Corvinus Economics Working Papers

05/2023

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http://unipub.lib.uni-corvinus.hu/8316

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Which Sectors Go On When There Is a Sudden Stop? An Empirical Analysis*

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June 2023

Abstract

This paper analyzes the dynamics of sectoral Real Gross Value Added (RGVA) around sudden stops in foreign capital inflows. We identify sudden stop episodes statistically from changes in gross capital inflows from the financial account, and use an event study methodology to compare RGVA before and after the start of sudden stops. In the baseline specification, we estimate changes in the growth rate of sectoral RGVA during sudden stops and in the few quarters following them. In an additional exercise, we analyze deviations from the sectors' long-run growth path. Our findings indicate that: (i) tradable sectors, especially manufacturing, face larger damages during sudden stops than nontradable sectors, (ii) but they also lead the recovery after recessions that accompany sudden stops on impact, partly due to the fact that they benefit from the depreciation of the domestic currency that occurs during sudden stops, (iii) construction and professional services are the most seriously hurt nontradable sectors during sudden stops, while information and communication, and financial services grow slower even in the aftermath of the events than before their onset. However, this slowdown only constitutes a return to their long-run sectoral growth paths. Overall, our results suggest a prolonged reallocation of economic activity away from service

*We are grateful to Szilárd Benk, Gergő Motyovszki, Balázs Reizer, Yoto Yotov, participants at the 14th Annual Conference of the Hungarian Society of Economics, and at the 15th FIW-Research Conference 'International Economics' for their helpful comments. Special thanks to Kristóf Németh for his early contributions to our work. All remaining errors are ours. The research was supported by the Thematic Excellence Program 2020 – Institutional Excellence Sub-program of the Ministry for Innovation and Technology in Hungary, within the framework of the 4th thematic program "Enhancing the Role of Domestic Companies in the Reindustrialization of Hungary" of the University of Pécs (grant number: 2020-4.1.1.-TKP2020); and by the Hungarian National Research, Development and Innovation Office (NKFIH), project No. K-143420.

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sectors, towards the production of goods. This is consistent with a traditional view of the role of tradable and nontradable sectors in a sudden stop episode.

JEL codes: F31, F32, O24, O25

Keywords: sudden stop, sectoral adjustment, capital flows, exchange rate

1 Introduction

As the pace of financial liberalization has increased, and as financial integration has strengthened, the role played by foreign capital in financing real economic activities has become more and more important all around the world. The liberalization of international capital flows has significantly contributed to global economic growth since the 1970s, but it has also increased the vulnerability of economies to potential reversals of foreign capital inflows (Tornell et al., 2003; Rancière et al., 2008). In recent decades, several financial crises have drawn attention to the fact that sudden stops in foreign capital inflows may cause severe damage not just in the financial sector, but in the real sector of the economy, as well. Sudden stops are large and unexpected reversals in foreign capital inflows (Calvo et al., 2004). They first appeared in the aftermath of the oil crises around the end of the 1970s, and started to draw considerable attention in the 1990s as a result of the Mexican tequila crisis (1994), Argentina's external debt crisis (1995), and the Asian (1997) and the Russian (1998) financial crises, during which several emerging economies experienced sudden stops in capital inflows. The global financial crisis of 2008 has made it clear that sudden stops are not just developing-economy phenomena, but developed economies, like several member states of the European Union have to face the risk of sudden stops, as well (Merler – Pisani-Ferry, 2012). Eichengreen and Gupta (2018) show that the bunching of sudden stop episodes has become more pronounced after 2002, suggesting that sudden stops are not just regional phenomena anymore, but they easily spread around the world globally. Other examples of sudden stops that were triggered by large and unexpected increases in macroeconomic uncertainty were observable during the coronavirus pandemic. Recently, increases in political uncertainty and sanctions led to sudden stops in Russia and Ukraine during the Crimean invasion (2014) and the war between the two countries (2022).

Many empirical studies analyze the characteristics of sudden stops. Some of them aim to find the most important factors that make economies especially vulnerable to sudden stops by trying to predict the probability of such an event with different explanatory variables. A high rate of domestic liability dollarization, large current account deficits relative to the demand for tradable goods (Calvo et al., 2004), perceptions of high global risk and contagion (Forbes – Warnock, 2012), a large size of the nontradable sector relative to that of the tradable one (Kalantzis, 2015), a surge in foreign capital inflows (Benigno et al., 2015), a high volatility of interest rates at which countries borrow (Reyes-Heroles - Tenorio, 2019), and external overborrowing (Pierri et al., 2020) have all been shown to increase the risk of a sudden stop. Cavallo and Frankel (2008) show that a higher degree of openness to trade decreases the probability that a sudden stop hits.

Another line of empirical research investigates the consequences of sudden stops. It is a robust finding in the literature that sudden stops lead to a significant decline in GDP growth (Calvo – Reinhart, 2000; Calvo et al., 2006; Edwards, 2007; Eichengreen – Gupta, 2018) and to a depreciation of the real exchange rate (Eichengreen – Gupta, 2018). Guidotti et al. (2004) show that the recession following a sudden stop is deepened by a high rate of domestic liability dollarization, but it is mitigated by a high degree of openness to trade and by a floating exchange rate regime. According to the results of Rothenberg and Warnock (2011) and Cavallo et al. (2015), sudden drops in net capital inflows caused by a fall in gross capital inflows are more disruptive and lead to sharper real depreciations than those resulted in by an increase in gross capital outflows.

The above-mentioned papers focus on the macro-level consequences of sudden stops without analyzing how they emerge from the heterogeneous dynamics of different sectors of the economy around the sudden stop. We aim to fill this gap by finding answers to the following questions. Is it possible to identify sectors that are more vulnerable to sudden stops than others? Can we find sectors that are able to help the economy in accommodating sudden stops? If yes, what drives their accommodation? Are there sectoral structures that are more resilient to sudden stops than others? By answering these questions, we hope that we will be able to contribute to debates about industrial policy with some new aspects regarding the resilience of economies with different sectoral structures to sudden stops in capital inflows.

We apply an event study methodology to describe the typical dynamics followed by different sectors around sudden stops. First, we detect sudden stop episodes in a wide range of countries based on quarterly financial account data about gross capital inflows. In case of each detected episode, we determine an event window consisting of the 10-10 quarters preceding and following the beginning of the episode, as well as the quarter when the sudden stop hits. Using panel regressions with episode fixed effects, we estimate the extent to which the growth rates of real gross value added (RGVA) in various sectors of the economy differ from their pre-episode averages during the sudden stop (i.e. in the short run) and in the following few quarters (i.e. in the medium run).

According to our main results, the construction sector experiences the sharpest drop in its growth rate during a sudden stop. The decline in the growth rates of professional services and the industrial sector – and manufacturing in particular – are also measured to be substantial. On the other hand, the growth rate of the public sector, real estate activities, and agriculture do not significantly differ from its pre-episode average during the sudden stop. In general, the growth rate of the tradable sector falls by more than that of the nontradable sector, however, both sectors experience a significant slowdown. This is consistent with the Mexican micro evidence presented by Tornell et al. (2003), according to which firms in the tradable sector rely more on foreign capital financing than firms in the nontradable sector.

After sudden stops, we find smaller deviations from the pre-episode trend growth rates than during sudden stops. In addition, the average post-episode growth rate of industry and manufacturing in particular, as well as the growth rate of the overall tradable sector is measured to be significantly *greater* than its average pre-episode growth rate. In spite of being one of the most struggling sectors in the short run, industry turns out to lead the recovery from the sudden stop recession. Only two sectors are measured to have significantly smaller growth rates after the sudden stop than before that: information and communication, and the financial sector. They are responsible for the significantly lower post-episode growth rate of the overall nontradable sector, as well.

We also show that all sectors experience a significant *rebound effect*: a larger negative gap between a sectors's GVA from its long-run trend path during the sudden stop is followed by significantly higher sectoral growth rates after the episode. Industry, and manufacturing in particular, and as a result, the overall tradable sector are also shown to benefit from the depreciation of the domestic currency around sudden stops: during episodes that are associated with sharper real depreciations, these sectors experience significantly smaller drops in their GVA growth rates, and the same is true for their post-episode growth rates, as well.

Two robustness analyses are conducted. First, as around half of the sudden stop episodes in our sample is from around the global financial crisis (GFC) of 2008, we run our main regressions for the subsample of those episodes that are not from the time period of the GFC (non-GFC episodes), as well as for the subsample of GFC episodes. Our results in the GFC subsample are qualitatively the same as in the full sample, but quantitatively, we measure larger changes in the sectoral growth rates. In the non-GFC sample we generally find qualitatively similar results, but lower siginficance levels and smaller point estimates.

In our second robustness analysis, we run the main regressions using *sectoral output gaps* as dependent variables. The output gap of a sector is measured as the percentage deviation of its GVA from its Hodrick-Prescott trend path. This analysis aims to determine if sudden stops are preceeded by unsustainable growth in certain sectors, and if yes, whether their slowdown during and/or after the sudden stop is just a correction towards their sustainable growth path. We find that sudden stops are preceeded by unsustainable growth in all sectors except of agriculture and the public sector. Industry, and manufacturing in particular, and the tradable sector fall significantly below their trend path during the sudden stop, and stay below that even after the episode has finished, but the gap between their actual and trend RGVA starts closing because of their significantly higher post-episode growth rates. The least favorable adjustment takes place in the nontradable sector, due to the dynamics of construction, real estate activities, professional services, and arts and entertainment. They are measured to fall back on their trend growth path during the sudden stop, but then fall even further, ending up significantly below their long-run growth path after the episode.

We know about two papers only that aim to assess the effects of events similar to sudden stops at the sectoral level. The research that is closest to ours was conducted by Craighead and Hineline (2014). The authors study sectoral adjustment around current account reversals and consistently with our results, they find that the construction sector suffers the largest damages after such events, while manufacturing is the second most seriously affected sector in developed countries. Their results suggest that investment-related sectors – e.g. construction – face the most serious losses consistently with the stylized fact that among the expenditure-side components of GDP, investment experiences the largest fall following current account reversals. They also find that nontradable sectors suffer larger damages than tradable ones in developing countries. However, they find the opposite to be true in developed countries where the tradable sector has to face more serious losses.

Our research differs from the one carried out by Craighead and Hineline (2014) in the following respects. First, we study sectoral adjustment around *sudden stops* instead of *current account reversals*. The former are most appropriately detected on the basis of gross capital inflow observations from the financial account instead of the current account. Second, we work with a different sample than Craighead and Hineline (2014). Partly this is because we have been able to collect more recent data about international capital flows and sectoral value added. More importantly, while their data about annual sectoral RGVA stems from the 10-sector database of the Groningen Growth and Development Center (Timmer – de Vries, 2009), we work with quarterly observations, which increases the robustness of our findings thanks to both a larger number of observations, and a more precise measurement of sectoral dynamics around sudden stops. In particular, the use of quarterly data allows us to explicitly distinguish between sectoral adjustment during and after sudden stops. Third, we study how the real depreciation of the domestic currency affects sectoral adjustment around sudden stops. Finally, we do not only use the growth rates of sectoral GVA as dependent variables, but also the sectoral output gaps, which allows us to study if sectors tend to grow in an unsustainable way before sudden stops, and if the slowdown of a sector around a sudden stop is just a correction towards its sustainable growth path, or it falls below that.

The other paper that studies the consequences of sudden stops at the sectoral level is that of Cowan and Raddatz (2013). The authors consider sectors within manufacturing only, and find that sectors that are more exposed to external financing and that are less capable of expanding their exports in the aftermath of sudden stops suffer larger damages. The same is true for industries that produce durable goods. Our results complement these ones well.

The rest of the paper is organized as follows. In Section 2, we describe our dataset about sectoral real gross value added and real exchange rates, as well as the data and the algorithm that we use to detect sudden stop episodes. The empirical methodology that we use to measure sectoral dynamics around sudden stops is outlined in Section 3. Section 4 and Section 5 present the main results and our robustness analyses, respectively, while Section 6 concludes.

2 Data

2.1 Sectoral value added

The most problematic part of the exercise is finding quarterly volume series for sectoral value added. Most data, such as the EU-KLEMS project, contain annual information. The advantage of using annual data would be we can collect sectoral value added data from around more episodes at this frequency. However, many interesting details of sectoral dynamics around stops are observable at the quarterly frequency only, since much of the quarterly fluctuations in sectoral GVA get smoothed out by annual aggregation. Therefore, we decided to work with quarterly data at the cost of being able to include somewhat less episodes in our sample than in case of using annual observations.[1]

We found two fairly comprehensive data sources about quarterly sectoral RGVA: Eurostat and the OECD. In both cases, the sectors are the following; the classifications follow the NACE Rev. 2 (ISIC Rev. 4) categorization used by Eurostat (and the OECD).

- A: Agriculture, forestry and fishing
- B-E: Industry
- C: Manufacturing
- F: Construction
- G-I: Wholesale and retail trade, transport, accommodation and food service activities
- J: Information and communication
- K: Financial and insurance activities
- L: Real estate activities
- M-N: Professional, scientific and technical activities; administrative and support service activities
- O-Q: Public administration, defence, education, human health and social work activities

[1]This cost does not seem to be very large: the number of episodes in our sample would increase from 64 to 87 if we worked with annual data. We redid all of our exercises using annual observations, but some of our findings got lost even when we restricted the set of episodes to be the same at both frequencies. This clearly indicates that annual aggregation masks important details of the quarterly dynamics.

- R-U: Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies

In the subsequent analysis, we use these sectors and report all results at this level of disaggregation. As a robustness exercise, we also aggregate sectoral data into tradable (T) and nontradable (NT) categories, where the former includes sectors A and B-E, while the latter includes all other sectors. Aggregation weights require nominal sectoral value added, which we get from the same sources (Eurostat and OECD). In a few cases, either nominal value added is not available, or data for component sectors are missing, so the T and NT sample is marginally smaller than some sectoral samples. Specifically, the number of episodes we can work with reduces from 64 to 60 in case of the tradable sector and to 57 in case of the nontradable sector.[2]

From Eurostat[3] we use table `namq_10_a10`, and collect chain-linked time series on gross value added. From the OECD[4] we use the dataset "Quarterly National Accounts". This also reports chain-linked gross value added volumes for the same sectors (national currency and national reference years). Combining the two sources provides us with our raw sectoral dataset. The sample contains 53 countries, and runs until 2022Q3. The starting observation differs across countries: for Australia, data starts in 1974Q3. More typically, we have sectoral value added observations starting from the mid 1990s.

The Eurostat and OECD series often use different reference years. To merge them, we work with the chain linked growth rates that are independent of the reference year. Once we merge the growth rates from the two data sources, we use the first year of the overall series as the reference year. Since our empirical exercise is based on growth rates, the choice of a reference year is without loss of generality.

To keep as many countries and periods as possible, we download seasonally unadjusted series, since seasonally adjusted data is available only sporadically. We use the `Seasonal` package in R[5] to do the seasonal adjustment ourselves.

[2]The lost episodes are Korea 1997Q2-1999Q3, Korea 2008Q2-2009Q3, Chile 2009Q1-2009Q4, and New Zealand 2008Q2-2009Q2 in case of the tradable sector. For the two latter episodes, there is data available about the RGVAs of all tradable subsectors, but nominal GVA is not available. The three additional episodes lost in case of the nontradable sector are Brazil 1999Q1-1999Q2, Brazil 2008Q2-2009Q3, and Brazil 2015Q3-2016Q2.

[3]https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=namq_10_a10&lang=en

[4]https://stats.oecd.org/Index.aspx?DataSetCode=QNA

[5]https://cran.r-project.org/web/packages/seasonal/seasonal.pdf

2.2 Detecting sudden stop episodes

2.2.1 Capital flows

The algorithm that we use to detect sudden stop episodes requires data about the evolution of capital inflows. We focus our attention on *gross* capital inflows, which is measured by the sum of inflows of direct investments, portfolio investments, and other investments from the financial account.[6] The source of our financial account data is the Balance of Payments and International Investment Position Statistics (BOP/IIP) database of the International Monetary Fund (IMF). We work with the *analytic presentation* of the balance of payments, in which the financial account does not include exceptional financing and changes in international reserves, hence, it captures market-based capital flows only. The frequency of the applied time series is quarterly, and its length varies from country to country.[7]

The raw data available in the BOP/IIP needs to be cleaned in order to become applicable for the algorithm. We carry out two data-cleaning exercises following Forbes and Warnock (2012). First, we drop all countries from our sample for which we do not have at least 2 consecutive years of observations. Second, the quarterly time series of gross capital inflows contains missing values in case of several countries. If the annual observation is available for a year, about which we do not have quarterly data, we divide the annual value among the four quarters equally. If not all quarterly observations are missing from a particular year and the annual observation is also available, we subtract the available quarterly values from the annual one, and equally divide the resulting number among the quarters with missing values. If the annual observation is not available, we keep only one continuous part of the raw time series that does not contain any missing values. We always keep the longest continuous part.

The algorithm also needs data about real GDP growth. First, we collect data about the level of seasonally and calendar adjusted real GDP for as many countries as possible from the databases of Eurostat and the OECD. Then, we calculate the time series of quarterly GDP growth rates and feed them to our algorithm.

[6] See Rothenberg - Warnock (2011), Forbes – Warnock (2012), and Cavallo et al. (2015) for comparisons between the characteristics of sudden stop episodes triggered by extreme changes in *net* capital inflows and those resulted in by sharp drops/peaks in *gross* capital inflows/outflows.

[7] The earliest available observation about gross capital inflows is from Canada: it stems from 1950Q1. The most recent observations that we use are from 2021Q4.

2.2.2 The algorithm

The algorithm that we apply to detect sudden stop episodes consists of two parts, and it is a refined variant of the one developed by Calvo et al. (2004). Its first part closely follows the lines of the one described by Forbes and Warnock (2012). We start by annualizing quarterly data about gross capital inflows in order to filter out seasonal fluctuations and to mute down potential noise in the time series. If $GIF_{n,t}$ denotes gross capital inflows to country n in quarter t, the annualized $C_{n,t}$ value of gross inflows to country n in quarter t can be obtained as

$$C_{n,t} = \sum_{\tau=0}^{3} GIF_{n,t-\tau}, \quad n = 1, 2, \ldots, N \,\text{and}\, t = 4, 5, \ldots, T_n.$$

N is the number of countries in the sample, and T_n is the length of the raw gross capital inflow time series for country n. In our case, $N = 150$.

Then, we compute the year-on-year change in $C_{n,t}$ as

$$\Delta C_{n,t} = C_{n,t} - C_{n,t-4}, \quad n = 1, 2, \ldots, N \,\text{and}\, t = 8, 9, \ldots, T_n.$$

$\Delta C_{n,t}$ will be our measure for the changes in gross capital inflows. At this point, we drop all countries from our sample for which the resulting time series of $\Delta C_{n,t}$ is shorter than 5 years (20 quarters). We are left with 137 countries.

In the next step, we compute the rolling means and the rolling standard deviations of $\Delta C_{n,t}$ for each quarter in each country over the preceeding 5 years. A sudden stop is defined as an episode when the change in gross capital inflows falls by at least two standard deviations below its mean, where the mean and the standard deviation are the rolling mean and standard deviation calculated over the preceeding 5 years. The episode begins when $\Delta C_{n,t}$ falls below the mean minus one standard deviation threshold, and ends when it returns above this threshold value.[8] Thanks to the adaptive nature of the thresholds, the detected episodes reflect two important properties of sudden stops: they are considered to be *large* and *unexpected* drops in capital inflows (Calvo et al., 2004). Of course, what is considered as large and unexpected changes with the state of the economy. The adaptive thresholds try to capture these changes by tracking the variable volatility of capital inflows with the help of the rolling means and standard deviations. Finally, we

[8]Note that $\Delta C_{n,t}$ has to cross the mean minus two standard deviations threshold between the two quarters in order for the episode to qualify as a sudden stop.

drop all detected episodes that last only one quarter, and we merge all pairs of detected episodes that are closer to each other than one year.

The first part of the algorithm detects several *false positive* episodes that are actually not sudden stops. One reason for this is that realized foreign capital inflows are equilibrium outcomes of the interaction between the demand and supply of foreign capital. Only large and unexpected drops in the *supply* of foreign capital to the country are sudden stops, but sometimes we can see large and unexpected drops in capital inflows because the need for foreign capital falls in the country (demand decreases). This can occur for example when the country experiences a large positive terms of trade shock due to e.g. a spike in global commodity prices, assuming that the country is a commodity exporter. Such positive terms of trade shocks may lead to substantial improvements in the country's current account, leading to a sharp fall in the demand for foreign capital and in actual capital inflows. Such events are not what is usually meant by a sudden stop. Another possible reason for the appearance of false positive episodes – especially in small countries – can be a large investment made by a multinational company in the country, the effect of which disappears in the next year, indicating a large fall in capital inflows. Multinational companies often let capital flow through their subsidiaries or special purpose enitities that they own outside of their base country. Such events and other rearrangements of their asset portfolios may result in large swings in gross capital flows, especially in small countries. These swings do not represent a systematic flight of foreign investors from the country, therefore, they should not be considered as sudden stops.

The second part of the algorithm serves to filter out these false positive episodes. The idea behind it is that if a country is actually in the need of external financing, but capital inflows still substantially fall, then it has to cause some kind of a systematic damage to the real economy. Hence, we only keep those detected episodes in our sample that coincide with a *recession*.[9] We define a country to be in a recession during a particular quarter if at least one of the two following conditions holds:

1. Its real GDP falls.

2. Its real GDP growth slows down substantially.

In order to be consistent with the detection of capital flow windows, and to have capital flow windows and recession windows that actually correspond to each other, we annualize

[9] Calvo et al. (2004), Cavallo and Frankel (2008), Cowan and Raddatz (2013), and Benigno et al. (2015) all use some kind of a GDP-based criterion to filter out false positive episodes from their sample.

quarterly GDP growth rates in a similar way we did with gross capital inflows. If $g^q_{n,t}$ is the quarterly growth rate of real GDP for country n in quarter t, measured in percentages, then the annualized $g_{n,t}$ growth rate of real GDP for country n in quarter t is calculated as

$$g_{n,t} = \left[\prod_{\tau=0}^{3}\left(1+\frac{g^q_{n,t}}{100}\right)-1\right]\times 100, \quad n=1,2,\ldots,N^g \,\text{and}\, t=4,5,\ldots,T^g_n,$$

which is also measured in percentages. N^g is the number of countries, about which we have GDP data, and T^g_n is the length of the quarterly GDP growth rate time series for country n. In our sample, $N^g = 49$.[10]

If $g_{n,t}$ is negative, then the first of the above-mentioned conditions is satisfied, and country n is detected to be in a recession in quarter t.

We also compute the year-on-year change in $g_{n,t}$ as

$$\Delta g_{n,t} = g_{n,t} - g_{n,t-4}, \quad n=1,2,\ldots,N^g \,\text{and}\, t=8,9,\ldots,T^g_n.$$

$\Delta g_{n,t}$ measures the changes in real GDP growth in percentage points.

We define the slowdown in real GDP growth to be substantial if $\Delta g_{n,t}$ falls by at least one standard deviation below its mean. The recession window begins when $\Delta g_{n,t}$ falls below the mean minus half standard deviation threshold, and ends when it returns above this threshold value.[11] There are two important differences compared to the detection of capital flow windows:

1. We apply less strict threshold values as we already consider a one standard deviation fall in the change of GDP growth below its mean to be a substantial damage to the real economy relative to the preceeding quarters.

2. We use fixed threshold values instead of the adaptive ones applied in the first part of the algorithm. The reason for this is that $\Delta C_{n,t}$ has an increasing volatility over time that has to be tracked with the rolling means and standard deviations, but $\Delta g_{n,t}$ is stationary, hence, adaptive thresholds would lead to the detection of spurious recessions in periods of stable GDP growth. For a given country, the constant mean and standard deviation that serve as the basis for determining its fixed threshold values

[10] N^g is much smaller than N, i.e. we have GDP data for much less countries than we have financial account data for. However, this is not what restricts the size of our final sample, since Eurostat and OECD report data about quarterly sectoral RGVA for even fewer countries.

[11] Again, note that $\Delta g_{n,t}$ has to cross the mean minus one standard deviation threshold between the two quarters in order for the event to qualify as a recession.

are calculated from a sample that begins in the first quarter when an observation about $\Delta g_{n,t}$ is available, and ends in 2020Q1. We leave out the time period since the beginning of the coronavirus pandemic from this sample because its exceptionally high volatility in terms of GDP growth would lead to too strict thresholds in case of some countries.

After determining the quarters in which different countries experienced recessions, we only keep those episodes detected in the first part of the algorithm, during which there was at least one recessionary quarter in the country according to at least one of the two above-mentioned conditions.

The algorithm detects 74 sudden stop episodes in our dataset, however the lack of availability of quarterly data about sectoral RGVA constrains the set of episodes that we can use to study sectoral adjustment around sudden stops (see Subsection 2.1). Our empirical strategy requires data about the growth rate of sectoral RGVA to be available 10 quarters before and after the beginning of each sudden stop episode that is involved in the estimation. Hence, we have to drop all episodes for which such data is not completely available. In 7 cases, it is completely unavailable[12], while in 2 cases, not all 21 event periods are available[13]. The latter are cases where periods are missing either at the beginning, or at the end of the full event window.[14] We also drop an episode detected in Ireland between 2016Q4-2017Q1, which is an obvious false positive that the second part of the algorithm cannot filter out. In 2015, Apple shifted all of its intellectual property assets to an Irish domicile, boosting capital flows to the country, and leading to 26% growth in its GDP (Pogatchnik, 2021). The resulting high basis has led to the detection of a false positive episode in 2016. The final number of episodes that we can keep in our sample is 64.[15]

[12]These cases are Iceland 2001Q2-2002Q1, Iceland 2008Q2-2009Q3, Israel 2001Q1-2002Q2, Israel 2007Q4-2009Q2, Israel 2011Q4-2012Q3, Russia 2008Q4-2009Q3, and USA 2008Q1-2009Q2. In case of the latter, there is quarterly data available about sectoral RGVA, but not according to the same classification of sectors as for other episodes.

[13]These cases are Finland 1991Q1-1992Q2 and France 2020Q2-2020Q3. We also ran regressions when these episodes are included, and the results are essentially identical to the ones we report.

[14]This almost always happens for all sectors symmetrically. There are only six cases, in which data are available for some sectors, while they are missing for other ones: Brazil 1999Q1-1999Q2, Brazil 2008Q2-2009Q3, Brazil 2015Q3-2016Q2 (sector R-U is missing), Chile 2009Q1-2009Q4 (sectors K, M-N, and R-U are missing), Korea 1997Q2-1999Q3 and Korea 2008Q2-2009Q3 (sectors B-E, G-I, and O-Q are missing). In addition, data about the real effective exchange rate is missing in 5 cases: Albania 2019Q4-2020Q1, Bosnia and Herzegovina 2019Q3-2020Q2, North Macedonia 2007Q1-2007Q2, North Macedonia 2009Q2-2009Q3, and Montenegro 2016Q1-2016Q3.

[15]These 64 episodes still include three counterintuitive ones: Ireland 2018Q2-2018Q3, Luxembourg 2014Q2-2014Q4, and Switzerland 2018Q1-2019Q1. As we found no clear objective reason for dropping them from our sample, we decided to keep them. The significance of some of our findings improves in case of dropping them.

2.2.3 An example

Figure 1 presents an example of applying the algorithm. It illustrates the detection of sudden stop episodes in case of Hungary. The upper panel presents the first part of the algorithm where a capital flow window is detected if the year-on-year change in annualized gross capital inflows (the solid black line) falls below the two standard deviation threshold (the dashed gray line) for at least one quarter. The episode begins when it crosses the one standard deviation threshold (the dotted gray line), and ends when it returns above this line. Recession windows are detected with the help of the lower panel of Figure 1, on which a recession is detected if the year-on-year change in the annualized GDP growth rate (the solid black line) falls below the one standard deviation threshold (the dashed gray line) for at least one quarter. The recession begins when it crosses the half standard deviation threshold (the dotted gray line), and ends when it gets above this line again.[16]

Five capital flow windows are detected on the basis of the top panel of Figure 1: 1996Q4-1997Q1, 2002Q2, 2009Q1-2010Q2, 2017Q4-2018Q3, and 2021Q2-2021Q4. Only one of these (2009Q1-2010Q2, the one related to the global financial crisis) qualifies as a sudden stop in our final sample after filtering out false positive episodes in the second part of the algorithm, since this is the only one that coincides with a recession according to our definition.[17] Following Forbes and Warnock (2012) and Eichengreen and Gupta (2018), another reason why the capital flow window in 2002Q2 is filtered out is that it lasts only one quarter, hence, it is likely to be a result of noise.

2.2.4 Detected sudden stop episodes

The 64 sudden stop episodes included in our final sample are listed in Table 9 of Appendix B. They come from 36 countries, some of which have experienced more than one sudden stop over the past decades. Their geographical and time distribution is presented on Figure 2.

The time dimension of the distribution makes it clear that somewhat more than half of our episodes (35 out of 64) stem from around the global financial crisis (from the period

[16]Additionally, we also consider the country to be in a recession in a given quarter if its annualized GDP growth rate is negative – in case the described procedure does not already qualify it as a recessionary quarter.

[17]The capital flow window between 1996Q4 and 1997Q1 may actually be a sudden stop related to austerity measures introduced by the Hungarian government in 1995 in response to severe external and internal imbalances. However, the first observation about the change in annualized GDP growth is only available for 1997Q1 when Hungarian GDP growth already started accelerating.

Figure 1: Detecting sudden stop episodes in Hungary

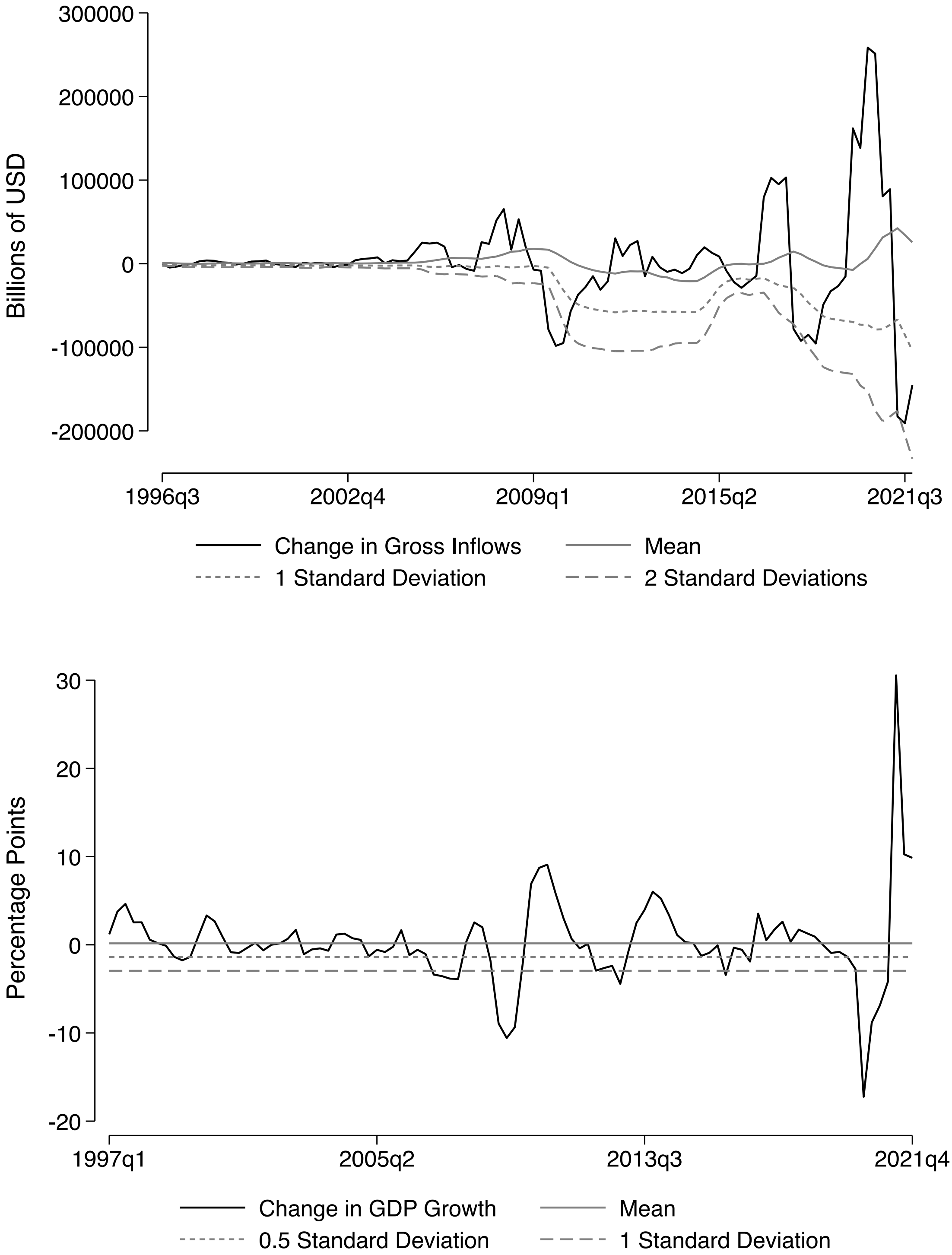
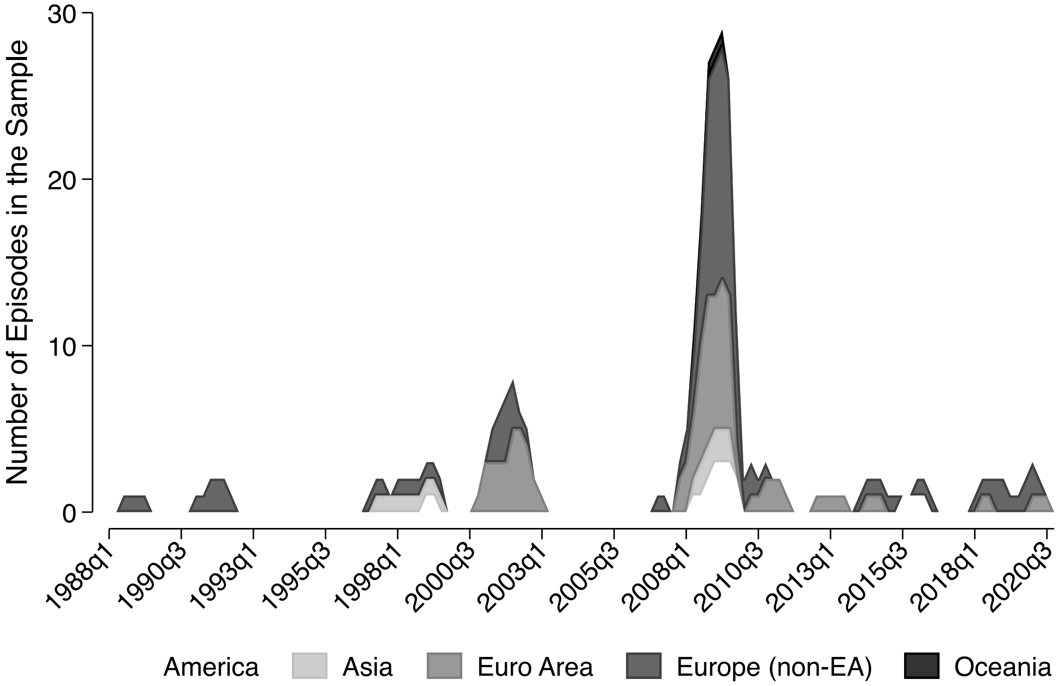


Figure 2: The geographical and time distribution of detected sudden stop episodes



2007Q3-2012Q4). There is a visible bunching of episodes around the 2001-2002 recession, as well. A few episodes are concentrated around the time of the Asian and Russian financial crises (1997-1999), but South Korea and Japan are the only Asian countries for which we have satisfying sectoral value added data.

Regarding the geographical dimension of the distribution, data availability makes our sample dominated by European episodes. However, these European episodes are quite heterogeneous: their source countries range from high-income EU member states (Germany, France, Netherlands, etc.) to middle-income countries from outside the EU (Montenegro, Russia, Turkey, etc.). 22 of our 55 European episodes occured in Euro Area member states, while the remaining 33 are from outside the Euro Area. This facilitates the comparison of sectoral adjustment between episodes around which substantial exchange rate movements took place, and episodes around which the domestic currency was not able to depreciate relative to the currencies of the country's key trading partners, as they belong to the same currency area. Despite the European dominance in our sample, it also contains 9 episodes from other continents (America, Asia, and Oceania).

2.3 Other variables

In addition to sectoral GVA, we also include two additional aggregate variables in our dataset. These are real gross domestic product (GDP) and the real effective exchange rate (REER).

GDP and REER data also come from Eurostat and the OECD. For GDP, we use the `namq_10_gdp` table of Eurostat, and Quarterly National Accounts from the OECD. Similarly to sectoral GVA, we work with chain linked growth rates from both sources. Sources for the REER data are the `ert_eff_ic_q` table of Eurostat, and Monthly Economic Indicators (MEI) of the OECD. The base year is 2010 for Eurostat data and 2015 for OECD data – for the latter, we use the average of quarterly 2010 levels to convert the base year to 2010.

3 Methodology

3.1 Event windows

As we discussed in the Introduction, our basic approach uses an event study methodology. We follow the procedure described by Cavallo et al. (2015) with some modifications. The method relies on identifying sudden stop episodes, and studying the economic variable of interest before and after the starting period of the sudden stop. Comparing the pre-crisis developments with the post-crisis dynamics, we can run statistical tests on whether there are significant changes around the sudden stop. The main differences from Cavallo et al. (2015) are the following:

1. We apply the method to sectoral real gross value added, not just to macro-level real GDP.

2. We use the quarterly growth rates of sectoral GVA instead of their levels as dependent variables in our regressions, hence, we drop the deterministic time trend from the set of explanatory variables used in the regressions of Cavallo et al. (2015). This allows us to control for episode-specific heterogeneity in sectoral trend growth rates by episode fixed effects, leading to more precise estimates.

3. As a robustness exercise, we also apply sectoral output gaps as dependent variables. The output gap of a sector is measured as the percentage deviation of its actual GVA

from its Hodrick-Prescott trend path. The smoothing parameter of the Hodrick-Prescott filter is set to 1600, which is the standard value used in case of quarterly data.

4. We do not simply compare pre-crisis and post-crisis growth rates, but we also split the post-crisis segment of the event window into two parts: the period of the sudden stop and the aftermath of the sudden stop. This will allow us to distinguish between short-run sectoral adjustment during the sudden stop, and medium-run sectoral adjustment after the sudden stop. The length of these two parts varies from episode to episode according to the length of each event.

Based on Cavallo et al. (2015), we proceed as follows. First, we merge the sectoral data and the identified sudden stop episodes discussed in the previous section. We define a sudden stop episode by its starting date and by its end date. For each episode, we define an event window, which is set to 10 quarters before and after the start of the event. This means that for each sudden stop episode, we have a time series of 21 observations. We do this for each sector separately, using the chain-linked growth rates for sectoral GVA as our main variable of interest.

We work with two samples to present our main results. The first one is used for the regression analyses, and it includes all the 64 identified sudden stop events and the 11 sectors. For each sector, we have a panel where the identifiers are the episodes and "time" (the event periods before and after the sudden stop starts). The second sample is derived from the first one by averaging the levels of sectoral RGVA over the sudden stop episodes for each event period and sector. Sectoral RGVA levels are normalized to 100 in the first quarter of the sudden stop. This yields simple time series for the 11 sectors with 21 observations. Averaging gives us a "generic" sudden stop where idiosyncratic factors are filtered out. This second sample will only be used in Subsection 4.1 for some exploratory data analysis.

In Subsection 5.1, we also split our panel data into two subsamples to investigate how robust our findings are for the exclusion of episodes related to the global financial crisis. Our GFC subsample contains all episodes that started between 2007Q3 and 2012Q4, and it includes 35 sudden stop events. The remaining 29 episodes constitute our non-GFC subsample.

3.2 Estimation

Recall that our variable of interest is chain-linked gross value added. For all sectors, this is typically growing over time, at different paces around different sudden stop episodes. Therefore, we look for changes in its *growth rate* after the sudden stop hits, as this will allow us to control for episode-specific average pre-crisis growth rates.

For carrying out the regression analyses, we use our panel data structure, where each sudden stop episode is a separate time series. Our basic specification is the following:

$$y^j_{i,t} = \beta^j_0 + \beta^j_1 SS_{i,t} + \beta^j_2 SS^{post}_{i,t} + \eta^j_i + \epsilon^j_{i,t}, \quad (1)$$

where in the main specification, $y^j_{i,t} = 100 \times \Delta \log RGVA^j_{i,t}$ is the log-change in the real gross value added of sector j from event period $t-1$ to event period t, expressed in percentage terms. $SS_{i,t}$ is a sudden stop dummy, $SS^{post}_{i,t}$ is a post sudden stop dummy, i indexes the sudden stop episodes, t is time (within the 21-period event window), η^j_i is an episode fixed effect for sector j and $\epsilon^j_{i,t}$ is an error term. The sudden stop dummy takes the value of 1 during the sudden stop, i.e. $SS_{i,t} = 1$ when $0 \leq t \leq T^{end}_i$, where 0 is the start date and T^{end}_i is the end date of episode i. The post sudden stop dummy takes the value of 1 after the sudden stop, in the remaining part of the event window, i.e. $SS^{post}_{i,t} = 1$ when $T^{end}_i < t \leq 10$. Coefficient β^j_1 measures the short-run adjustment of sector j during the sudden stop, and β^j_2 measures its medium-run adjustment that takes place after the sudden stop has finished. These coefficients measure average deviations from the pre-crisis trend growth rate during and after the sudden stop. Negative values indicate a shortfall, and positive values indicate that a sector surpasses its pre-crisis trend growth. We run regressions for each sector separately.

It is important to note that the pre-crisis trend does not necessarily represent a "normal" period. Imagine, for example, that a sudden stop is preceded by an unsustainable housing boom. In this case, the construction sector appears to fall into a deep recession after the sudden stop hits, but at least part of this is a correction of previous imbalances. To investigate whether this is the case, we also estimate equation (1) for each sector with the *output gap* of sector j playing the role of $y^j_{i,t}$. The results of these estimations are presented in Subsection 5.2, and their interpretation requires some caution. In case of using sectoral output gaps as dependent variables, β^j_0 measures the average output gap of sector j in the 10 quarters preceding the sudden stop: if it is estimated to be significantly positive, it refers to unsustainable growth in sector j before the sudden stop. $\beta_0^j + \beta_1^j$ measures the average output gap of sector j during the sudden stop: if it estimated to be significantly negative, then the sector falls below its sustainable growth path during the event. However, if it is estimated to be insignificant, then the sector just returns to (or stays on) its sustainable growth path. Similarly, $\beta_0^j + \beta_2^j$ measures the average output gap of sector j in the quarters following the sudden stop.

For studying the role of exchange rate movements and the rebound effect in facilitating sectoral adjustment around sudden stops, we augment equation (1) the following way:

$$\begin{aligned} y_{i,t}^j = \gamma_0^j + \gamma_1^j SS_{i,t} + \gamma_2^j SS_{i,t}^{post} + \gamma_3^j RDEPR_i \times SS_{i,t} + \gamma_4^j RDEPR_i \times SS_{i,t}^{post} \\ + \gamma_5^j RECSS_i^j \times SS_{i,t}^{post} + \eta_i^j + \epsilon_{i,t}^j, \end{aligned} \tag{2}$$

where $y_{i,t}^j$ is always the log-change in the RGVA of sector j from event period $t-1$ to event period t, expressed in percentage terms. $RDEPR_i = -100 \times \Delta \log REER_{i,-1\text{-}10}$ is the real depreciation of the domestic currency from the period just preceeding the start of episode i until the end of the event window, measured as minus the log-change in the real effective exchange rate between event period -1 and 10, also expressed in percentage terms.

$RECSS_i^j$ is the depth of sector j's recession during the sudden stop within event window i, measured as the simple average of negative percentage deviations from the sector's Hodrick-Prescott trend path if $SS_{i,t} = 1$. Coefficients γ_0^j, γ_1^j, and γ_2^j can be interpreted similarly as coefficients β_0^j, β_1^j, and β_2^j in equation (1), with the exception that they must be interpreted conditional on no real depreciation occuring from the beginning of the sudden stop until the end of the event window, and on zero average sectoral output gap during the sudden stop. γ_3^j measures the percentage-point change in the average growth rate of sector j's RGVA during the sudden stop if it is accompanied by a 1 percentage point stronger real depreciation of the domestic currency, and γ_4^j measures the same for the post-episode average sectoral growth rate. If they turn out to be significantly positive, then real depreciation facilitates sector j's adjustment during or after the sudden stop, respectively. Finally, γ_5^j measures the percentage-point change in the average growth rate of sector j's RGVA after the sudden stop if it has experienced a 1 percentage point larger negative output gap during the sudden stop. A significantly positive value of γ_5^j refers to the presence of a significant rebound effect as it suggests that the more sector j falls below its sustainable growth path during the sudden stop, the faster it will grow after that.

4 Main results

4.1 Sectoral averages

We start the analysis with the sample where for each sector, we average period values across the sudden stop episodes. We only include episodes where the time coverage is complete, i.e. we have all the 21 observations: 10 quarters before and 10 quarters after the sudden stop starts. This guarantees that averaging uses the exact same sample of events for each period.

Figure 3: Sectoral dynamics around a synthetic sudden stop

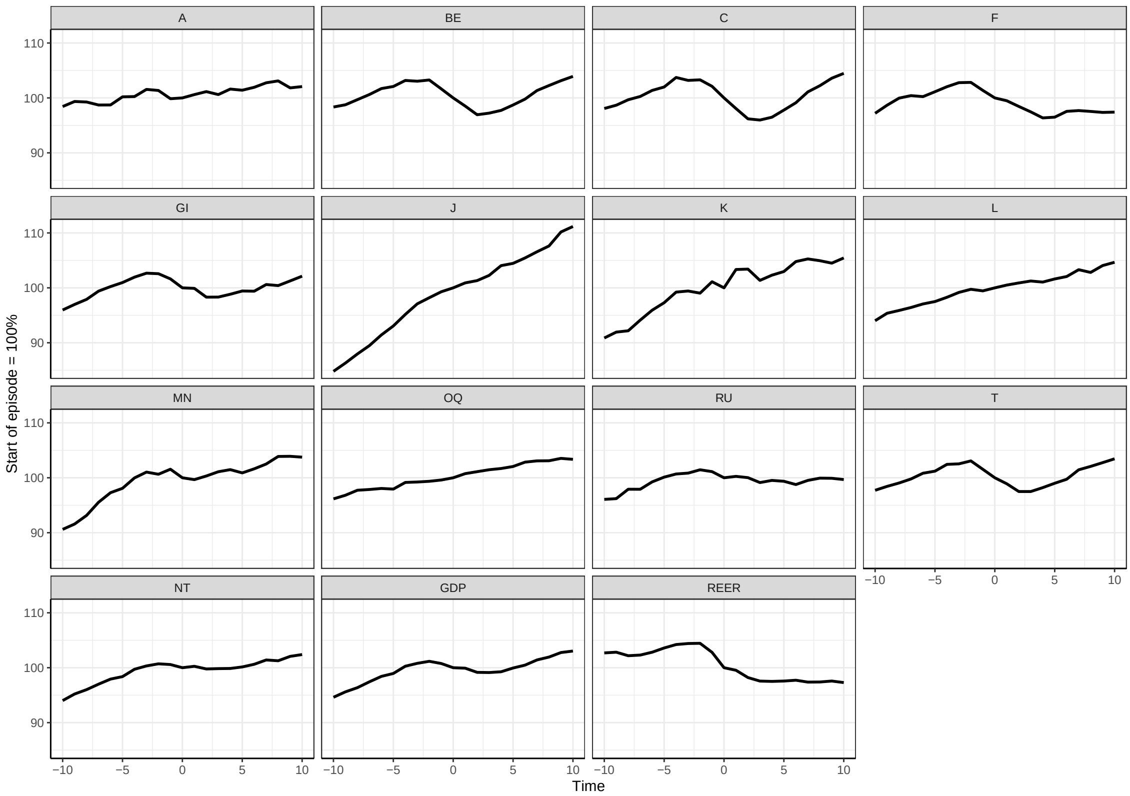


Figure 3 shows adjustments around a "representative" sudden stop for each of the 11 sectors. We plot GVA levels, choosing units such that at the beginning of a sudden stop ($t = 0$), GVA $= 100\%$. There are stark differences across sectors in how they behave around a sudden stop event. Agriculture (A) does not seem to be strongly affected by the sudden stop, either during or after the eposide. This is not surprising, since sectoral output is likely to be dominated by variation unrelated to financial conditions. In contrast, industry (B-E), manufacturing (C), and trade and hospitality (G-I) suffer a more protracted decline, and start to recover afterwards. Construction (F) peaks just before the sudden stop happens, declines for a few periods, and then levels off at a lower value. Service sectors in general (with the exception of G-I) tend to experience a growth slowdown: for arts and entertainment (R-U) this is highly visible, while for the public sector (O-Q) and real estate activities (L), there is no obvious slowdown. It is also interesting to note what happens before the sudden stop hits. Sudden stops appear to be preceded by a construction boom, which seems to be unsustainable afterwards.

The figure also shows the evolution of aggregate variables: real GDP, the real effective exchange rate (REER), and the behavior of the tradable and nontradable sectors, as defined earlier. Since we require GDP to decline during the detection of sudden stops, its fall is not surprising. The decline is concentrated in the tradable sector, while nontradables experience a significant growth slowdown. The REER – which appreciates on average before sudden stops – depreciates sharply during episodes, and (at least until the end of the event window) does not recover.

As the figure reveals, trend growth was present in most sectors pre-crisis, but with large variations across sectors. Information and communication (J), financial and insurance activities (K), and professional services (M-N) grow the fastest, while agriculture (A), industry (B-E), and manufacturing (C) grow the slowest in the periods preceding a sudden stop. To gauge the impact of sudden stops, it is therefore important to control for sector- (and episode-) specific growth.

While the figure is informative, there is a major reason why averaging across all sudden stop episodes may paint a misleading – or at least incomplete – picture. Sectoral growth rates are likely to differ across different episodes, partly independently from the sudden stop itself. Sectoral growth rates are likely to change both over time, and also across countries. Therefore, we need to control for these differing trends across episodes in order to isolate the changes related to the sudden stop. To do this, we use the panel dataset discussed earlier.

4.2 Panel regressions

We now turn to panel regressions using equation (1). We estimate the model for the sectors separately, adding episode fixed effects in each case. We split the overall table into three panels, due to the number of sectors. In addition to the 11 sectors, we also include regressions for tradables and nontradables (as defined earlier), and for two aggregate variables, GDP and the real effective exchange rate. Table 1 presents the results.

< Table 1 about here >

For the detailed sectoral results, we see that the short-run change in sectoral GVA during a sudden stop is almost always negative, and mostly highly significant. The exceptions are agriculture (A) where the response is negative, but insignificant; and sectors L and O-Q, where the point estimates are positive and insignificant. The immediate damage is largest for industry (B-E), manufacturing (C), construction (F), and professional services (M-N). These results are in line with the visual clues presented on Figure 3. We can order sectors according to the drop they are measured to face in their growth rates during sudden stops the following way. The order is ascending, and it is based on the point estimates only, ignoring standard errors.

O-Q, L, A, R-U, J, K, G-I, B-E, C, M-N, F

There is more heterogeneity when we look at the persistent changes after sudden stops, measured by the Post-Episode variable. Here, sectors A, F, G-I, M-N, O-Q, and R-U have insignificant coefficients, although the point estimates are negative. Sectors J, K, and L show significantly negative coefficients[18], i.e. growth rates are persistently lower after a sudden stop. Interestingly, for industry (B-E) and manufacturing (C), the estimated coefficients are significantly *positive* (the B-E results are likely to be driven by manufacturing). This means that manufacturing experiences a rebound after the immediate fall in activity during the sudden stop. We will return to this issue in the next section, where we explore facilitators for the rebound.

Again, we can rank sectors by the strength of the Post-Episode coefficent. Starting from the positive and significant coefficient in C, we can arrange sectors towards more negative values:

C, B-E, G-I, A, O-Q, M-N, L, F, R-U, J, K

The most negative coefficient is for sector K, which is somewhat surprising given the visual results on Figure 3.

Turning to tradables and nontradables, we find that both broad sectors experience a decline when the sudden stop hits the economy. There is a marked difference, however,

[18]However, the coefficient in sector L is significant only at the 10% level.

in the aftermath of the crisis. Tradables experience a rebound (again, likely driven by manufacturing). Nontradables, however, are subject to a protracted slowdown. As we saw in the previous paragraphs, these broad results mask significant heterogeneity, especially within nontradables.

Finally, we also ran regressions with GDP and the REER to see if the results confirm to basic intuition about the general macrodynamics around sudden stops. As expected, GDP growth falls on impact and remains lower in the subsequent quarters, although the latter coefficient is not significant. Sudden stops are by our definition recessionary, although sectoral differences are important. The real exchange rate depreciates on impact, which is again as expected: a real depreciation may facilitate adjustment through its effects on tradables. The effect is persistent in the sense that the REER depreciation is not reversed within the event window, i.e. the real exchange rate remains persistently lower.

To sum up, our results lead to the following broad conclusions about the sectoral and aggregate dynamics around sudden stops. First, sudden stops are generally recessionary, both at the sectoral level and in the aggregate (by definition). Second, there are significant sectoral asymmetries, especially in the periods following the sudden stop itself. Tradable sectors rebound faster, with some business services featuring a similar pattern. Public services are affected the least. According to Figure 3, construction follows a boom and bust pattern before and after the sudden stop. This suggests that the sector may serve as an early warning indicator to forecast future sudden stops. We investigate this issue later in more detail.

4.3 Hypothesis tests

In Subsection 4.2, we ordered sectors according to the size of the fall in their growth rates, without formally verifying if the changes differ significantly across sectors. In order to test this, we estimate another panel regression, which allows us to measure changes in sectoral growth rates simultaneously, and to perform F-tests on the equality of sectoral coefficients.

In particular, we estimate the following regression:

$$y_{i,t}^{j} = \delta_0 + \sum_{j=1}^{J} \delta_1^j SEC^j \times SS_{i,t} + \sum_{j=1}^{J} \delta_2^j SEC^j \times SS_{i,t}^{post} + \theta_i^j + \epsilon_{i,t}^{j}, \tag{3}$$

where SEC^j is a sector dummy equal to 1 if an observation belongs to sector j, J is the number of sectors, θ_i^j is a sector-episode fixed effect, while δ_0, $\left\{\delta_1^j\right\}_{j=1}^J$, and $\left\{\delta_2^j\right\}_{j=1}^J$ are the regression coefficients.

The key difference between equations (1) and (3) is that the former is estimated separately for each sector, while the latter is estimated simultaneously for all sectors, including the tradable and nontradable aggregates and the GDP. The point estimates of $\left\{\delta_1^j\right\}_{j=1}^J$ and $\left\{\delta_2^j\right\}_{j=1}^J$ in equation (3) are exactly the same as those of $\left\{\beta_1^j\right\}_{j=1}^J$ and $\left\{\beta_2^j\right\}_{j=1}^J$ in equation (1) because of the Frisch - Waugh (1933) theorem. Their standard errors differ negligibly.[19] The reason why we prefer specification (1) to (3) is that the former allows us to estimate sector-specific pre-episode trend growth rates (constant terms), while the latter does not. However, the latter makes it possible to run F-tests on the null hypotheses that $\delta_1^j = \delta_1^k$ or $\delta_2^j = \delta_2^k$ for any pair of sectors $j \neq k$. That is, we can test if sectoral adjustments do not differ significantly during and after sudden stops.

Reporting the test results for each possible pair of sectors would be cumbersome, therefore, we only report two interesting subsets of them. Table 2 reports the estimated differences $\delta_1^j - \delta_1^{GDP}$ and $\delta_2^j - \delta_2^{GDP}$ for each sector j, i.e. the differences in the changes in sectoral growth rates compared to that of GDP. In parentheses, we report the p-values from testing the null hypothesis of equal changes in growth rates during and after the sudden stop, respectively.

< Table 2 about here >

During sudden stops, the construction sector (F), professional services (M-N), and manufacturing (C) experience significantly larger drops in their growth rates than GDP, which confirms our previous intuition that the main sources of the recession faced by the macroeconomy during sudden stops are these sectors. At the same time, the growth rates of the public sector (O-Q) and real estate activities (L) fall by significantly less than that of GDP. (Actually, they are measured to increase insignificantly.) The short-run adjustment of all the other sectors, including tradable and nontradable aggregates, does not differ significantly from that of GDP.

Turning to post-episode adjustment, we can see that the growth rates of information and communication (J) and financial services (K) fall to a significantly larger extent than that of GDP after sudden stops, compared to the pre-episode trend growth rates. This again confirms our previous intuition that these two sectors are the most important reasons

[19]The results of estimating equation (3) are available from the authors upon request.

for the persistent slowdown in macroeconomic growth after sudden stops. On the other hand, industry (B-E), manufacturing (C) in particular, and as a result, the broad tradable sector experience a significantly smaller fall in their growth rates than GDP. (Actually, their growth rates significantly rise compared to their pre-episode averages.) This also confirms our finding, according to which these sectors lead the economy's recovery from a sudden stop recession. The post-episode adjustment of other sectors, including the nontradable aggregate, does not differ significantly from that of GDP.

Another interesting comparison is the one between the adjustment of the broad tradable and nontradable sectors. Table 3 reports the estimated differences $\delta_1^T - \delta_1^{NT}$ and $\delta_2^T - \delta_2^{NT}$, i.e. the difference between the change in the tradable sector's growth rate and the change in the nontradable sector's growth rate during and after sudden stops. p-values from the F-tests of equal changes in sectoral growth rates are again in parentheses.

$<$ Table 3 about here $>$

The point estimates suggest that the growth rate of the tradable sector falls by 0.42 percentage point more than that of the nontradable sector during sudden stops, which is an economically significant difference, but it is not significant statistically. However, our finding, according to which the post-episode fall in the tradable sector's growth rate is smaller – by 0.786 percentage point – than that in the nontradable sector's, is strongly significant. (Actually, the tradable sector experiences a rise in its growth rate after the episode, compared to the pre-episode average.) This may point out an interesting trade-off for industrial policy: the nontradable sector is more resistent to sudden stops on impact (although not significantly in a statistical sense), but the tradable sector rebounds more quickly after sudden stops.

4.4 Adjustment channels

We examine two additional hypotheses to get a more detailed picture on the sectoral responses uncovered in the previous sections. First, economic theory highlights the role of the nominal exchange rate in facilitating adjustments to external shocks. Tradable sectors, in particular, can take advantage of an exchange rate depreciation to gain market share in foreign markets (via exports), or at home (via import competition). As the literature argues (Kehoe and Ruhl, 2009; Guidotti et al., 2004; Benczur and Konya, 2016), this mechanism works better in countries with flexible exchange rate arrangements.

To evaluate the role of the exchange rate in sectoral adjustment, we add the change in the real effective exchange rate (REER) as an additional variable in the estimation as discussed in Section 3. We use the REER for two main reasons. First, categorizing exchange rate regimes is notoriously difficult. De jure and de facto regimes can differ significantly, and for many countries the picture is fuzzy. Second, fixed or managed exchange rates are typically defined against a single currency. In case of the Eurozone, the currency itself is freely floating, but individual member states cannot devalue against each other. Using the REER means that we are controlling directly for the adjustment channel. This naturally raises endogeneity issues, but since our goal is mostly descriptive, we view this as a secondary issue relative to the obvious problems with using pre-defined categories. We look at the role of the REER both on impact and after the sudden stop episode itself ends, in line with the previous section.

The second adjustment channel, which again was discussed in Section 3, is the tendency of sectoral output to return to its "natural" level (or more precisely, trend). While this idea is not without problems[20], it is ultimately an empirical question whether such correction mechanism indeed exists. Therefore, we also include the average negative deviation of sectoral output from its Hodrick-Prescott trend path during the sudden stop as a proxy for deviations from the "natural" level of sectoral output. Since our variable is the depth of the sectoral recession during the episode, we add an interaction only to the post-episode dummy. Results are presented in Table 4.

< Table 4 about here >

Starting with the exchange rate channel, we find evidence that REER depreciation facilitates adjustment in the tradable sector – and manufacturing in particular – as expected, but not in any of the nontradable sectors. On the other hand, this does not seem to significantly help cushion overall GDP in the short run. The positive impact for manufacturing persists after the episode itself ends, but again without a clear positive effect on overall GDP. The exchange rate channel seems to lead to faster and stronger sectoral realignment, but we do not find evidence for an overall positive impact on aggregate economic activity.

Turning to the correction hypothesis, we find strong support for a stronger rebound in the sectors that are worse effected by the sudden stop on impact. The interaction variables are highly significant, with similar point estimates across sectors. Not surprisingly, the same result holds for tradables, nontradables, and overall GDP. While only suggestive, our

[20]See e.g. Ball (2014), Blanchard et al. (2015), or Váry (2022) for evidence about the possible hysteresis effects of cyclical movements in GDP on its long-run growth path.

results support the idea that a deeper decline is followed by a stronger rebound at both the sectoral and at the aggregate level.

It is worth noting that the post-episode dummy turns from significantly positive into insignificantly negative in sectors B-E, C, and in the broad tradable sector after controlling for real depreciation and the rebound effect. This suggest that these two adjustment channels explain why these sectors grow faster after sudden stops than before them. Controlling for the rebound effect, construction, trade and hospitality, professional services, arts and entertainment, and real estate activities also display significantly lower growth rates after sudden stops than in the quarters preceding them.

5 Robustness

5.1 Splitting the sample

In our first robustness exercise we estimate the baseline specification for two separate subsamples, the global financial crisis of 2008-2012 (GFC) and all other episodes (non-GFC). The GFC was unique – at least in our sample period – from many perspectives, hitting the global economy more-or-less simultaneously. Other episodes were either country- or at most region-specific. If our main results are driven by the GFC alone, we have to be more careful about the interpretation and generalization of the key messages.

< Table 5 about here >

Table 5 presents results for the non-GFC sample. The estimates are largely in line with Table 1, although significance levels drop measurably (partly due to the smaller sample). Post-episode dummies are marginally significant only for broad industry (B-E) and manufacturing (C). On impact, manufacturing, trade and hospitality (G-I), and information and communication (J) experience declines, along with – but statistically less significantly – construction (F), professional services (M-N), and arts and entertainment (R-U). Not surprisingly, one of the most substantial significance losses occurs in financial services (K). Aggregate activity (GDP) drops, but the negative point estimate of the real effective exchange rate is measured noisily.

< Table 6 about here >

The results are stronger for the GFC subsample. The point estimates are generally larger than, and significance levels are quite similar to the baseline results. Almost all sectors decline during the aftermath of the sudden stop. Manufacturing and industry rebounds, while some service sectors perform significantly worse even after the episode (J, K, and M-N). Tradable, nontradable, GDP, and REER patterns match what we found for the general sample.

To sum up, we find that our general results are to some extent driven by the GFC. Since these episodes constitute roughly half of the overall sample, and because the GFC was a large and synchronized shock to the global economy, the fact that we find cleaner results there is neither surprising nor necessarily detrimental to the overall conclusions. Point estimates are qualitatively similar for the non-GFC sample, but significances are lower. It would be very useful to find more earlier sudden stop episodes to expand the non-GFC sample, but unfortunately, the availability of quarterly sectoral GVA data constrained our efforts in this direction.

5.2 Sectoral output gaps

We also run regressions where in the baseline specification, we replace the left-hand side variable (sectoral GVA growth) with sectoral output gaps. The latter are simply calculated by using the Hodrick-Prescott filter on (the log of) real GVA data for each country and each sector where data is available. The output gap is the cyclical component from the HP procedure.

$<$ Table 7 about here $>$

Table 7 shows the estimation results. The episode dummies are negative (except for sector O-Q) and highly significant for the majority of the sectors. Results are stronger for tradable sectors and for business services (G-I, J, M-N). The latter drive the significant coefficient on the nontradable sector. Interestingly, we find even more negative and significant coefficients for the post episode dummy. With the exception of agriculture (A) and the public sector (O-Q), all other sectors have significantly lower output gaps than before the crisis.

The interpretation of these results requires some caution, however. Note that the constant here represents the sectoral output gaps *before the sudden stop hits.* These constants – with the exception of the public sector and agriculture again – are strongly and significantly *positive.* This means that before a sudden stop, the economy and most of its sectors tended to overheat. The question is, then, if the adjustment observed during and after an episode is correction for previous excess, or goes beyond that. To test these hypotheses, we conduct F-tests for the significance of the sum of the constant and the episode or post-episode dummies. The results are presented in Table 8, where the coefficient rows include the sums with p-values below in parentheses.

< Table 8 about here >

The output gap is significantly negative during and after the episode for sectors B-E, C, G-I, M-N, and the aggregate variables, with the important distinction that it is closing over time in the former three and in the tradable aggregate, while it is widening over time in sector M-N, the nontradable aggregate, and for GDP. The closing of the sectoral output gap is especially pronounced in industry, manufacturing, and the tradable aggregate, thanks to their post-episode rebound discussed in Section 4.

Moving from the sudden stop period to the post-episode period, the sectoral output gap turns from insignificant to significantly negative for construction (F) and arts and entertainment (R-U). In agriculture (A), information and communication (J), and the public sector (O-Q), the output gap is not significantly different from zero, although the coefficients are positive for the latter sector. The insignificant output gaps in information and communication suggest that the persistent slowdown in the sector presented in Section 4 may in fact be a favorable type of adjustment leading the sector back on its sustainable growth path. Finally, in finance (K) and real estate (L), a significantly positive output gap during the episode turns negative, significantly so for sector L. The lack of a significantly negative output gap in financial services suggests that its persistent slowdown may also be a healthy correction of previous imbalances, just like in the case of information and communication. Overall, sudden stops lead to lasting negative output gaps for most sectors, and for aggregate economic activity.

6 Conclusion

This paper explored the dyanmics of economic activity around sudden stops, measured by the growth rate of real gross value added, at the level of broad production sectors. Sudden stops were defined as large and unexpected drops in capital inflows, along with declines in aggregate GDP growth. The sample is constrained by the availability of quarterly real (and nominal) GVA data, which leaves us with 64 sudden stop episodes, around half of which happened during the global financial crisis of 2008-2012.

After presenting the results for a synthetic, "average" sudden stop, we estimated panel regressions to tease out the sectoral adjustment processes in detail. The baseline specification contained a dummy indicating the time period of a sudden stop, along with a post-episode dummy. We also investigated the potential channels that facilitate or influence sectoral adjustment: the real exchange rate in general and the depth of the (sectoral) recession on impact for the post-episode adjustment. Robustness checks included splitting the sample between GFC and non-GFC episodes, and using sectoral output gaps as dependent variables.

According to our main results, the construction sector, professional services, and the industrial sector – and manufacturing in particular – experience the sharpest drops in their growth rates during sudden stops. In general, the growth rate of the tradable sector falls by more than that of the nontradable sector, but both broad sectors experience a significant slowdown. After sudden stops, we measured that tradable, industrial sectors lead the recovery from the recession, as the average post-episode growth rates of industry, and manufacturing in particular, and the overall tradable sector were significantly greater than their average pre-episode growth rates. Information and communication, financial services, and the nontradable aggregate were measured to have significantly smaller growth rates after the sudden stop than before that.

The significantly higher post-episode growth rates of industry, manufacturing, and the overall tradable sector were shown to be supported by the depreciation of the domestic currency around sudden stops and by a rebound effect that facilitates post-event growth in these highly damaged sectors towards their long-run growth path.

By restricting our sample to sudden stops not related to the GFC, we found similar patterns as in the full sample, but the measured changes turned out to be smaller, less persistent, and somewhat less significant. Significance losses were the most substantial in the construction sector and in financial services. Our GFC subsample mirrored the full-sample results with larger changes measured in sectoral growth rates.

By using secotral output gaps as dependent variables, we found that sudden stops tended to be preceded by unsustainable growth in most sectors. We may have found favorable type of adjustment processes in two high-growth sectors, information and communication, and financial services. Both of them return to their long-run growth paths during sudden stops, without experiencing significantly negative output gaps in a statistical sense, however, their measured post-episode negative output gaps are not insignificant in an economic sense. Other sectors, except for agriculture and the public sector, experience significantly negative output gaps either during, or after sudden stops, with these gaps closing within our event window in the cases of industry, manufacturing, trade and hopsitality, and the tradable sector, and widening in the other sectors.

Our findings have important policy implications. They point out that reindustrialization policies may work as a double-edged sword in making the economy more resilient to sudden stops. Industrial sectors seem to lead the economy's recovery process after a sudden stop recession. However, their high reliance on foreign capital puts them among the most seriously damaged sectors when the sudden stop hits. This also implies that policymakers face a trade-off when changing the industrial structure of an economy. Increasing the share of the nontradable sector may make the economy more resistent to sudden stops on impact, but it may hinder its recovery from the recession after the episodes. Our results may also be suggestive about the importance of high-growth sectors, like information and communication and financial services in assuring a quick correction towards the economy's long-run sustainable growth path after sudden stops. Our results have shown that these sectors do not seem to experience significantly negative output gaps either during, or after sudden stops in a statistical sense. Note, however, that the sizes of their negative post-episode output gaps are not negligible economically. Finally, our results can also be interpreted as arguments in favor of floating exchange rate regimes because tradable sectors are only able to benefit from the real depreciation of the domestic currency under such an exchange rate arrangement, assuming that price stickiness generates similar movements in the floating nominal exchange rate and the real exchange rate in the short run. However, deciding about the exchange rate regime is a more complex choice that requires further aspects to be considered.

Our work is mostly descriptive, with many potential areas of future research. First and foremost, it would be useful to collect more data to include less recent episodes. The main constraint is sectoral value added at the quarterly frequency. Using annual data has not turned out to be fruitful because it has the serious drawback that sudden stops are often not very long, and an annual frequency masks much of the dynamics we can uncover at the quarterly level. Also, we would like to investigate whether the sectoral adjustment dynamics are changing over time, especially in the case of business services that are becoming easier and easier to trade. Data availability is the main constraint for answering many of these additional questions, which should be a priority for future research.

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A Tables

Table 1: Results from the panel specification

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Episode	-0.434	-1.656***	-2.132***	-2.424***	-1.581***
	(0.485)	(0.303)	(0.303)	(0.543)	(0.242)
Post-Episode	-0.039	0.688***	0.756***	-0.471	-0.025
	(0.317)	(0.157)	(0.171)	(0.396)	(0.179)
Constant	0.327*	0.492***	0.664***	0.737***	0.756***
	(0.177)	(0.083)	(0.079)	(0.212)	(0.070)
Observations	1,344	1,302	1,344	1,344	1,302
R-squared	0.001	0.044	0.058	0.023	0.028
Episode FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Episode	-1.394***	-1.396***	0.037	-2.289***	0.158
	(0.253)	(0.368)	(0.270)	(0.424)	(0.171)
Post-Episode	-0.503**	-0.946***	-0.311*	-0.298	-0.040
	(0.202)	(0.350)	(0.166)	(0.226)	(0.116)
Constant	1.860***	1.388***	0.642***	1.353***	0.350***
	(0.101)	(0.160)	(0.086)	(0.117)	(0.060)
Observations	1,344	1,323	1,344	1,323	1,302
R-squared	0.019	0.008	0.001	0.037	0.001
Episode FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP	(15) REER
Episode	-1.253***	-1.518***	-1.098***	-1.204***	-1.375**
	(0.279)	(0.277)	(0.191)	(0.160)	(0.561)
Post-Episode	-0.478	0.528***	-0.258**	-0.035	-0.223
	(0.295)	(0.132)	(0.117)	(0.091)	(0.274)
Constant	0.718***	0.505***	0.808***	0.763***	0.193
	(0.120)	(0.073)	(0.066)	(0.050)	(0.173)
Observations	1,260	1,260	1,197	1,344	1,239
R-squared	0.009	0.040	0.036	0.065	0.014
Episode FE	YES	YES	YES	YES	YES

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

The dependent variable is the log-change in real gross value added for a sector.

Coefficients are presented in percentages for easier interpretation.

Table 2: Sectoral Adjustments Relative to GDP Adjustment

	Difference of the Change in the Sectoral Growth Rate Relative to that of GDP	
	Episode	Post-Episode
A	0,769	-0,003
	(0,129)	(0,992)
B-E	-0,453	0,724***
	-0,183	(0,000)
C	-0,928***	0,792***
	(0,006)	(0,000)
F	-1,221**	-0,435
	(0,030)	(0,281)
G-I	-0,378	0,010
	(0,189)	(0,960)
J	-0,190	-0,468**
	(0,522)	(0,034)
K	-0,192	-0,911**
	(0,630)	(0,011)
L	1,241***	-0,276
	(0,000)	(0,143)
M-N	-1,086**	-0,263
	(0,016)	(0,277)
O-Q	1,361***	-0,004
	(0,000)	(0,978)
R-U	-0,049	-0,443
	(0,878)	(0,149)
T	-0,315	0,563***
	(0,322)	(0,000)
NT	0,105	-0,223
	(0,671)	(0,131)

p-values from the F-test of the null hypothesis, according to which the change in the sectoral growth rate is equal to the change in the GDP growth rate are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3: Differences between the Adjustment of the Tradable and the Nontradable Sector

	Difference between the Change in the T Sector's Growth Rate Relative to that of the NT Sector	
	Episode	Post-Episode
T	-0,420	0,786***
	(0,210)	(0,000)

p-values from the F-test of the null hypothesis, according to which the change in the T sector's growth rate is equal to the change in the NT sector's growth rate are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Adjustment: exchange rate and recession depth

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Episode	-0.476	-1.622***	-2.079***	-2.521***	-1.567***
	(0.526)	(0.309)	(0.321)	(0.520)	(0.224)
Depreciation x Episode	0.016	0.017**	0.018**	-0.023	-0.008
	(0.011)	(0.008)	(0.007)	(0.021)	(0.007)
Post-Episode	-0.131	-0.173	-0.298	-0.984***	-0.761***
	(0.289)	(0.248)	(0.266)	(0.286)	(0.158)
Depreciation x Post-Episode	0.004	0.008*	0.010**	-0.016	-0.001
	(0.007)	(0.005)	(0.005)	(0.011)	(0.004)
Sector Decline x Post-Episode	0.416***	0.297***	0.296***	0.461***	0.399***
	(0.054)	(0.057)	(0.053)	(0.039)	(0.067)
Constant	0.298	0.484***	0.623***	0.688***	0.741***
	(0.182)	(0.098)	(0.100)	(0.205)	(0.078)
Observations	1,239	1,197	1,239	1,239	1,197
R-squared	0.009	0.063	0.080	0.061	0.049
Episode FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Episode	-1.422***	-1.065***	-0.308*	-1.676***	0.0256
	(0.276)	(0.369)	(0.167)	(0.231)	(0.107)
Depreciation x Episode	0.005	-0.027*	0.003	-0.010	-0.007
	(0.009)	(0.014)	(0.006)	(0.008)	(0.006)
Post-Episode	-0.593***	-0.491**	-0.258**	-0.731***	-0.059
	(0.155)	(0.237)	(0.098)	(0.143)	(0.055)
Depreciation x Post-Episode	0.002	-0.006	0.002	-0.012	-0.001
	(0.006)	(0.009)	(0.003)	(0.008)	(0.003)
Sector Decline x Post-Episode	0.459***	0.553***	0.578***	0.462***	0.545***
	(0.074)	(0.089)	(0.100)	(0.054)	(0.035)
Constant	1.870***	1.286***	0.703***	1.169***	0.373***
	(0.097)	(0.131)	(0.061)	(0.091)	(0.039)
Observations	1,239	1,218	1,239	1,218	1,197
R-squared	0.042	0.024	0.020	0.055	0.033
Episode FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP
Episode	-1.085***	-1.608***	-1.088***	-1.226***
	(0.279)	(0.288)	(0.170)	(0.157)
Depreciation x Episode	-0.003	0.027***	-0.018	-0.001
	(0.013)	(0.008)	(0.012)	(0.005)
Post-Episode	-0.354**	-0.178	-0.522***	-0.415***
	(0.140)	(0.236)	(0.093)	(0.075)
Depreciation x Post-Episode	-0.013	0.011**	-0.012	-0.001
	(0.008)	(0.005)	(0.008)	(0.002)
Sector Decline x Post-Episode	0.435***	0.276***	0.434***	0.305***
	(0.061)	(0.059)	(0.054)	(0.034)
Constant	0.697***	0.513***	0.793***	0.758***
	(0.090)	(0.093)	(0.068)	(0.052)
Observations	1,155	1,155	1,092	1,239
R-squared	0.030	0.057	0.081	0.093
Episode FE	YES	YES	YES	YES

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

The dependent variable is the log-change in real gross value added for a sector.

Coefficients are presented in percentages for easier interpretation.

Table 5: Panel results, non-GFC episodes

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Episode	-0.865*	-0.625	-1.049***	-1.076*	-0.953***
	(0.489)	(0.422)	(0.379)	(0.545)	(0.312)
Post-Episode	0.053	0.514*	0.522*	0.077	-0.056
	(0.420)	(0.256)	(0.273)	(0.403)	(0.298)
Constant	0.523**	0.658***	0.820***	0.505***	0.754***
	(0.213)	(0.137)	(0.127)	(0.173)	(0.079)
Observations	609	588	609	609	588
R-squared	0.003	0.009	0.016	0.006	0.006
Episode FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Episode	-0.828***	-0.657	0.297	-1.734**	0.153
	(0.239)	(0.466)	(0.386)	(0.662)	(0.268)
Post-Episode	-0.180	-0.074	-0.320	0.105	0.032
	(0.264)	(0.409)	(0.254)	(0.372)	(0.155)
Constant	1.939***	1.028***	0.650***	1.215***	0.413***
	(0.105)	(0.195)	(0.099)	(0.149)	(0.089)
Observations	609	609	609	609	588
R-squared	0.008	0.001	0.002	0.021	0.000
Episode FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP	(15) REER
Episode	-0.609**	-0.490	-0.524**	-0.627***	-1.478
	(0.266)	(0.342)	(0.195)	(0.163)	(1.190)
Post-Episode	-0.205	0.412*	-0.002	0.105	-0.048
	(0.372)	(0.207)	(0.162)	(0.120)	(0.458)
Constant	0.575***	0.602***	0.758***	0.744***	-0.444
	(0.110)	(0.110)	(0.062)	(0.042)	(0.342)
Observations	567	588	546	609	525
R-squared	0.002	0.009	0.006	0.017	0.009
Episode FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
The dependent variable is the log-change in real gross value added for a sector.
Coefficients are presented in percentages for easier interpretation.

Table 6: Panel results, GFC episodes

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Episode	-0.141	-2.339***	-2.869***	-3.389***	-2.001***
	(0.753)	(0.374)	(0.391)	(0.815)	(0.332)
Post-Episode	-0.134	0.888***	0.998***	-0.943	0.025
	(0.472)	(0.194)	(0.212)	(0.652)	(0.204)
Constant	0.166	0.354***	0.534***	0.926**	0.756***
	(0.272)	(0.0998)	(0.0944)	(0.348)	(0.108)
Observations	735	714	735	735	714
R-squared	0.000	0.096	0.108	0.041	0.071
Episode FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Episode	-1.804***	-1.970***	-0.142	-2.707***	0.157
	(0.385)	(0.526)	(0.376)	(0.556)	(0.226)
Post-Episode	-0.787**	-1.756***	-0.296	-0.668**	-0.107
	(0.294)	(0.526)	(0.217)	(0.244)	(0.175)
Constant	1.793***	1.692***	0.635***	1.469***	0.299***
	(0.157)	(0.229)	(0.135)	(0.170)	(0.081)
Observations	735	714	735	714	714
R-squared	0.030	0.024	0.001	0.055	0.002
Episode FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP	(15) REER
Episode	-1.713***	-2.240***	-1.511***	-1.611***	-1.318**
	(0.430)	(0.357)	(0.275)	(0.223)	(0.537)
Post-Episode	-0.710	0.684***	-0.481***	-0.150	-0.367
	(0.449)	(0.176)	(0.156)	(0.132)	(0.340)
Constant	0.833***	0.419***	0.848***	0.778***	0.660***
	(0.195)	(0.094)	(0.100)	(0.078)	(0.173)
Observations	693	672	651	735	714
R-squared	0.020	0.079	0.097	0.136	0.026
Episode FE	YES	YES	YES	YES	YES

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

The dependent variable is the log-change real gross value added for a sector.

Coefficients are presented in percentages for easier interpretation.

Table 7: Results with sectoral output gaps

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Episode	-0.235	-4.802***	-5.973***	-3.033***	-3.981***
	(0.687)	(0.699)	(0.792)	(0.972)	(0.546)
Post-Episode	-0.081	-3.223***	-4.280***	-5.068***	-3.953***
	(0.467)	(0.574)	(0.610)	(1.283)	(0.592)
Constant	0.060	2.196***	2.782***	2.652***	2.354***
	(0.253)	(0.293)	(0.319)	(0.564)	(0.276)
Observations	1,344	1,302	1,344	1,344	1,302
R-squared	0.000	0.166	0.205	0.082	0.176
Episode FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Episode	-0.957**	-0.656	-0.140	-3.382***	0.054
	(0.462)	(0.540)	(0.359)	(0.740)	(0.178)
Post-Episode	-1.454***	-2.538***	-1.342***	-4.026***	0.209
	(0.538)	(0.840)	(0.453)	(1.112)	(0.318)
Constant	0.960***	1.701***	0.643***	2.445***	-0.034
	(0.237)	(0.334)	(0.184)	(0.452)	(0.102)
Observations	1,344	1,323	1,344	1,323	1,302
R-squared	0.022	0.034	0.017	0.101	0.002
Episode FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP
Episode	-1.339	-4.038***	-1.851***	-2.541***
	(0.803)	(0.640)	(0.357)	(0.367)
Post-Episode	-2.849***	-2.713***	-2.546***	-2.646***
	(0.789)	(0.523)	(0.465)	(0.361)
Constant	1.541***	1.862***	1.501***	1.638***
	(0.382)	(0.265)	(0.211)	(0.175)
Observations	1,260	1,260	1,197	1,344
R-squared	0.046	0.146	0.165	0.218
Episode FE	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log-deviation of real gross value added for a sector from its Hodrick-Prescott trend path. Coefficients are presented in percentages for easier interpretation.

Table 8: Significance of sectoral output gaps

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Output Gap (Episode)	-0.175	-2.606***	-3.191***	-0.381	-1.627***
(p-value)	(0.720)	(0.000)	(0.000)	(0.495)	(0.000)
Output Gap (Post-Ep.)	-0.021	-1.027***	-1.499***	-2.416***	-1.599***
(p-value)	(0.943)	(0.003)	(0.000)	(0.002)	(0.000)

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Output Gap (Episode)	0.003	1.045***	0.502*	-0.937*	0.021
(p-value)	(0.992)	(0.005)	(0.056)	(0.052)	(0.908)
Output Gap (Post-Ep.)	-0.494	-0.837	-0.699**	-1.581**	0.175
(p-value)	(0.138)	(0.121)	(0.021)	(0.027)	(0.442)

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP
Output Gap (Episode)	0.202	-2.176***	-0.350*	-0.903***
(p-value)	(0.688)	(0.000)	(0.065)	(0.000)
Output Gap (Post-Ep.)	-1.308***	-0.850***	-1.046***	-1.008***
(p-value)	(0.006)	(0.008)	(0.000)	(0.000)

Sectoral output gaps are the sum of regression constants and the coefficient of the appropriate dummy variable from Table 7. p-values represent F-test results for the significance of these sums. *** p<0.01, ** p<0.05, * p<0.1.

B Episodes

Table 9: Sudden stop events with sectoral coverage

Country	Start	End	Country	Start	End
Albania	2019 Q4	2020 Q1	Latvia	2008 Q3	2009 Q4
Belgium	2008 Q4	2009 Q4	Lithuania	2008 Q3	2009 Q4
Bulgaria	2008 Q4	2010 Q1	Luxembourg	2008 Q4	2009 Q2
Bosnia & Herzegovina	2019 Q3	2020 Q2	Luxembourg	2014 Q2	2014 Q4
Brazil	1999 Q1	1999 Q2	Malta	2008 Q3	2009 Q4
Brazil	2008 Q2	2009 Q3	Montenegro	2016 Q1	2016 Q3
Brazil	2015 Q3	2016 Q2	North Macedonia	2007 Q1	2007 Q4
Chile	2009 Q1	2009 Q4	North Macedonia	2009 Q2	2010 Q1
Costa Rica	2008 Q4	2009 Q4	Netherlands	2002 Q1	2002 Q4
Croatia	2010 Q2	2010 Q4	Netherlands	2008 Q2	2009 Q3
Czechia	2008 Q4	2009 Q3	New Zealand	2008 Q2	2009 Q2
Denmark	2001 Q2	2002 Q1	Norway	1988 Q3	1989 Q2
Denmark	2008 Q4	2009 Q4	Norway	1991 Q3	1993 Q1
Estonia	1998 Q4	1999 Q3	Norway	2001 Q3	2002 Q1
Estonia	2008 Q2	2009 Q3	Norway	2007 Q4	2009 Q4
Finland	2001 Q1	2002 Q1	Poland	2001 Q4	2002 Q3
Finland	2009 Q2	2009 Q3	Poland	2008 Q4	2009 Q3
Finland	2012 Q3	2013 Q3	Portugal	2002 Q2	2003 Q1
Finland	2020 Q1	2020 Q3	Portugal	2010 Q4	2011 Q3
France	1991 Q1	1992 Q1	Romania	1998 Q1	1998 Q3
France	2002 Q1	2002 Q3	Romania	2008 Q3	2009 Q4
France	2008 Q1	2009 Q3	Russia	2014 Q1	2015 Q2
Germany	2001 Q1	2002 Q2	Slovenia	2008 Q3	2009 Q3
Germany	2008 Q3	2009 Q3	Spain	2007 Q4	2009 Q3
Greece	2010 Q2	2011 Q2	Sweden	1997 Q1	1997 Q3
Hungary	2009 Q1	2010 Q2	Sweden	2008 Q4	2009 Q3
Ireland	2018 Q2	2019 Q1	Switzerland	2008 Q1	2009 Q1
Italy	2000 Q4	2002 Q3	Switzerland	2018 Q1	2019 Q1
Italy	2007 Q4	2008 Q4	Turkey	2001 Q2	2001 Q4
Japan	2008 Q3	2009 Q3	Turkey	2008 Q4	2009 Q4
Korea, Republic of	1997 Q2	1999 Q3	Turkey	2018 Q4	2019 Q2
Korea, Republic of	2008 Q2	2009 Q3	United Kingdom	2008 Q2	2009 Q2