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, firm-specific shocks account for more than two thirds of the variation in the headline CA growth rate and are the primary source of CA volatility. These shocks not only have a direct impact, but also propagate through firm linkages, amplifying their effect on aggregate fluctuations. Granularity in the CA also has broader macroeconomic implications: using a granular instrumental variable approach, we show that CA movements can affect the exchange rate. Our findings highlight the importance of firm-level heterogeneity in assessing external sector risks and understanding their broader macroeconomic implications.

JEL classification: F32, F23.
Keywords: current account, granularity, granular instrumental variable

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1 Introduction

Current account (CA) volatility has been a persistent feature of both advanced and emerging market economies over the past few decades. 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 drivers of CA volatility is therefore crucial to assess potential risks from sudden movements in a country's external position.

While prior studies have focused on the macroeconomic determinants of CA balances, little attention has been given to the role of firm-level dynamics.[1] Our paper investigates the granular hypothesis in the context of CA balances. We study how idiosyncratic shocks to large firms affect fluctuations in the CA balance and how they contribute to overall CA balance volatility. In his seminal contribution, Gabaix (2011) posits that, due to the fat-tailed distribution of firm sizes, idiosyncratic shocks to individual large firms do not average out. Instead, they lead to movements in aggregate outcomes, challenging the assumptions of standard macroeconomic models.[2]

We find that idiosyncratic, firm-level shocks account for more than two thirds of fluctuations in the headline CA balance. They are also the primary driver of CA volatility. Shedding light on the underlying mechanisms, we find that idiosyncratic shocks are amplified through linkages across firms, and that firm concentration plays a critical role in driving CA dynamics. Investigating broader macroeconomic implications of our findings, we leverage idiosyncratic shocks to construct granular instrumental variables (GIVs) for CA flows and revisit the endogenous relationship between the CA and the exchange rate. We find that exogenous changes in the CA balance can lead to exchange rate movements.[3] Our analyses thus offer new insights into the implications of firm-specific dynamics in the external sector.

Central to this analysis is our novel firm-level dataset, which offers the first comprehensive firm-level account of the CA balance. Following statistical conventions (IMF, 2009), we define the CA balance as the sum of net flows in goods, services, and income between the domestic economy and the rest of the world. We construct our firm-level dataset by combining administrative customs data with quarterly surveys on services and

[1] Starting with Chinn and Prasad (2003), studies identify fundamentals such as demographics and policies such as the fiscal balance as important drivers (Bussière et al., 2004; Gruber and Kamin, 2007; Chinn and Ito, 2008; Ca'Zorzi et al., 2012; 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)

[2] Granularity has been well documented for several macroeconomic outcomes such as GDP, unemployment, and inflation (di Giovanni et al., 2014; Atalay, 2017; Carvalho and Grassi, 2019; Alvarez-Blaser et al., 2022; Grigoli et al., 2023; Di Giovanni et al., 2024), as well as for exports and imports (Eaton et al., 2011; Di Giovanni and Levchenko, 2012; Freund and Pierola, 2015; Bernard et al., 2018; Gaubert and Itskhoki, 2021).

[3] Introduced by Gabaix and Koijen (2024), the GIV approach has been applied to a variety of questions in macro and international banking in recent years (Gabaix and Koijen, 2021; Adrian et al., 2022; Camanho et al., 2022; Aldasoro et al., 2023).

income flows for Switzerland. The resulting dataset is rich: covering over 350,000 firms, 70 partner countries, and spanning 2015 to 2023 at the quarterly frequency. In addition, it covers all main components of the CA—goods, services, and income—with further breakdowns on 27 distinct subcomponents, which we refer to as products. Our dataset thus supports analysis across various levels of aggregation, from specific product-country pairs up to the headline, offering a refined lens through which to examine the granular effect driving CA growth and volatility.

Leveraging the richness of the data, we decompose the CA balance's growth rate into a common component and a granular residual (Gabaix, 2011; di Giovanni et al., 2014). 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. In contrast, we extract an idiosyncratic shock, which is simply the firm-level deviation from the product-country shock. The idiosyncratic shock thus captures how firm-level outcomes may differ from the common shock, and, if the granular hypothesis holds, impact overall growth rates. Then, the CA balance's growth rate, at various levels of aggregation, can be split into a common shock (the weighted sum of product-country shocks) and the granular residual (the weighted sum of idiosyncratic shocks).

Using a regression framework, we show strong granular effects in CA dynamics. At the product-country level, the granular residual explains about 60% of the year-on-year variation in CA growth. Importantly, these results more than subsist in the headline. The explanatory power of the granular residual becomes even more pronounced when considering the aggregate CA balance, explaining a striking 70% of year-on-year fluctuations in the headline CA. These findings are fully robust to various assumptions.[4] 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.

Performing a variance-covariance decomposition, we further identify the granular residual—that is, idiosyncratic volatility—as the dominant source of CA volatility, contributing substantially more to overall CA volatility than 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, whereas the firm linkages effect helps explain co-movements across CA components. This suggests that shocks

[4]We conduct a comprehensive series of robustness tests, as detailed in Section 4 and AppendixB. 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.

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.

Finally, granularity in the CA holds potential broader macroeconomic implications: Using a GIV approach (Gabaix and Koijen, 2024), we investigate how exogenous changes in the CA balance, driven by idiosyncratic shocks to large firms, influence the Swiss franc's real effective exchange rate. At the product-country level, we find a negative correlation between the CA balance and the exchange rate for certain products. This could reflect the J-curve effect, where firms experiencing positive idiosyncratic shocks increase exports by lowering prices, which initially places downward pressure on the currency's value (Rose and Yellen, 1989; Alessandria and Choi, 2021). Although no significant relationship emerges at the aggregate CA level, the observed product-level impacts suggest that movements in the CA balance can exert currency pressure within particular market segments. These initial insights underscore the potential of the GIV approach in addressing endogeneity in the CA-exchange rate relationship.

Overall, our findings highlight the importance of accounting for firm-level heterogeneity in external sector assessments and exchange rate considerations. First, our research identifies an important, but overlooked driver of CA movements, particularly in periods when macroeconomic fundamentals remain stable and do not offer an obvious explanation for fluctuations in external balances. Second, by showing the substantial influence that large firms exert on the external sector, we emphasize the importance of accounting for these firms in managing overall external balances. Finally, our analysis suggests that firm-level shocks can exert currency pressures, highlighting the need for exchange rate policy to take firm-specific drivers into account. This is especially relevant for economies with large, globally integrated firms whose performance may substantially influence both external balances and currency stability.

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 presents our analysis of idiosyncratic shocks and exchange rate movements. Section 7 concludes.

2 Empirical framework

2.1 Modelling the current account

Following the IMF's guidelines (IMF, 2009), 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. Formally,

the headline CA, denoted as ca_t, is defined as:

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

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 subcomponent of the CA or the type of flows, e.g., net exports of agricultural products, net exports of intellectual property, or net interest payments on debt instruments. Products may be comprised in any of the main CA component (goods, service, and income). For simplicity, we abstract from this distinction.

To incorporate firm-level heterogeneity, we express the aggregate CA balance as the sum of firm-level CA balances, modeling it as:

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

where ca_{ipct} represents the contribution of firm i to flows of product p vis-à-vis country c at time t. Our unit of observation is thus the *firm-product-country* flow, allowing us to capture firm-specific dynamics in the CA balance.

2.2 Defining CA growth rates

To study the movements in the CA balance over time, we calculate the mid-point CA growth rate g_t, which captures the relative change in the CA balance between t and $t-k$ as a function of total flows:

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

This growth rate is particularly suited for our analysis, because it is symmetric around zero, bounded—effectively capturing large swings in CA balances without extreme values—and accommodates firm entry and exit (Törnqvist et al., 1985; Davis et al., 1996). Moreover, it facilitates analysis at multiple levels of aggregation: from the detailed product-country flows to the headline CA balance.

Extending this definition to the firm level, we define the aggregate CA growth rate as a sum of firm-level growth rates g_{ipct}, weighted by the relative size of each firm's transactions:

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

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 assume that the firm-level growth rate g_{ipct} can be decomposed into two components: a product-country shock δ_{pct} and a firm-specific idiosyncratic shock ε_{ipct}:

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

The product-country shock δ_{pct} captures macroeconomic influences shared across firms in a given product-country flow, and is calculated as the average growth rate:

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

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

This framework thus assumes 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 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.

The idiosyncratic shock ε_{ipct} captures the deviations of individual firms from the common 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 characterized by large, dominant firms that experience unique supply or demand conditions.

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:

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

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 volatility. The second term captures the impact of idiosyncratic 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. The granular residual plays a crucial role in understanding how firm-specific shocks propagate to the aggregate level. If the distribution of firm sizes is fat-tailed, then large firms may have an outsized influence on aggregate outcomes.

This framework thus 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. The flexibility of the framework also allows for different 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, 2024). We leverage three mutually exclusive firm-level data sources, each covering different aspects of Switzerland's official CA statistics. First, we use customs data from the Swiss Federal Office for Border and Customs Security (FOBCS), 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 and covering 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 combine these three data sources to construct a unique firm-level panel dataset.[5] To form our unit of observation, the CA balance of firm i in product p vis-à-vis partner country c at time t, we align frequency, sample period, country breakdowns, and product classifications according to the official reporting structure.[6] To capture product-specific heterogeneity, we further decompose goods trade based on the official FOBCS classifications.[7] This yields 27 distinct products p, encompassing three aggregate components: goods, services, and income. Additionally, we account for trade with 70 partner countries c or country groups, providing global coverage through regional aggregates for smaller economies.[8] Our dataset is structured at quarterly frequency, spanning from Q1 2015 through Q4 2023, allowing us to capture both longer-term trends and short-term fluctuations in the CA balance.

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.[9] In contrast, merchanting expenses as a statistical concept do not exist. This asymmetric treatment does not fit the empirical framework outlined in Section 2 and further leads to negative receipts across partner countries, especially when countries serve as suppliers rather than buyers in merchanting transactions. Due to the prevalence of these negative values, including merchanting in our panel would result in nonsensical growth rates and weights. For these reasons, we 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.[10]

[5]Additional data sources used in Swiss CA statistics, such as those for public sector transactions, income on reserves, and household transfers, are beyond the scope of this analysis. Similarly, certain data sources, such as tourism services or labor income, are not readily available at the micro level.

[6]Refer to the SNB data portal.

[7]Specifically, we use the "nature of goods" classification, available on the FOCBS data portal.

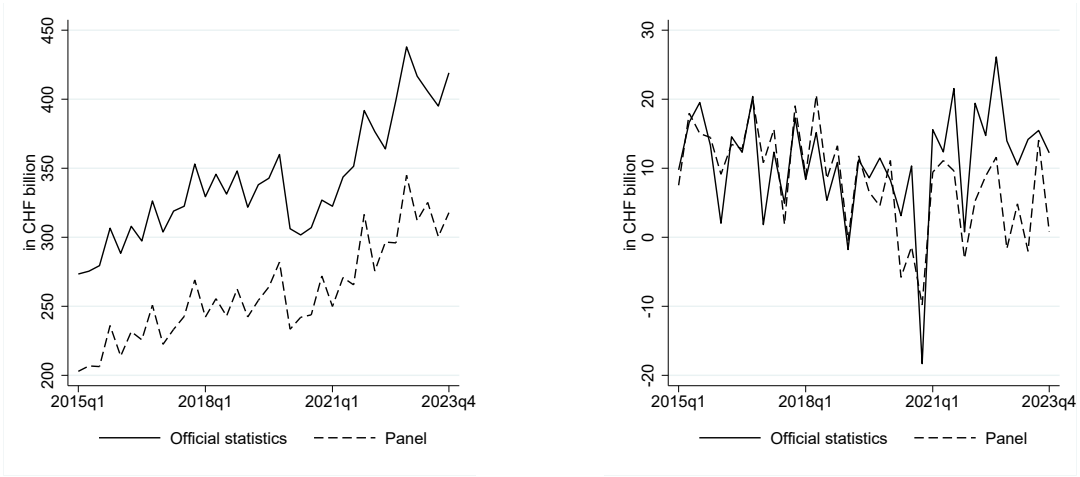
[8]Table A1 in the Appendix details the product and partner country breakdowns.

[9]Merchanting is goods trade that does not cross the border of the firm's resident country, common in the activities of commodity traders and some multinational enterprises engaged in global value chains. Merchanting data are collected through the SNB's CA surveys.

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

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 approximate 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.

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.

3.2 Summary statistics

Based on this dataset, 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 due to 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 32 million observations, spanning 2016 Q1-2023 Q4, 27 products, 70 partner countries, and more than 350,000 firms. 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

Table 1: Summary statistics

	N. obs.	Mean	St. Dev.	Min	Max
Firm size w_{ipct} (%)	31,864,878	0.0001	0.00	0.00	0.03
Firm-level growth rate g_{ipct}	31,864,878	-0.0785	3.33	-4.0	4.0
Idiosyncratic shocks ε_{ipct}	31,864,878	0.0000	3.32	-6.9	7.3
Product-country shocks δ_{pct}	59,790	-0.0386	0.78	-4.0	4.0

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

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 60,000 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.

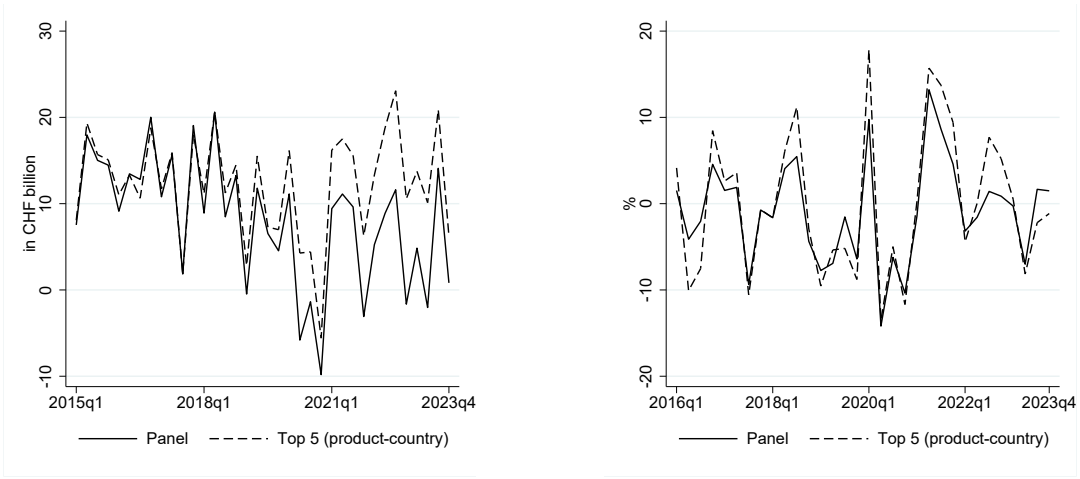
3.3 Granularity in the CA: descriptive evidence

To build intuition around the concept of granularity, we begin with a purely descriptive analysis. Figures 2a and 2b compare the contribution of the top 5 firms within each product-country pair to the overall CA balance.[11] 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 0.83, while the correlation between the CA growth rate generated by the top five and the panel is 0.98.

Figures 2a and 2b provide compelling evidence of the dominance of a few large firms, but they do not directly confirm the granular hypothesis. The granular hypothesis be-

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

Figure 2: Contribution of top 5 firms in the CA



(a) CA balance

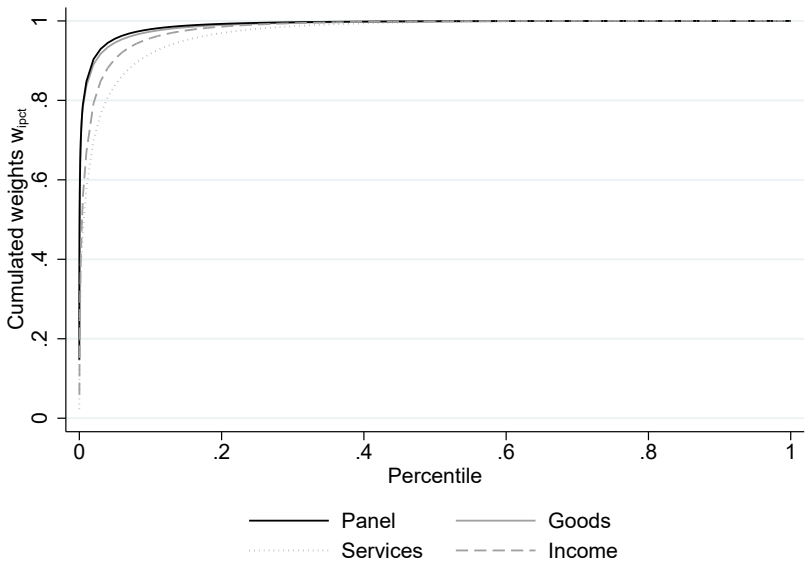
(b) CA balance growth

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.

comes empirically relevant only if the distribution of firm sizes is fat-tailed. Figure 3 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, 56% of services trade, and 67% of income flows. Thus, both at the level of main CA components and for the full panel, a minute 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.[12]

[12]These patterns are influenced by the underlying datasets, as the FOCBS 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 firms, further confirming the presence of fat tails in the firm size distribution.

Figure 3: 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).

4 Regression analysis

4.1 Product-country 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:

$$g_{pct} = \alpha + \beta \Gamma_{pct} + \mu_p + \theta_{ct} + \eta_{pct}, \tag{10}$$

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, with weights normalized by the share of product-country pair p, c in total CA flows, and μ_p and θ_{ct} are product and country-time fixed effects, respectively. The error term η_{pct} captures any unexplained variation in the growth rate.

Table 2 presents the regression results. Overall, the granular residual significantly explains CA fluctuations. It accounts for more than half of the variation in the CA 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

Table 2: Regression results – granular residual at product-country level

	(1)	(2)
	g_{pct}	g_{pct}
Granular residual Γ_{pct}	0.885^{***}	0.888^{***}
	(0.003)	(0.003)
Observations	59,790	59,790
Adjusted R^2	0.59	0.62
Country-time FE	no	yes
Product FE	no	yes

Notes: The dependent variable is the year-on-year growth rate of the product-country CA balance 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. $***p < 0.01, **p < 0.05, *p < 0.1$

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.

4.2 Aggregate level regressions

To complement the product-country level analysis, we extend our investigation to the aggregate level, assessing the impact of the granular residual on the overall growth rate of the headline CA. The regression specification for the headline CA is as follows:

$$g_t = \alpha + \beta\Gamma_t + \eta_t, \tag{11}$$

where g_t is the aggregate year-on-year growth rate of the headline CA and Γ_t is the granular residual as defined in equation (9). This approach allows us to examine whether the effects observed at the product-country level carry over to the aggregate level, and to evaluate the extent to which firm-specific shocks drive movements in the overall CA balance.

Table 3 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 0.71, indicating that granular shocks explain about 70% 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 robustness of this granular effect at the aggregate level reinforces the granular

Table 3: Regression results – granular residual in the headline CA

	g_t
Granular residual Γ_t	0.681^{***}
	(0.079)
Observations	32
Adjusted R^2	0.71

Notes: The dependent variable is the year-on-year growth rate of the headline CA g_t. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

hypothesis, showing that idiosyncratic shocks at the firm level do not dissipate when aggregated across products and partner countries. Instead, they significantly impact 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.

4.3 Granular effects across products

This section examines the heterogeneity in granular effects across different products within the CA. We first consider subsamples by aggregate components: goods, services, and income. Table 4 shows the regression results for these subsamples, presenting estimates for the product-country level and the aggregate balance within each main component. 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 1), 0.8 in the services component (column 2), and 0.9 in the income component (Column 3). Adjusted R^2 are also similar, about 0.6.

Turning to the aggregate balance of each main component, results are slightly less homogeneous, but largely in line with our baseline scenario. The results are weakest for the goods trade balance, with a coefficient of 0.5 and an R^2 of 0.5. In contrast, we find large coefficients for the services and income balances of about 0.9, with R^2 of 0.6 and 0.9 respectively. Thus, when contrasting these results with those of the headline CA, as shown in Table 3, 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.

Table 4: Regression results — aggregate components

	g_{pct}			g_t		
	(1) Goods	(2) Services	(3) Income	(4) Goods	(5) Services	(6) Income
Granular residual Γ_{pct}	0.921***	0.834***	0.909***			
	(0.005)	(0.006)	(0.009)			
Granular residual Γ_t				0.512***	0.864***	0.939***
				(0.092)	(0.138)	(0.059)
Observations	30,940	20,038	8,812	32	32	32
Adjusted R^2	0.61	0.61	0.62	0.53	0.57	0.85
Country-time FE	yes	yes	yes	no	no	no
Product FE	yes	yes	yes	no	no	no

Notes: The dependent variable is the year-on-year growth rate of the product-country pair g_{pct} and of the aggregate balance g_t within each main CA component (goods, services, and income). To construct the granular residual, weights are normalized by the share of each main component in total CA flows. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

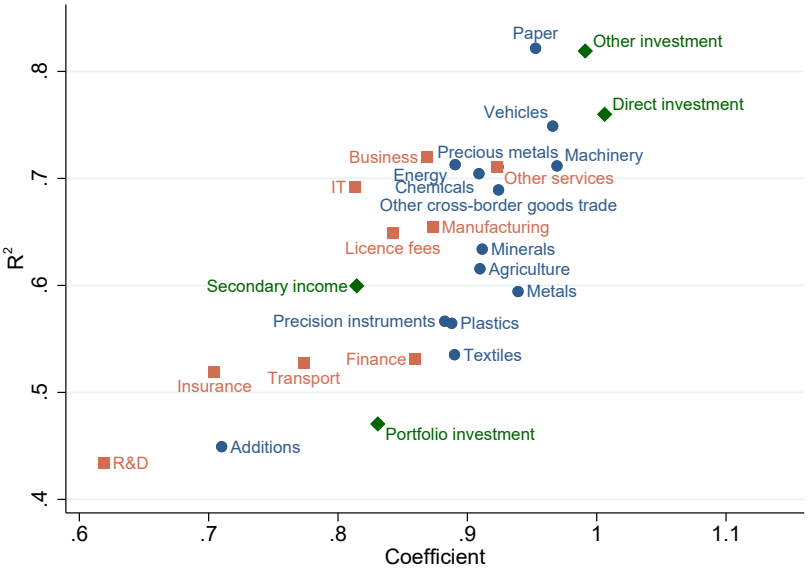
Next, we go a step further and consider single products. When analyzing the relationship between the granular residual and the CA growth rate at this disaggregated level, we find substantial variation in both the magnitude of the coefficients and the explanatory power of the granular residual across products. Figure 4 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 4: Granularity across products



Notes: This figure plots the R^2 against the coefficients of product-level regressions: $g_{ct} = \alpha + \beta\Gamma_{pct} + \mu_c + \theta_t + \eta_{pct}$ by product p. To construct the granular residual Γ_{pct}, weights are normalized by the share of product-country pair p, c in total CA flows. Blue dots comprise products within the goods component, orange squares those within services, and green diamonds those within income.

4.4 Robustness

The richness of our data enables an extensive series of robustness tests to validate the consistency of our findings. In a first robustness check, we consider the frequency of the panel. We collapse the baseline panel over years and replicate the analysis of Table 2 considering yearly changes. Table 5 presents 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 5. 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.[13] 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

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

Table 5: Regression results — yearly panel

	(1)	(2)
	g_{pct}	g_{pct}
Granular residual Γ_{pct}	0.839^{***}	0.848^{***}
	(0.007)	(0.008)
Observations	15,027	15,027
Adjusted R^2	0.59	0.62
Country-time FE	no	yes
Product FE	no	yes

Notes: This table presents the baseline results using the panel collapsed to the yearly frequency. The dependent variable is the yearly growth rate of the product-country pair g_{pct} based on the yearly panel. 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. $***p < 0.01, **p < 0.05, *p < 0.1$

the observed effects are driven by firms with regular cross-border activities. Table 6 presents the results for this intensive margin subsample. At the product-country level, the granular residual remains highly statistically significant, with a coefficient size close to that of the main analysis. 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. This is also reflected in the number of observations, which declines from 59,790 in the extensive margin to 46,106 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. The granular effect persists at the aggregate level (Column 2), with a coefficient of 0.68 and an adjusted R^2 of 0.62. This result indicates that at the most aggregated level, the impact of idiosyncratic shocks on headline CA growth is robust among firms with sustained economic activity in the external sector. This suggests that large firms, with significant and persistent cross-border linkages, drive most of the effect.

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.[14] This assumption has a substantial impact on gross flows, and thus firm weights, as merchanting receipts shoot up from a quarterly average of CHF 12.7 under the netting approach to 209 billion applying our approach. Furthermore, we adjust the treatment

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

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. Table 7 shows 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 0.21. 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. We add variability that does not align well with the primary drivers of CA fluctuations, thereby weakening the explanatory power of the model in the headline CA context. Overall, however, we can still confidently confirm the significant relationship between the granular residual and 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.

Table 6: Regression results — intensive margin

	(1)	(2)
	g_{pct}	g_t
Granular residual Γ_{pct}	0.889^{***}	
	(0.007)	
Granular residual Γ_t		0.677^{***}
		(0.132)
Observations	46,106	32
Adjusted R^2	0.31	0.63
Country-time FE	yes	no
Product FE	yes	no

Notes: This table presents the baseline results with a panel restricted to the intensive margin. The dependent variables are the year-on-year growth rates of the product-country pair g_{pct} and of the headline CA g_t. 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. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 7: Regression results — extended panel

	(1)	(2)
	g_{cpt}	g_t
Granular residual Γ_{pct}	0.862^{***}	
	(0.004)	
Granular residual Γ_t		0.195^{***}
		(0.069)
Observations	72,266	32
Adjusted R^2	0.54	0.21
Country-time FE	yes	no
Product FE	yes	no

Notes: This table presents the baseline results with an extended panel, including merchanting and trade subtractions. The dependent variable is the year-on-year growth rate of the product-country pair g_{pct} and of the headline CA g_t. 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. $***p < 0.01, **p < 0.05, *p < 0.1$

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:

$$g_{t|\tau} = \sum_{p,c} w_{pc\tau}\delta_{pct} + \sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct}, \tag{12}$$

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:

$$\begin{aligned}\sigma^2_\tau = \quad & \underbrace{var(\sum_{p,c} w_{pc\tau}\delta_{pct})}_{\sigma^2_{\delta,\tau}\text{: product-country volatility}} \quad + \quad \underbrace{var(\sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct})}_{\sigma^2_{\varepsilon,\tau}\text{: idiosyncratic volatility}} \\ & \underbrace{+ 2cov(\sum_{p,c} w_{pc\tau}\delta_{pct}, \sum_{i,p,c} w_{ipc\tau}\varepsilon_{ipct})}_{\text{covariance term}} .\end{aligned} \tag{13}$$

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 8 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 0.4 relative to the overall CA volatility. Idiosyncratic shocks are thus the main drivers of aggregate volatility. Indeed, we find that idiosyncratic shocks are 2.9 times more important compared to product-country shocks. These results are broadly in

Table 8: 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)
	0.0925	0.0368	0.1067	0.40	1.15	2.90
By main component						
	(1)	(2)	(3)	(4)	(5)	(6)
Goods	0.1180	0.0689	0.1372	0.58	1.16	1.99
Services	0.0943	0.0400	0.0980	0.42	1.04	2.45
Income	0.2929	0.0630	0.2793	0.22	0.95	4.43

Notes: The table reports the decomposition of headline CA volatility, following equation (13), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016Q1}^{2023Q4} \sigma_{\varepsilon,\tau}$.

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 8 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 0.6. In contrast, product-country volatility only accounts for 0.4 and 0.2 of aggregate volatility for the services and income component, respectively. We further find a ratio of idiosyncratic to aggregate volatility of 1.16 in the goods component, 1.04 in the services component, and 0.95 in the income component. Importantly, these results imply stark differences in the relative importance of idiosyncratic volatility to that of product-country volatility: 2 in goods, 2.5 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 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 5 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.

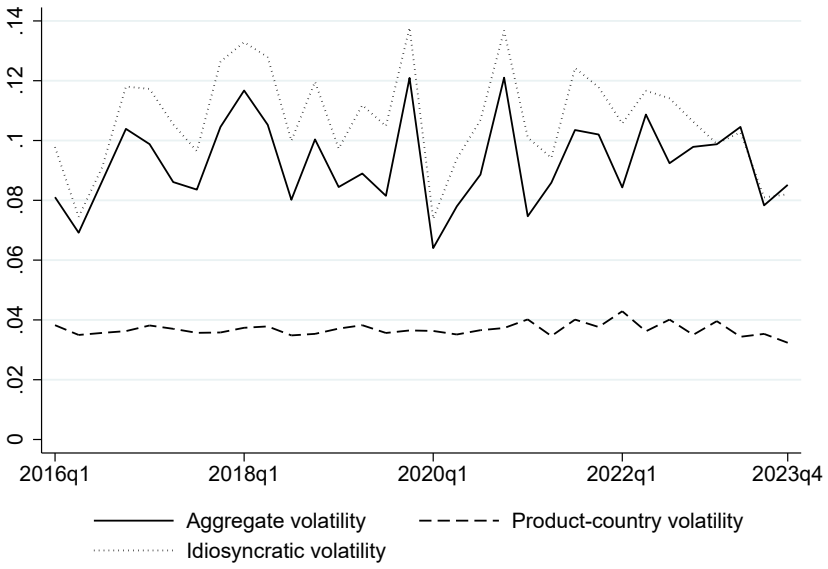
In contrast, product-country volatility remains stable throughout the period, despite

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 5: Standard deviations over time



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

5.2 Granularity and firm linkages

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:

$$\sigma^2_{\varepsilon,\tau} = \underbrace{\sum_{i,p,c} w^2_{ipc\tau} var(\varepsilon_{ipct})}_{\sigma^2_{G,\tau}\text{: granularity}} + \underbrace{\sum_{i,p,c} \sum_{j\neq i;p,q;c,d} w_{ipc\tau} w_{jqd\tau} cov(\varepsilon_{ipct}, \varepsilon_{jdqt})}_{\sigma^2_{L,\tau}\text{: firm linkages}} \tag{14}$$

This 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 9 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 0.69 to the total idiosyncratic volatility, while the linkages effect contributes a ratio of 0.71. This suggests that both effects are broadly as important, with a ratio of 0.97 between the

Table 9: 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)
0.1067	0.0736	0.0757	0.69	0.71	0.97

Notes: The table reports the decomposition of idiosyncratic volatility, following equation (14), as average standard deviations over the sample period, e.g., $\sigma_\varepsilon = 1/T \sum_{\tau=2016Q1}^{2023Q4} \sigma_\tau$.

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 $var(\varepsilon_{fipt}) = var(\varepsilon)$, then:

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

Figure 6 illustrates this relationship by plotting the granular effect against the HHI across different products.[15] 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.

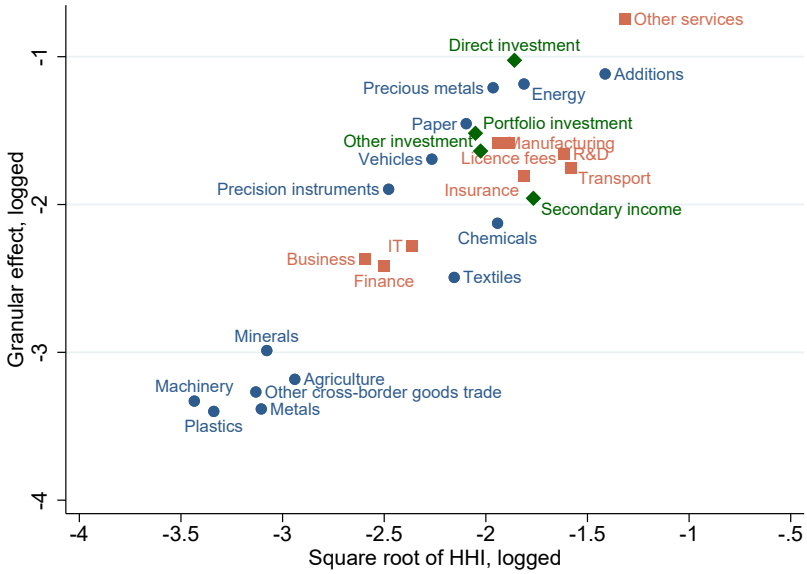
Breaking down the three main CA components reveals several products where concentration significantly drives the granular effect. Notably, precious metals in goods trade (represented by blue dots) and other services in services trade (orange squares) show considerable contributions. Similarly, direct 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

[15]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.

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.

Figure 6: 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 tested directly, as there is no clear mapping between CA products and industries used in compiling input-output tables. Nevertheless, the intuition for the propagation is straightforward as firms often operate across multiple CA components, particularly multinational enter-

prises (MNEs), which play a significant role in the external sector. For instance, consider a global pharmaceutical company based in Switzerland. Such a firm 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. As a result, an idiosyncratic shock affecting the firm's goods trade balance could also influence its services trade balance (either positively or negatively, depending on its production process) and its income balance (which could shift based on the firm's ownership structure and profit distribution).

To quantify the linkages effect across CA products, denoted by c, and consistent with equation (14), we calculate

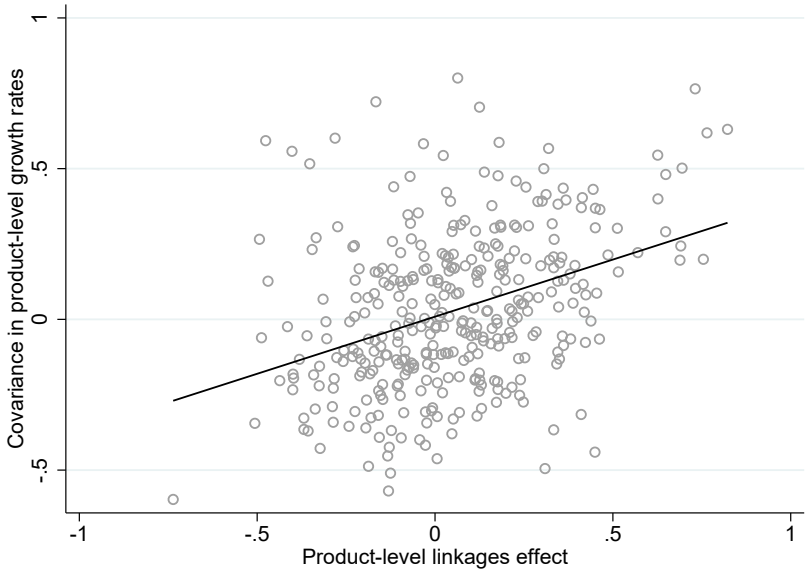
$$\sigma^2_{L,pq,\tau} = \sum_{j \neq i;p,q;c,d} w_{ipc\tau} w_{jqd\tau} cov(\varepsilon_{ipct}, \varepsilon_{jqdt}), \tag{15}$$

where the weights are normalized by the size of the respective product flows in total CA receipts and expenses. Due to negative covariances, we cannot simply present standard deviations. Instead, we normalize the linkages effects by the relevant product-level idiosyncratic volatility, i.e., $\sigma^2_{L,pq,\tau}/\sigma_{\epsilon,p,\tau}\sigma_{\epsilon,q,\tau}$.

We relate the linkages effects to the Pearson correlation coefficient across observed product-level growth rates, $\rho_{g_{pt},g_{qt}} = cov(g_{pt}, g_{qt})/[sd(g_{pt})sd(g_{qt})]$. Figure 7 plots both measures. We find a positive relationship between both measures, suggesting that firm linkages propagate idiosyncratic shocks across products and contribute to aggregate covariances. Fitting a simple linear relationship between both variables shows a statistically significant slope of 0.4.

As an alternative exercise, we consider the linkages effect across the main CA components. We find a positive covariance of idiosyncratic shocks within both goods and services trade, 1.09 and 1.03 respectively. Firm-specific shocks are overall positively correlated within these two components. This result aligns with the input-output linkages hypothesis. In contrast, we find a negative covariance of the firm linkages effect within the income component, for which theoretical expectations are less clear. We further find a negative covariance between the goods trade balance and the other two components, services and income, -0.12 and -0.27 respectively. This suggests that idiosyncratic shocks boosting the goods trade balance propagate to the other components in the opposite direction, thereby offsetting gains in the overall CA balance. This dynamic is reflected aggregate patterns of the Swiss CA balance, in which the growth of the goods trade surplus is offset by the growth in the services trade and income balance—likely driven, at least in part, by firm-level shocks. While these results may be unique to Switzerland, the broader insights gained from this case study suggest that propagation of idiosyncratic shocks through firm linkages can have a substantial impact on CA volatility.

Figure 7: Firm linkages effect



Notes: This figure shows the pairwise product-level linkages effect $\sigma^2_{L,pq}$, normalized by product-level idiosyncratic volatility $\sigma_{\epsilon,p,\tau}$ and $\sigma_{\epsilon,q,\tau}$, with respective product-level weights normalized by product-level flows in total receipts and expenses, against the Pearson correlation effect of actual product-level growth rates, $\rho_{g_{pt},g_{qt}} = cov(g_{pt}, g_{qt})/[sd(g_{pt})sd(g_{qt})]$. We report the linkages effects as an average over the sample period.

5.3 Robustness

To conclude this section of the analysis, we consider several robustness tests to validate the consistency of our findings. 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 10 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 0.4 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 11 reports the results of the volatility decomposition restricting the sample to the intensive margin, symmetrically to the exercise of Section 4.4. 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 1.5 compared to 2.9 in our baseline. This again underlines that a major contributor to idiosyncratic volatility are entry and exit of firms in cross-border transactions.

Table 10: Volatility decomposition — yearly frequency

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)
0.0769	0.0316	0.0903	0.41	1.17	2.86

Notes: The table reports the decomposition of headline CA volatility collapsing our baseline panel at the yearly frequency. The decomposition is shown as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016}^{2023} \sigma_{\varepsilon,\tau}$.

Table 11: Volatility decomposition — intensive margin

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)
0.0619	0.0398	0.0592	0.64	0.96	1.49

Notes: The table reports the decomposition of headline CA volatility, following equation (13), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016Q1}^{2023Q4} \sigma_{\varepsilon,\tau}$, using the panel restricted to the intensive margin.

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 12 shows, when accounting for those two additional products, idiosyncratic shocks contribute to aggregate volatility with a ratio of 0.96 and are more influential than product-macro shocks with a ratio of 1.5 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.

Table 12: Volatility decomposition — extended sample

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)
0.0460	0.0579	0.0732	1.26	1.59	1.26

Notes: The table reports the decomposition of headline CA volatility, following equation (13), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2016Q1}^{2023Q4} \sigma_{\varepsilon,\tau}$, using the panel extended to include merchanting and trade subtractions flows.

6 Idiosyncratic shocks and exchange rate dynamics

Building on the explanatory power of the granular residual in driving CA fluctuations, this section extends the analysis beyond the direct impact of idiosyncratic shocks on the CA. Specifically, we explore the broader macroeconomic implications of granularity in the CA. Studying the relationship between the CA and the exchange rate is challenging, given that the two variables are often jointly determined (Obstfeld and Rogoff, 1995; Obstfeld and Rogoff, 2005). Movements in the CA change the demand for a country's currency, thereby affecting the exchange rate. At the same time, changes in the exchange rate alter the relative prices of exports and imports, which influences the CA balance. This endogeneity between CA and exchange rate movements complicates the task of disentangling their causal relationship.

We propose an identification strategy that can address this endogeneity issue and estimate the causal effect of CA movements on the exchange rate. Specifically, we construct a granular instrumental variable (GIV) for the CA growth rate, building on the granular residual. Following Gabaix and Koijen (2024), we compute the GIV as the difference between the size-weighted and equal-weighted sums of idiosyncratic shocks at the product-country level. We define the GIV as z_t as follows:

$$z_t = \underbrace{\sum_{i,p,c} w_{ipct}\varepsilon_{ipct}}_{\Gamma_t\text{: granular residual}} - \frac{1}{N_{pct}} \sum_{i,p,c} \varepsilon_{ipct}.$$

The size-weighted sum, the granular residual Γ_t, reflects the granular effect driven by large firms. The equal-weighted sum captures the average impact of idiosyncratic shocks across all firms, thus providing a measure of common shocks. By removing the common factor of average shocks, the GIV removes the influence of common aggregate shocks (which would affect both large and small firms similarly), isolating the firm-specific, granular component. This ensures that our instrument primarily reflects firm-level variations in the CA that are not driven by broader macroeconomic variables like interest

rates, inflation, or global trade policies.

Additionally, the GIV should affect the exchange rate only through its impact on the CA, and not via any other channels. We thus assume that idiosyncratic shocks affect the exchange rate by impacting the CA balance (through trade, investment, or other international transactions), rather than through other channels, such as capital flows or market expectations. As such, we expect the GIV to have a high correlation with the CA balance, our endogenous variables of interest, and no correlation with the error term.

With the instrument at hand, we can estimate the relationship between the CA and the exchange rate as follows:

$$\begin{aligned} \text{First Stage:} \quad & g_t = \alpha + \beta z_t + \nu_t \\ \text{Second Stage:} \quad & \Delta q_t = \alpha + \beta \hat{g}_t + \mu_t \end{aligned} \tag{16}$$

where, again, g_t is the year-on-year CA growth rate and $\Delta q_t = q_t - q_{t-4}$, is the year-on-year change in the Swiss franc real effective exchange rate (CHF REER).

Table 13 presents the regression results for both the headline CA and the main CA components (goods, services, and income). For each regression, we show the reduced form, first-stage, and second-stage results. Overall, we find no significant relationship between CA movements and exchange rate changes at the aggregate level, with weak model fit and insignificant coefficients. The model thus cannot explain the variation in exchange rate movements. Similarly, some coefficients are unusually large, which may indicate instability in the estimates, potentially due to the limited sample size and weak instrument strength.

Extending the analysis to the product level uncovers significant results for specific products. Table 14 highlights findings for the products precision instruments, license fees, and other investment within the main CA components. Results for these products show significant reduced form, first stage, and second stage coefficients as well as strong first stage F-tests, supporting the validity of the instrument.[16]

To the extent that we can interpret an IV regression with 32 observations, we find that the CA and the exchange rate are negatively correlated. This suggests that improvements in the CA balance are associated with a depreciation of the exchange rate, at product level. This result may seem counterintuitive, as one may expect that a stronger CA would increase demand for the domestic currency. The relationship may reflect the J-curve effect, when firms that experience positive idiosyncratic shocks increase exports by lowering prices, which could reduce the value of the currency (Rose and Yellen, 1989; Alessandria and Choi, 2021). These product-specific effects thus suggest that idiosyncratic shocks in certain market segments can indeed influence currency movements, with

[16]Tables D1 through D3 report results for all 27 products in our sample.

Table 13: GIV regression results, headline and main CA components

	Headline			Goods			Service			Income		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) g_{pct}	(8) Δq_t	(9) Δq_t	(10) Δq_t	(11) g_{pct}	(12) Δq_t
z_t	-0.000	0.000		0.004	0.000		-0.004	0.000**		0.002	0.000	
	(0.006)	(0.000)		(0.012)	(0.000)		(0.008)	(0.000)		(0.020)	(0.001)	
$\hat{g_{pct}}$			-2.377			73.705			-8.161			3.924
			(99.454)			(415.409)			(15.881)			(53.093)
Observations	32	32	32	32	32	32	32	32	32	32	32	32
(Partial) R^2	0.00	0.01		0.01	0.00		0.01	0.18		0.00	0.00	

Notes: Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 14: GIV regression results, single products

	Precision instruments			License fees			Other investment		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	-0 146***	0 014***		-0 056	0 009***		-0 091**	0 010***	
	(0 033)	(0 002)		(0 035)	(0 003)		(0 043)	(0 002)	
$\hat{g_{pct}}$			-10 229***			-6 193*			-9 359*
			(3 474)			(3 687)			(4 966)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	0 22	0 62		0 11	0 33		0 14	0 47	
First stage F-statistic			43.25			11.93			26.23

Notes: Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

potential macroeconomic implications.

Lastly, we have to acknowledge that our IV estimator will likely suffer from small-sample bias and results should be interpreted with caution. Our primary aim of the exercise is to demonstrate the viability of the GIV as an identification tool, while acknowledging that a more robust analysis would require a larger dataset to obtain reliable inference.

7 Conclusion

This paper investigates the role of granularity in the context of current account (CA) balances. More specifically, we quantify the effect of idiosyncratic shocks to large firms in explaining CA fluctuations and contributing to overall CA balance volatility. We also explore the relationship between the CA and the exchange rate, leveraging the heterogeneity in the firm size distribution as instrument. As key support for the analysis, we construct a unique and comprehensive firm-level dataset for Switzerland covering the period 2015–2023. Our analysis provides new insights into the mechanisms driving the CA and its macroeconomic implications.

We show that idiosyncratic shocks to large firms are a significant driver of CA fluctuations, explaining 70% of the variation in the headline CA growth rate. We also find that idiosyncratic shocks are the dominant drivers of CA volatility. Further, these shocks also propagate through firm linkages, amplifying their effect on aggregate fluctuations. 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.

Our exploration of the use of a granular instrumental variable (GIV) represents a valuable step towards addressing the endogeneity inherent in the relationship between the CA and the exchange rate. However, given the constraints of a limited sample, our findings should be seen as preliminary. Certain products show an association between the CA and exchange rates, pointing to product-level currency pressures. This analysis underscores the value of firm-level data in capturing the heterogeneity that standard aggregate analyses would overlook.

Taken together, our findings highlights the importance of firm-level heterogeneity in shaping CA dynamics and external balance adjustments. For policymakers, recognizing the granular sources of CA volatility may improve the effectiveness of policies aimed at stabilizing external balances and mitigating exchange rate pressures.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012, 09). The Network Origins of Aggregate Fluctuations. *Econometrica*, *80*(5), 1977-2016.

Adrian, T., Grinberg, F., Liang, N., Malik, S., and Yu, J. (2022). The term structure of growth-at-risk. *American Economic Journal: Macroeconomics*, *14*(3), 283–323.

Aldasoro, I., Beltrán, P., Grinberg, F., and Mancini-Griffoli, T. (2023). The macro-financial effects of international bank lending on emerging markets. *Journal of International Economics*, *142*, 103733.

Alessandria, G., and Choi, H. (2021). The dynamics of the us trade balance and real exchange rate: The j curve and trade costs? *Journal of International Economics*, *132*, 103511.

Allen, C., Casas, C., Ganelli, M. G., Juvenal, L., Leigh, M. D., Rabanal, M. P., ... Jalles, J. T. (2023). *2022 update of the external balance assessment methodology*. International Monetary Fund.

Alvarez-Blaser, S., Auer, R., Lein, S. M., and Levchenko, A. (2022). The granular origins of inflation and its international comovement. *work in progress*.

Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics*, *9*(4), 254–280.

Behringer, J., and Van Treeck, T. (2018). Income distribution and the current account. *Journal of International Economics*, *114*, 238–254.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2018). Global firms. *Journal of Economic Literature*, *56*(2).

Boer, L., Lee, J., and Sun, M. (2024). Dominant drivers of current account dynamics.

Bussière, M., Fratzscher, M., and Müller, G. J. (2004). Current account dynamics in OECD and EU acceding countries-an intertemporal approach. *ECB Working Paper*, *No. 311*.

Camanho, N., Hau, H., and Rey, H. (2022). Global portfolio rebalancing and exchange rates. *The Review of Financial Studies*, *35*(11), 5228–5274.

Carvalho, V., and Gabaix, X. (2013). The great diversification and its undoing. *American Economic Review*, *103*(5), 1697–1727.

Carvalho, V., and Grassi, B. (2019). Large firm dynamics and the business cycle. *American Economic Review*, *109*(4), 1375–1425.

Ca'Zorzi, M., Chudik, A., and Dieppe, A. (2012). Thousands of models, one story: Current account imbalances in the global economy. *Journal of International Money and Finance*, *31*(6), 1319-1338.

Chinn, M. D., and Ito, H. (2008). Global current account imbalances: American fiscal policy versus east asian savings. *Review of International Economics*, *16*(3), 479-498.

Chinn, M. D., and Ito, H. (2022). A requiem for "blame it on beijing" interpreting rotating global current account surpluses. *Journal of International Money and Finance*, *121*, 102510.

Chinn, M. D., and Prasad, E. S. (2003). Medium-term determinants of current accounts in industrial and developing countries: An empirical exploration. *Journal of International Economics*, *59*(1), 47–76.

Coutinho, L., Turrini, A., and Zeugner, S. (2022). Assessing the euro area current account. *Journal of International Money and Finance*, *121*, 102512.

Davis, S. J., Haltiwanger, J. C., and Schuh, S. (1996). Job creation and destruction. *MIT Press Books*, *1*.

Di Giovanni, J., and Levchenko, A. A. (2012). Country size, international trade, and aggregate fluctuations in granular economies. *Journal of Political Economy*, *120*(6), 1083–1132.

di Giovanni, J., Levchenko, A. A., and Mejean, I. (2014). Firms, destinations, and aggregate fluctuations. *Econometrica*, *82*(4), 1303-1340.

Di Giovanni, J., Levchenko, A. A., and Mejean, I. (2024). Foreign shocks as granular fluctuations. *Journal of Political Economy*, *132*(2), 391–433.

Eaton, J., Kortum, S., and Kramarz, F. (2011). An anatomy of international trade: Evidence from French firms. *Econometrica*, *79*(5), 1453-1498.

Freund, C., and Pierola, M. D. (2015). Export superstars. *Review of Economics and Statistics*, *97*(5), 1023–1032.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, *79*(3), 733–772.

Gabaix, X., and Koijen, R. S. (2021). *In search of the origins of financial fluctuations: The inelastic markets hypothesis* (Tech. Rep.). NBER Working Paper No. 28967.

Gabaix, X., and Koijen, R. S. (2024). Granular instrumental variables. *Journal of Political Economy*, *132*(7), 000–000.

Gaubert, C., and Itskhoki, O. (2021). Granular comparative advantage. *Journal of Political Economy*, *129*(3), 871–939.

Gourinchas, P.-O., and Rey, H. (2014). External adjustment, global imbalances, valuation effects. In *Handbook of International Economics* (Vol. 4, pp. 585–645). Elsevier.

Grigoli, F., Luttini, E., and Sandri, D. (2023). Idiosyncratic shocks and aggregate fluctuations in an emerging market. *Journal of Development Economics*, *160*, 102949.

Gruber, J. W., and Kamin, S. B. (2007). Explaining the global pattern of current account imbalances. *Journal of International Money and Finance*, *26*, 500-522.

IMF. (2009). *Balance of payments and international investment position manual. sixth edition (bpm6).* New York: International Monetary Fund.

Koomen, M., and Wicht, L. (2022). Pension systems and the current account: An empirical exploration. *Journal of International Money and Finance*, *120*, 102520.

Koomen, M., and Wicht, L. (2023). Demographics and current account imbalances: Accounting for the full age distribution. *IMF Economic Review*, *71*(3), 719–758.

Obstfeld, M. (2012). Does the current account still matter? *American Economic Review*, *102*(3), 1–23.

Obstfeld, M., and Rogoff, K. (1995). The intertemporal approach to the current account. *Handbook of International Economics*, *3*, 1731–1799.

Obstfeld, M., and Rogoff, K. S. (2005). Global current account imbalances and exchange rate adjustments. *Brookings Papers on Economic Activity*, *2005*(1), 67–146.

Rose, A. K., and Yellen, J. L. (1989). Is there a j-curve? *Journal of Monetary Economics*, *24*(1), 53–68.

Törnqvist, L., Vartia, P., and Vartia, Y. O. (1985). How should relative changes be measured? *The American Statistician*, *39*(1), 43–46.

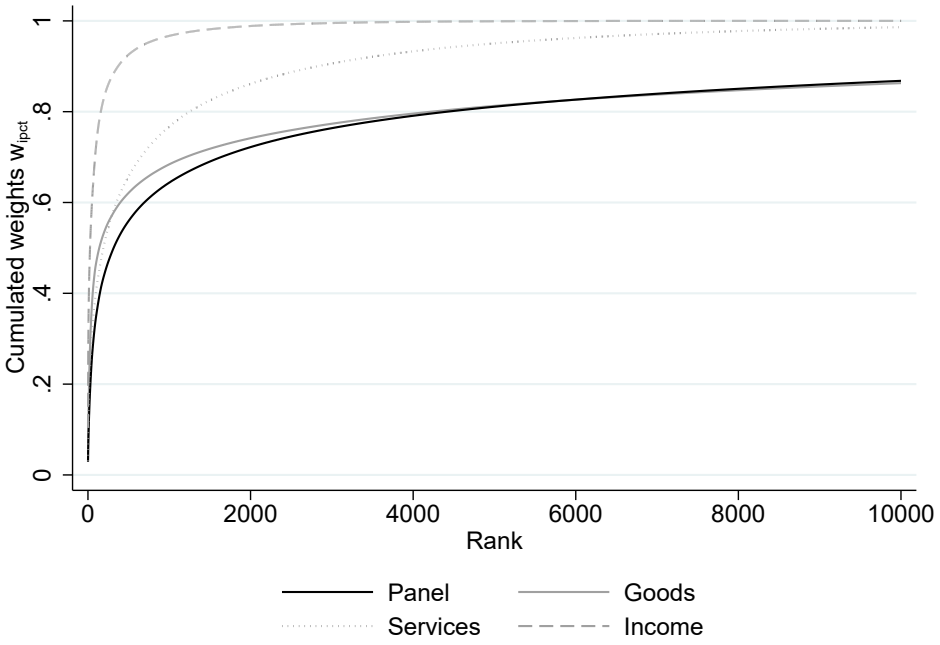
Wicht, L., and Yeşin, P. (2024). An anatomy of the external sector: Evidence from Switzerland. *Swiss National Bank, mimeo*.

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).

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).

B Regression appendix

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

	(1)	(2)	(3)
	g_{pct}	g_{pct}	g_t
Granular residual Γ_{pct}	0.882***	0.883***	
	(0.003)	(0.003)	
Granular residual Γ_t			0.713***
			(0.071)
Observations	65,310	65,310	35
Adjusted R^2	0.59	0.61	0.59
Country-time FE	no	yes	no
Product FE	no	yes	no

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_{cpt} 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_{cpt}	0.855***	0.917***
	(0.005)	(0.005)
Observations	29,933	29,857
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_{cpt} is constructed with weights normalized to the size of product-country pair p, c in total CA flows. The pre-Covid period encompass 2015-Q1 to 2019-Q4. The during and post-Covid period cover 2020-Q1 to 2023-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_{pct}	g_t
Granular residual Γ_{cpt}	0.892***	
	(0.003)	
Granular residual Γ_t		0.862***
		(0.096)
Observations	59,790	32
Adjusted R^2	0.62	0.76
Country-time FE	yes	no
Product FE	yes	no

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_{cpt} 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)
0.0823	0.0436	0.0976	0.53	1.19	2.24

Notes: The table reports the decomposition of headline CA volatility, following equation (13), as average standard deviations over the sample period, e.g., $\sigma = 1/T \sum_{\tau=2015Q2}^{2023Q4} \sigma_{\varepsilon,\tau}$, 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	0.1012	0.0299	0.1160	0.30	1.15	3.88

Notes: The table reports the decomposition of aggregate volatility, following equation (13), for two subperiods, pre-Covid (2016Q1-2019Q4) and post-Covid CA (2020Q1-2023Q4). Growth rates and weights are restricted to those two subsamples for the construction of synthetic growth rates.

D GIV appendix

Table D1: GIV regression results for products in the goods component

	Agriculture			Energy			Textiles		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	-0.046	0.003**		-0.046*	-0.022***		-0.048	0.006*	
	(0.069)	(0.001)		(0.026)	(0.008)		(0.077)	(0.004)	
$\hat{g_{pct}}$			-15.145			2.061**			-7.940
			(22.976)			(1.006)			(9.959)
Observations	32	32	32	32	32	32	32	32	32
Partial R^2	0.02	0.13		0.06	0.21		0.01	0.12	
First stage F-statistic			4.92			8.18			3.01

	Paper			Plastics			Chemicals		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	0.050	0.009		-0.197***	0.002		-0.086	0.006***	
	(0.051)	(0.006)		(0.067)	(0.002)		(0.074)	(0.002)	
$\hat{g_{pct}}$			5.574			-110.382			-13.273
			(5.872)			(134.169)			(10.929)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	0.01	0.04		0.19	0.00		0.01	0.16	
First stage F-statistic			2.47			1.01			7.99

	Minerals			Metals			Machinery		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	0.033	0.001		0.062	0.005***		-0.116	0.004***	
	(0.029)	(0.001)		(0.050)	(0.002)		(0.073)	(0.001)	
$\hat{g_{pct}}$			32.211			12.084			-29.757
			(25.587)			(8.327)			(19.290)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	-0.01	-0.01		-0.01	0.22		0.03	0.16	
First stage F-statistic			1.23			10.41			9.38

	Vehicles			Precision instruments			Other cross-border goods trade		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	0.005	0.007**		-0.146***	0.014***		0.068	0.004	
	(0.044)	(0.003)		(0.033)	(0.002)		(0.104)	(0.004)	
$\hat{g_{pct}}$			0.685			-10.229***			16.064
			(5.752)			(3.474)			(19.573)
Observations	32	32	32	32	32	32	32	32	32
Partial R^2	-0.03	0.08		0.20	0.61		-0.02	0.00	
First stage F-statistic			6.26			43.25			1.07

	Precious metals			Additions		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t
z_t	-0.034	-0.003		0.071***	0.023***	
	(0.033)	(0.002)		(0.015)	(0.005)	
$\hat{g_{pct}}$			10.747			3.101***
			(15.161)			(0.924)
Observations	32	32	32	32	32	32
(Partial) R^2	-0.00	0.03		0.38	0.42	
First stage F-statistic			2.27			18.16

Notes: Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table D2: GIV regression results for products in the services component

	Transport			Insurance			Finance		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	-0.039*	0.005***		0.037	0.000		-0.170**	0.005*	
	(0.021)	(0.001)		(0.050)	(0.004)		(0.071)	(0.003)	
$\hat{g_{pct}}$			-7.496*			78.725			-35.456*
			(4.218)			(665.356)			(19.874)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	0.05	0.49		-0.02	-0.03		0.11	0.05	
First stage F-statistic			16.35			0.01			3.02

	License fees			IT			Manufacturing		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	-0.056	0.009***		0.113*	0.008***		-0.017	0.010***	
	(0.035)	(0.003)		(0.059)	(0.002)		(0.035)	(0.001)	
$\hat{g_{pct}}$			-6.193*			13.903**			-1.594
			(3.687)			(7.034)			(3.156)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	0.08	0.31		0.06	0.28		-0.02	0.58	
First stage F-statistic			11.93			22.58			50.48

	R&D			Business			Other services		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t	(7) Δq_t	(8) g_{pct}	(9) Δq_t
z_t	0.110***	0.002		0.063	0.002		0.001	0.018***	
	(0.032)	(0.002)		(0.060)	(0.003)		(0.011)	(0.002)	
$\hat{g_{pct}}$			48.478			27.490			0.040
			(39.582)			(40.015)			(0.558)
Observations	32	32	32	32	32	32	32	32	32
(Partial) R^2	0.19	-0.01		-0.00	-0.01		-0.03	0.68	
First stage F-statistic			1.46			0.64			58.93

Notes: Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table D3: GIV regression results for products in the income component

	Direct investment			Portfolio investment		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t
z_t	0.007	0.004		0.001	-0.005	
	(0.029)	(0.004)		(0.031)	(0.007)	
$\hat{g_{pct}}$			1.996			-0.118
			(7.746)			(5.963)
Observations	32	32	32	32	32	32
(Partial) R^2	-0.03	-0.00		-0.03	-0.01	
First stage F-statistic			0.87			0.46

	Other investment			Secondary income		
	(1) Δq_t	(2) g_{pct}	(3) Δq_t	(4) Δq_t	(5) g_{pct}	(6) Δq_t
z_t	-0.091**	0.010***		0.077**	0.000	
	(0.043)	(0.002)		(0.028)	(0.002)	
$\hat{g_{pct}}$			-9.359*			394.309
			(4.966)			(4482.760)
Observations	32	32	32	32	32	32
(Partial) R^2	0.11	0.45		0.08	-0.03	
First stage F-statistic			26.23			0.01

Notes: Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$