Journal of International Money and Finance 146 (2024) 103110

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

Which sectors go on when there is a sudden stop? An empirical analysis

István Kónya [a,b,c], Miklós Váry [a,b,c,d,*]

[a] Corvinus University of Budapest – Institute of Economics, Fővám tér 8., H-1093 Budapest, Hungary
[b] HUN-REN Centre for Economic and Regional Studies – Institute of Economics, Tóth Kálmán utca 4., H-1097 Budapest, Hungary
[c] University of Pécs – Faculty of Business and Economics – Department of Economics and Econometrics, Rákóczi út 80., H-7622 Pécs, Hungary
[d] University of Pécs – Faculty of Business and Economics – Centre of Excellence of Economic Studies, Rákóczi út 80., H-7622 Pécs, Hungary

ARTICLE INFO

JEL classification:
F31
F32
O24
O25

Keywords:
Sudden stop
Sectoral adjustment
Capital flows
Exchange rate

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. In the baseline specification, we estimate changes in the growth rate of sectoral RGVA during sudden stops and in the few quarters preceding and following them. We also look at whether real exchange rate movements and the depth of the RGVA decline on impact explain different sectoral dynamics afterwards. In an additional exercise, we analyze deviations from the sectors' long-run growth path. Our findings indicate that: (i) the construction sector experiences the largest drop in its growth rate during sudden stops; (ii) generally, tradable sectors, especially manufacturing, face larger damages during sudden stops than nontradable sectors, but they decelerate less in the medium run than some service sectors; (iii) the depth of the initial slowdown is related to a more favorable subsequent performance (a rebound effect), while we find only very weak evidence that real exchange rate depreciations facilitate adjustment. Overall, our results suggest a prolonged reallocation of economic activity away from service 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.

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

* Corresponding author at: Corvinus University of Budapest – Institute of Economics, Fővám tér 8., H-1093 Budapest, Hungary.
E-mail addresses: istvan.konya@uni-corvinus.hu (I. Kónya), miklos.vary@uni-corvinus.hu (M. Váry).

https://doi.org/10.1016/j.jimonfin.2024.103110

Available online 5 June 2024

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 countries, like several member states of the European Union have to face the risk of sudden stops, as well (Merler and 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 (Calvo et al., 2004; Cavallo and Frankel, 2008; Forbes and Warnock, 2012; Kalantzis, 2015; Benigno et al., 2015; Reyes-Heroles and Tenorio, 2019; Pierri et al., 2020), while another line of empirical research investigates the consequences of sudden stops (Calvo and Reinhart, 2000; Guidotti et al., 2004; Calvo et al., 2006; Edwards, 2007; Rothenberg and Warnock, 2011; Cavallo et al., 2015; Eichengreen and Gupta, 2018). These papers all focus on the macro-level consequences 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 use quarterly gross value added data to analyze 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. In a panel of 46 countries, we use regressions with country and time fixed effects to estimate the average extent to which the growth rates of real gross value added (RGVA) in various sectors of the economy change (i) well ahead of a sudden stop, (ii) in the year just preceding it, (iii) during the event (i.e. in the short run), and (iv) in the following few quarters (i.e. in the medium run), compared to the counterfactual of no sudden stop occurring within the event window in the same country at the same time.

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, financial services, the industrial sector – manufacturing in particular –, and agriculture are also measured to be substantial. On the other hand, the growth rates of the public sector and real estate activities do not significantly differ from the counterfactual of experiencing no sudden stop around a given country-quarter. In general, the growth rate of the tradable sector is estimated to fall by more than that of the nontradable sector, however, both sectors experience a significant slowdown.

After sudden stops, we find smaller deviations from the normal, counterfactual growth rates than during sudden stops. In addition, the average post-episode growth rate of agriculture, industry, and manufacturing in particular, as well as the growth rate of the overall tradable sector is measured to be *greater* than what would be experienced without a sudden stop occurring. The differences from the counterfactual growth rates are significant in an economic, but not in a statistical sense. This suggests that in spite of being one of the most struggling sectors in the short run, industry may lead the recovery from the sudden stop recession. Only three sectors' growth rates are measured to fall significantly below their normal values after sudden stops: the financial sector, professional services, and trade and hospitality. They are responsible for the significantly lower post-episode growth rate of the overall nontradable sector, as well.

To gain insight into developments before the sudden stop hits, we split the 10 quarters before the start of an episode into two parts. We find that growth slowdowns already start 2–3 quarters ahead of a sudden stop in construction, professional services, trade and hospitality, industry, and manufacturing in particular, as well as in the overall tradable and nontradable sectors. The result that these sectors' growth rates start falling already before the episodes suggests that sudden stops themselves may also be endogenous events, the causes of which are related to declining performance in some sectors of the economy. On the other hand, RGVA growth rates are not statistically different from "normal" times earlier, i.e. in the -10 to -4 quarters of the event window.

We also show that almost 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. *Real exchange rate movements* are also shown to have an influence on sectoral adjustment around sudden stops. We find weak evidence that agriculture, industry, and manufacturing in particular, and as a result, the overall tradable sector might benefit from the depreciation of the domestic currency around sudden stops: after episodes that are associated with sharper real depreciations, these sectors are measured to experience smaller drops in their GVA growth rates. The differences from the counterfactual normal growth rates are not significant statistically. However, industry and the overall tradable sector are estimated to grow significantly slower *immediately before* sudden stops that are followed by sharper real depreciations. As we indicated before, this also suggests that a worsening pre-episode industrial performance may lead to a worse sudden stop, which then triggers a stronger real exchange rate adjustment. This then may facilitate the return of tradable, industrial sectors to their normal growth rates. On the other hand, the adjustment of the construction sector, financial services, trade and hospitality, and professional services is measured to be significantly *negatively* influenced by real depreciation. In general, tradable growth is estimated to be accelerated, while nontradable growth is estimated to be decelerated by real depreciation compared to the "no sudden stop" counterfactual. The differences are not significant statistically, but taking into account the significantly slower pre-episode tradable growth in cases of sharper real depreciations means a faster rebound relative to those quarters for tradables.

Two robustness analyses are conducted. First, as somewhat more than half of the sudden stop episodes in our sample are from around the global financial crisis (GFC) of 2008, we check whether sectoral dynamics is significantly different around those episodes that are from the time period of the GFC than around those that are not. With some minor exceptions, we find no significant differences between sectoral adjustment around the two groups of events. This increases our confidence that our results are not driven by the GFC.

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 infer if sudden stops are preceded 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 tendencies towards unsustainable growth before sudden stops (in the prelude period) in all sectors except for agriculture, infocommunications, and the public sector. Most sectors' during-episode output gaps are statistically similar to what they would be without the sudden stop occurring, and they may even be lower. The during-episode output gap is estimated to be significantly lower than the counterfactual in manufacturing and in professional services. Some sectors' performance may drop even further, resulting in significantly lower sectoral output gaps compared to the "no sudden stop" counterfactual after the episode. These are the construction sector, trade and hospitality, and as a result, the overall nontradable sector.

The rest of the paper is organized as follows. Section 2 summarizes its relation to the existing literature. In Section 3, we describe the data and the algorithm that we use to detect sudden stop episodes, as well as our dataset about sectoral real gross value added and real exchange rates. Section 4 presents our basic results, including an event-based approach, the baseline estimation, and exploring adjustment channels. Section 5 details our robustness analyses. Finally, Section 6 concludes.

2. Related literature

Most of the empirical literature about sudden stops studies their causes and consequences at the macro level of the economy. The first strand of this literature aims to find variables that help predict the occurrence of a sudden stop. 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 and 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 and 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.

The second strand of the empirical sudden stop literature focuses on the impacts of such events on key macro variables. It is a robust finding that sudden stops lead to a significant decline in GDP growth (Calvo and Reinhart, 2000; Calvo et al., 2006; Edwards, 2007; Eichengreen and Gupta, 2018) and to a depreciation of the real exchange rate (Eichengreen and 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.

We know about two papers only that are similar to this one in the sense that they aim to assess adjustment processes around 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 work with a different sample. 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 and 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. A lot of the fine details of these dynamics are not observable at the annual frequency, but they are at the quarterly one. In particular, the use of quarterly data allows us to explicitly distinguish between short-term sectoral adjustment during sudden stops and medium-term adjustment after sudden stops. Second, we study how real exchange rate movements play a role in shaping sectoral dynamics around sudden stops, while Craighead and Hineline (2014) do not. Third, 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. Finally, 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, and do not necessarily coincide with a change in the sign of the current account.

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, but our paper studies broader sectors, only one of which is manufacturing.

Our results can also be related to further empirical and theoretical papers. First, we estimate the fall in the tradable sector's growth rate to be larger than that in the nontradable sector's during sudden stops. 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.

Second, the medium-term reallocation of resources from nontradable towards tradable sectors, which is suggested by our estimates, is consistent with several theoretical models from the literature. They typically explain this reallocation by the increased scarcity and the resulting relative price increase of tradable goods during sudden stops (Kehoe and Ruhl, 2009), by tightening financing constraints (Tornell and Westermann, 2002), or by both (Mendoza, 2005; Bianchi and Mendoza, 2020). E.g. in Tornell and Westermann (2002), financing constraints are asymmetric at the expense of nontradable firms, in line with some empirical evidence.[1]

Third, in the theoretical models of Mendoza (2005) and Benguria et al. (2022), real depreciations help the economy in accommodating sudden stops. Mendoza (2005) points out that real depreciations during sudden stops occur mostly due to the relative price decrease of nontradables, which can explain why only tradable sectors may be able to benefit from real depreciations according to our results. This finding is also consistent with the empirical evidence of Guidotti et al. (2004), Gros and Alcidi (2015), and David and Gonçalves (2021), which highlight that recoveries from sudden stop recessions tend to be slower under fixed exchange rate regimes or in the European Monetary Union. However, they carry out country-level analyses without studying sectoral-level differences.

3. Data

3.1. Detecting sudden stop episodes

3.1.1. 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.[2] 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.[3]

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.

3.1.2. 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 $GIF_{i,t}$ denotes gross capital inflows to country i in quarter t, the annualized $C_{i,t}$ value of gross inflows to country i in quarter t can be obtained as

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

[1] Tornell and Westermann (2002) study twin crises (joint currency and banking crises), which are not the same as sudden stops, but they are similar events.

[2] See Rothenberg and Warnock (2011), Forbes and 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 caused by sharp drops/peaks in *gross* capital inflows/outflows.

[3] The earliest available observation about gross capital inflows is from Canada, starting in 1950 Q1. The most recent observations that we use are from 2021 Q4.

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

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

$$\Delta C_{i,t} = C_{i,t} - C_{i,t-4}, \quad i = 1, 2, \dots, N \text{ and } t = 8, 9, \dots, T_i.$$

$\Delta C_{i,t}$ 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 $\Delta C_{i,t}$ 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 $\Delta C_{i,t}$ for each quarter in each country over the preceding 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 preceding 5 years. The episode begins when $\Delta C_{i,t}$ falls below the mean minus one standard deviation threshold, and ends when it returns above this threshold value.[4] 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 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 entities 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*.[5] 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 quarterly GDP growth rates in a similar way we did with gross capital inflows. If $g^q_{i,t}$ is the quarterly growth rate of real GDP for country i in quarter t, measured in percentages, then the annualized $g_{i,t}$ growth rate of real GDP for country i in quarter t is calculated as

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

which is also measured in percentages. N^g is the number of countries, about which we have GDP data, and T^g_i is the length of the quarterly GDP growth rate time series for country i. In our sample, $N^g = 49$.[6]

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

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

$$\Delta g_{i,t} = g_{i,t} - g_{i,t-4}, \quad i = 1, 2, \dots, N^g \text{ and } t = 8, 9, \dots, T^g_i.$$

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

[4] Note that $\Delta C_{i,t}$ 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.

[5] 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.

[6] 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 data about quarterly sectoral RGVA is reported for a similar number of countries by Eurostat and the OECD.

We define the slowdown in real GDP growth to be substantial if $\Delta g_{i,t}$ falls by at least one standard deviation below its mean. The recession window begins when $\Delta g_{i,t}$ falls below the mean minus half standard deviation threshold, and ends when it returns above this threshold value.[7] 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 preceding 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 $\Delta C_{i,t}$ has an increasing volatility over time that has to be tracked with the rolling means and standard deviations, but $\Delta g_{i,t}$ 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 are calculated from a sample that begins in the first quarter when an observation about $\Delta g_{i,t}$ 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 3.2). Our empirical strategy requires data about the growth rate of sectoral RGVA to be at least partially available before and after the beginning of each sudden stop episode that is included in the panel dataset used for running regressions. Hence, we have to drop all episodes for which such data is not available. There are 6 such cases[8] with 6 additional ones, in which data are available for some sectors, while they are missing for other ones[9]. 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 67.[10]

3.1.3. An example

Fig. 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 Fig. 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.[11]

Five capital flow windows are detected on the basis of the top panel of Fig. 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.[12] 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.

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

[8] These are Iceland 2001Q2-2002Q1, Iceland 2008Q2-2009Q3, Israel 2001Q1-2002Q2, Israel 2007Q4-2009Q2, 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.

[9] These additional cases are the following: 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.

[10] These 67 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.

[11] 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.

[12] The capital flow window between 1996 Q4 and 1997 Q1 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 1997 Q1 when Hungarian GDP growth already started accelerating.

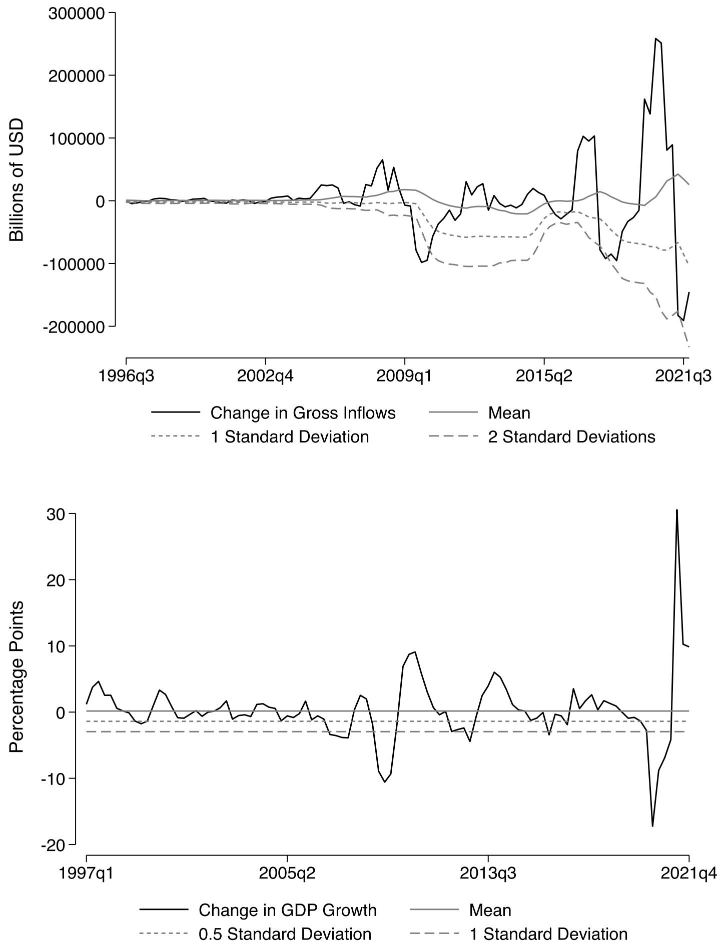

Fig. 1. Detecting sudden stop episodes in Hungary. *Notes*: The graph illustrates how sudden stop episodes are detected in Hungary. The upper panel presents the first part of the algorithm where a capital flow window is detected if the year-on-year change in annualized gross capital inflows falls below the two standard deviation threshold. The episode begins when it crosses the one standard deviation threshold, and ends when it returns above this line. Recession windows are detected in the lower panel, on which a recession is detected if the year-on-year change in the annualized GDP growth rate falls below the one standard deviation threshold. The recession begins when it crosses the half standard deviation threshold, and ends when it gets above this line again. Additionally, we also consider the country to be in a recession in a given quarter if its annualized GDP growth rate is negative. Only those capital flow windows are kept as sudden stop episodes that overlap with a recession window. Source: IMF BOP/IIP, Eurostat, and own calculations.

3.1.4. Detected sudden stop episodes

The 67 sudden stop episodes included in our final sample are listed in Table 8 in the Appendix. They come from 40 countries, some of which have experienced more than one sudden stop over the past decades. Their geographical and time distribution is presented on Fig. 2.

The time dimension of the distribution makes it clear that somewhat more than half of our episodes (37 out of 67) stem from around the global financial crisis (starting in the period 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 sufficient 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.). 23 of our 57 European episodes occurred in Euro Area member states, while the remaining 34 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 10 episodes from other continents (America, Asia, and Oceania).

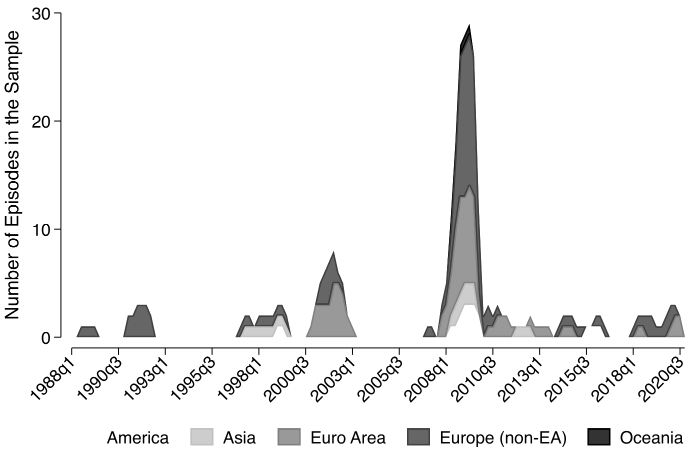

Fig. 2. The geographical and time distribution of detected sudden stop episodes. *Notes*: For each quarter, the graph presents the number of ongoing sudden stop episodes that are included in our final sample. The different shades of gray highlight how these episodes are distributed among different geographical areas. Source: IMF BOP/IIP, Eurostat, OECD, and own calculations.

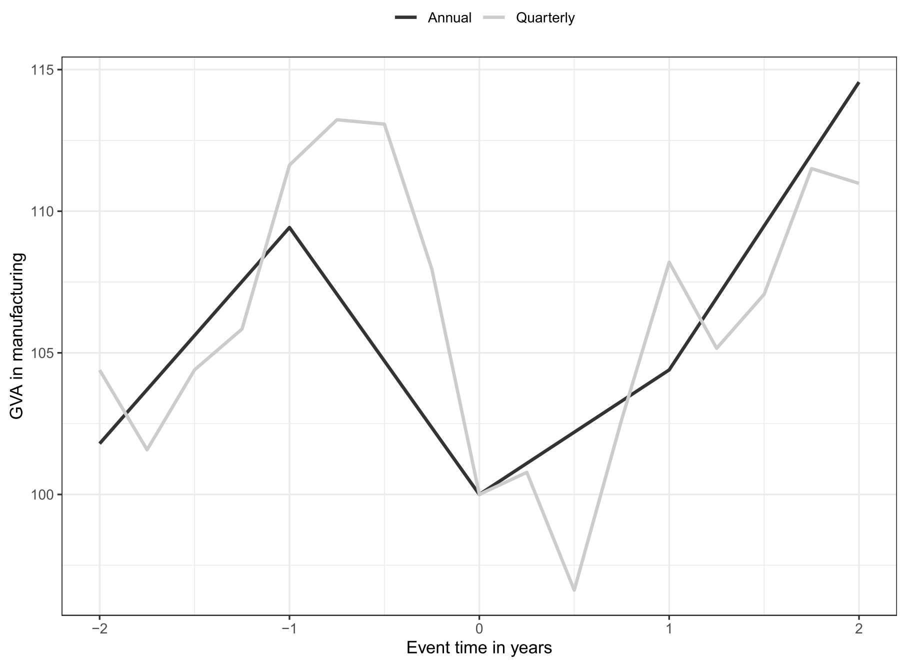

Fig. 3. Quarterly vs. annual data about manufacturing RGVA from around the Turkish sudden stop between 2001Q2–2001Q4. *Notes*: The figure plots real GVA levels for Turkey around its identified sudden stop episode in 2001, using both annual and quarterly data. GVA is normalized at both frequencies such that it equals 100% at the onset of the sudden stop, 2001 (annual) and 2001 Q2 (quarterly). Source: Eurostat.

3.2. Sectoral value added

The most problematic part of our 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 that we could collect sectoral value added 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. This cost does not seem to be very large: the number of episodes in our sample would increase from 67 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.

To illustrate the advantages of quarterly data, Fig. 3 plots real GVA levels for manufacturing (C) for a particular sudden stop episode, Turkey 2001Q2–2001Q4. The chart compares the evolution of real GVA when using annual data, as opposed to quarterly

Table 1
Production sectors, codes, and abbreviations.

Sector	Short name	Full name
A	Agriculture	Agriculture, forestry and fishing
B-E	Industry	Industry
C	Manufacturing	Manufacturing
F	Construction	Construction
G-I	Trade and hospitality	Wholesale and retail trade, transport, accommodation and food service activities
J	Info-communication	Information and communication
K	Finance	Financial and insurance activities
L	Real estate	Real estate activities
M-N	Professional services	Professional, scientific and technical activities; administrative and support service activities
O-Q	Public services	Public administration, defence, education, human health and social work activities
R-U	Arts and other services	Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies

Notes: The table lists the 10+1 sectors, about which the quarterly sectoral value added data were collected. The +1 additional sector is C (manufacturing) that is a subsector of sector B-E (industry). The classification follows the NACE Rev. 2 (ISIC Rev. 4) categorization used by Eurostat and the OECD.

data. In both cases, we normalize the time series so that RGVA equals 100% at the beginning of the sudden stop (2001 in the annual case, and 2001 Q2 in the quarterly case). Two main differences stand out from the figure. First, annual data misses important aspects of the periods immediately before the sudden stop. In particular, it averages out the large increase and subsequent decline in the times series over the year preceding the shock. Looking at the quarterly series, we see that RGVA was still increasing in the first half of that year, but we do not see this at the annual frequency. Second, annual data also misses the "double dip" during the sudden stop, followed by a sharp rebound within the first year following the start of the episode. Such fine-grained details may not always be important, but having quarterly observations allows us to let the data decide if this is indeed the case. Using a quarterly frequency in our view is a significant advantage over the previous literature, such as Craighead and Hineline (2014).

We use two fairly comprehensive data sources about quarterly sectoral RGVA: Eurostat and the OECD. In both cases, the sectors are those listed in Table 1; the classifications follow the NACE Rev. 2 (ISIC Rev. 4) categorization used by Eurostat (and the OECD). 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.[13]

From Eurostat[14] we use table `namq_10_a10`, and collect chain-linked time series on gross value added. From the OECD[15] 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 46 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[16] to do the seasonal adjustment ourselves.

3.3. *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.

[13] Specifically, we lose 5 countries in case of the tradable sector: Australia, Chile, Israel, Korea, and New Zealand. This leads to the loss of 5 sudden stop episodes: Chile 2009Q1-2009Q4, Israel 2011Q4-2012Q3, Korea 1997Q2-1999Q3, Korea 2008Q2-2009Q3, and New Zealand 2008Q2-2009Q2. For all of these countries except for Korea, there is data available about the RGVAs of all tradable subsectors, but nominal GVA is not available. 1 additional country is lost in case of the nontradable sector: Brazil. This causes the loss of 3 further episodes: Brazil 1999Q1-1999Q2, Brazil 2008Q2-2009Q3, and Brazil 2015Q3-2016Q2.

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

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

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

3.4. The final panel dataset

The data about sectoral GVA, GDP, and the REER are collected in a panel structure where the cross-sectional units of observation are countries and the time dimension is made up of quarters defined in calendar time. Based on the results of the sudden stop detection described in Subsection 3.1, we are able to determine for most quarters in each country if the country faced a sudden stop in that quarter. The final panel dataset that serves as the basis for our regression analyses are made up of those country-quarters for which information about sectoral value added and sudden stop occurrences are simultaneously available.

The dataset contains observations about 46 countries. In a few of them, the GVA of some sectors, or the time series of the REER is not available. The length of the available time series differs from country to country. For each country, Table 9 in the Appendix specifies the quarters covered by the sample. Note that the dataset contains some countries in which no sudden stop episodes have been detected.[17] The observations from them will be part of the control group when estimating the changes in sectoral growth rates around sudden stop events.

4. Main results

We use two related, but distinct approaches to estimate changes in sectoral value added growth around sudden stops. Our main results are derived from the country-time panel dataset described in the previous section. Before we turn to formal estimation, however, we show suggestive evidence from an event-based approach, where we organize the data around sudden stop episodes.

4.1. Event windows

To gain some preliminary insights about sectoral dynamics around sudden stops, we follow the procedure described by Cavallo et al. (2015) with some modifications, mostly due to the fact that we work with sectoral GVA in addition to aggregate GDP. 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.

Based on Cavallo et al. (2015), we proceed as follows. 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 volumes of sectoral GVA as our main variable of interest. We also retain aggregate GDP, the real exchange rate, and the tradeable and nontradable composites as additional indicators. The synthetic panels include 66 identified sudden stop events[18] for the 11 sectors and the 4 additional variables. In each panel, the identifiers are the episodes and “event time” (the event periods before and after the sudden stop starts). Variables are used in quarterly growth rates just as in the regressions below, including the real effective exchange rate.

To visualize dynamic adjustment processes around sudden stops, we average the growth rates of sectoral RGVA, GDP and the REER over the sudden stop episodes for each event period and sector. This process yields simple time series for the 15 variables with 21 observations. Averaging gives us a “generic” sudden stop where idiosyncratic factors are filtered out.

Fig. 4 shows adjustments around a “representative” sudden stop for each of the 15 indicators. 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 episode. This is not surprising, since sectoral output here 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) growth starts declining early on, turns negative just before the sudden stop, and does not return to previous levels. Service sectors in general (with the exception of G-I) tend to experience a growth slowdown: for arts and other services (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. In about half of the sectors RGVA growth starts slowing already before the start of the sudden stop (manufacturing, construction, trade and hospitality, info-communication, professional services, and arts and other services).

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 with only a very mild actual recession. The REER – which appreciates mildly on average before sudden stops – starts depreciating sharply just before episodes, and (at least until the end of the event window) does not recover.

While the figure is informative, there are major reasons why averaging across sudden stop episodes may paint a misleading – or at least incomplete – picture. First, as the figure reveals, trend growth was present in most sectors pre-crisis, but with large variations across sectors, and probably also across countries. 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. Therefore, we need to control for these differing trends across sectors and countries in order to isolate the changes related to the sudden stop.

[17] These countries are Australia, Austria, Colombia, Cyprus, Serbia, and Slovakia.

[18] The total number of episodes included in our panel dataset is 67. We leave out one episode from this exercise: Israel 2011Q4-2012Q3. The reason is that sectoral GVA data for Israel is available from 2012 Q1 only, which is after the start of the sudden stop.

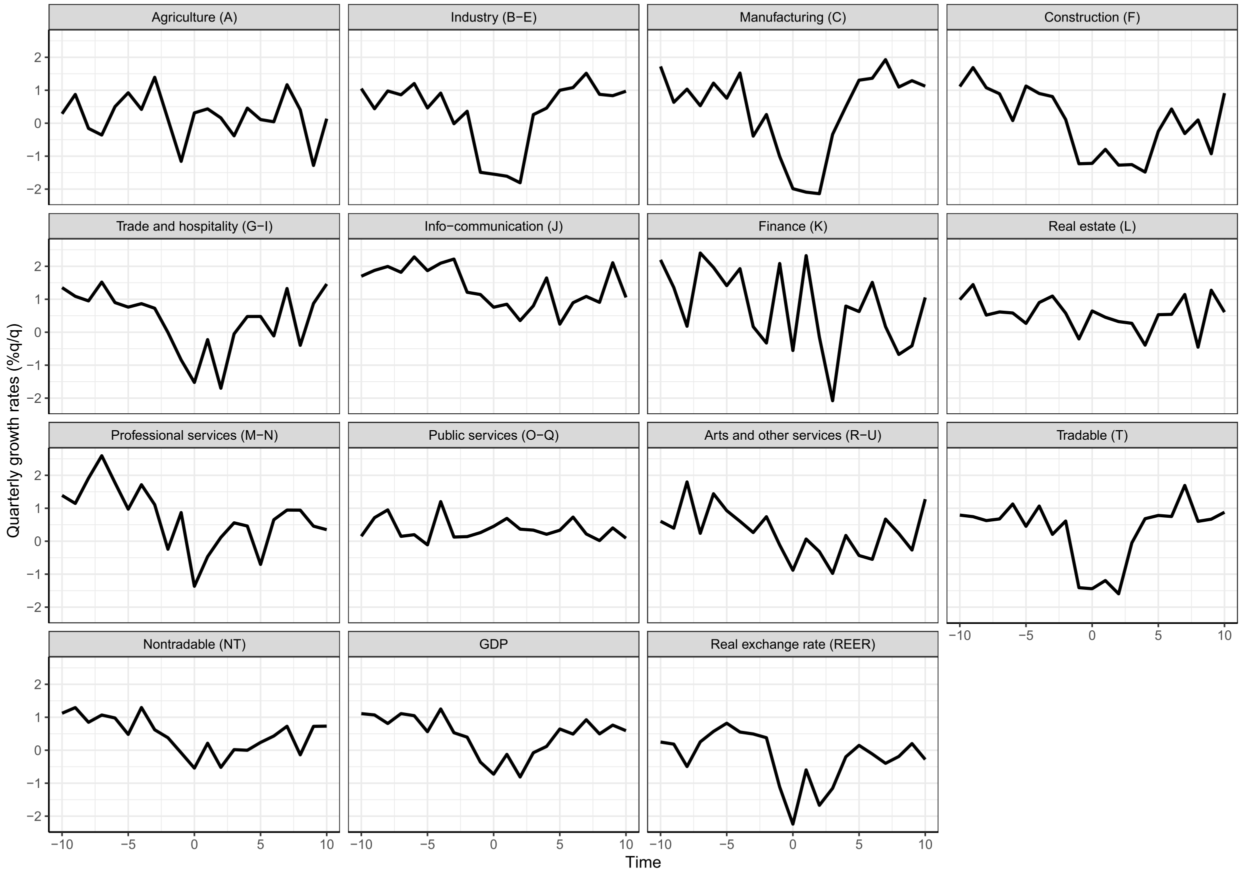

Fig. 4. Sectoral dynamics around a synthetic sudden stop. *Notes*: The figure shows average sectoral value added growth rates before and after sudden stops. Time is set to 0 in the quarter when the sudden stop starts. The values plotted are the across-episode averages of the respective variables for each event period. Sector abbreviations are more precisely defined in Table 1. Source: Eurostat, OECD, and own calculations.

Second, controlling for countries and sectors may not be sufficient if common shocks arrive at a higher frequency. This is a weakness of event-based approaches, such as Cavallo et al. (2015): changes attributed to a sudden stop may be caused by other – possibly global – shocks, that need not be related to the sudden stop. For example, a significant part of the sudden stops in our sample are from the global financial crisis (GFC). It is possible that the sectoral patterns we see during the GFC episodes are in fact caused by other, common events across countries. Therefore we turn to our second approach based on the original country-time panel dataset, where we can control for this possibility.

4.2. Baseline estimation

As discussed before, our main variable of interest is chain-linked gross value added. For all sectors, this is typically growing over time, at different paces in different country-sectors and around different sudden stop episodes. Therefore, we estimate changes in *growth rates* before and after the sudden stop hits the economy. To isolate the changes related to sudden stops as well as possible, we also need to control for country differences and common shocks across countries and sectors not necessarily related to sudden stops. As in the event-based approach, we focus our attention on the event window, defined as plus and minus 10 quarters around the start of a sudden stop event. Guided by Fig. 4, we split the 21 quarters into four periods: -10 to -5 (the “prelude”), -4 to -1 (the “build-up”), 0 to the (varying) end of the sudden stop (the “episode”), and from the end of an episode to 10 (the “post-episode”).

For carrying out the actual regression analyses, we use our panel data structure, where one observation is a country-time cell for a particular sector. Our basic specification is the following:

$$y_{i,t}^j = \beta_1^j SS_{i,t}^{pre} + \beta_2^j SS_{i,t}^{build} + \beta_3^j SS_{i,t} + \beta_4^j SS_{i,t}^{post} + \eta_i^j + \eta_t^j + \epsilon_{i,t}^j, \tag{1}$$

where $y_{i,t}^j = 100 \times \Delta \log RGVA_{i,t}^j$ is the log-change in the real gross value added of sector j from (calendar) period $t-1$ to period t, expressed in percentage terms. $SS_{i,t}$ is a sudden stop dummy, defined to equal 1 during the sudden stop episode as identified earlier. $SS_{i,t}^{pre}$, $SS_{i,t}^{build}$ and $SS_{i,t}^{post}$ are dummy variables that equal 1 in different parts of the event window, respectively. i indexes countries, t is calendar time, η_i^j and η_t^j are country and time fixed effects for sector j, and $\epsilon_{i,t}^j$ is a standard error term.

Table 2
Results from the main panel specification.

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Prelude	−0.391	−0.457	−0.557*	−0.079	−0.175
	(0.340)	(0.280)	(0.312)	(0.310)	(0.146)
Build-Up	−0.597	−0.820***	−0.904***	−1.139**	−0.815***
	(0.606)	(0.280)	(0.300)	(0.446)	(0.196)
Episode	−0.921**	−0.966***	−1.201***	−2.384***	−0.765***
	(0.408)	(0.336)	(0.353)	(0.499)	(0.272)
Post-Episode	0.079	0.151	0.023	−0.451	−0.410**
	(0.383)	(0.227)	(0.241)	(0.338)	(0.164)
Observations	2,960	2,827	2,960	2,960	2,827
R-squared	0.078	0.165	0.182	0.070	0.141
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Prelude	0.047	−0.019	−0.116	−0.545	−0.167
	(0.232)	(0.271)	(0.229)	(0.339)	(0.103)
Build-Up	−0.019	0.073	0.267	−0.988***	−0.095
	(0.247)	(0.383)	(0.421)	(0.301)	(0.098)
Episode	−0.605**	−1.033***	0.066	−1.614***	0.080
	(0.239)	(0.312)	(0.275)	(0.375)	(0.212)
Post-Episode	−0.115	−0.739**	−0.191	−0.448**	−0.025
	(0.178)	(0.343)	(0.139)	(0.195)	(0.165)
Observations	2,960	2,908	2,960	2,908	2,827
R-squared	0.080	0.076	0.033	0.080	0.038
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP	(15) REER
Prelude	0.174	−0.418	−0.110	−0.245**	−0.337
	(0.234)	(0.266)	(0.122)	(0.094)	(0.287)
Build-Up	−0.572*	−0.687**	−0.303**	−0.449***	−0.974*
	(0.318)	(0.272)	(0.142)	(0.114)	(0.515)
Episode	−1.077***	−0.890***	−0.616***	−0.803***	−1.696**
	(0.311)	(0.297)	(0.180)	(0.153)	(0.680)
Post-Episode	−0.120	0.180	−0.210**	−0.183*	−0.519*
	(0.233)	(0.228)	(0.0804)	(0.100)	(0.279)
Observations	2,807	2,614	2,534	2,960	2,855
R-squared	0.045	0.179	0.173	0.270	0.105
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Notes: The table presents the results of estimating equation (1). In each column, the dependent variable is 100 times the quarterly log-change in real gross value added for the sector denoted in the column header. Sector abbreviations are defined in Table 1. T, NT, and REER denote the tradable and the nontradable sector, and the real effective exchange rate, respectively. Prelude, Build-Up, Episode, and Post-Episode refer to the respective sudden stop dummies. The estimated coefficients can be interpreted as percentage-point differences from the counterfactual sectoral growth rates. Robust standard errors are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Coefficient β_3^j measures the short-run adjustment of sector j during the sudden stop, and β_4^j measures its medium-run adjustment that takes place after the sudden stop has finished. The coefficients β_1^j and β_2^j measure if the sector experiences deviations in its GVA growth *before* the sudden stop, shedding light on the build-up toward a sudden stop episode. Given the country and time fixed effects, the coefficients measure average deviations from a hypothetical counterfactual, where the control is the same country at the same period, without experiencing a sudden stop event. We run regressions for each sector separately, which simplifies the interpretation of the results and leads to cleaner regression tables. Later we also report results from a pooled regression, where we test differences of the estimated coefficients across sectors.

Results are reported in Table 2. 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 the two aggregate variables, GDP and the real effective exchange rate (REER).

The short-run change in sectoral GVA during a sudden stop is almost always negative, and mostly highly significant. The exceptions are sectors L and O-Q, where the point estimates are positive, but insignificant. The immediate decline is largest for construction (F), professional services (M-N), and manufacturing (C). We can order sectors according to the drop they face in their growth rates during sudden stops as follows. The order is ascending, and it is based on the point estimates only, ignoring standard errors:

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

These results are partly in line with the visual clues presented on Fig. 4 (sectors C and F), but there are also differences. For example, sectors G-I (trade and hospitality) are visually among the most hurt, but the estimated coefficient is much smaller (although highly significant). Time fixed effects are likely the reason why the event study approach and the panel estimation lead to somewhat different results.

There is more heterogeneity when we look at the persistent changes after sudden stops, measured by the Post-Episode variable. Here, the majority of sectors have insignificant coefficients, although the sign of the point estimates are instructive. Goods producing sectors (A, B-E, and C) have positive coefficients, while construction and services have negative ones. For sectors G-I, K, and M-N they are also statistically significant, i.e. growth rates are persistently lower after the sudden stop. In case of goods, while the point estimates are not significant, their sign suggests that tradables rebound better after a sudden stop. We return to this question when we explore facilitators of adjustment later. Overall, the point estimates again are in line with Fig. 4, but significance levels are weak.

Interestingly, in several cases the sudden stop dummies for the "build-up" period (β_2^j) are also significantly negative (the exceptions are sectors A, J, K, L, O-Q, where the point estimates are not significant). This means that sudden stops are already precipitated by economic weakness, which is exacerbated by the shock. On the other hand, the "prelude" period dummies are not significant (except for manufacturing at the 10% level), so the slowdown is concentrated at the quarters immediately preceding the shock. Also, the prelude point estimates are mostly negative, so we do not find evidence for above-average growth rates preceding the sudden stop, although such a possibility was suggested by Fig. 4 (for example, for construction F). Note, however, that our estimation uses sectoral growth rates, which are not the right variables to measure overheating. It is possible that a sector's GVA is above its sustainable growth path *in levels*, but not in *growth rates*. To investigate overheating, we therefore turn to the concept of the output gap in a later section.

Apart from the sectoral results, we also estimate more aggregate adjustment dynamics. As suggested by the previous discussion, the tradable sector performs worse and is hit harder on impact, than the nontradable sector. On the other hand, it suffers less in the medium run. In fact, we find weak evidence for a post-crisis rebound (a positive, but not significant point estimate), whereas the NT sector continues to grow slower than it would otherwise have without the sudden stop. Note that both the T and NT sectors grow slower already immediately before a sudden stop, but the point estimate is larger for tradables. Overall, the evidence suggests a slowdown concentrated among tradables before the shock, a sharp but temporary decline on impact for tradables, and a smaller, but more lasting decline in nontradables.

The aggregate implications can be seen in the evolution of real GDP, which is already growing slower before the shock, slows even more on impact, and remains weak after the sudden stop ends. Finally, the real exchange rate follows a similar pattern, with a weak starting position, a sharp drop on impact, some of which persists after the shock itself ends. The REER coefficient in the prelude period differ from what Fig. 4 suggests, where we see a mild appreciation until just before the sudden stop hits. While not significant, the point estimate is negative, suggesting that the REER is already depreciating well before the shock arrives.

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 experience a deeper recession on impact, but fare better once the sudden stop ends. The public sector's performance changes the least. Some sectors start declining already ahead of the shock, but we do not find above average growth rates in the quarters preceding the immediate precursor of a sudden stop. We return to the question of overheating later.

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:

$$y_{i,t}^j = \sum_{j=1}^{J} \delta_1^j SEC^j \times SS_{i,t}^{pre} + \sum_{j=1}^{J} \delta_2^j SEC^j \times SS_{i,t}^{build} + \sum_{j=1}^{J} \delta_3^j SEC^j \times SS_{i,t} + \sum_{j=1}^{J} \delta_4^j SEC^j \times SS_{i,t}^{post} + \theta_i^j + \theta_t^j + \epsilon_{i,t}^j, \tag{2}$$

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 country-sector fixed effect, θ_t^j is a sector-time fixed effect, while $\left\{\delta_1^j\right\}_{j=1}^J$, $\left\{\delta_2^j\right\}_{j=1}^J$, $\left\{\delta_3^j\right\}_{j=1}^J$, and $\left\{\delta_4^j\right\}_{j=1}^J$ are the regression coefficients for the sudden stop dummies as defined in the previous section.

Table 3
Sectoral adjustments relative to GDP adjustment.

	Difference of the Change in the Sectoral Growth Rate Relative to That of GDP			
	Prelude	Build-Up	Episode	Post-Episode
A	−0.146	−0.148	−0.118	0.262
	(0.785)	(0.804)	(0.843)	(0.573)
B-E	−0.212	−0.371	−0.163	0.334
	(0.558)	(0.317)	(0.642)	(0.219)
C	−0.312	−0.455	−0.398	0.205
	(0.374)	(0.215)	(0.275)	(0.479)
F	0.166	−0.690	−1.581***	−0.268
	(0.659)	(0.123)	(0.000)	(0.576)
G-I	0.070	−0.366	0.038	−0.227
	(0.745)	(0.112)	(0.905)	(0.261)
J	0.292	0.430	0.198	0.067
	(0.264)	(0.233)	(0.547)	(0.791)
K	0.226	0.522	−0.230	−0.556
	(0.540)	(0.252)	(0.652)	(0.171)
L	0.129	0.716	0.869**	−0.008
	(0.649)	(0.230)	(0.019)	(0.985)
M-N	−0.301	−0.539	−0.811*	−0.265
	(0.374)	(0.140)	(0.054)	(0.503)
O-Q	0.078	0.354	0.883***	0.158
	(0.730)	(0.342)	(0.003)	(0.421)
R-U	0.419	−0.123	−0.274	0.063
	(0.180)	(0.760)	(0.591)	(0.840)
T	−0.174	−0.238	−0.087	0.363
	(0.628)	(0.513)	(0.804)	(0.191)
NT	0.135	0.146	0.187	−0.027
	(0.440)	(0.537)	(0.414)	(0.872)

Notes: The values in a row of the table are equal to the average differences of the respective sector's growth rates in the prelude, build-up, during-episode, and post-episode periods from its corresponding counterfactual growth rates minus the same average differences for GDP. That is, they are equal to the sector's corresponding coefficients from Table 2 minus those of GDP. Sector abbreviation are defined in Table 1. T and NT denote the tradable and the nontradable sector, respectively. 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.

The key difference between equations (1) and (2) is that the former are estimated separately for each sector, while the latter is estimated simultaneously for all sectors, including the tradable and nontradable aggregates and GDP. The point estimates of $\left\{\delta_1^j\right\}_{j=1}^J$, $\left\{\delta_2^j\right\}_{j=1}^J$, $\left\{\delta_3^j\right\}_{j=1}^J$, and $\left\{\delta_4^j\right\}_{j=1}^J$ in equation (2) are exactly the same as those of $\left\{\beta_1^j\right\}_{j=1}^J$, $\left\{\beta_2^j\right\}_{j=1}^J$, $\left\{\beta_3^j\right\}_{j=1}^J$, and $\left\{\beta_4^j\right\}_{j=1}^J$ in equation (1) because of the Frisch and Waugh (1933) theorem. Their standard errors differ to a small extent.[19] The reason why we prefer specification (1) to (2) is that the former allows for easier interpretation and cleaner regression tables. However, the latter makes it possible to run F-tests on the null hypotheses that $\delta_1^j = \delta_1^k$, $\delta_2^j = \delta_2^k$, $\delta_3^j = \delta_3^k$, or $\delta_4^j = \delta_4^k$ for any pair of sectors $j \neq k$. That is, we can test if sectoral adjustments differ significantly before, 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 3 reports the estimated differences $\delta_1^j - \delta_1^{GDP}$, $\delta_2^j - \delta_2^{GDP}$, $\delta_3^j - \delta_3^{GDP}$, and $\delta_4^j - \delta_4^{GDP}$ for each sector j, i.e. the changes in sectoral growth rates compared to that of GDP. The reason why these comparisons are interesting is that the dynamics of GDP can be interpreted as the dynamics of the average sector. Hence, they will inform us about whether the adjustment process in a particular sector follows significantly different patterns than in the average one. In parentheses, we report the p-values from testing the null hypothesis of equal changes in growth rates before, just before, during, and after the sudden stop, respectively.

No sector's pre-episode adjustment differs significantly from GDP's, either in the prelude or in the build-up period. During sudden stops, the construction sector (F) and professional services (M-N) experience significantly larger drops in their growth rates than GDP. In case of the former, the difference is significant at the 1% level, while in case of the latter, it is significant at the 10% level only. This confirms our previous intuition that an important source of the recession faced by the macroeconomy during sudden stops is the construction sector. 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 agriculture (A), industry (B-E), manufacturing (C) in particular, and as a result, the broad tradable sector are estimated to experience a smaller fall in their growth rates than GDP. (Actually, their growth

[19] The results of estimating equation (2) are available from the authors upon request.

Table 4
Tradable adjustment relative to nontradable adjustment.

	Difference between the Change in the T Sector's Growth Rate and that in the NT Sector's			
	Prelude	Build-Up	Episode	Post-Episode
T	−0.308	−0.383	−0.274	0.390
	(0.396)	(0.329)	(0.449)	(0.191)

Notes: The values in the table are equal to the average differences of the tradable sector's growth rates in the prelude, build-up, during-episode, and post-episode periods from its corresponding counterfactual growth rates minus the same average differences for the nontradable sector. That is, they are equal to the tradable sector's corresponding coefficients from Table 2 minus those of the nontradable sector. T and NT denote the tradable and the nontradable sector, respectively. 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.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

rates are estimated to rise compared to their counterfactual values.) The differences are economically significant, which suggests that these sectors might lead the economy's recovery from a sudden stop recession. However, statistical significance is not confirmed at the conventional levels. The post-episode adjustment of nontradable sectors, including the nontradable aggregate, does not differ significantly from that of GDP in a statistical sense, either. In some nontradable sectors, the difference seems to be economically significant, but not in the nontradable aggregate.

Another interesting comparison is the one between the adjustment of the broad tradable and nontradable sectors. Table 4 reports the estimated differences $\delta_1^T - \delta_1^{NT}$, $\delta_2^T - \delta_2^{NT}$, $\delta_3^T - \delta_3^{NT}$, and $\delta_4^T - \delta_4^{NT}$, i.e. the difference between the change in the tradable sector's growth rate and the change in the nontradable sector's growth rate before, just before, during, and after sudden stops. *p*-values from the F-tests of equal changes in sectoral growth rates are again in parentheses.

The point estimates suggest that the growth rate of the tradable sector falls by 0.31 percentage point more than that of the nontradable sector already well before sudden stops, by 0.38 percentage point more just before the shock, and by 0.27 percentage point more during sudden stops. On the other hand, the post-episode fall in the tradable sector's growth rate is smaller – by 0.39 percentage point – than that in the nontradable sector's. (Actually, the tradable sector is estimated to experience a rise in its growth rate after the episode, compared to the counterfactual.) This may point out an interesting trade-off for industrial policy: the nontradable sector is more resistent to sudden stops on impact, but the tradable sector rebounds more quickly after sudden stops. All these differences between the tradable and the nontradable sector's adjustment are economically significant, but they are not significant statistically.

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. 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 before and just before the episode, on impact, as well as after the sudden stop episode itself ends, in line with the previous sections.

The second adjustment channel 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.

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

$$\begin{aligned} y_{i,t}^j = {} & \gamma_1^j SS_{i,t}^{pre} + \gamma_2^j SS_{i,t}^{build} + \gamma_3^j SS_{i,t} + \gamma_4^j SS_{i,t}^{post} + \gamma_5^j RDEPR_{i,t} \times SS_{i,t}^{pre} + \gamma_6^j RDEPR_{i,t} \times SS_{i,t}^{build} \\ & + \gamma_7^j RDEPR_{i,t} \times SS_{i,t} + \gamma_8^j RDEPR_{i,t} \times SS_{i,t}^{post} + \gamma_9^j RECSS_{i,t}^j \times SS_{i,t}^{post} + \eta_i^j + \eta_t^j + \epsilon_{i,t}^j, \end{aligned} \tag{3}$$

[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.

where $y^j_{i,t}$ is always the log-change in the RGVA of sector j from period $t-1$ to period t, expressed in percentage terms. Let $RDEPR_k = -100 \times \Delta \log REER_{k,-1\text{-}10}$ be the real depreciation of the domestic currency from the period just preceding the start of episode k until the end of the event window (±10 quarters), measured as minus the log-change in the real effective exchange rate between event period −1 and 10, also expressed in percentage terms. $RDEPR_{i,t}$ in equation (3) is equal to $RDEPR_k$ for those country-quarters that are within the event window of episode k.[21] Similarly, let $RECSS^j_k$ be the depth of sector j's recession during sudden stop k, measured as the simple average of negative percentage deviations from the sector's Hodrick-Prescott trend path if $SS_{i,t} = 1$ within episode k's event window. $RECSS^j_{i,t}$ in equation (3) equals $RECSS^j_k$ for country-quarters within the event window of episode k.[22]

Coefficients γ^j_1, γ^j_2, γ^j_3, and γ^j_4 are similar to coefficients β^j_1, β^j_2, β^j_3, and β^j_4 in equation (1), with the exception that they must be interpreted conditional on no real depreciation occurring 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^j_7 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^j_8 measures the same for the post-episode average sectoral growth rate.[23] If they turn out to be significantly positive (negative), then real depreciation facilitates (hinders) sector j's adjustment during or after the sudden stop, respectively. For completeness, we also include the interaction of real depreciation with the pre-episode dummies, the coefficients of which (γ^j_5 and γ^j_6) are less straightforward to interpret. They measure the change in the average growth rate of sector j's RGVA during the prelude and build-up periods if real depreciation is by 1 percentage point stronger in the second half of the event window. Real depreciation in the second half of the event window obviously cannot affect sectoral performance during the pre-episode phase, but weaker pre-episode sectoral growth can lead to a sharper depreciation during or after the sudden stop, which may result in a significant γ^j_6 (and possibly γ^j_5) coefficient. Finally, γ^j_9 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^j_9 refers to the presence of a significant rebound effect as it suggests that the more sector j falls below its long-run trend path during the sudden stop, the faster it will grow after that.

Results are presented in Table 5. Perhaps surprisingly, we do not find strong evidence that REER depreciation leads to improved sectoral outcomes anywhere. On impact, almost all interaction terms are negative, and in a few sectors – financial services (K) and trade and hospitality (G-I) –, highly significantly so. One possible interpretation for these results is that stronger REER depreciation is a consequence of having been harder hit in a sudden stop, so we are measuring reverse causality. Another possibility is that depreciation triggers a Fisherian type of debt-deflation mechanism in countries that enter the sudden stop with a large stock of FX-denominated loans (Korinek and Mendoza, 2014). This might explain why financial services – and in the medium run, construction – are among the sectors most strongly hurt by depreciation. Given that our purpose is mostly descriptive and the limitations of our data, we cannot establish a causal link between GVA growth and real depreciation. Looking at the post-episode interaction, the point estimates are more in line with our expectations: they are positive in the tradable sectors, and negative in construction and nontradables. The estimates are mostly statistically insignificant, and economically small. In manufacturing, for example, a 10% real depreciation leads to a growth increase of only 0.02 percentage points (the average real deprecation during and after sudden stops is around 6% in our sample).

However, the estimated coefficients of the interaction between real depreciation and the *build-up* dummy qualify these conclusions. These are significantly negative in industry and the tradable aggregate, suggesting that weaker industrial/tradable growth *before* a sudden stop triggers a sharper depreciation during and after the event. This may help restoring industrial/tradable growth to, or even above, its counterfactual rate in the post-episode phase. However, we still cannot exclude that the real depreciation variable simply proxies the size of the sudden stop. If this is the case, then the significance of its interaction with the prelude dummy just signals that weaker pre-crisis performance by the tradable sector is usually followed by larger sudden stops.

Turning to the correction hypothesis, we find strong support for a stronger rebound in the sectors that face larger damages during the sudden stop on impact, at least in construction and services. The interaction variables in these sectors are highly significant, with some heterogeneity across sectors. Not surprisingly, the same result holds for nontradables and overall GDP. In manufacturing and industry more broadly, the estimated coefficients are only significant at the 10% level, with a noisy (but also positive) point estimate for tradables. While only suggestive, our results support the idea that a deeper decline is followed by a stronger rebound at both the sectoral and at the aggregate level, driven mostly by the performance of the non-tradable sector.

[21] The values of $RDEPR_{i,t}$ outside of the event windows are irrelevant, as all sudden stop dummies equal 0 outside of the event windows, hence, their interactions with the real depreciation variable will also be 0.

[22] Again, the values of $RECSS^j_{i,t}$ outside of the event windows are irrelevant, as the post sudden stop dummy equals 0 outside of the event windows, hence, its interaction with the sectoral recession depth variable will also be 0.

[23] These changes are again to be interpreted relative to the counterfactual of no sudden stop occurring within the event-window of the same quarter in the same country.

Table 5
Adjustment channels: exchange rate and recession depth.

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Prelude	−0.476	−0.349	−0.409	−0.319	−0.257*
	(0.335)	(0.302)	(0.318)	(0.251)	(0.135)
Depreciation x Prelude	−0.001	0.001	0.003	0.028	0.006
	(0.018)	(0.013)	(0.009)	(0.021)	(0.008)
Build-Up	−0.453	−0.741**	−0.889***	−0.997**	−0.701***
	(0.648)	(0.281)	(0.280)	(0.422)	(0.161)
Depreciation x Build-Up	−0.015	−0.023***	−0.022***	−0.021	−0.017*
	(0.016)	(0.008)	(0.008)	(0.013)	(0.009)
Episode	−0.968**	−0.732**	−0.910***	−2.145***	−0.729***
	(0.435)	(0.294)	(0.309)	(0.405)	(0.264)
Depreciation x Episode	0.011	−0.006	−0.005	−0.038*	−0.027***
	(0.007)	(0.007)	(0.008)	(0.022)	(0.009)
Post-Episode	−0.118	−0.157	−0.309	−0.681**	−0.666***
	(0.424)	(0.261)	(0.286)	(0.291)	(0.173)
Depreciation x Post-Episode	0.004	0.000	0.002	−0.020**	−0.006
	(0.008)	(0.006)	(0.006)	(0.008)	(0.004)
Sector Decline x Post-Episode	0.211***	0.108*	0.102*	0.276***	0.204***
	(0.049)	(0.061)	(0.059)	(0.031)	(0.034)
Observations	2,897	2,764	2,897	2,897	2,764
R-squared	0.080	0.176	0.196	0.085	0.147
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M-N	(10) O-Q
Prelude	−0.107	0.029	0.029	−0.785**	−0.153*
	(0.215)	(0.286)	(0.185)	(0.316)	(0.082)
Depreciation x Prelude	0.007	−0.016	0.003	0.013	−0.016
	(0.014)	(0.019)	(0.011)	(0.010)	(0.013)
Build-Up	0.052	−0.149	−0.079	−0.997***	−0.124
	(0.286)	(0.319)	(0.217)	(0.330)	(0.096)
Depreciation x Build-Up	−0.007	0.009	−0.006	0.003	0.002
	(0.020)	(0.018)	(0.008)	(0.010)	(0.004)
Episode	−0.567**	−0.721**	−0.183	−1.317***	−0.054
	(0.257)	(0.317)	(0.151)	(0.379)	(0.099)
Depreciation x Episode	−0.012	−0.034***	0.003	−0.021*	−0.008
	(0.010)	(0.008)	(0.006)	(0.011)	(0.008)
Post-Episode	−0.156	−0.237	−0.218**	−0.616***	−0.082
	(0.223)	(0.274)	(0.105)	(0.187)	(0.097)
Depreciation x Post-Episode	−0.005	−0.009	−0.001	−0.012***	−0.000
	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)
Sector Decline x Post-Episode	0.150**	0.383***	0.267**	0.223***	0.447***
	(0.063)	(0.098)	(0.101)	(0.038)	(0.043)
Observations	2,897	2,845	2,897	2,845	2,764
R-squared	0.087	0.086	0.041	0.093	0.053
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

(*continued on next page*)

5. Robustness

5.1. Were sudden stops different during the global financial crisis?

37 out of the 67 sudden stop episodes in our sample are from the time period around the global financial crisis of 2007–2012 (GFC), i.e. somewhat more than half of them started between 2007Q3 and 2012Q4. 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. This comes with a risk that our main results are actually driven by the GFC alone, instead of capturing sectoral dynamics around sudden stops in general. If this is the case, we have to be more careful about the interpretation and generalization of the key messages. Therefore, our first robustness exercise is about investigating if sudden stops related to the GFC are different from the remaining ones. We do this by estimating the following specification for each sector separately.

Table 5 (*continued*)

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP
Prelude	0.048	−0.387	−0.138	−0.290***
	(0.278)	(0.292)	(0.126)	(0.099)
Depreciation x Prelude	0.003	−0.005	0.013	0.005
	(0.018)	(0.015)	(0.014)	(0.005)
Build-Up	−0.470	−0.620**	−0.344***	−0.422***
	(0.330)	(0.270)	(0.118)	(0.100)
Depreciation x Build-Up	−0.009	−0.026***	−0.007	−0.009*
	(0.016)	(0.009)	(0.010)	(0.005)
Episode	−1.002***	−0.784***	−0.586***	−0.711***
	(0.308)	(0.285)	(0.155)	(0.142)
Depreciation x Episode	−0.008	0.004	−0.024	−0.013**
	(0.014)	(0.007)	(0.017)	(0.006)
Post-Episode	0.051	−0.148	−0.313***	−0.400***
	(0.260)	(0.255)	(0.104)	(0.115)
Depreciation x Post-Episode	−0.024*	0.004	−0.007	−0.005
	(0.012)	(0.007)	(0.006)	(0.003)
Sector Decline x Post-Episode	0.215***	0.077	0.151***	0.188***
	(0.068)	(0.063)	(0.032)	(0.031)
Observations	2,744	2,558	2,478	2,897
R-squared	0.053	0.187	0.193	0.292
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: The table presents the results of estimating equation (3). In each column, the dependent variable is 100 times the quarterly log-change in real gross value added for the sector denoted in the column header. Sector abbreviations are defined in Table 1. T and NT denote the tradable and the nontradable sector, respectively. Prelude, Build-Up, Episode, and Post-Episode refer to the respective sudden stop dummies. Depreciation is minus the log-change in the real effective exchange rate from the quarter preceding the start of the sudden stop until the tenth quarter after that. Sector Decline is 100 times the average log-deviation of the respective sector's real gross value added from its Hodrick-Prescott trend path during the episode. The estimated coefficients can be interpreted as percentage-point differences from the counterfactual sectoral growth rates. Robust standard errors are in parentheses.

***p < 0.01, **p < 0.05, *p < 0.1.

$$y_{i,t}^j = \phi_1^j SS_{i,t}^{pre} + \phi_2^j SS_{i,t}^{build} + \phi_3^j SS_{i,t} + \phi_4^j SS_{i,t}^{post} + \phi_5^j GFC_t \times SS_{i,t}^{pre} + \phi_6^j GFC_t \times SS_{i,t}^{build}$$
$$+ \phi_7^j GFC_t \times SS_{i,t} + \phi_8^j GFC_t \times SS_{i,t}^{post} + \eta_i^j + \eta_t^j + \epsilon_{i,t}^j, \tag{4}$$

where GFC_t is a dummy variable equal to 1 within the event windows of those sudden stop episodes that started between 2007Q3 and 2012Q4, while $\phi_1^j, \dots, \phi_8^j$ are coefficients to be estimated. The significance of ϕ_5^j, ϕ_6^j, ϕ_7^j, or ϕ_8^j would indicate systematically different adjustment dynamics in sector j around GFC-related sudden stops than around non-GFC-related ones. The remaining notations are the same as in case of equation (1).

Table 6 presents the results of estimating equation (4). The interactions between the GFC dummy and the sudden stop dummies almost never turn out to be significant. One minor exception can be found in case of the construction sector (F), the post-episode growth rate of which is estimated to be significantly higher around GFC episodes than around non-GFC episodes. We might also see significantly less depreciation in the real effective exchange rate (REER) during GFC episodes than during non-GFC episodes, but the difference is significant at the 10% level only.

To sum up, the general insignificance of the interactions between the GFC dummy and the sudden stop dummies increases our confidence that our main results are mostly not driven by the GFC, thus, they capture more general adjustment dynamics around sudden stops. This must be related to the inclusion of time fixed effects in equation (4) that seem to control for the common shocks of the GFC-period sufficiently.[24]

5.2. Sectoral output gaps

We also run regressions where in the baseline specification (1), 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 shows the estimation results.

[24] Reestimating equation (4) without time fixed effects increases the significance of many of the interactions between the GFC dummy and the sudden stop dummies, suggesting that time fixed effects actually play an important role in allowing us to disentangle sectoral dynamics associated with the GFC from those associated with sudden stops in general. Results are available from the authors upon request.

Table 6
Sectoral adjustment around episodes related versus episodes not related to the global financial crisis.

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Prelude	−0.352	−0.344	−0.481	0.080	−0.265
	(0.271)	(0.432)	(0.446)	(0.496)	(0.176)
GFC x Prelude	−0.144	−0.287	−0.189	−0.339	0.176
	(0.652)	(0.470)	(0.520)	(0.872)	(0.335)
Build-Up	−0.450	−0.747**	−0.830**	−1.576***	−0.666***
	(0.407)	(0.349)	(0.318)	(0.488)	(0.227)
GFC x Build-Up	−0.400	−0.230	−0.187	0.852	−0.262
	(1.260)	(0.703)	(0.689)	(0.814)	(0.395)
Episode	−0.817**	−0.802**	−1.207***	−2.072***	−0.861***
	(0.322)	(0.383)	(0.390)	(0.665)	(0.298)
GFC x Episode	−0.327	−0.345	−0.025	−0.416	0.171
	(0.788)	(0.634)	(0.677)	(1.049)	(0.573)
Post-Episode	0.228	0.071	0.010	−1.022**	−0.478**
	(0.422)	(0.305)	(0.323)	(0.457)	(0.183)
GFC x Post-Episode	−0.366	0.168	0.033	1.286**	0.151
	(0.619)	(0.409)	(0.414)	(0.608)	(0.283)
Observations	2,960	2,827	2,960	2,960	2,827
R-squared	0.078	0.166	0.182	0.071	0.141
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M_N	(10) O-Q
Prelude	−0.062	−0.162	0.177	−0.614***	−0.287
	(0.274)	(0.384)	(0.150)	(0.208)	(0.233)
GFC x Prelude	0.165	0.388	−0.580	0.023	0.220
	(0.348)	(0.637)	(0.482)	(0.637)	(0.526)
Build-Up	0.121	−0.080	−0.100	−0.758**	−0.033
	(0.288)	(0.424)	(0.156)	(0.373)	(0.162)
GFC x Build-Up	−0.348	0.410	0.725	−0.621	−0.154
	(0.495)	(0.604)	(0.825)	(0.783)	(0.277)
Episode	−0.417	−1.109**	0.098	−1.293***	0.238
	(0.321)	(0.468)	(0.293)	(0.384)	(0.333)
GFC x Episode	−0.430	0.209	0.046	−0.769	−0.342
	(0.528)	(0.940)	(0.333)	(0.874)	(0.329)
Post-Episode	−0.183	−0.576*	−0.319***	−0.495	0.085
	(0.267)	(0.324)	(0.115)	(0.301)	(0.247)
GFC x Post-Episode	0.097	−0.366	0.340	0.025	−0.284
	(0.506)	(0.669)	(0.375)	(0.344)	(0.240)
Observations	2,960	2,908	2,960	2,908	2,827
R-squared	0.080	0.076	0.034	0.081	0.039
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

(*continued on next page*)

The two pre-episode coefficients are estimated to be significantly positive in almost all sectors, with some minor differences between the prelude and build-up periods. This means that sectoral output gaps tend to be significantly higher in quarters preceding sudden stops than in the same quarters of a given country with no sudden stop occurring within the event window. In other words, almost all sectors have a tendency to overheat before sudden stops. This tendency is measured to be the strongest in the construction sector (F) and in financial services (K). Recall that the growth rates of industry (B-E), manufacturing (C), construction (F), trade and hospitality (G-I), and professional services (M-N), as well as the tradable (T) and nontradable (NT) aggregates, and GDP were estimated to be lower than their counterfactual values in the build-up period according to the results reported in Table 2. Putting the two sets of results together, it seems that these sectors tend to follow an unsustainable growth path before sudden stops, but their growth already starts slowing down possibly in the prelude, and definitely in the build-up period. In spite of the decelerating GVA growth, their GVA levels still tend to be above trend.

Only two sectors' during-episode coefficients are estimated to be positive. These are financial services (K) and real estate activities (L), and even their coefficients are only marginally significant (in case of the former), or not significant at all at the usual levels (in case of the latter). This suggests that the tendency to overheat disappears from most sectors during sudden stops, and it may even turn into an overcooling tendency, lowering several sectors' output gaps compared to the counterfactual. This during-episode tendency to overcool is statistically significant – and the strongest according to the point estimates – in manufacturing (C) and in professional

Table 6 (*continued*)

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP	(15) REER
Prelude	0.164	−0.333	−0.116	−0.277**	−0.652
	(0.324)	(0.419)	(0.085)	(0.130)	(0.489)
GFC x Prelude	−0.040	−0.235	−0.007	0.063	0.946
	(0.466)	(0.490)	(0.261)	(0.190)	(0.586)
Build-Up	−0.679**	−0.602*	−0.337**	−0.443***	−1.426*
	(0.275)	(0.343)	(0.132)	(0.141)	(0.817)
GFC x Build-Up	0.115	−0.246	0.034	−0.007	1.313
	(0.611)	(0.680)	(0.295)	(0.191)	(1.003)
Episode	−0.689***	−0.769**	−0.470*	−0.778***	−2.327**
	(0.220)	(0.330)	(0.256)	(0.184)	(0.886)
GFC x Episode	−0.755	−0.272	−0.274	−0.036	1.565*
	(0.583)	(0.625)	(0.423)	(0.335)	(0.877)
Post-Episode	−0.257	0.116	−0.207**	−0.248*	−0.567*
	(0.214)	(0.330)	(0.090)	(0.138)	(0.307)
GFC x Post-Episode	0.231	0.145	−0.027	0.141	0.235
	(0.649)	(0.436)	(0.151)	(0.160)	(0.494)
Observations	2,807	2,614	2,534	2,960	2,855
R-squared	0.045	0.179	0.173	0.270	0.108
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Notes: The table presents the results of estimating equation (4). In each column, the dependent variable is 100 times the quarterly log-change in real gross value added for the sector denoted in the column header. Sector abbreviations are defined in Table 1. T, NT, and REER denote the tradable and the nontradable sector, and the real effective exchange rate, respectively. Prelude, Build-Up, Episode, and Post-Episode refer to the respective sudden stop dummies. GFC is a dummy variable equal to 1 within the event windows of sudden stops that started between 2007Q3–2012Q4. The estimated coefficients can be interpreted as percentage-point differences from the counterfactual sectoral growth rates. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

services (M-N). The GDP output gap is also lower compared to its counterfactual value during sudden stops, and the same holds for the broad tradable sector and nontradable sectors. The coefficients, however, are only marginally significant for GDP, and not at all for the T and NT sectors.

The post-episode coefficients are estimated to be positive in agriculture (A) and in arts and other services (R-U), but they are neither economically, nor statistically significant. All other sectors' post-episode coefficients are estimated to be negative, suggesting that no sector has a significant tendency to overheat in the aftermath of sudden stops, some of them do not have a significant tendency to overcool, either, while the remaining sectors' output gaps are significantly lower compared to their counterfactual values. These are the construction sector (F) and trade and hospitality (G-I). The point estimates of their post-episode coefficients are also the largest, and they are also the reasons why the broad nontradable sector and the whole macroeconomy have significantly lower output gaps in the aftermath of sudden stops compared to the counterfactual values. The post-episode coefficient of real estate activities (L) is also significantly negative, but only at the 10% level.

To sum up, most sectors have a tendency to overheat before sudden stops, but not all of them have a significant tendency to overcool during or after the episodes. The best examples are the financial sector (K) and arts and other services (R-U) that have the second and the third strongest tendencies to overheat pre-episode, but their during-episode and post-episode output gaps do not fall significantly below their counterfactual values either in an economic, or in a statistical sense. Other sectors turn from an overheating tendency to an overcooling tendency either during, or after the sudden stop. The best example for such a sector is construction (F), which has the strongest tendency to overheat before sudden stops, as well as the strongest tendency to overcool in the aftermath of the events. Thus, sudden stops simply initiate a correction of previous imbalances in some sectors, while they tend to cause more serious damages in others.

6. Conclusion

This paper explored the dynamics 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 67 sudden stop episodes, somewhat more than half of which happened during the global financial crisis of 2007–2012.

After presenting the results for a synthetic, "average" sudden stop, we estimated regressions in a country-time panel with 46 countries 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 two pre-episode and one 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

Table 7
Results with sectoral output gaps.

Panel I

	(1) A	(2) B-E	(3) C	(4) F	(5) G-I
Prelude	−0.815	0.641	0.941**	1.517*	1.149***
	(0.632)	(0.410)	(0.435)	(0.764)	(0.279)
Build-Up	0.210	0.829**	1.106**	2.536***	0.919*
	(0.846)	(0.406)	(0.485)	(0.772)	(0.463)
Episode	−1.054	−0.912	−1.428**	−0.181	−0.883
	(0.735)	(0.594)	(0.665)	(0.982)	(0.592)
Post-Episode	0.245	−0.638	−1.012	−1.989***	−1.068***
	(0.690)	(0.682)	(0.783)	(0.585)	(0.347)
Observations	2,960	2,827	2,960	2,960	2,827
R-squared	0.067	0.333	0.373	0.135	0.369
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel II

	(6) J	(7) K	(8) L	(9) M-N	(10) O-Q
Prelude	0.321	1.405***	0.561**	1.022*	−0.006
	(0.419)	(0.495)	(0.256)	(0.591)	(0.171)
Build-Up	1.055**	1.469**	0.892**	0.814	−0.154
	(0.523)	(0.623)	(0.398)	(0.597)	(0.283)
Episode	−0.287	1.350*	0.598	−1.718**	−0.227
	(0.726)	(0.687)	(0.466)	(0.837)	(0.304)
Post-Episode	−0.452	−0.224	−0.468*	−0.963	−0.022
	(0.458)	(0.852)	(0.278)	(0.809)	(0.277)
Observations	2,960	2,909	2,960	2,909	2,827
R-squared	0.138	0.107	0.056	0.241	0.041
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel III

	(11) R-U	(12) T	(13) NT	(14) GDP
Prelude	0.877**	0.243	0.524**	0.649***
	(0.421)	(0.412)	(0.201)	(0.163)
Build-Up	1.507**	0.822**	0.776**	0.836***
	(0.602)	(0.401)	(0.335)	(0.273)
Episode	−0.202	−0.824	−0.307	−0.721*
	(0.985)	(0.499)	(0.417)	(0.361)
Post-Episode	0.025	−0.493	−0.697**	−0.716***
	(0.612)	(0.619)	(0.303)	(0.257)
Observations	2,807	2,614	2,534	2,960
R-squared	0.138	0.325	0.361	0.445
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Notes: The table presents the results of estimating equation (1). In each column, the dependent variable is 100 times the log-deviation of real gross value added from its Hodrick-Prescott trend path for the sector denoted in the column header. Sector abbreviations are defined in Table 1. T and NT denote the tradable and the nontradable sector, respectively. Prelude, Build-Up, Episode, and Post-Episode refer to the respective sudden stop dummies. The estimated coefficients can be interpreted as percentage-point differences from the counterfactual sectoral output gaps. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

for the post-episode adjustment. Robustness checks included checking if sectoral dynamics were different during GFC-episodes than otherwise, and using sectoral output gaps as dependent variables.

According to our main results, the construction sector, professional services, financial 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 the average post-episode growth rates of agriculture, industry, manufacturing in particular, and the overall tradable sector were not significantly different from their counterfactual values, suggesting that these sectors may lead the recovery from the sudden stop recession. Financial services, professional services, trade and hospitality, and the nontradable aggregate were measured to have significantly lower growth rates after the sudden stop compared to the counterfactual.

We found only very weak evidence that the recovery process of tradable sectors (agriculture, industry, and manufacturing in particular) was facilitated by the depreciation of the domestic currency around sudden stops. However, financial services, trade and hospitality, construction, and professional services were found to face significantly more serious damages during or after sudden stops that are accompanied by sharper real depreciations. At the same time, the post-episode growth rates of most sectors were shown to benefit from a rebound effect that helps them return to their long-run growth path.

Only minor and mostly insignificant differences were found between sectoral adjustment dynamics around GFC-related and non-GFC-related sudden stops. This increases our confidence that our main results are not driven by the GFC, but by more general properties of sudden stops.

By using sectoral output gaps as dependent variables, we found that sudden stops tended to be preceded by overheating tendencies, i.e. significantly higher output gaps in most sectors. These disappear by the end of the event window in all sectors. In some of them – e.g., financial services and arts and other services –, the sudden stop simply eliminates the significant tendency to overheat. In others – e.g., construction, trade and hospitality, manufacturing, and professional services –, it brings about a significant tendency to overcool either during, or after the episode. The output gaps of agriculture, public services, and perhaps even info-communication are not significantly different from the counterfactual values throughout the whole event window.

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 in making the economy more resilient to sudden stops. Info-communication faces only moderate damages during sudden stops and does not have strong tendencies either to overheat before them, or to overcool during and after them. Finally, our results only very weakly support the view that real depreciations facilitate tradable sectors' adjustment after sudden stops, while some nontradable sectors' during- or post-episode growth rates are significantly lower under sharper real depreciations. These findings suggest that the advantages of running a floating exchange rate regime may be quite small in facilitating an economy's adjustment to sudden stops. 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.

Funding sources

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).

The funding sources had no involvement in the study design, collection, analysis, and interpretation of the data, report writing, and the decision to submit the article for publication.

CRediT authorship contribution statement

István Kónya: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Miklós Váry:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are grateful to *Szilárd Benk*, *Róbert Lieli*, *Gergő Motyovszki*, *Ágoston Reguly*, *Balázs Reizer*, *Jamel Saadaoui*, *Yoto Yotov*, an anonymous referee, 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.

Appendix. Episodes and the country-time panel

Table 8
Sudden stop events with sectoral coverage.

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

Notes: The table lists the sudden stop events that are included in the final dataset, which serves as the basis for estimating panel regressions. That is, it lists all the episodes, in the event windows of which sectoral value added data is available. For Israel 2011Q4–2012Q3, such data is available from 2012 Q1 only.

Table 9
Sample coverage by country, for quarters with simultaneous information about sectoral value added and sudden stop occurrence.

Country	Start	End	Country	Start	End
Albania	2014 Q4	2021 Q4	Japan	2002 Q4	2020 Q4
Australia	1995 Q4	2020 Q4	Korea, Republic of	1982 Q4	2020 Q4
Austria	2011 Q4	2021 Q4	Latvia	2001 Q4	2021 Q4
Belgium	2008 Q4	2021 Q4	Lithuania	1999 Q4	2021 Q4
Bosnia & Herzegovina	2013 Q4	2021 Q4	Luxembourg	2008 Q4	2021 Q4
Brazil	1996 Q1	2020 Q4	Malta	2001 Q4	2021 Q4
Bulgaria	1998 Q4	2021 Q4	Montenegro	2013 Q4	2021 Q4
Chile	1997 Q4	2020 Q4	Netherlands	1995 Q1	2021 Q4
Colombia	2005 Q1	2020 Q4	New Zealand	2007 Q1	2020 Q4
Costa Rica	2005 Q4	2020 Q4	North Macedonia	2002 Q4	2021 Q4
Croatia	1999 Q4	2021 Q4	Norway	1981 Q4	2021 Q4
Cyprus	2007 Q4	2021 Q3	Poland	2001 Q4	2021 Q4
Czechia	1999 Q4	2021 Q4	Portugal	1995 Q1	2021 Q4
Denmark	1995 Q2	2021 Q4	Romania	1997 Q4	2021 Q4
Estonia	1998 Q4	2021 Q4	Russia	2011 Q1	2020 Q4
Finland	1990 Q1	2021 Q4	Serbia	2013 Q4	2021 Q4
France	1981 Q4	2021 Q4	Slovakia	1999 Q4	2021 Q4
Germany	1991 Q1	2021 Q4	Slovenia	2001 Q4	2021 Q4
Greece	2005 Q4	2021 Q4	Spain	1995 Q2	2021 Q4
Hungary	1997 Q2	2021 Q4	Sweden	1993 Q1	2021 Q4

(*continued on next page*)

Table 9 (*continued*)

Country	Start	End	Country	Start	End
Ireland	2011 Q4	2021 Q4	Switzerland	2005 Q4	2021 Q4
Israel	2012 Q1	2020 Q4	Turkey	1998 Q1	2021 Q4
Italy	1996 Q1	2021 Q4	United Kingdom	1995 Q1	2020 Q4

Notes: The table lists the countries and quarters that are included in the final country-time panel dataset, which serves as the basis for estimating panel regressions. A country-quarter qualifies into the sample if information about sectoral value added and sudden stop occurrence are simultaneously available for it. There is another available observation for Hungary 1996 Q3 that is not listed in the table.

References

Ball, L.M., 2014. Long-term damage from the great recession in OECD countries. Eur. J. Econ. Econ. Policies 11, 149–160. https://doi.org/10.4337/ejeep.2014.02.02.

Benczur, P., Konya, I., 2016. Interest premium, sudden stop, and adjustment in a small open economy. East. Europ. Econ. 54, 271–295. https://doi.org/10.1080/00128775.2016.1196109.

Bianchi, J., Mendoza, E.G., 2020. A fisherian approach to financial crises: lessons from the sudden stops literature. Rev. Econ. Dyn. 37, S254–S283. https://doi.org/10.1016/j.red.2020.06.001.

Benguria, F., Matsumoto, H., Saffie, F., 2022. Productivity and trade dynamics in sudden stops. J. Int. Econ. 139, 103631. https://doi.org/10.1016/j.jinteco.2022.103631.

Benigno, G., Converse, N., Fornaro, L., 2015. Large capital inflows, sectoral allocation, and economic performance. J. Int. Money Financ. 55, 60–87. https://doi.org/10.1016/j.jimonfin.2015.02.015.

Blanchard, O.J., Cerutti, E., Summers, L.H., 2015. Inflation and activity. Two explorations and their monetary policy implications. IMF Work. Pap. 15, 230. https://doi.org/10.5089/9781513536613.001.

Calvo, G.A., Reinhart, C.M., 2000. When capital inflows come to a sudden stop: consequences and policy options. In: Kenen, P., Swoboda, A. (Eds.), Reforming the International Monetary and Financial System. International Monetary Fund, Washington, D.C., pp. 175–201.

Calvo, G.A., Izquierdo, A., Mejía, L., 2004. On the empirics of sudden stops: the relevance of balance-sheet effects. NBER Working Paper, No. 10520. https://doi.org/10.3386/w10520.

Calvo, G.A., Izquierdo, A., Talvi, E., 2006. Sudden stops and Phoenix miracles in emerging markets. Am. Econ. Rev. 96, 405–410. https://doi.org/10.1257/000282806777211856.

Cavallo, E.A., Frankel, J.A., 2008. Does openness to trade make countries more vulnerable to sudden stops, or less? Using gravity to establish causality. J. Int. Money Financ. 27, 1430–1452. https://doi.org/10.1016/j.jimonfin.2007.10.004.

Cavallo, E., Powell, A., Pedemonte, M., Tavella, P., 2015. A new taxonomy of sudden stops: which sudden stops should countries be most concerned about? J. Int. Money Financ. 51, 47–70. https://doi.org/10.1016/j.jimonfin.2014.10.001.

Cowan, K., Raddatz, C., 2013. Sudden stops and financial frictions: evidence from industry-level data. J. Int. Money Financ. 32, 99–128. https://doi.org/10.1016/j.jimonfin.2012.03.009.

Craighead, W.D., Hineline, D.R., 2014. Current account reversals and structural change in developing and industrialized countries. J. Int. Trade Econ. Dev. 24, 147–171. https://doi.org/10.1080/09638199.2014.881416.

David, A.C., Gonçalves, C.E., 2021. In search of lost time: examining the duration of growth-reducing sudden stops. J. Int. Money Financ. 117, 102450. https://doi.org/10.1016/j.jimonfin.2021.102450.

Edwards, S., 2007. Capital controls, sudden stops, and current account reversals. In: Edwards, S. (Ed.), Capital Controls and Capital Flows in Emerging Economies: Policies, Practicies and Consequences. University of Chicago Press, Chicago, pp. 73–113.

Eichengreen, B., Gupta, P., 2018. Managing sudden stops. In: Mendoza, E.G., Pastén, E., Saravia, D. (Eds.), Monetary Policy and Global Spillovers: Mechanisms, Effects, and Policy Measures. Central Bank of Chile, Santiago, pp. 9–47.

Forbes, K.J., Warnock, F.E., 2012. Capital flow waves: surges, stops, flight, and retrenchment. J. Int. Econ. 88, 235–251. https://doi.org/10.1016/j.jinteco.2012.03.006.

Frisch, R., Waugh, F.V., 1933. Partial time regressions as compared with individual trends. Econometrica 1, 387–401. https://doi.org/10.2307/1907330.

Guidotti, P.E., Sturzenegger, F., Villar, A., 2004. On the consequences of sudden stops. Economía 4, 171–203. https://doi.org/10.1353/eco.2004.0016.

Gros, D., Alcidi, C., 2015. Country adjustment to a 'sudden stop': does the euro make a difference? Int. Econ. Econ. Policy 12, 5–20. https://doi.org/10.1007/s10368-014-0286-7.

Kalantzis, Y., 2015. Financial fragility in small open economies: firm balance sheets and the sectoral structure. Rev. Econ. Stud. 82, 1194–1222. https://doi.org/10.1093/restud/rdv011.

Kehoe, T., Ruhl, K., 2009. Sudden stops, sectoral reallocations, and the real exchange rate. J. Dev. Econ. 89, 235–249. https://doi.org/10.1016/j.jdeveco.2009.01.003.

Korinek, A., Mendoza, E.G., 2014. From sudden stops to fisherian deflation: quantitative theory and policy. Annu. Rev. Econ. 6, 299–332. https://doi.org/10.1146/annurev-economics-080213-041005.

Mendoza, E.G., 2005. Real exchange rate volatility and the price of nontradable goods in economies prone to sudden stops. Economía 6, 103–148. https://doi.org/10.1353/eco.2006.0008.

Merler, S., Pisani-Ferry, J., 2012. Sudden stops in the euro area. Rev. Econ. Inst. 3, 5. https://doi.org/10.5202/rei.v3i3.97.

Pierri, D., Montes-Rojas, G., Mira-Llambi, P., 2020. The Empirical Dimension of Overborrowing. Universidad de San Andrés Working Paper, No. 146.

Pogatchnik, S., 2021. Multinationals Make Ireland's GDP Growth 'Clearly Misleading'. Politico. Downloaded: Politico. https://www.politico.eu/article/ireland-gdp-growth-multinationals-misleading/, 5 February 2023.

Rancière, R., Tornell, A., Westermann, F., 2008. Systemic crises and growth. Q. J. Econ. 123, 359–406. https://doi.org/10.1162/qjec.2008.123.1.359.

Reyes-Heroles, R., Tenorio, G., 2019. Regime-switching in emerging market business cycles: interest rate volatility and sudden stops. J. Int. Money Financ. 93, 81–100. https://doi.org/10.1016/j.jimonfin.2018.12.012.

Rothenberg, A.D., Warnock, F.E., 2011. Sudden flight and true sudden stops. Rev. Int. Econ. 19, 509–524. https://doi.org/10.1111/j.1467-9396.2011.00962.x.

Timmer, M.P., de Vries, G.J., 2009. Structural change and growth accelerations in Asia and Latin America: a new sectoral data set. Cliometrica 3, 165–190. https://doi.org/10.1007/s11698-008-0029-5.

Tornell, A., Westermann, F., 2002. Boom-bust cycles in middle income countries: facts and explanation. IMF Staff Pap. 49, 111–155. https://doi.org/10.2307/3872474.

Tornell, A., Westermann, F., Martínez, L., 2003. Liberalization, growth, and financial crises: lessons from Mexico and the developing world. Brookings Pap. Econ. Act. 2003, 1–88. https://doi.org/10.1353/eca.2004.0009.

Váry, M., 2022. Do menu costs lead to hysteresis in aggregate output? The experiences of some agent-based simulations. Acta Oecon. 72, 499–529. https://doi.org/10.1556/032.2022.00033.