pct} = \sum_i w_{ipct}$ is the weight of product-country pair p, c within total CA transactions at time t. The first term captures the contribution of product-country shocks, reflecting the influence of broad, shared factors across firms within each product-country pair, to headline growth. The second term captures the impact of common shocks, aggregated across firms. Following Gabaix (2011), we denote this term, $\sum_{i,p,c} w_{ipct}\varepsilon_{ipct}$, as the granular residual Γ_t, which is the size-weighted sum of idiosyncratic shocks. If the distribution of firm sizes is fat-tailed, then large firms may have an outsized influence on aggregate outcomes.[4]

Overall, our framework provides a way to analyze CA movements both at the micro level, capturing firm-specific shocks, and at the macro level, capturing the aggregate impact of these shocks on the headline CA balance. Its flexibility also allows for different

[4]Prior work (e.g., di Giovanni et al., 2014; Alvarez-Blaser et al., 2025) estimates firm-level residuals from a fitted regression model and computes the granular residual as the size-weighted sum of estimated residuals. By contrast, we construct the granular residual directly from the data using the average growth rate within each product-country cell. While both methods yield equivalent granular residuals, the estimation approach produces regression residuals subject to specification error, while our construction method is fully non-parametric.

levels of aggregation, facilitating analysis across product-country pairs and the headline CA balance.

3 Data and descriptive evidence

3.1 Panel construction

This paper is among the first to construct a firm-level dataset for the CA (Wicht and Yeşin, 2025). We leverage three mutually exclusive firm-level data sources, each covering different aspects of Switzerland's official CA statistics. First, we use the customs data from the Swiss Federal Office for Customs and Border Security (FOCBS), which forms the foundation for the goods trade component. Second, we use the CA surveys conducted by the Swiss National Bank (SNB), which mainly capture services trade and secondary income. Third, we use the SNB's quarterly cross-border capital linkages survey (INQ survey), which collects data on cross-border stocks and capital flows. While the INQ survey is primarily designed for the compilation of the international investment position and the financial account, it also provides information on investment income linked to cross-border assets and liabilities, making it relevant for the CA.

These data sources differ substantially in structure and coverage: The customs data is an administrative dataset recorded daily, capturing the full universe of Swiss cross-border goods transactions by approximately 375,000 firms. In contrast, the CA and INQ surveys target the largest transactions, rather than the full universe of cross-border activities. The CA surveys cover firms with quarterly transactions exceeding 100,000 Swiss francs, and the INQ survey focuses on firms with foreign transactions above 1 million Swiss francs per reporting item, or cross-border stocks exceeding 10 million Swiss francs per reporting item. The CA surveys cover around 1,300 firms, the INQ survey around 800 firms.

Following the methodology used in Swiss official statistics, we append these three data sources to construct a unique firm-level dataset. Importantly, data sources are not merged at the micro level as firm identifiers are not easily reconcilable across the three data sources. This approach to constructing the panel is consistent with our framework, in which the unit of observation is the firm-product-country triplet. In addition, the panel is unbalanced. Given the different natures of the data sources—administrative versus survey data—a firm may only appear in a specific data source, which is also an underlying feature of official statistics.

In constructing the panel, we align frequency, sample period, country breakdowns, and product classifications according to the official reporting structure to form our unit of observation: the CA balance of firm i in product p vis-à-vis partner country c at time t. Our dataset is structured at quarterly frequency, spanning from Q1 2015 through Q4 2024, allowing us to capture both longer-term trends and short-term fluctuations in the CA balance. Additionally, we account for cross-border transactions with 70 partner countries c or country groups, providing global coverage through regional aggregates for smaller economies.[5] Finally, to capture product-specific heterogeneity, we follow official breakdowns to construct products and further decompose goods trade based on the official FOCBS classifications.[6] This yields 27 distinct products p, encompassing three aggregate components: goods, services, and income.

While our panel aligns closely with official CA statistics, we make two adjustments by excluding two specific products: merchanting and goods trade subtractions. Official statistics report merchanting receipts, which are defined as net merchanting, i.e., the margin on sales.[7] In contrast, merchanting expenses, as a statistical concept, do not exist. This asymmetric treatment implies negative receipts across partner countries, typically if countries serve as suppliers rather than buyers in merchanting transactions. Given negative receipts and non-existent expenses, including merchanting in our panel would result in nonsensical growth rates and weights. We thus exclude that product from our baseline panel. Furthermore, we exclude trade subtractions, which by definition are deducted from receipts and expenses in official statistics and reported as negative entries. Again, we abstract from subtractions to avoid negative entries.[8]

The resulting panel approximates official statistics very well. Figure 1 shows our coverage of official statistics. Figure 1a depicts the coverage of gross flows, defined as receipts plus expenses. Overall, our panel captures about three quarters of quarterly gross flows and closely replicates the evolution of gross flows over the sample period. Figure 1b shows the coverage of the CA balance. Our panel closely approximates the level and movements in the CA balance, with a correlation between the two series of 0.6. Given the high coverage of both gross and net flows, and its ability to closely replicate CA fluctuations, we conclude that our panel is highly suited for analysis.

Importantly, all three data sources are key to closely approximate movements in the CA balance. Figure 2 shows the decomposition of the level and growth rate of the headline CA based on the panel into aggregate components (goods, services, and income), which, as mentioned above, are each mainly derived from one of the three data sources: customs, the CA surveys, and the capital linkages survey, respectively. All three aggregate components play a major role in determining the headline CA balance. As shown in Figure 2a, the headline CA does not equate the goods trade balance. Instead, while the goods surplus is persistent and sizeable, a systematic and growing services trade deficit as well as a

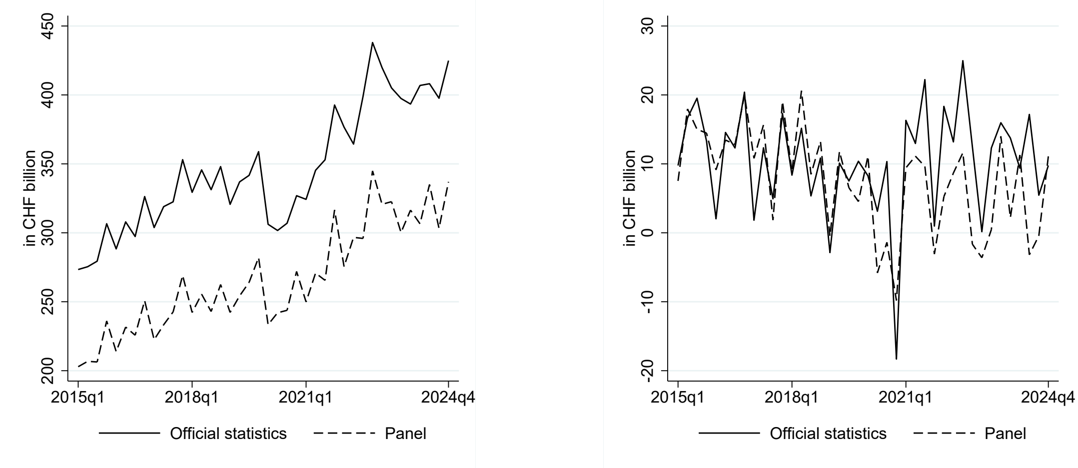
[5] Table A1 in the Appendix details the product and partner country breakdowns.

[6] Refer to the SNB data portal. For the breakdowns of goods trade, we use the “nature of goods” classification, available on the FOCBS data portal.

[7] Merchanting is defined as goods trade that does not cross the border of the firm’s resident country, common in the activities of commodity traders and global value chain management of large multinationals. Merchanting data are collected through the SNB’s CA surveys.

[8] In a robustness test, we test our analysis by including those two components under specific assumptions.

Figure 1: Coverage of the quarterly CA



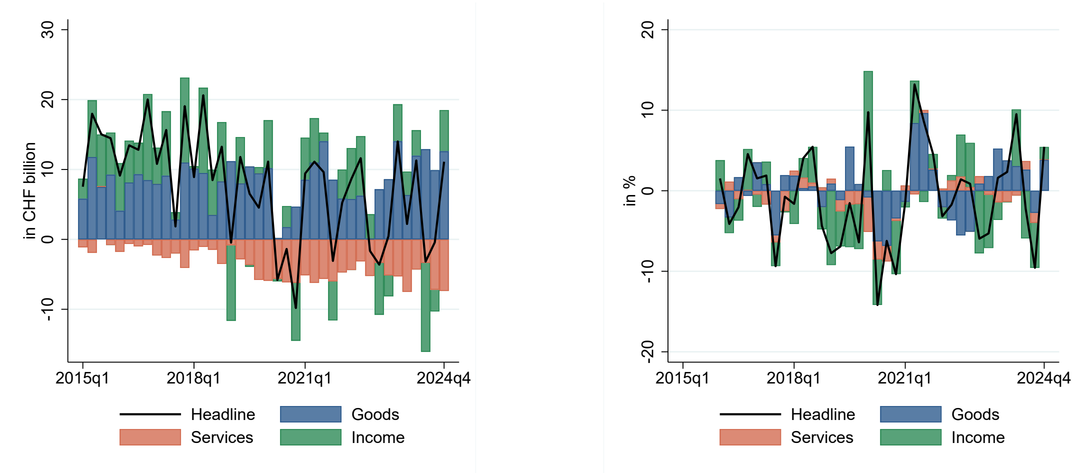
(a) Gross flows

(b) Balance

Notes: This figure reports the coverage of official CA statistics by our panel in (a) gross flows (receipts plus expenses), and (b) the balance. The solid line shows official statistics. The dashed line shows the firm-level panel.

volatile but on average positive income balance also distinctly shape the headline CA. Then, Figure 2b confirms that no single component drives movements in the headline CA. Developments in all three aggregate components, sometimes offsetting each other, sometimes reinforcing each other, contribute to the headline CA growth rate.

Figure 2: Headline CA and aggregate components



(a) Level

(b) Growth rate

Notes: This figure reports the headline CA and its decomposition into the three aggregate components (goods, services, and income) based on the panel. Figure (a) shows the levels in CHF billion and Figure (b) shows the year-on-year growth rate.

3.2 Summary statistics

Based on this panel, we construct the relevant variables as defined in Section 2. Namely, we construct firm weights according to equation (5) and firm-level growth rates based on equation (6). Then we extract idiosyncratic and product-country shocks using equations (7) and (8). In our baseline results, we consider year-on-year growth rates to both exploit the quarterly frequency of our panel and reduce noise from seasonal patterns in the CA balance.

Table 1 provides summary statistics of the distribution and variation in those variables. Our final sample results in about 36 million observations, spanning 2016 Q1-2024 Q4, 27 products, 70 partner countries, and more than 350,000 firms.[9] The firm size w_{ipct}, calculated as the relative weight of each firm's transactions in total CA transactions, has an average value close to zero, with a maximum of 0.03%. This low mean is due to the large number of firms that engage in CA transactions only sporadically or in small volumes, resulting in many entries with values close to or at zero. The firm-level growth rate, g_{ipct}, with a mean near zero, has a standard deviation indicating significant variability in CA dynamics across firms, products, and countries. The minimum and maximum values of -4% and 4%, respectively, reflect the bounded nature of our measure, a characteristic that arises from our choice to use the mid-point growth rate.

Idiosyncratic shocks, ε_{ipct}, which represent firm-specific deviations from product-country averages, have substantial variability, as shown by the standard deviation. This indicates that individual firms experience distinct shocks that may not be attributable to broader product-country trends. The standard deviations are very similar compared to the actual firm-level growth rates, indicating that they largely determine firm-level growth. In contrast, product-country shocks, δ_{pct}, observed at a more aggregated level (about 67,000 observations), are much less volatile. This stability aligns with expectations, as product-country shocks capture macroeconomic and industry-wide factors rather than firm-specific factors.

[9] Most observations of the panel come from the goods trade component given the extensiveness of the customs data. As shown in Figure 2, however, all three aggregate components are key for the headline CA. For clarity, Table A2 in the Appendix reports summary statistics by aggregate component.

Table 1: Summary statistics

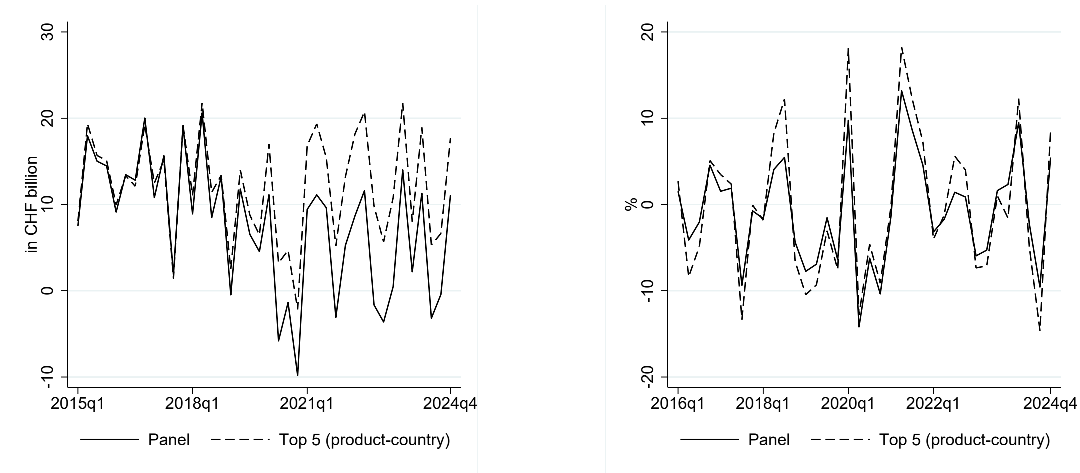
	N. obs.	Mean	St. Dev.	Min	Max
Firm size w_{ipct} (%)	36,050,088	0.0001	0.00	0.00	0.03
Firm-level growth rate g_{ipct}	36,050,088	-0.0550	3.33	-4.0	4.0
Idiosyncratic shocks ε_{ipct}	36,050,088	0.0000	3.32	-6.9	7.3
Product-country shocks δ_{pct}	67,222	-0.0364	0.77	-4.0	4.0

Notes: This table presents summary statistics of the main variables in the analysis, following equations (5), (6), (7) and (8).

3.3 Granularity in the CA: descriptive evidence

To build intuition around the concept of granularity, we begin with a purely descriptive analysis. Figures 3a and 3b compare the contribution of the top 5 firms within each product-country pair to the overall CA balance.[10] Both figures demonstrate that the top 5 firms account for a significant portion of the CA balance, both in terms of its level and its growth rate. The correlation between the CA balance generated by the top 5 firms and the panel is 0.87, while the correlation between the CA growth rate generated by the top five and the panel is 0.96.

Figure 3: Contribution of top 5 firms in the CA



(a) CA balance

(b) CA balance growth

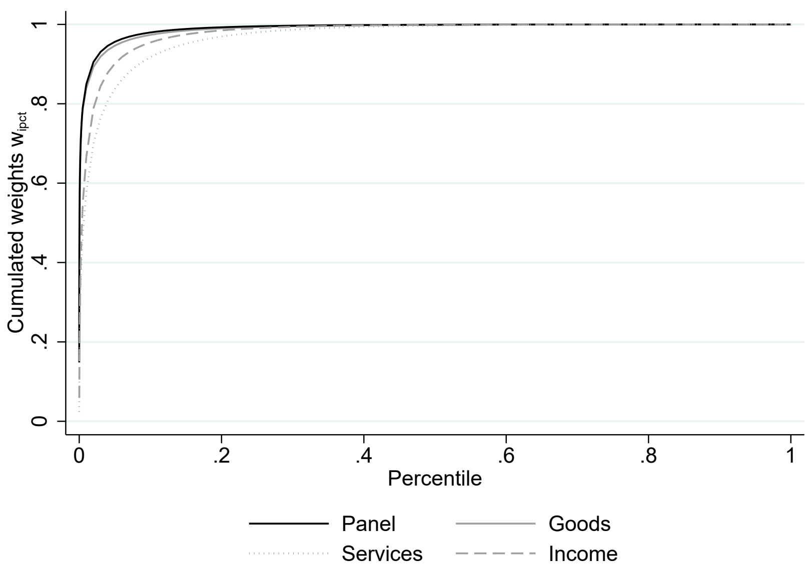
Note: Figure (a) shows the CA balance in CHF billion in our panel (solid line) and generated by the top 5 firms across product-country pairs. Figure (b) shows the growth rate in the CA balance in the panel (solid line) and generated by the top 5 firms across product-country pairs.

Figures 3a and 3b provide compelling evidence of the dominance of a few large firms, but they do not directly confirm the granular hypothesis. The granular hypothesis be-

[10]The top 5 is the five firms with the largest weights, or flows, within a product-country pair within a quarter.

comes empirically relevant only if the distribution of firm sizes is fat-tailed. Figure 4 presents the distribution of firm sizes in our data, as captured by the weights w_{ipct}. The solid black line illustrates that the vast majority of CA flows are associated with a very small fraction of firms. Specifically, the top 1 percentile of firms account for nearly 85% of CA receipts and expenses. Similarly, the top 1 percentile account for 84% of goods trade, 58% of services trade, and 67% of income flows. Thus, both at the level of main CA components and for the full panel, a fraction of firms with very large weights contribute a disproportionately large share of flows. This pattern clearly demonstrates the fat-tailed nature of the firm size distribution in the Swiss CA balance.[11] This pattern further echoes the well-established empirical fact in the international trade literature that a few firms dominate exports and imports (e.g., Freund and Pierola, 2015, Bernard et al., 2018), while showing that this prevalence goes beyond goods trade and applies to other CA components.[12]

Figure 4: Firm size distribution in the CA



Note: This figure shows the firm size distribution. The x-axis represents the percentiles of the firm size distribution, while the y-axis shows the cumulative weights in CA receipts and expenses, as defined in equation (5), and as an average over time.

[11]These patterns are influenced by the underlying datasets, as the customs data covers the entire universe of firms, while the surveys focus on the largest firms. Figure A1 in the Appendix shows the cumulative weights generated by the top 10,000 firm weights, further confirming the presence of fat tails in the firm size distribution.

[12]Figure A2 in Appendix A further documents that this pattern is not driven by a specific direction of trade flows. Instead, the bottom percentiles in the firm size distribution explain both a significant share of exports and of imports.

4 Regression analysis

4.1 Aggregate level regressions

To empirically assess the role of granularity in driving CA fluctuations, we estimate the relationship between the granular residual and the growth rate of the CA balance. The granular residual captures the size-weighted sum of idiosyncratic firm-level shocks, following the approach outlined in Gabaix (2011). Our objective is to quantify the sensitivity of the CA growth rate to these idiosyncratic shocks.

Formally, we estimate the following regression:

$$g_t = \alpha + \beta \Gamma_t + \eta_t, \tag{10}$$

where g_t is the aggregate year-on-year growth rate of the headline CA as defined in equation (4) and Γ_t is the granular residual as defined in equation (9).

Table 2 displays the regression results for the headline CA. We find a highly statistically significant and strong effect of the granular residual on the aggregate CA, with an adjusted R^2 of 0.63, indicating that granular shocks explain about two thirds of the variation in the headline CA growth rate. The coefficient implies that a 1 percentage point increase in the granular residual is associated with a roughly 0.7 pp increase in the growth rate of the headline CA. The granular residual thus significantly impacts the headline CA balance, suggesting that large firms' shocks can meaningfully shape external balances. This finding challenges the assumptions of an atomistic firm framework, where individual shocks are expected to cancel out in the aggregate, and highlights the critical role of firm-level granularity in understanding CA volatility.

Table 2 further shows the impact of the granular residual on sub-samples by aggregate components. We thus consider the growth of the goods trade balance, services trade balance, and income balance and construct the corresponding granular residual g_t for each sub-sample separately. Overall, we find that the granular impacts the growth rate of each aggregate component but with varying magnitudes. The results are weakest for the goods trade balance, with a coefficient of 0.4 and an R^2 of 0.4. In contrast, we find large coefficients for the services and income balances of about 0.8 and 0.9, with R^2 of 0.5 and 0.9 respectively.

Thus, when contrasting these results with those of the headline CA, we conclude that equating the CA balance with the goods trade balance would overlook heterogeneous patterns in CA dynamics. Indeed, the income balance is by far the most subject to idiosyncratic patterns and has a significant impact on the headline CA growth. This pattern is shown more concretely in Figure 5, which decomposes the contribution of each aggregate component to the granular residual Γ_t. The goods and income component play a major role in driving the granular residual, whereas services are less determining.

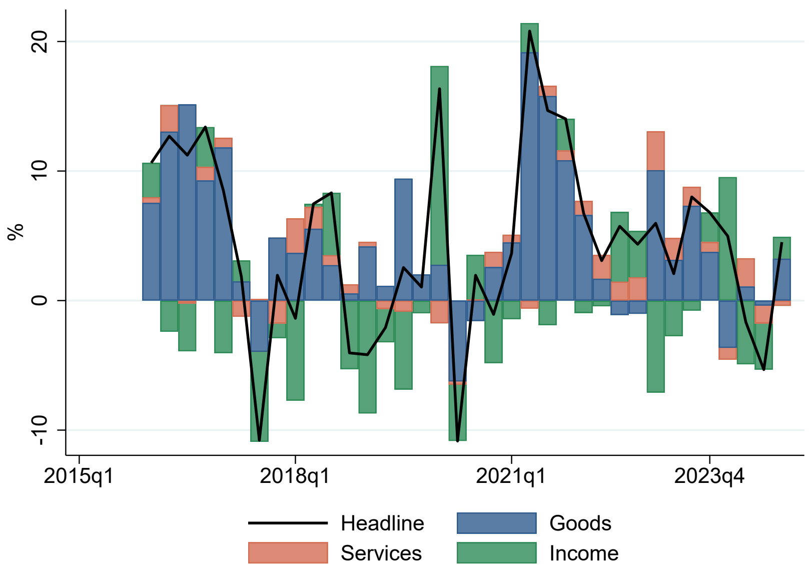
Table 2: Regression results – granular residual in the headline CA

	(1) Headline CA	(2) Goods	(3) Services	(4) Income
Granular residual Γ_t	0.692***	0.441***	0.775***	0.926***
	(0.074)	(0.104)	(0.123)	(0.056)
Observations	36	36	36	36
Adjusted R^2	0.63	0.40	0.54	0.87

Notes: The dependent variable is the year-on-year growth rate g_t of the headline CA in (1). Then, Column (2) through (3) consider the growth rate g_t based on sub-samples: the goods trade balance in (2), the services trade balance in (3) and the income balance in (4). Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Overall, idiosyncratic shocks in the goods components have contributed positively to the headline, whereas idiosyncratic shocks in the income balance tended to offset positive shocks.[13]

Figure 5: Granular residual — contribution of aggregate components



Notes: This figure shows the contribution of each aggregate component—goods, services, and income—to the headline granular residual Γ_t.

[13]We are currently implementing an Expectation-Maximization Principal Component Analysis (EMPCA), following Gabaix and Koijen (2024), to purge remaining macroeconomic components from the idiosyncratic shocks. Because our panel is highly unbalanced, applying EMPCA at the firm level would require extensive imputation and risks overfitting. We therefore perform the analysis at the product-country level, where the data are more complete. The resulting purged shocks yield results that are nearly identical to the baseline, suggesting that the aggregation may limit the usefulness of EMPCA by substantially reducing firm-level variation.

Table 3: Regression results – granular residual at product-country level

	(1) Full sample	(2) Full sample	(3) Goods	(4) Services	(5) Income
Granular residual Γ_{pct}	0.886***	0.888***	0.919***	0.834***	0.909***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.008)
Observations	67,222	67,222	34,767	22,548	9,907
Adjusted R^2	0.60	0.61	0.62	0.61	0.63
Country-time FE	no	yes	yes	yes	yes
Product FE	no	yes	yes	yes	yes

Notes: The dependent variable is the year-on-year growth rate g_{pct} of the product-country CA in (1) and (2), the goods trade balance in (3), the services trade balance in (4) and the income balance in (5). To construct the granular residual Γ_{pct}, weights are normalized by the share of product-country pair p, c in total CA flows. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

4.2 Product-country level regressions

The richness of the data allows us to extend our investigation to the product-country level, assessing the impact of the product-country granular residual on the growth rate of product-country pairs. The regression specification for the product-country level is as follows:

$$g_{pct} = \alpha + \beta\Gamma_{pct} + \mu_p + \theta_{ct} + \eta_{pct}, \tag{11}$$

where g_{pct} represents the year-on-year growth rate of the quarterly CA balance for a given product-country pair; Γ_{pct} is the granular residual within a product-country pair, with weights normalized by the share of product-country pair p, c in total CA flows.[14] The higher level of disaggregation allows us to control for product fixed effects μ_p and country-time fixed effects θ_{ct}.

Table 3 presents the regression results. Overall, the granular residual significantly explains fluctuations at the product-country level. It accounts for more than half of the variation in the growth rate, with an adjusted R^2 of about 0.6. The estimated effect size indicates that a 1 percentage point (pp) increase in the granular residual is associated with a roughly 0.9 pp increase in the growth rate of the product-country pair. This robust relationship highlights the substantial impact of idiosyncratic shocks on CA dynamics. Notably, the coefficient remains stable with the inclusion of country-time and product fixed effects, suggesting that unobserved factors are not a major influence within our framework.

The robustness of this granular effect at the product-country level reinforces the granular hypothesis, showing that the effect found for the headline are not driven by a specific type of product or partner country, but are persistent across product-country pairs. The

[14]This exercise boils down to applying the framework described in Section 2 to the CA flows of a given product-country pair p, c, i.e., $ca_{pct} = \sum_i ca_{ipct}$. Then, the granular residual is: $\Gamma_{pct} = \sum_i w_{ipct}\varepsilon_{ipct}$, where $w_{ipct} = (x_{ipct} + x_{ipct-k} + m_{ipct} + m_{ipct-k})/(x_{pct-k} + x_{pct-k} + m_{pct} + m_{pct-k})$.

results are further fully robust across subsamples for each aggregate component. As shown in Table 3, the results confirm that the granular residual has a strong and statistically significant effect on CA growth across all three components. For example, in the goods component, a 1 percentage point (pp) increase in the granular residual is associated with a roughly 0.9 pp increase in the CA growth rate (Column 3), 0.8 in the services component (Column 4), and 0.9 in the income component (Column 5). Adjusted R^2 are also similar, about 0.6.

Taking a step further, we consider subsamples of single products. For each product p, we estimate:

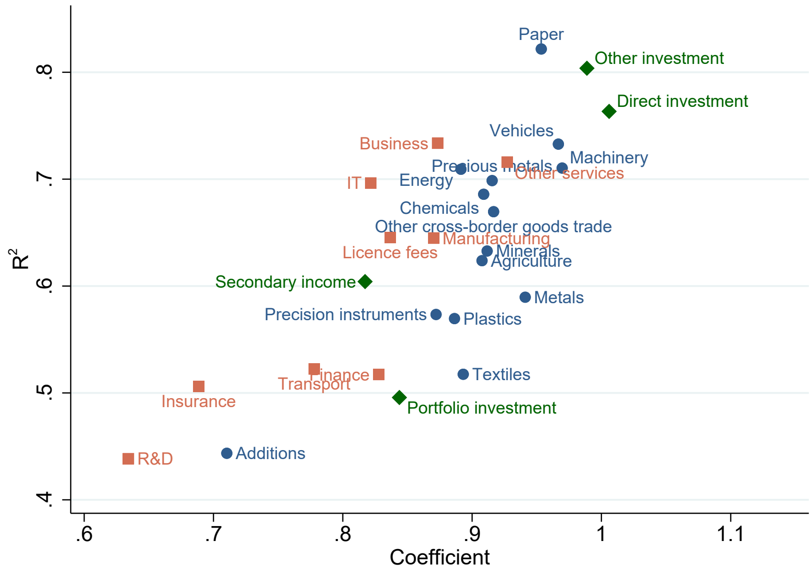
$$g_{pct} = \alpha + \beta\Gamma_{pct} + \mu_c + \theta_t + \eta_{pct}, \tag{12}$$

where g_{pct} is the growth rate of the CA balance for product-country pair p, c, Γ_{pct} is the granular residual within product-country pair p, c, in which weights are normalized by the share of the product-country pair in total CA flows, μ_c and θ_t are country and time fixed effects.

When analyzing the relationship between the granular residual and the CA growth rate at this disaggregated level, we find substantial variation in both the magnitude of the coefficients and the explanatory power of the granular residual across products. Figure 6 presents the results by plotting the estimated coefficients against the R^2 values for each product regression. Several products display pronounced granular effects, with high coefficients and substantial R^2 values, indicating that idiosyncratic shocks to large firms within these products significantly drive CA fluctuations. Notably, other investment and direct investment exhibit the largest coefficients and highest R^2 values. In contrast, R&D and insurance show relatively lower coefficients and R^2 values, indicating that idiosyncratic shocks within these products have a relatively minor influence on headline CA fluctuations. This variation likely reflects underlying differences in market structure and firm concentration across products. Overall, most products within the income component display large coefficients and high R^2 values, underscoring that idiosyncratic shocks to firms in this component are particularly influential in driving CA volatility. In contrast, products within the services component tend to have smaller coefficients and lower R^2 values, suggesting a lesser role for granular effects in that component.

This variation across products and CA components underscores the relevance of analyzing CA granularity at a more detailed level. While aggregate measures can capture the broad significance of idiosyncratic shocks, a disaggregated approach reveals the specific products where firm-level heterogeneity plays a particularly important role. These findings reinforce the importance of considering product-level dynamics to understand the full impact of firm-level shocks on the CA balance.

Figure 6: Granularity across products



Notes: This figure plots the R^2 against the coefficients from the regressions based on equation (12). Blue dots comprise products within the goods component, orange squares those within services, and green diamonds those within income.

4.3 Robustness

To conclude our regression analysis, we conduct an extensive series of robustness tests to validate the consistency of our findings, which we present in Table 4. In a first robustness check, we consider the frequency of the panel. We collapse the baseline panel over years and replicate the analysis at the product-country level.

Columns (1) and (2) of Table 4 present the results. Overall, the results are entirely robust, both in terms of the magnitude of the coefficients and the explanatory power. We find a coefficient of about 0.8 and a R^2 of about 0.6. We thus conclude that the strong relationship between idiosyncratic shocks and CA fluctuations extends beyond business cycle variations. It persists at the medium-term, as evidenced by the results of Table 4. This finding speaks to the literature on CA determinants (Chinn and Prasad, 2003), which often focuses on annual data. The persistence of this effect at both quarterly and annual frequencies underscores the central role of granularity in explaining CA dynamics over different time horizons.

The second robustness check focuses on the intensive margin, where we exclude firms that either start or stop to trade a particular product with a particular trading partner.[15] The main analysis accounts for the extensive margin, as this is crucial for replicating the official CA balance and understanding patterns in the published data. By restricting the analysis to firms consistently reporting non-zero CA transactions, we assess whether

[15]Formally, we restrict the panel to firms that incurred net flows from and to a particular trading partner for a given product between each period t and $t - k$.

the observed effects are driven by firms with regular cross-border activities. Columns (3) and (4) of Table 4 present the results for this intensive margin subsample. The granular effect first persists at the aggregate level (Column 3), with a coefficient of 0.70 and an adjusted R^2 of 0.69. This result indicates that in the headline, the impact of idiosyncratic shocks on headline CA growth is robust among firms with sustained economic activity in the external sector. Large firms, with significant and persistent cross-border linkages, thus drive most of the effect. At the product-country level, the granular residual remains highly statistically significant, with a coefficient size close to that of the main analysis (Column 4). The R^2, however, is halved. This suggests that including firms with zero observations (i.e., firms that are intermittently active or contribute to CA fluctuations only sporadically) captures more of the variability in the CA growth rate at a finer level of aggregation. This is also reflected in the number of observations, which declines from 67,222 in the extensive margin to 52,089 in the intensive margin. This implies that a significant share of product-country pairs only reflects flows by on-and-off cross-border relationships, rather than continuing ones.

In a third robustness check, we extend the sample to include merchanting flows and trade subtractions. To include merchanting, we assign merchanting sales to receipts and merchanting purchases to expenses, rather than relying on the official netting approach.[16] This assumption has a substantial impact on gross flows, and thus firm weights, as merchanting receipts shoot up from a quarterly average of CHF 12.5 billion under the netting approach to CHF 210 billion applying our approach. Furthermore, we adjust the treatment of goods trade subtractions. We simply reverse the signs, treating receipts as expenses and expenses as receipts. Compared to published data, this adjustment distorts gross flows, again affecting firm weights.

Columns (5) and (6) of Table 4 show that while these adjustments do not greatly alter our findings at the product-country level—where the granular effect and explanatory power of our model remain robust—the aggregate CA level reveals notable discrepancies. With the inclusion of merchanting flows and trade subtractions, the headline coefficient drops to 0.2, and the adjusted R^2 declines to 0.22. This result is likely primarily driven by the inclusion of merchanting, as it markedly shifts firm weights, distorting the prominence of firms involved in merchanting relative to others in the CA. It suggests that the additional noise introduced by these flows reduces our ability to explain CA fluctuations at the aggregate level through the lens of the granular hypothesis. Merchanting flows, which play an exceptionally outsized role in the Swiss external sector, may be on average less granular: common shocks, such as shifts in commodity prices, are likely to play a relatively more important role than purely idiosyncratic ones. Nevertheless, we can still confidently confirm the significant relationship between the granular residual and

[16]While gross merchanting flows are not part of the official CA statistics, they are published as part of supplementary tables.

Table 4: Regression results — robustness tests

	Yearly sample		Intensive margin		Extended sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	g_{pct}	g_{pct}	g_t	g_{pct}	g_t	g_{pct}
Granular residual Γ_{pct}	0.842***	0.849***		0.881***		0.887***
	(0.007)	(0.007)		(0.006)		(0.003)
Granular residual Γ_t			0.701***		0.201***	
			(0.102)		(0.065)	
Observations	16,896	16,896	36	52,089	36	72,254
Adjusted R^2	0.59	0.63	0.69	0.31	0.22	0.62
Country-time FE	no	yes	no	yes	no	yes
Product FE	no	yes	no	yes	no	yes

Notes: This table presents robustness results using a yearly panel (Columns 1 and 2), restricting the panel to the intensive margin (Columns 3 and 4), and extending the panel to include merchanting and trade subtractions (Columns 5 and 6). The dependent variables are the year-on-year growth rates of the headline CA g_t and of the product-country pair g_{pct}. To construct the granular residual Γ_{pct}, weights are normalized by the share of product-country pair p, c in total CA flows. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

CA growth. As such, this robustness check validates the generalizability of our granular analysis across the full CA.

Appendix B shows three additional robustness checks. We find that our results are robust to using quarter-on-quarter changes in the CA balance, to splitting the sample into pre- and post-Covid periods, and to redefining the granular residual to include only the top 5 firms. These robustness checks further validate the consistency of the granular effect in explaining CA fluctuations. Overall, these results reinforce the importance of firm-level dynamics in shaping aggregate external sector outcomes and provide additional support for the central role of idiosyncratic shocks in CA fluctuations.

5 Variance decomposition of CA volatility

5.1 Product-country and idiosyncratic volatility

To assess the impact of idiosyncratic shocks on the volatility of the CA balance, we perform a variance decomposition. This decomposition, based on equation (9), is complicated by the time-varying nature of firm weights w_{ipct}. Akin to the analyses performed in Carvalho and Gabaix (2013) and di Giovanni et al. (2014), we generate synthetic growth rates by fixing the firm weights over time to simplify the analysis. Formally:

$$g_{t|\tau} = \sum_{p,c} w_{pc\tau}\delta_{pct} + \sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct}, \tag{13}$$

where $g_{t|\tau}$ is the CA growth rate with fixed firm weights $w_{ipc\tau}$ for a given period τ, combined with shocks from period t. For $\tau = t$, the synthetic growth rate coincides with the actual growth rate.

The variance of the headline CA growth rate, conditional on τ, can then be decomposed as follows:

$$\begin{aligned}\sigma_\tau^2 = \quad & \underbrace{var(\sum_{p,c} w_{pc\tau}\delta_{pct})}_{\sigma^2_{\delta,\tau}\text{: product-country volatility}} \quad + \quad \underbrace{var(\sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct})}_{\sigma^2_{\varepsilon,\tau}\text{: idiosyncratic volatility}} \\ & + \underbrace{2cov(\sum_{p,c} w_{pc\tau}\delta_{pct}, \sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct})}_{\text{covariance term}}\,.\end{aligned} \tag{14}$$

The first term in the decomposition measures the contribution of the volatility of product-country shocks, which affect all firms within a given product-country pair, to aggregate volatility. The second term captures the volatility of idiosyncratic shocks, which can exert a disproportionate influence on aggregate volatility when the firm size distribution is fat-tailed.

Table 5 presents our estimates from the variance decomposition. In line with previous literature, we report standard deviations as measures of volatility and provide average volatility estimates for σ_τ, $\sigma_{\delta,\tau}$, and $\sigma_{\varepsilon,\tau}$ over the sample period. Our results indicate that idiosyncratic shocks are a major driver of headline CA volatility. Specifically, the standard deviation of idiosyncratic volatility is 1.15 times that of the aggregate volatility. Product-country shocks are less influential: their contribution accounts for a standard deviation of 0.47 relative to the overall CA volatility. Idiosyncratic shocks are thus the main drivers of aggregate volatility. Indeed, we find that idiosyncratic shocks are 2.5 times more important compared to product-country shocks. These results are broadly in line with the findings of di Giovanni et al. (2014), who similarly report the dominant role of firm-specific shocks in explaining aggregate volatility in sales growth.

Table 5 further reports the results of the volatility decomposition by major CA components. Across goods, services, and income, we consistently find that idiosyncratic volatility is the major driver of CA volatility. The magnitude of the effect, however, varies across components. Thus, product-country volatility is most relevant for the goods components, with a ratio to aggregate volatility of 0.66. In contrast, product-country volatility only accounts for 0.46 and 0.22 of aggregate volatility for the services and income component, respectively. We further find a ratio of idiosyncratic to aggregate volatility of 1.17 in the goods component, 1.05 in the services component, and 0.97 in the income component. Importantly, these results imply stark differences in the relative importance of idiosyncratic volatility to that of product-country volatility: 1.8 in goods, 2.3 in services, and 4.4 in income. Then, although the contribution of idiosyncratic shocks to aggregate volatility is the highest for the goods component, we find that idiosyncratic

Table 5: The impact of idiosyncratic shocks on CA volatility

	Standard deviation			Relative standard deviation		
	Total	Product-country	Idiosyncratic	Product-country to total	Idiosyncratic to total	Idiosyncratic to prod.-country
	σ	σ_δ	σ_ε	σ_δ/σ	$\sigma_\varepsilon/\sigma$	$\sigma_\varepsilon/\sigma_\delta$
Headline CA						
	(1)	(2)	(3)	(4)	(5)	(6)
	0.0915	0.0427	0.1052	0.47	1.15	2.46
By main component						
	(1)	(2)	(3)	(4)	(5)	(6)
Goods	0.1174	0.0775	0.1379	0.66	1.17	1.78
Services	0.0913	0.0419	0.0959	0.46	1.05	2.29
Income	0.2699	0.0597	0.2610	0.22	0.97	4.37

Notes: The table reports the decomposition of headline CA volatility, following equation (14), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016Q1}^{2024Q4} \sigma_{\varepsilon,\tau}$.

shocks are much more influential than product-country shocks for the services and income components. These nuanced results underline again that dynamics in the CA balance may hide heterogeneous patterns, not always driven by the commonly studied goods trade balance.

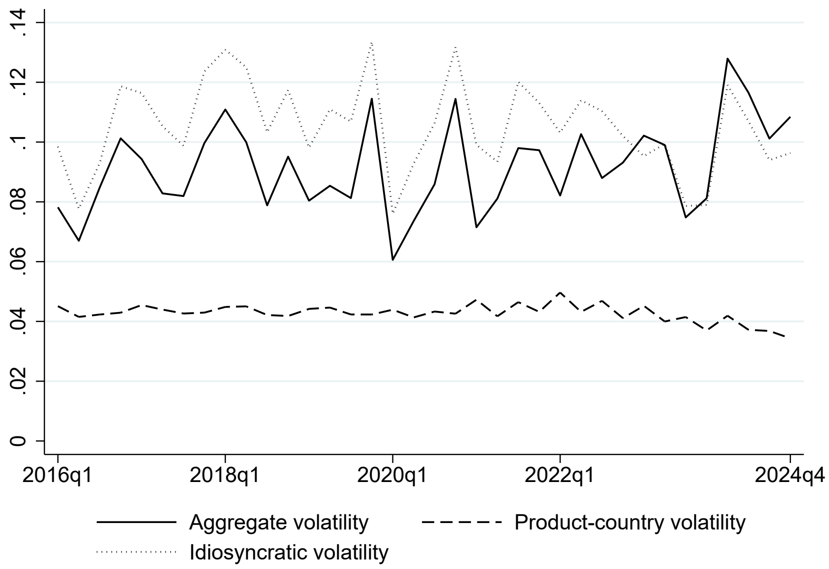
Figure 7 shows the standard deviations of headline CA volatility (solid line), alongside the product-country volatility (dashed line) and idiosyncratic volatility (dotted line) over time. Again, idiosyncratic volatility, rather than product-country volatility, is the dominant factor driving headline CA fluctuations. The dotted line closely mirrors the movements in headline CA volatility, suggesting that idiosyncratic shocks are responsible for the bulk of CA volatility.

In contrast, product-country volatility remains stable throughout the period, despite global events such as the Covid-19 pandemic and geopolitical shifts. This stability implies that broader macroeconomic fundamentals—such as global interest rates, inflation, and aggregate demand—may not have been the primary drivers of CA volatility during this period. Instead, the results suggest that firm-specific factors, perhaps tied to large multinationals in key industries, played a more significant role in shaping the external balance.

It may seem surprising that product-country volatility plays a relatively smaller role. However, as firms dominating the CA have well-integrated global supply chains, firm-level shocks—such as supply disruptions or demand fluctuations—may propagate through the economy more readily. This could result in large idiosyncratic effects that outpace product-country volatility. Moreover, stable product-country volatility may also suggest that policy measures, such as monetary or fiscal responses, have been effective at stabilizing the broader economy, but not necessarily in shielding individual firms or industries from shocks.

These findings, while consistent with patterns observed in the existing literature, reveal some notable differences in the relative contributions of product-country and idiosyncratic shocks. Similar to di Giovanni et al. (2014) and Grigoli et al. (2023), we observe that the contribution of product-country volatility remains relatively stable over the observation period. However, in our analysis, idiosyncratic shocks play a quantitatively more important role compared to existing studies. The higher relative contribution of idiosyncratic shocks in our findings could reflect differences in the industrial structure or the role of key firms in Switzerland's external sector, where concentrated flows and firm-specific risks play an outsized role in shaping the overall CA balance.

Figure 7: Standard deviations over time



Note: This figure shows the decomposition of headline CA volatility into product-country and idiosyncratic volatility over time.

5.2 Decomposition of idiosyncratic volatility

To gain a better understanding of the underlying mechanisms of idiosyncratic shocks, we follow the framework proposed by Carvalho and Gabaix (2013) and further decompose idiosyncratic volatility into two components: individual firm variances and firm linkages. This decomposition is formalized as follows:

$$\sigma^2_{\varepsilon,\tau} = \underbrace{\sum_{i,p,c} w^2_{ipc\tau} var(\varepsilon_{ipct})}_{\sigma^2_{G,\tau}\text{: granularity}} + \underbrace{\sum_{i,p,c} \sum_{j \neq i;p,q;c,d} w_{ipc\tau} w_{jqd\tau} cov(\varepsilon_{ipct}, \varepsilon_{jdqt})}_{\sigma^2_{L,\tau}\text{: firm linkages}} \tag{15}$$

Table 6: Decomposing idiosyncratic volatility in granular and firm-linkages effects

Standard deviation			Relative standard deviation		
Idiosyncratic	Granularity	Linkages	Granularity to idiosyncratic	Linkages to idiosyncratic	Granularity to linkages
σ_ε	σ_G	σ_L	$\sigma_G/\sigma_\varepsilon$	$\sigma_L/\sigma_\varepsilon$	σ_G/σ_L
(1)	(2)	(3)	(4)	(5)	(6)
0.1052	0.0713	0.0761	0.68	0.72	0.94

Notes: The table reports the decomposition of idiosyncratic volatility, following equation (15), as average standard deviations over the sample period, e.g., $\sigma_\varepsilon = 1/T \sum_{\tau=2016Q1}^{2024Q4} \sigma_\tau$.

The first term of this decomposition, $\sigma^2_{G,\tau}$, captures the granular effect, which reflects the direct contribution of individual firms to overall volatility based on their size and firm-specific shocks. The second term, $\sigma_{L,\tau}$, represents the firm linkages effect. This term captures the propagation of idiosyncratic shocks across firms. This mechanism is particularly relevant in the context of the CA, where large firms often engage in transactions across multiple products (within goods, services, and income).

Table 6 presents our estimates of the decomposition of idiosyncratic volatility into granular and linkage effects. These results, reported as standard deviations and averages over the sample period, indicate that both effects play a significant role in explaining idiosyncratic volatility. We find that the granular effect contributes with a ratio of 0.68 to the total idiosyncratic volatility, while the linkages effect contributes a ratio of 0.72. This suggests that both effects are broadly as important, with a ratio of 0.94 between the two components. Our findings contrast slightly with the existing literature. For instance, di Giovanni et al. (2014) and Grigoli et al. (2023) both report a more dominant role for the linkages effect, in their studies of French and Chilean exports.

5.2.1 Concentration

Given the relative importance of the granular effect, we further explore the direct contribution of firm-level concentration to overall volatility. We relate granular volatility to the Herfindahl-Hirschman Index (HHI), a widely used measure of market concentration. The HHI is particularly relevant in our context, as it captures the degree of concentration within a product type, which directly influences the magnitude of the granular effect. When the variances of idiosyncratic shocks are assumed to be equal across firms, the granular effect becomes proportional to the HHI. Formally, if $var(\varepsilon_{ipct}) = var(\varepsilon)$, then:

$$\sigma^2_{G,\tau} = var(\varepsilon) \sum_{i,p,c} w^2_{ipc\tau} = var(\varepsilon) \times HHI_\tau.$$

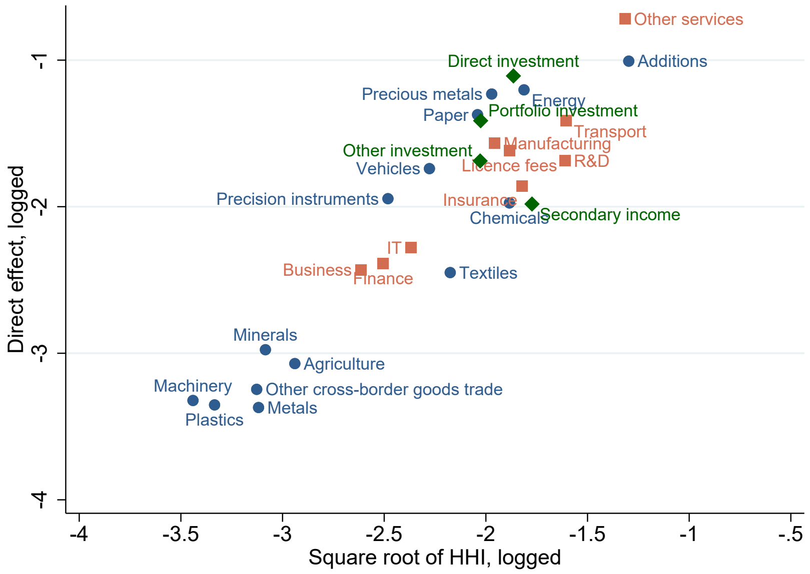
Figure 8 illustrates this relationship by plotting the granular effect against the HHI across different products.[17] As expected, product flows with higher levels of concentration among firms exhibit stronger granular effects, with a correlation of 0.88 between the two measures. This highlights the role of market structure in amplifying firm-specific shocks and their contribution to aggregate volatility.

Breaking down the three main CA components reveals several products where concentration significantly drives the granular effect. Notably, precious metals in goods trade (represented by blue dots) and other services in services trade (orange squares) show considerable contributions. Similarly, direct investment (green diamonds) stands out as flows where the granular effect is particularly pronounced. Income flows are characterized by a high concentration of large firms, which heightens their sensitivity of the CA to idiosyncratic shocks. In contrast, flows with lower degrees of concentration, particularly in goods trade (e.g., machinery, plastics, and metals), contribute less to the direct effect. These flows, represented by lower HHI values, reveal a more diversified firm structure, which reduces the impact of idiosyncratic shocks on aggregate fluctuations.

This analysis emphasizes the importance of moving beyond traditional aggregate measures, such as the goods trade balance, to fully understand fluctuations in the CA. Product-level heterogeneity, particularly in terms of concentration across firms, plays a critical role in driving CA dynamics. By linking granular volatility to concentration metrics like the HHI, we demonstrate that product-level flows dominated by a few large firms are more susceptible to firm-specific risks.

[17] To construct product-level granular effects $\sigma_{G,p}$, we normalize firm-level weights by the size of product-level flows in total CA receipts and expenses.

Figure 8: Granularity and concentration



Notes: This figure plots the product-level granular effect $\sigma_{G,p}$, with weights normalized by product-level flows in total receipts and expenses, against the product-level HHI. We report the granular volatility as a standard deviation and an average over the sample period.

5.2.2 Firm linkages

Next, we consider the firm linkages effect. In the literature, linkages are often studied through the lens of input-output relationships. When firms are interconnected—such as through buyer-supplier relationships—shocks to individual firms may propagate throughout the economy rather than dissipate at the aggregate level (Acemoglu et al., 2012). In our framework, the traditional input-output linkages hypothesis cannot be applied in a straightforward manner, as there is no one-to-one mapping between products of the CA and industries used in compiling input-output tables. For example, license fees in the services trade component or direct investment flows in the income component are not generated by a singular industry but reflect activities of firms across industries, particularly those of multinationals (MNEs). To illustrate this point, consider a global pharmaceutical company which may engage in goods production, leading to both goods imports and exports, while simultaneously participating in services trade (e.g., through R&D activities or license fees) and generating income flows by redistributing profits domestically or internationally. Acknowledging this nature of products in the CA, we explore the linkages effect in two steps: first, we test the input-output hypothesis for linkages between products that can plausibly be tied to an industry and where the input-output linkages may thus reasonably apply. Second, we investigate the linkages effect for those other products, particularly those of the income component, which do not have a counterpart in an industry classification through the lens of MNE activities.

We first test the input-output linkages hypothesis for products that can plausibly be linked to industries represented in input-output tables.[18] To quantify the linkages effect across products, consistent with equation (15), we calculate:

$$\sigma^2_{L,pq,\tau} = \sum_{j \neq i;p,q;c,d} w_{ipc\tau} w_{jqd\tau} cov(\varepsilon_{ipct}, \varepsilon_{jqdt}), \tag{16}$$

where the weights are normalized by the size of the respective product flows in total CA receipts and expenses. As negative covariances prevent us from reporting standard deviations , we simply consider the square root of the *absolute* value of the linkages effects. We thus focus on the size of the linkages, rather than its sign, which is more relevant for a net outcome such as the CA balance. Namely, an idiosyncratic shock, which increases the CA balance in one product, may propagate to another product and lead to either an increase or a decrease in the CA balance of that product, given that both outflows and inflows react.

Following di Giovanni et al. (2014), we relate the linkages effect to the mean intensity of input-output linkages, defined as $0.5 * [(1 - \lambda_p)\rho_{pq} + (1 - \lambda_q)\rho_{qp}]$, where λ_p is the share of value added in total output of product p and ρ_{pq} is the share of inputs q in total intermediate inputs used by product p. [19] Figure 9 shows the results. We find a positive relationship between the (logged) linkages effects and the (logged) input-output mean intensity, with a correlation of 0.28. These findings are broadly consistent with prior evidence. For example, di Giovanni et al. (2014) report a correlation of 0.29 for French sales. Taken together, our results underscore the importance of input-output linkages as a key propagation channel through which idiosyncratic shocks affect the CA balance.

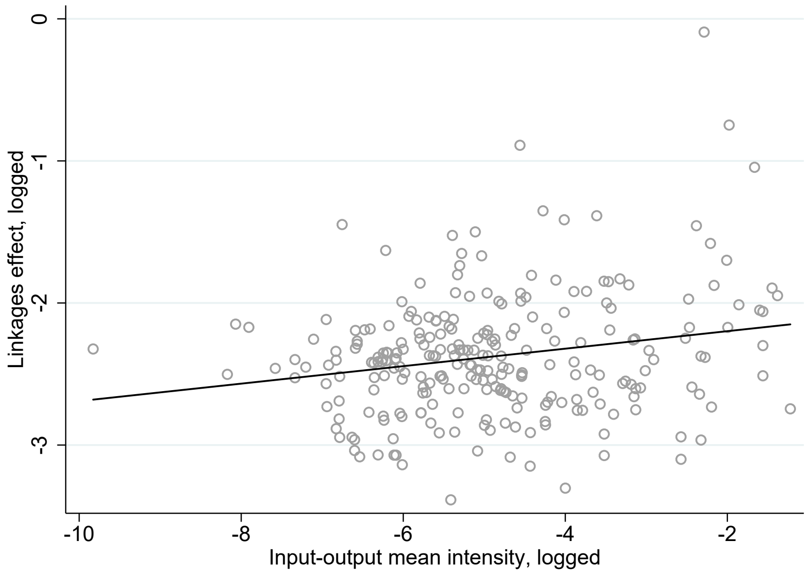
We now turn to products that cannot be linked to specific industries, in particular, investment income products in the income component. Investment income is tightly linked to the activities of MNEs. Returning to our example of a pharmaceutical company, an increase in profits from goods production or services provision should be linked to profit distribution to ultimate cross-border investors and thus captured in the income component as dividend or interest payments in either direct, portfolio, or other investment. Then, idiosyncratic shocks to goods and services trade are expected to have a counterpart in the income component as they should impact profitability and ultimately the distribution of profits.

To illustrate this mechanism, we relate the linkages effect between products of the income component and products that can be linked to a specific industry, to a measure of industry-level MNE-intensity. For example, we relate the linkages effect between goods trade of the pharmaceutical industry (i.e., the pharmaceutical product) and the direct

[18] Table A3 in the Appendix reports the concordance between products and industries.

[19] Both the valued-added share and the input share are taken from the Swiss input-output table for 2017 published by the Swiss Federal Statistical Office (SFSO).

Figure 9: Firm linkages and input-output linkages



Notes: The x-axis shows the (logged) input-output mean intensity defined as $0.5*[(1-\lambda_p)\rho_{pq}+(1-\lambda_q)\rho_{qp}]$, where λ_p is the share of value added in total output of product p and ρ_{pq} is the share of inputs q in total intermediate inputs used by product p. The y-axis shows the pairwise product-level linkages effect $\sigma^2_{L,pq}$, expressed as the square root of its absolute value, an average over time periods τ and logged, with respective product-level weights normalized by product-level flows in total receipts and expenses.

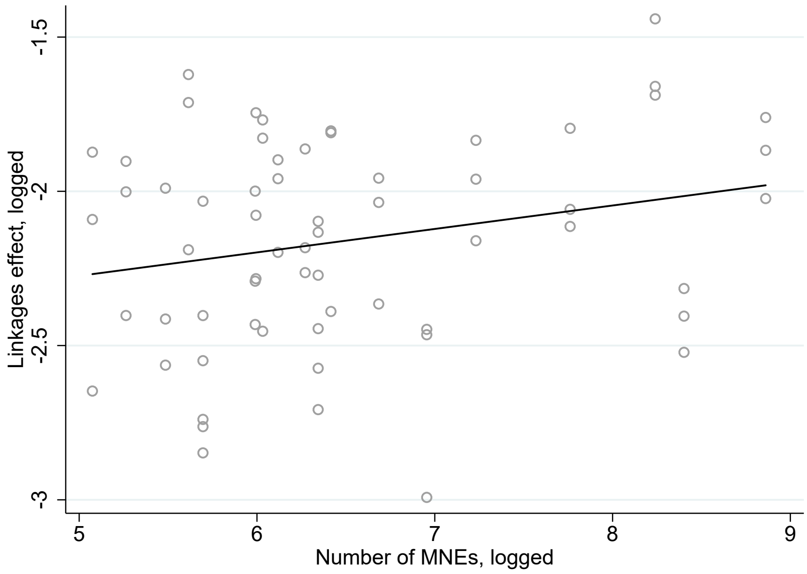
investment product to the MNE-intensity of the pharmaceutical industry. To broadly proxy for the MNE-intensity of an industry, we use the number of MNEs per industry, consistent with the literature (e.g., Cravino and Levchenko, 2016; Alviarez, 2019).[20] As in the first exercise, we express the linkages effect as the square root of the absolute value of the pairwise covariance defined in equation (16).

Figure 10 shows the results. Overall, we find the expected positive relationship between the (logged) linkages effects and the (logged) industry-level number of MNEs, with a correlation of 0.23. This suggests that the income component is indeed not an isolated feature of the CA balance. Instead, idiosyncratic shocks in industries with a large presence of MNEs propagate to and from the income component.[21] Idiosyncratic shocks thus shape the trade balance and the income balance, and thus jointly determine movements in the headline CA. This emphasizes the importance of adopting a holistic view of the CA balance, rather than to focus on the trade balance, as motivated earlier in Figure 2 of this paper.

[20] We rely on the SFSO enterprise groups statistics (STAGRE), which publish the number of firms, sales, and employment attributed to enterprise groups, including foreign-owned and domestically-owned MNEs, under various breakdowns, including by industries. We consider an average over the years 2015-2022.

[21] A similar positive relationship holds when using sales by enterprise groups, rather than the number of MNEs, as shown in Figure C1 of Appendix C. We rely on the number of MNEs as the first best as sales data by enterprise groups is only a proxy for sales of MNEs. Sales by MNEs are only partially available at the industry level given confidentiality restrictions.

Figure 10: Firm linkages and MNE-intensity



Notes: The x-axis shows the number of MNEs present in industry/product p, logged, as a proxy for MNE-intensity. The y-axis shows the pairwise product-level linkages effect $\sigma^2_{L,pq}$, between product p and product q in the income component. The pairwise linkages effect is expressed as the square root of its absolute value, an average over time periods τ and logged, with respective product-level weights normalized by product-level flows in total receipts and expenses.

5.3 Robustness

To conclude this section of the analysis, we consider several robustness tests to validate the consistency of our findings presented in Table 7. In doing so, we investigate along similar lines to the robustness with our regression framework. In a first robustness check, we consider how the baseline results perform based on a yearly panel rather than a quarterly panel. Table 7 shows that the results are robust. Idiosyncratic volatility remains the main driver of headline CA volatility, with a ratio of 1.2 to aggregate volatility. In contrast, product-country volatility only accounts for 0.6 of aggregate volatility. While we interpret these results with caution given the limited number of observations in the yearly panel, such findings suggest that our baseline results are not driven by the business cycle frequency.

In a second robustness check, Table 7 further reports the results of the volatility decomposition restricting the sample to the intensive margin, symmetrically to the exercise of Section 4.3. Overall, our results hold, although they are somewhat weaker. Specifically, the standard deviation of idiosyncratic volatility is 0.96 times that of the aggregate volatility, while product-country shocks account for 0.6 times that of the overall CA volatility. Thus, while idiosyncratic shocks remain the primary driver of CA volatility, their influence compared to product-country volatility is lesser than in the baseline results, with a ratio 1.6 compared to 2.5 in our baseline. This again underlines that a

Table 7: Volatility decomposition – robustness tests

	Standard deviation			Relative standard deviation		
	Total σ (1)	Product-country σ_δ (2)	Idiosyncratic σ_ε (3)	Product-country to total σ_δ/σ (4)	Idiosyncratic to total $\sigma_\varepsilon/\sigma$ (5)	Idiosyncratic to prod.-country $\sigma_\varepsilon/\sigma_\delta$ (6)
Robustness sample						
Yearly frequency	0.0766	0.0455	0.0918	0.59	1.20	2.02
Intensive margin	0.0640	0.0404	0.0644	0.63	1.01	1.59
Extended sample	0.0464	0.0585	0.0755	1.26	1.63	1.29

Notes: The table reports three robustness tests of the volatility exercise: (i) decomposition of headline CA volatility based on a yearly panel; the decomposition is shown as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016}^{2024} \sigma_{\varepsilon,\tau}$; (ii) decomposition of headline CA volatility using a panel restricted to the intensive margin and (iii) using an extended panel including merchanting and trade subtractions, respectively. Average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016Q1}^{2024Q4} \sigma_{\varepsilon,\tau}$ are shown.

major contributor to idiosyncratic volatility are entry and exit of firms in cross-border transactions.

In a third robustness check, we extend the sample to include merchanting flows and trade subtractions. Broadly, results still hold, but are slightly weaker. Table 7 finally shows that, when accounting for those two additional products, idiosyncratic shocks contribute to aggregate volatility with a ratio of 1.6 and are more influential than product-macro shocks with a ratio of 1.3 between the two factors. Compared to the baseline, the prevalence of idiosyncratic shocks as the primary driver of volatility thus declines. Notably, we find that product-country volatility account for 0.6 times that of the aggregate volatility. Among all our results, this is the highest contribution of the product-country, common volatility. This may reflect the significant weight of merchanting in gross flows in this alternative panel and the fact that merchanting flows may be strongly affected by common shocks, such as commodity prices shocks.

Appendix C shows two additional robustness tests. There, we show that our results are broadly robust to using quarter-on-quarter changes in the CA balance as underlying growth rates for the volatility decomposition and to splitting the sample into pre-and post-Covid periods.

6 Conclusion

This paper provides new empirical evidence on the role of granularity in the context of current account (CA) balances. We quantify the effect of idiosyncratic shocks to large firms in explaining CA fluctuations and contributing to CA volatility. Using a unique and comprehensive firm-level dataset for Switzerland, we show that idiosyncratic shocks to large firms are a significant driver of short-term and medium-term fluctuations in the CA balance. They explain almost two thirds of the variation in the headline CA growth rate. We also find that idiosyncratic shocks are the dominant drivers of CA volatility. Idiosyncratic volatility is driven not only by individual firm variances, but also by propagation through firm linkages. We find evidence for propagation mechanisms through input-output linkages and through the structure of multinational enterprises. These findings are consistent with the granular hypothesis, suggesting that individual shocks to a few dominant firms play a critical role in determining overall CA fluctuations.

More broadly, our analysis shows that large swings in CA balances may in part reflect firm-level dynamics and not necessarily point towards macroeconomic risks. At the same time, granularity in the external sector may introduce new forms of aggregate vulnerability, as shocks to a small number of firms can produce outsized effects at the macro level. Accounting for these micro-level sources of variation may help to improve the interpretation of external imbalances, particularly in countries where cross-border flows are concentrated in a small number of firms.

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A Data appendix

Table A1: Product and country breakdowns

Product breakdown	
Goods	Agriculture, Energy, Textiles, Paper, Plastics, Chemicals, Minerals, Metals, Machinery, Vehicles, Precision instruments, Other cross-border goods trade, Precious metals, Additions
Services	Transport, Insurance, Finance, License fees, IT, Manufacturing, R&D, Business, Other services
Income	Direct investment, Portfolio investment, Other investment, Secondary income
Country breakdown	
Europe	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Turkey, United Kingdom, Other European countries
Americas	Canada, Greenland, United States, Mexico Other Central American countries, Argentina, Brazil, Chile, Uruguay, Venezuela, Other South American countries
Asia	Israel, Iran, Gulf Arabian countries, Other Near and Middle East countries, China, Hong Kong, India, Indonesia, Japan, Malaysia, Philippines, Singapore, Taiwan, Thailand, South Korea, Other Asian countries
Other	Egypt, Morocco, North Africa (other), Nigeria, South Africa, Other African countries, Australia, New Zealand, Other Oceania countries, Not allocated (including international organizations).

Table A2: Summary statistics by aggregate components

	N. obs.	Mean	St. Dev.	Min	Max
Goods					
Firm size w_{ipct} (%)	34,196,356	0.0001	0.00	0.00	0.03
Firm-level growth rate g_{ipct}	34,196,356	-0.0559	3.37	-4.0	4.0
Idiosyncratic shocks ε_{ipct}	34,196,356	0.0000	3.36	-6.9	7.3
Product-country shocks δ_{pct}	34,767	-0.0556	0.78	-4.0	4.0
Services					
Firm size w_{ipct} (%)	1,396,627	0.0005	0.01	0.00	0.01
Firm-level growth rate g_{ipct}	1,396,627	-0.0471	2.51	-4.0	4.0
Idiosyncratic shocks ε_{ipct}	1,396,627	0.0000	2.48	-6.8	6.7
Product-country shocks δ_{pct}	22,548	-0.0279	0.71	-4.0	4.0
Income					
Firm size w_{ipct} (%)	457,105	0.0018	0.02	0.00	0.03
Firm-level growth rate g_{ipct}	457,105	-0.0060	2.70	-4.0	4.0
Idiosyncratic shocks ε_{ipct}	457,105	-0.0000	2.67	-6.7	7.1
Product-country shocks δ_{pct}	9,907	0.0117	0.85	-4.0	4.0

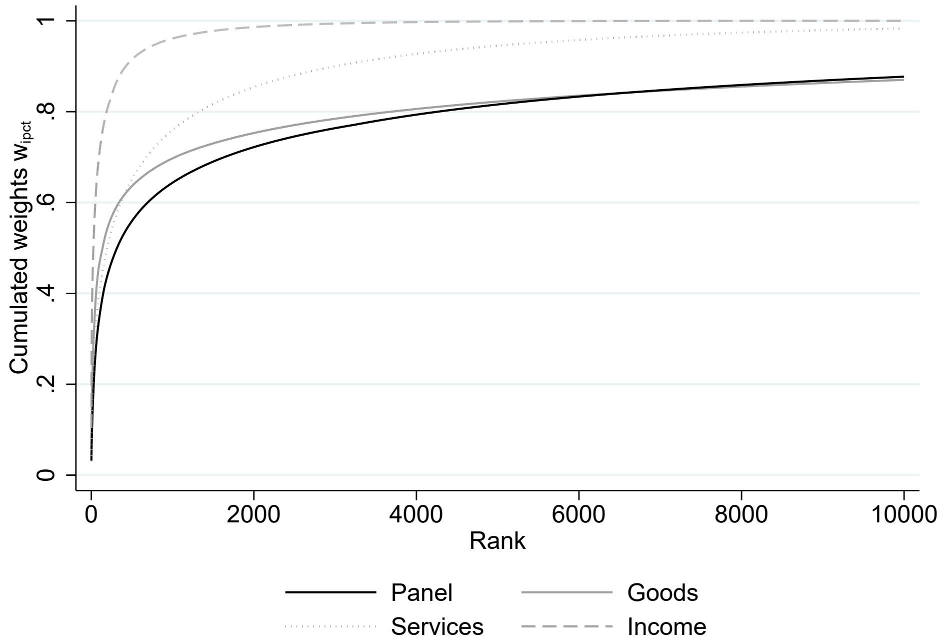
Notes: This table presents summary statistics of the main variables in the analysis, following equations (5), (6), (7) and (8) by aggregate components.

Table A3: Product and industry concordance

Product	Industry
1. Agriculture	01-03,10-12
2. Energy	05-09, 35
3. Textiles	13-15
4. Paper	16-18
5. Plastics	22-23
6. Chemicals	19-21
7. Minerals	22-23
8. Metals	24-25
9. Machinery	27-28
10. Vehicles	29-30, 45
11. Precision instruments	26
12. Other cross-border goods trade	31-33
13. Precious metals	24-25
14. Additions	-
15. Transport	49-53
16. Insurance	65
17. Finance	64
18. License fees	-
19. IT	58-63
20. Manufacturing	33,41-43
21. R&D	72
22. Business	69-71, 73-75, 77-82
23. Other services	49-99, nec.
24. Direct investment	-
25. Portfolio investment	-
26. Other investment	-
27. Secondary income	65

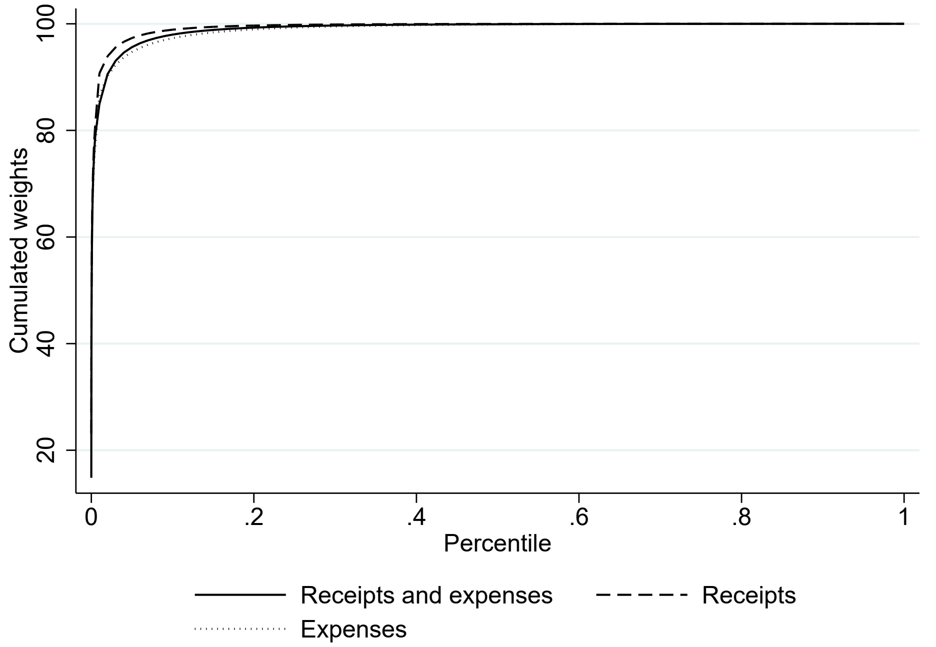
Notes: This table presents the concordance between the products of the CA and the industry classification (NOGA). A dash indicates that no corresponding industry can be assigned to a product.

Figure A1: Distribution by rank



Note: This figure shows the firm-size distribution. The x-axis shows firm-size by rank (from 1 the largest to 10000). The y-axis shows the cumulated weights in CA receipts and expenses, as defined in equation (5).

Figure A2: Distribution — receipts and expenses



Note: This figure shows the percentile explaining most of cumulated weights w_{ipct} based on the sum of receipts and expenses also explain most of cumulated shares in total receipts (exports) and expenses (imports).

B Regression appendix

Table B1: Robustness—quarter-on-quarter growth rate

	(1)	(2)	(3)
	g_t	g_{pct}	g_{pct}
Granular residual Γ_t	0.717***		
	(0.064)		
Granular residual Γ_{pct}		0.885***	0.886***
		(0.003)	(0.003)
Observations	39	72,739	72,739
Adjusted R^2	0.58	0.59	0.61
Country-time FE	no	no	yes
Product FE	no	no	yes

Notes: The dependent variables are the quarter-on-quarter growth rates of the product-country pair g_{pct} and the year-on-year growth rate of the headline CA g_t. The granular residual Γ_{pct} is constructed with weights normalized to the size of product-country pair p, c in total CA flows. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B2: Robustness—pre- and during/post-Covid periods

	Pre Covid	During and post Covid
	(1)	(2)
	g_{pct}	g_{pct}
Granular residual Γ_{pct}	0.855***	0.913***
	(0.005)	(0.004)
Observations	29,933	37,289
Adjusted R^2	0.59	0.63
Country-time FE	yes	yes
Product FE	yes	yes

Notes: The dependent variables are the year-on-year growth rates of the product-country pair g_{pct}. The granular residual Γ_{pct} is constructed with weights normalized to the size of product-country pair p, c in total CA flows. The pre-Covid period encompasses 2015-Q1 to 2019-Q4. The during and post-Covid period covers 2020-Q1 to 2024-Q4. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table B3: Robustness—restricting granular residual to top 5 firms

	(1)	(2)
	g_t	g_{pct}
Granular residual Γ_t	0.906***	
	(0.090)	
Granular residual Γ_{pct}		0.892***
		(0.003)
Observations	36	67,222
Adjusted R^2	0.74	0.62
Country-time FE	no	yes
Product FE	no	yes

Notes: The dependent variables are the year-on-year growth rates of the product-country pair g_{pct} and the year-on-year growth rate of the headline CA g_t. The granular residual Γ_{pct} is constructed with weights normalized to the size of product-country pair p, c in total CA flows. The granular residual is constructed using only the idiosyncratic shocks of firms with the five largest weights within each product-country pair p, c at any time t. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C Decomposition appendix

Table C1: Volatility decomposition — quarter-on-quarter growth rates

Standard deviation			Relative standard deviation		
Total	Product-country	Idiosyncratic	Product-country to total	Idiosyncratic to total	Idiosyncratic to prod.-country
σ	σ_δ	σ_ε	σ_δ/σ	$\sigma_\varepsilon/\sigma$	$\sigma_\varepsilon/\sigma_\delta$
(1)	(2)	(3)	(4)	(5)	(6)
0.0779	0.0423	0.0926	0.54	1.19	2.19

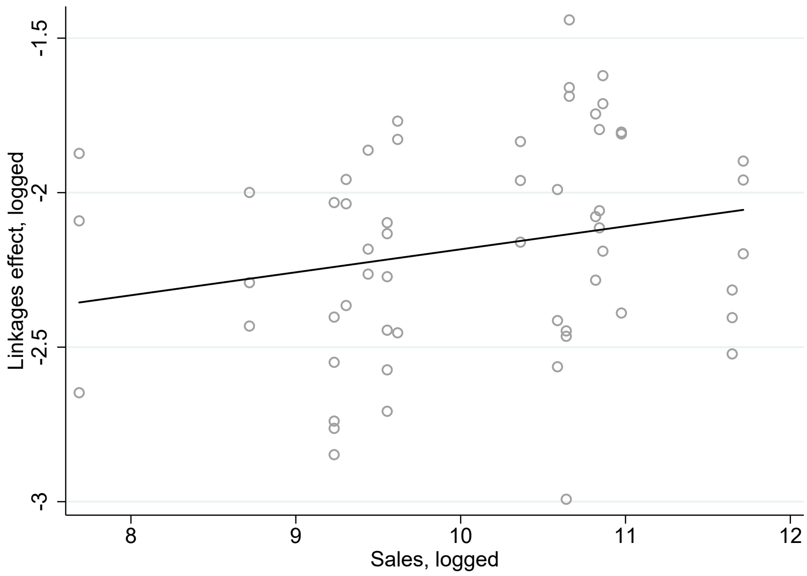
Notes: The table reports the decomposition of headline CA volatility, following equation (14), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2015Q2}^{2024Q4} \sigma_{\varepsilon,\tau}$, using quarter-on-quarter growth rates.

Table C2: Volatility decomposition — pre- and during/post-Covid periods

	Standard deviation			Relative standard deviation		
	Total	Product-country	Idiosyncratic	Product-country to total	Idiosyncratic to total	Idiosyncratic to prod.-country
	σ	σ_δ	σ_ε	σ_δ/σ	$\sigma_\varepsilon/\sigma$	$\sigma_\varepsilon/\sigma_\delta$
Period	(1)	(2)	(3)	(4)	(5)	(6)
Pre-covid	0.0723	0.0447	0.1002	0.62	1.38	2.24
Post-covid	0.0935	0.0428	0.1071	0.46	1.15	2.50

Notes: The table reports the decomposition of aggregate volatility, following equation (14), for two subperiods, pre-Covid (2016Q1-2019Q4) and post-Covid CA (2020Q1-2024Q4). Growth rates and weights are restricted to those two subsamples for the construction of synthetic growth rates.

Figure C1: Firm linkages and industry-level MNE presence using sales



Notes: The x-axis shows the sales by enterprise groups (close proxy to sales by MNEs) in industry/product p, logged. The y-axis shows the pairwise product-level linkages effect $\sigma^2_{L,pq}$, between product p and product q in the income component. The pairwise linkages effect is expressed as the square root of its absolute value, an average over time periods τ and logged, with respective product-level weights normalized by product-level flows in total receipts and expenses.