Large current account deficits and neglected vulnerabilities *

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Abstract

Using a sample covering 50 advanced and emerging economies over 1990-2017, it is found that large current account deficits are followed by systematic negative surprises in economic growth. This regularity is verified both in the case of advanced economies and emerging economies. In addition, large current account deficits are reversed significantly faster than what forecasters anticipate and are followed by low asset returns and drops in sentiment. The findings are robust to changes in the specification and do not seem to be explained by efficient learning dynamics. This evidence indicates that analysts are unable to incorporate the negative information transmitted by large current account deficits and has implications for the understanding of past economic events and for the design of macro-prudential policies.

Keywords: current account balance; macroeconomic vulnerability; economic forecast
JEL Codes: E3, F4, E7, O4

1 Introduction

Large current account deficits have drawn the attention of analysts in a recurrent manner.[1] These analyses have evaluated vulnerabilities that could be manifested by current account deficits. These vulnerabilities can be linked to macroeconomic trajectories that

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[1]See, for example, Sachs 1983, Heymann 1994, Kaminsky et al. 2003, Reinhart & Rogoff 2009, Milesi-Ferretti & Razin 1996, Blanchard & Giavazzi 2002, Edwards 2004, Bernanke 2005, Cavallo et al. 2018, Pierri et al.2020, Obstfeld & Rogoff 2007 and Adam et al. 2012.

are eventually proven unsustainable and to changes in the conditions that allow for the financing of the deficits. From inspecting the relevant literature, it becomes clear that assessing these vulnerabilities is a complex task that requires contemplating a diverse set of factors such as the future rate of productivity growth, demographic dynamics, financial interdependencies and the stability of economic perceptions.

Given these analytical challenges, it is not self-evident that the expectations of economic agents and analysts must reflect, in an accurate manner, the vulnerabilities associated with current account deficits. The relevance of this subject goes beyond forecasting practices. The presence of systematic errors in expectations has implications for the interpretation of past macroeconomic events, such as crises, and for the design of macroprudential policies.

In this work, a database covering 50 advanced and emerging economies between 1990 and 2017 is used to characterize expectations and macroeconomic trajectories around instances of large current account deficits. The study intends to measure the extent to which risks associated with large current account deficits are adequately contemplated by analysts and economic actors. With this objective, a large collection of macroeconomic forecasts is evaluated. Forecasts correspond to those reported by World Economic Outlook Historical Forecast Database. To gain a broader perspective, this dataset is complemented with information from asset markets and indicators of economic sentiment.

This study shows that large current account deficits are followed, on average, by significant negative surprises in GDP growth. More specifically, when percentile 10 is used as a threshold for event identification, large current account deficits anticipate a 4.3% drop in the mean difference between realized and forecast GDP growth over the following three-year-period. This type of association is verified for different forecast horizons and thresholds. This evidence suggests that forecasters do not contemplate vulnerabilities in an adequate manner. Further analysis shows that this anomaly is present both in the case of advanced countries and emerging countries. While the evidence on anomalies is strong for both country groups, the intensity of the systematic errors is higher in the case of emerging countries.

The examination of GDP growth forecasts, is complemented with the study of other indicators that provide further evidence on disregarded risks. Two types of indicators are considered: asset prices and the tone of media content. These additional evaluations serve as robustness tests and, at the same time, allow for a richer characterization of the extent to which vulnerabilities are neglected by a diverse group of actors. It is found that large current account deficits are followed by lower stock market returns and drops in economic press sentiment. These regularities constitute additional evidence consistent with overlooked risks.

A more detailed characterization of the anomalies surrounding instances of large current account deficits is provided inspecting related macroeconomic indicators. First, it is documented that large current account deficits are followed by systematic errors in current account balance forecasts. Conditional on a large current account deficit event, forecasted deficits are significantly larger than realized deficits. In other words, current account reversals are faster and more intense than expected. Second, applying standard time series filtering techniques, it is shown that, in the early stage of the events, GDP is above its trend. In the late stage, GDP reverses towards its trend. This result suggests that the anomalies are in part explained by the inability to distinguish between the cyclical and trend components of GDP. Additionally, the analysis of financial indicators shows that large current account deficits that coincide with credit booms are associated with particularly intense anomalies. That is, analyst are not able to assess in a adequate manner the heightened risks associated with credit expansions.

Extended analyses are implemented to evaluate the robustness of the results and the suggested interpretations. First, very similar anomalies are found studying a collection of GDP growth forecasts released by private consultants. This result reinforces the conclusion that the documented systematic errors are manifested by an ample set of economic actors and analysts. Second, out of sample GDP growth forecasts exercises are implemented to evaluate if past information could have been used to anticipate vulnerabilities. The evidence indicates that trained models are able to incorporate the negative information provided by large current account deficits. Hence, the documented anomalies cannot be explained satisfactorily by efficient learning processes that take place in the context of a changing environment (Batchelor 2007). Also, this result suggest that the reported anomalies are plausibly a persistent characteristic of macroeconomic expectations.

This paper is related to an extensive literature that analyzes large current account deficits and the likelihood and consequences of current account reversals. One message from this literature is that current account deficits are not necessarily a signal of unsustainable trajectories or an indicator of impending negative shocks. In principle, the deficit could reflect optimal intertemporal arrangements that allow for consumption smoothing and investment in profitable projects (Sachs 1983, Blanchard & Giavazzi 2002, Bernanke 2005, Arezki 2017). On the other hand, as long as future productive capacities and financial market conditions are uncertain, large deficits can result in exposure to substantive risks (Heymann 1994, Kaminsky et al. 2003, Reinhart & Rogoff 2009, Milesi-Ferretti & Razin 1996). These concerns do not only involve fragile emerging economies. For example, the US current account deficit triggered significant discussions of its determinants and sustainability (Mann 2002, Bernanke 2005, Obstfeld & Rogoff 2007).

An important fraction of the empirical literature has documented associations between current account reversals and macroeconomic performance. Most results point to a negative association with economic growth but, the intensity of this association is reported to be heterogeneous. For example, in a study of an extensive period that starts in the late 19th century, Adalet & Eichengreen (2007) find a negative relationship between current account reversals and growth. Importantly, the intensity of this association is different depending on the period under analysis. Negative connections between reversals and growth are also reported in Edwards (2004) for a large set of countries and Freund (2000) for advanced economies. On the other hand, studying low and middle income economies, Milesi-Ferreti & Razin (2000) indicate that the association between reversals and growth is heterogeneous and fail to find a statistically significant relationship. These studies focus on short term associations. Taking a long term perspective, de Mello et al. (2011) show that current account reversals are linked to structural breaks in growth trends. According to their analyses, the long term relationship becomes positive, that is, an improvement in the external position increases the probability of a sustained growth acceleration.

An overview of this literature suggests that, in the short and medium horizon, large current account deficits are commonly followed by negative outcomes. This is a concern that is very likely contemplated by analyst assessing future scenarios. At the same time, from reading the literature, it is clear that significant levels of uncertainty remain regarding the likelihood, timing and severity of negative developments. Hence, assessing the implications of current account deficits is a challenging task and it is plausible that analysts might fail to incorporate all relevant information in an appropriate manner.

This work is also related to a body of empirical literature that documents evidence consistent with inadequate assessments of vulnerabilities following expansions in the financial system (Baron & Xiong 2017, López-Salido et al. 2017, Mian et al. 2017, Greenwood et al. 2020). This literature is inspired by traditional analyses that have pointed to recurrent patterns in which crises are facilitated by excessive optimism (Minsky 1977, Kindleberger 1978).

In addition, this work is related to theoretical contributions that consider cognitive limits and resulting simplified representations and noisy perceptions. Under these conditions, expectations are unable to reflect available information in an adequate manner (Maćkowiak & Wiederholt 2015, Gennaioli et al. 2012, Bordalo et al. 2018). While a precise identification of the cognitive mechanisms that result in the documented neglected vulnerabilities is beyond the scope of the current work, plausible mechanisms can be associated with naive projection of previous trajectories (Hirshleifer et al. 2015), imperfect memory (Afrouzi et al. 2020, da Silveira et al. 2020), disregard of mean reverting processes (Beshears et al. 2013) and categorical reasoning (Mullainathan 2002).

The paper is organized as follows. In the next section the data used in the analyses is described. Section 4 provides evidence consistent with the existence of vulnerability neglect. Extended analyses are presented in the following section. Concluding remarks are presented in section 5.

2 Data

The main source of data for this study is the World Economic Outlook's Historical Forecasts Database. A large collection of forecasts produced by International Monetary Fund's staff is distributed through this database. This study uses GDP growth and current account balance forecasts corresponding to April's World Economic Outlook releases from 1990 through 2017. Forecasts used in this study correspond to one-year-ahead through five-year-ahead horizons. This database was also used to obtain real-time current account deficit information. The sampled countries are given by the largest 50 economies according to 2000 GDP in US dollars as reported by WEOs database.[2]

In addition to WEO's data, asset returns and a sentiment metric are used in the analyses reported below. Asset returns are given by the returns of stock market indices expressed in dollars. More specifically, the information is from Standard & Poor's Global Equity Indices and is distributed by the World Bank. For the early part of the sample, for some countries, this data was not available from this source. As a result, supplementary data was obtained from a private data vendor[3] and, in a few cases, from the relevant stock exchange. Given the value of the stock market index of country c at the end of year t (p_{ct}), the annual return in year t for country c is given by the log difference of the index: $r_{ct} = log(p_{ct}) - log(p_{ct-1})$.

An indicator of sentiment is constructed processing text from world economic press content. More specifically, the index of sentiment is based on articles published by two prominent sources for news and opinion: The Wall Street Journal and The Economist.[4] The level of optimism or pessimism is approximated computing the frequency of words with negative content in relevant subsets of sampled texts. This is a plain approach that has proven useful in related exercises.[5]

[2]We excluded oil exporting countries. Sampled countries are: Argentina, Australia, Austria, Bangladesh, Belgium, Bolivia, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Puerto Rico, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Kingdom and United States.

[3]www.tradingeconomics.com

[4]Due to constraints on data availability, The Wall Street Journal content correspond to years 1984-2013 while The Economist articles are for the period 1992-2013.

[5]See, for example, Tetlock (2007) and Garcia (2013).

The computation of this indicator can be described as a three-stage process: text extraction, calculation of the raw indicator and conversion to a standardized metric of change in sentiment. The first step for the construction of the index involves selecting pieces of text associated with sampled countries. With this objective, for each country, a list of keywords is created. The selected keywords correspond to: name of country, capital city and demonym. Next, for each year, the set of articles in which at least one of these keywords is present is identified. For each of these articles, the portions of text that are sufficiently close to a keyword associated with the relevant country are selected. More specifically, the selection corresponds to words that are up to 50 words before or 50 words after one of the keywords associated with the country. The strings of text associated with country c and year t are merged resulting in a list of words labeled K_{ct}. This step concludes the text extraction stage.

In the second stage, the computation of the raw sentiment indicator requires identifying a set of words with negative content. Following Tetlock (2007), the list of negative words is built identifying words labeled as negative by General Inquirer, a platform for analysis of textual data.[6] The original list includes 2291 words. To improve the precision of the index, this original list was expanded to include plural noun forms, different verb tenses and adverbs. This procedure results in a list of 5364 words. Let T_{ct} be the number of words in K_{ct}, the collection of text corresponding to year t and country c, and let N_{ct} be the number of times a negative word is detected in K_{ct}. Then, the corresponding value of sentiment index is given by $s_{ct} = -N_{ct}/T_{ct}$ where the ratio is multiplied by -1 so that higher values are associated with more optimism.

In the third step, the original index is converted to obtain an indicator of changes in sentiment. With this objective, the change in the index is adjusted by historic volatility. More specifically, the indicator of change in sentiment cs_{ct} is given by $cs_{ct} = (s_{ct} - s_{ct-1})/vs_{ct}$ where vs_{ct} is the sample standard deviation that is computed using values for the index during the preceding seven years. In the evaluations presented below, the cumulative change in sentiment over k years is defined as: $sent^k_{ct} = \sum_{j=1}^{k} cs_{ct+j}$.

[6] http://www.wjh.harvard.edu/ inquirer/homecat.htm

Table 1 provides descriptive statistics corresponding to the data used in the analyses presented below. Realized current account balances present a very large range. The highest balance corresponds to Singapore in year 2003. Interestingly, the most negative current account balance corresponds to Greece in year 2008, a country that suffered a severe crisis in the subsequent years. GDP growth is also associated to an important range. The largest growth rate (26.3%) corresponds to Ireland in year 2015.[7] The lowest growth rate (-23.7%) corresponds to Ukraine in year 1994.

Table 1: Descriptive statistics

Activity Indicator	**Obs.**	**Mean**	**St. Dev.**	**Min**	**Max**
Current Account Balance					
Realization	1362	0.005	0.056	-0.146	0.292
One-year-ahead forecast	1361	0.002	0.052	-0.157	0.267
Three-year-ahead forecast	1361	0.002	0.049	-0.177	0.266
Five-year-ahead forecast	1360	0.002	0.047	-0.152	0.251
GDP growth					
Realization	1364	0.029	0.039	-0.237	0.263
One-year-ahead forecast	1364	0.035	0.018	-0.065	0.099
Three-year-ahead forecast	1364	0.039	0.017	-0.011	0.107
Five-year-ahead forecast	1364	0.039	0.017	-0.065	0.100
Other variables					
Stock market returns	1150	0.051	0.352	-1.847	1.345
Changes in Sentiment	1146	0.112	1.385	-5.484	7.430

Note: Data from the April releases of the WEO's Historical Forecasts Database for the period 1990-2017. Realizations data correspond to data reported in the WEO in t+2. Current account balance indicators are expressed as a fraction of GDP. GDP growth figures are annual growth rates. Yearly stock market returns correspond mainly to S&P's Global Equity Indices. Changes in sentiment are expressed as a fraction of country index standard deviation.

[7] This GDP growth rate is explained by the relocation of large multinational corporations (http://www.oecd.org/sdd/na/Irish-GDP-up-in-2015-OECD.pdf).

3 Evidence on neglected vulnerabilities

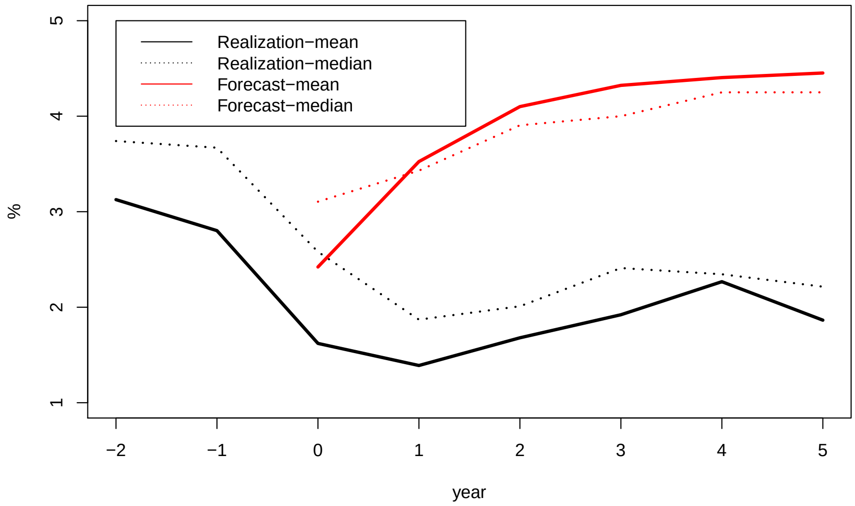
In this section, three indicators are analyzed. First, a comprehensive dataset of GDP growth forecasts will be used to evaluate surprises in GDP growth subsequent to large current account deficits. A systematic link between large deficits and negative surprises in GDP growth is interpreted as a strong indication of vulnerability neglect. Complementing the analysis of surprises in growth performance, additional evidence is provided evaluating associations between large current account deficits and subsequent asset returns. Finally, innovations in sentiment reflected in the economic press will be used as an additional indicator of information arrival. As in the case of GDP growth forecasts, the arrival of negative news, that is, low returns or drops in sentiment, is interpreted as evidence consistent with neglected vulnerabilities.

3.1 Growth forecast and current account deficits

WEO's Historical Forecast Database allows for a valuable analysis of the direction, timing and intensity of news arrival following large current account deficits. Preliminary evidence on the association between current account deficits and growth forecast errors is generated through an event study exercise. In this exercise, large current account deficits are identified as instances in which the current account balance is below percentile 10. More specifically, for each country and each April's WEO release, if the realized current account balance for the previous year is below percentile 10, an instance of large current account deficit is identified. The percentile is computed using the complete database. Having identified the set of events, GDP forecasts at the time of event identification are compared to the realized trajectories.

Figure 1 shows mean and median computations associated with the preliminary event study exercise. On the event identification year, GDP growth forecasts are similar to the values observed on the previous year. Interestingly, on average, growth is expected to pick up in the following years. In contrast, realizations point to an important drop in average and median growth levels. The differences between mean forecasts and realizations are economically significant. In each of the five years that follow the event, the mean difference is approximately 2%. Similar observations apply to median forecasts and realizations. This preliminary evidence indicates that, on average, large current account deficits are followed by the systematic arrival of negative surprises regarding economic growth.

Figure 1: GDP growth conditional on large current account deficits.



Notes: Large current account deficits are identified in year 0 if the current account deficit for year -1 is below percentile 10.

This preliminary exercise is complemented by a formal evaluation using non-overlapping forecast periods and identifying large deficits using exclusively the past distribution of the current account balance. Given a threshold parameter $x \in \{1, 50\}$, for each sample year t, percentile x is computed using information on realized current account deficits that is available at the time in which forecasts are released. Let p_t^x represent the corresponding percentile. A large current account deficit is identified in year t and country c if the latest available realization of current account balance, ca_{ct-1}, is below percentile x. On the other hand, the cumulative growth forecast error for k-year-ahead forecasts is given by:

$$gfe_{ct}^k = \sum_{j=1}^{k} GDPgr_{ct+j} - GDPgr_{ct+j}^t \tag{1}$$

where $GDPgr_{ct+j}$ is the annual GDP growth rate for year $t+j$ and $GDPgr^{t}_{ct+j}$ is the associated forecast released in year t. The empirical model used to estimate conditional forecast errors is given by:

$$gfe^{k}_{ct} = \alpha^{k}_{x} + \beta^{k}_{x} I_{(ca_{ct-1} < p^{x}_{t})} + u_{ct} \tag{2}$$

Where $I_{(ca_{ct-1} < p^{x}_{t})}$ is a dummy variable indicating large current account deficits and u_{ct} is an error term. The model estimates the mean forecast error conditional on large current account deficits. Standard errors are clustered by time and country. In the analysis presented below, three values are considered for the parameter x: 5, 10 and 25.[8]

Table 2 reports the estimated values for the parameter of interest, β^{k}_{x}. In all cases, the estimated values are negative and significantly different from zero. These results indicate that large current account deficits are followed by lower forecast errors, that is to say, larger differences between forecasts and realizations. Considering a three-year-ahead forecast horizon and percentile 10 as a threshold, large current account deficits are associated with a reduction of 4.3% in mean cumulative forecast errors. In other words, after large current account deficits, surprises in GDP growth turn more negative. Negative surprises in GDP growth point to the realization of negative scenarios that were not adequately considered at the time of forecast release.

It must be noted that, in addition to the reported conditional bias, the estimation of the model points to an unconditional overoptimism bias. In the case of the specification with percentile 10 as threshold and three-year-ahead forecast windows, the estimated constant ($\hat{\alpha}$) is -2.3%.[9]. As a result, the mean forecast error, conditional on an event, is approximately -6.6%. This is a substantive bias that can have important implications on economic behavior and associated macroeconomic outcomes.

[8] The methodology mimics the empirical strategy implemented in Baron & Xiong (2017) to identify large credit expansions. This model with a panel structure allows for the estimation of dually clustered standard errors.

[9] This regularity is consistent with previous findings in the literature. See, for example, Frankel 2011 and Aromí (2019).

Table 2: Mean growth forecast errors conditional on large current account deficits

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
	$\hat{\beta}_x^k$	-0.016***	-0.016***	-0.018***
k=1		[4.4]	[4.6]	[5.9]
	# obs. $< p_t^x$	330	145	79
	$\hat{\beta}_x^k$	-0.028***	-0.023***	-0.033***
k=2		[3.4]	[3.5]	[2.9]
	# obs. $< p_t^x$	158	69	36
	$\hat{\beta}_x^k$	-0.044***	-0.043***	-0.064***
k=3		[4.1]	[6.7]	[5.1]
	# obs. $< p_t^x$	106	48	29
	$\hat{\beta}_x^k$	-0.039***	-0.043***	-0.064***
k=4		[4.2]	[5.8]	[3.5]
	# obs. $< p_t^x$	76	34	19
	$\hat{\beta}_x^k$	-0.049***	-0.060***	-0.045***
k=5		[3.8]	[3.1]	[4.3]
	# obs. $< p_t^x$	54	30	15

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

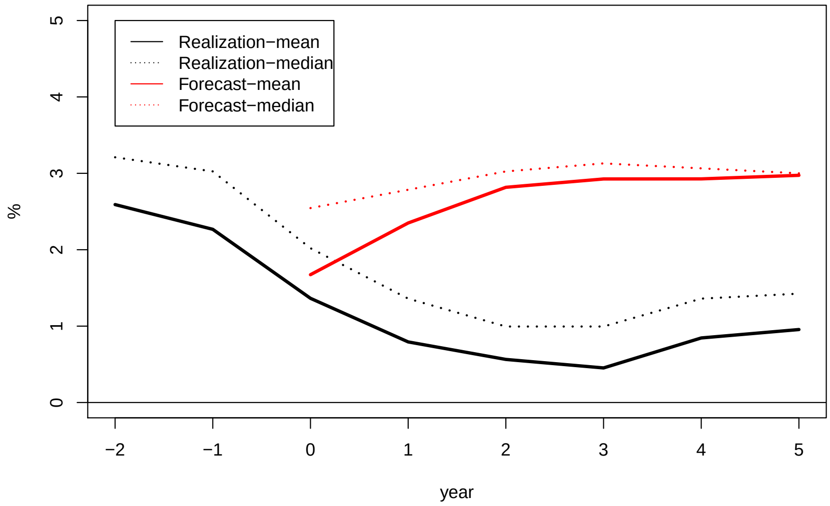
3.2 The evidence for advanced vs. emerging economies

Do the previously reported anomalies characterize both advanced and emerging countries? Countries with different levels of development can be conjectured to be exposed to different risks or vulnerabilities. For example, differences in business cycle properties (Aguiar & Gopinath 2007) can result in different exposures linked to external imbalances. Also, the differences in the institutional environment can be thought to have an impact on deficit sustainability (Bernanke 2005, Gruber & Kamin 2007, Chinn & Ito 2007).

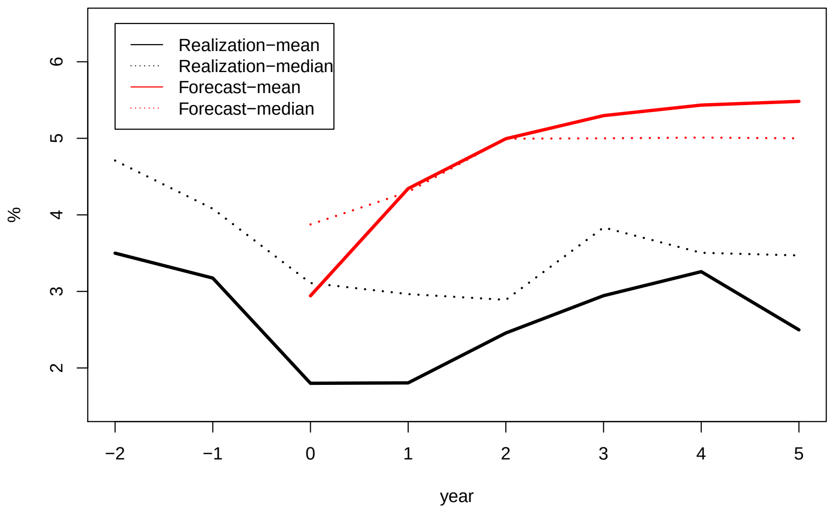
Having these concerns in mind, we split the sample of countries in two groups. Advanced countries are those classified as high income countries by the World Bank in year 2000. All other countries are classified as emerging countries. The split results in 25 countries in each group. Following the strategy used in the previous subsection, figure 2 shows the typical trajectories around instances of large current account deficits. Events where identified using decile 10 as a threshold. For both country groups, forecasts are seen to systematically over-predict growth in each of the subsequent 5 years. While the differences between forecasts and realizations are economically significant in both cases, the gap is larger in the case of emerging economies.

Figure 2: GDP growth conditional on large current account deficits.

A. Advanced Economies



B. Emerging Economies



Notes: Large current account deficits are identified in year 0 if the current account deficit for year -1 is below percentile 10.

To implement a formal analysis, the empirical model of the previous exercise is extended to measure forecasting anomalies separately for each country group:

$$gfe_{ct}^{k} = \alpha_x^k + \beta_x^{k,A} I_{(ca_{ct-1}<p_t^x)} I_c^A + \beta_x^{k,E} I_{(ca_{ct-1}<p_t^x)} (1 - I_c^A) + u_{ct} \tag{3}$$

where I_c^A is an indicator function that takes a value of 1 if country c is an advanced economy.

Table 3 shows the estimated parameters for different specifications of the event identification threshold and for different forecast horizons. The evidence confirms that the anomaly is verified for both country groups. At the same time, the anomaly is more important in the case of emerging economies. For example, in the case of percentile 10 and three-year-ahead forecasts, conditioning on an event, the mean forecast error falls by 3.4% in the case of advanced economies while the estimated drop is 5% in the case of emerging economies. Complementarily, it must also be noted that large current account deficits are more frequent in the case of emerging countries. In the case of percentile 10 and 3 year non-overlapping windows, out of 48 identified events, 29 correspond to emerging economics.

Table 3: Mean growth forecast errors: advanced vs. emerging economies

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
k=1	$\hat{\beta}_x^{k,A}$	-0.010***	-0.011***	-0.013***
		[3.0]	[4.9]	[3.3]
	$\hat{\beta}_x^{k,E}$	-0.019***	-0.019***	-0.021***
		[4.2]	[3.6]	[3.9]
k=2	$\hat{\beta}_x^{k,A}$	-0.020**	-0.020***	-0.031**
		[2.5]	[3.1]	[2.3]
	$\hat{\beta}_x^{k,E}$	-0.033***	-0.026***	-0.036**
		[3.0]	[2.5]	[2.1]
k=3	$\hat{\beta}_x^{k,A}$	-0.032***	-0.034***	-0.066***
		[3.2]	[2.7]	[2.6]
	$\hat{\beta}_x^{k,E}$	-0.052***	-0.050***	-0.063***
		[3.3]	[5.8]	[3.1]
k=4	$\hat{\beta}_x^{k,A}$	-0.030**	-0.048***	-0.052**
		[2.6]	[4.4]	[2.2]
	$\hat{\beta}_x^{k,E}$	-0.045***	-0.048***	-0.084***
		[3.1]	[5.3]	[3.5]
k=5	$\hat{\beta}_x^{k,A}$	-0.035**	-0.033	-0.036
		[2.1]	[1.5]	[1.4]
	$\hat{\beta}_x^{k,E}$	-0.060***	-0.089***	-0.053***
		[3.0]	[4.3]	[2.6]

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

3.3 Asset prices and sentiment following current account deficits

Beyond GDP growth forecasts, information originating in asset markets and a metric of economic sentiment are used to generate further evidence regarding the presence of neglected vulnerabilities associated with instances of large current account deficits. The heterogeneity in terms of the type of indicator and the sources of the data, imply that these evaluations serve as significant robustness tests of the previously reported regularities. In particular, these extensions might be valuable considering that macroeconomic forecasts might reflect nonstandard properties of the loss functions of the forecasters. In these scenarios, efficient point forecasts do not minimize mean square errors(Elliot et al. 2005). The analyses will replicate the methodology used in the case of GDP growth forecasts. The only modification involves substituting the dependent variable.

Asset prices provide information on prevailing opinions regarding future economic scenarios. More precisely, stock market returns are indicative of changes in average opinions regarding future profitability of listed companies and, plausibly, regarding the general performance of the economy. Low returns can naturally be interpreted as an indication of a downward adjustment in prevailing views regarding the prospects of the economy. The analyses shown below will evaluate cumulative returns over a k-year horizon $ret_{ct}^{k} = \sum_{s=1}^{k} r_{ct}$ with $k \in \{1, 2, 3, 4, 5\}$.

An alternative indicator of opinions regarding economic prospects is constructed summarizing information reported in the press. The underlying conjecture is that information in the press is reflective of a broad consensus that goes beyond the opinions held by journalists. This is a plausible conjecture that is consistent with the evidence that Gentzkow & Shapiro (2010) report on strategic media reporting. In the analyses below, the indicator of changes in sentiment, $sent_{ct}^{k}$, is used to characterize the change in opinions following large current account deficits.

In each case, the implemented empirical model follows the form proposed in the previous exercises:

$$Y_{ct}^{k} = \alpha_{x}^{k} + \beta_{x}^{k} I_{(ca_{ct-1} < p_{t}^{x})} + u_{ct} \tag{4}$$

Where Y_{ct}^k is the k-year cumulative return (ret_{ct}^k) or the cumulative change in sentiment ($sent_{ct}^k$) respectively.

Table 4 shows the estimations corresponding to these alternative indicators. Panel A points to a negative association between large current account deficits and subsequent stock market returns. The estimated coefficients are negative all cases but, plausibly due to low power, statistical significance is principally observed in the cases of short term returns ($k = 1$) or more extreme events ($x = 5$). Economically, the estimated coefficients are significant. For example, considering one-year-ahead returns, the absolute value of the estimated coefficient is similar or larger than 5.1%, the mean annual return for the whole sample. This anomaly is hard to reconcile resorting to a risk based explanation.

Panel B in table 4 shows that large current account deficits are followed by significant drops in sentiment. In the 3 years that follow the event, using percentile 10 as threshold, the cumulative standardized change in sentiment is estimated at -0.47. As in the case of GDP forecast errors, stock returns and changes in sentiment display patterns that are indicative of unattended vulnerabilities. On average, large current account deficits are followed by the arrival of negative surprises or weaker assessments regarding economic prospects.

Table 4: Asset returns and sentiment after large current account deficits

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
A. Stock market returns				
k=1	$\hat{\beta}_x^k$	-0.053***	-0.084***	-0.177***
		[2.9]	[2.8]	[2.9]
k=2	$\hat{\beta}_x^k$	-0.069	-0.135**	-0.297***
		[1.6]	[2.2]	[2.9]
k=3	$\hat{\beta}_x^k$	-0.077	-0.116	-0.316**
		[0.9]	[1.2]	[2.3]
k=4	$\hat{\beta}_x^k$	-0.152	-0.223	-0.436*
		[1.1]	[1.4]	[1.8]
k=5	$\hat{\beta}_x^k$	-0.164	-0.353*	-0.254***
		[0.8]	[1.9]	[2.9]
B. Change in sentiment				
k=1	$\hat{\beta}_x^k$	-0.08	-0.22*	-0.307**
		[1.0]	[1.8]	[2.1]
k=2	$\hat{\beta}_x^k$	-0.47***	-0.41***	-0.54***
		[5.2]	[3.3]	[2.6]
k=3	$\hat{\beta}_x^k$	-0.33*	-0.47**	-0.84***
		[2.0]	[2.1]	[3.1]
k=4	$\hat{\beta}_x^k$	-0.46	-0.57*	-0.86
		[1.2]	[1.7]	[1.2]
k=5	$\hat{\beta}_x^k$	-0.65*	-0.76**	-1.13***
		[1.8]	[2.0]	[9.1]

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

4 Extended analysis

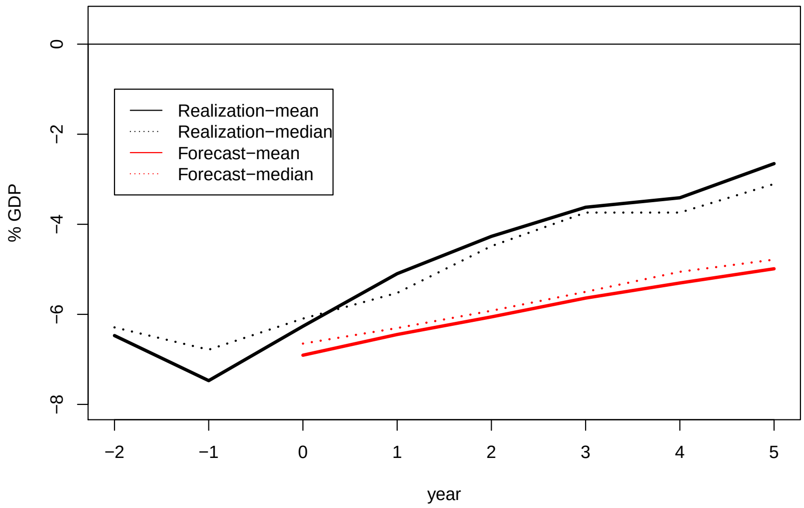
In this section, two sets of complementary exercises are presented. First, large current account deficit episodes are analyzed in more detail considering additional macroeconomic indicators around those events. The aspects under analysis are: current account forecasts, the evolution of the business cycle and credit expansions. Second, we conduct alternative evaluations of systematic errors in GDP growth forecasts. A collection of forecast released by private consulting firms is evaluated. Additionally, out of sample forecast are generated using a model trained with historical information.

4.1 Reversals of large current account deficits

In this subsection, current account balance forecasts and realizations are analyzed. As a preliminary analysis, before implementing a formal statistical model, a simple event study exercise is developed. In this preliminary exercise, large current account deficits are identified as instances in which the current account balance is below percentile 10. The percentile is computed using the complete database. Having identified the set of events, trajectories forecasted at the time of event identification are compared to realized trajectories.

Figure 3 shows the mean forecasted and realized trajectories around the event identification year (year 0). Some shared features can be observed in terms of levels and direction. Mean forecasts for year 0 are, on average, close to realizations observed in the previous year. Also, both lines display positive slopes, that is, at the time of event identification, large current account deficits are expected to be gradually corrected and realizations validate that expected direction of change. On the other hand, significant differences can be detected. For all years following the event, forecasts are clearly below realizations. In other words, the expected rate of adjustment of large current account deficits is markedly slower that the realized rate of adjustment. This behavior is also observed in the case of median trajectories, that is, these results are not driven by outliers. The areas between the mean and median trajectories suggest that the differences between forecast and realizations are economically significant. For sufficiently distant forecast horizons, the mean difference between realization and forecast is above 2% of GDP.

Figure 3: Current account balance conditional on large current account deficits.



Notes: Large current account deficits are identified in year 0 if the current account balance for year -1 is below percentile 10.

Moving beyond this exploratory exercise, an empirical model is proposed to implement a formal evaluation of systematic forecast errors. The model estimates the mean forecast error conditional on large current account deficits. The estimation is implemented using non-overlapping forecast windows and the computed standard errors are clustered by time and country. In addition, to avoid using forward looking information, large current account deficits are identified recursively using historic frequencies of current account balances.

Let ca_{ct} represent the current account balance, as a percentage of GDP, for country c and year t and let ca^t_{ct+j} represent the forecast for this indicator for year $t+j$ released in year t. Then, the cumulative k-year-ahead forecast error is given by: $cafe^k_{ct} = \sum_{j=1}^{k} ca_{ct+j} - ca^t_{ct+j}$. Given these definitions, the empirical model used to estimate conditional forecast errors is given by:

$$cafe_{ct}^{k} = \alpha_x^k + \beta_x^k I_{(ca_{ct-1} < p_t^x)} + u_{ct} \tag{5}$$

Where $I_{(ca_{ct-1} < p_t^x)}$ is a dummy variable indicating large current account deficits and u_{ct} is an error term.

Table 5 reports the estimated values for the parameter of interest, β_x^k, considering multiple values for the threshold parameter, x, and different forecast horizons, k. The estimated values are positive, in other words, the evidence points to higher mean forecast errors following large current account deficits. With a single exception, the estimated parameters are statistically significant. Setting percentile 10 as a threshold and considering three-year-ahead forecasts, large current account deficits are associated with cumulative forecast errors that are 5.3% higher. These results are consistent with the insights provided by the informal event analysis exercise. The speed at which current account deficits are reversed is significantly faster than what forecasters anticipate.

Jointly with the previously reported anomaly linked to GDP growth forecast, this systematic errors in expectations provide a more complete description of anomalies around large current account deficits. Expert forecasts fail to anticipate the trajectories GDP and current account balances.

Table 5: Mean current account forecast errors conditional on large current account deficits

		[1]	[2]	[3]
		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
k=1	$\hat{\beta}_x^k$	0.004	0.012**	0.012**
		[1.2]	[2.2]	[2.3]
k=3	$\hat{\beta}_x^k$	0.019	0.053***	0.076***
		[1.2]	[2.7]	[2.8]
k=5	$\hat{\beta}_x^k$	0.019	0.073	0.082
		[0.6]	[1.6]	[1.5]

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

4.2 Business cycle

Up to this point, the focus was placed on documenting systematic errors around large current account deficits. To gain a broader understanding of these anomalies, this subsection provides evidence related to the state of the business cycle. First, we evaluate if growth slowdowns are followed by anomalies which are similar to those found in the case large current account deficits. Second, we measure the state of the business cycle around instances of large current account deficits.

Business cycle conditions are measured applying the Hodrick-Prescott (HP) filter to real GDP.[10] Annual real GDP data is from WEOs database and starts in 1980. Let gdp_{ct} represent real GDP in year t for country c and let gdp_{ct}^{tr} represented trend GDP as estimated using the HP filter. Then, our measure of the state of the business cycle in

[10]Following Ravn & Uhlig (2002) the filter was applied setting parameter λ equal to 6.25.

country c and year t is given by the cyclical component of GDP as a fraction of trend GDP: $bc_{ct} = (gdp_{ct} - gdp_{ct}^{tr})/gdp_{ct}^{tr}$.

The first set of exercises evaluate whether growth slowdowns anticipate systematic errors in expectations. The methodology mimics that used in the case of large current account deficits. An event is identified in country c and year t if the cyclical component bc_{ct-1} is below percentile x. As in the main analysis presented above, three thresholds are considered: 5, 10 and 25. Percentiles are computed using only historical information, that is, information for year t-1 or before. Likewise, the HP filter is estimated using exclusively information available at the time of forecast release. Then, the empirical model is given by:

$$Y_{ct}^{k} = \alpha_x^k + \beta_x^k I_{(bc_{ct-1} < p_t^x)} + u_{ct} \tag{6}$$

Where Y_{ct}^{k} is the cumulative growth forecast error ($Y = gfe$) or cumulative current account forecast error ($Y = cafe$).

Table 6 reports the findings regarding anomalies following growth slowdowns. These exercises indicate that there is very little evidence suggesting a link between economic growth slowdowns and subsequent systematic forecast errors. This assertion holds both in the case of GDP growth forecasts and current account balance forecast. In particular, this findings indicate that, in contrast to the case of large current account deficits, growth slowdowns are not linked to neglected vulnerabilities.

Next, the state of the business is measured around large current account deficit episodes. In this way, the analysis moves beyond forecast errors and details how economic activity evolves before and after episodes. It must be noted that, in this exercise, the state of the business cycle is estimated using the HP filter trained using all the database. That is, the deviations from the trend are those corresponding to a retrospective perspective of an analyst that was able to observe the subsequent path followed by the economy. This perspective might differ from the trend perceived by an analyst in real-time (Heymann & Sanguinetti 1998).

Table 6: Forecast errors conditional on growth slowdown

		[1] $< p_t^{25}$	[2] $< p_t^{10}$	[3] $< p_t^{5}$
A. GDP growth				
k=1	$\hat{\beta}_x^k$	-0.000	-0.007	-0.004
		[0.1]	[1.3]	[0.5]
k=3	$\hat{\beta}_x^k$	-0.003	-0.005	0.001
		[0.5]	[0.4]	[0.1]
k=5	$\hat{\beta}_x^k$	0.030**	0.035	0.051
		[2.0]	[1.1]	[0.9]
B. Current Account Balance				
k=1	$\hat{\beta}_x^k$	0.003*	0.004	0.004
		[1.7]	[1.1]	[0.9]
k=3	$\hat{\beta}_x^k$	0.015	0.007	0.005
		[1.7]	[0.3]	[0.2]
k=5	$\hat{\beta}_x^k$	0.019	0.012	-0.010
		[1.1]	[1.2]	[0.1]

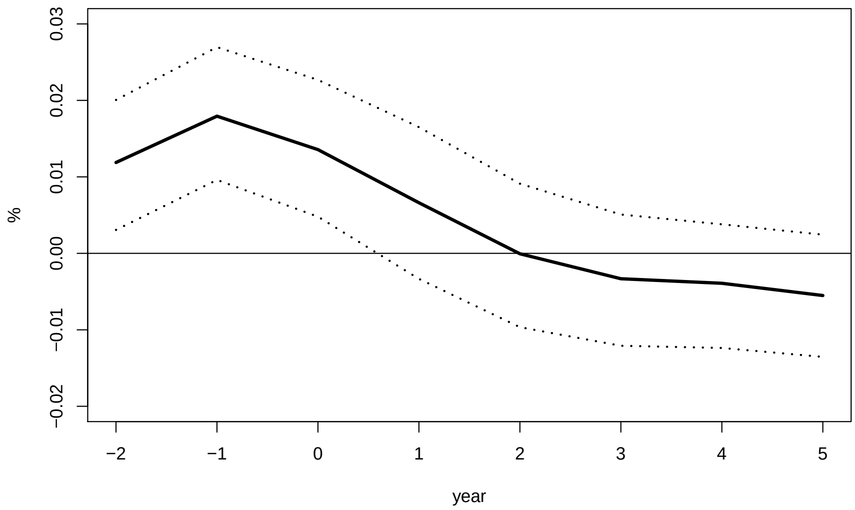
Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Figure 4 reports the mean trajectory of the cyclical component of GDP starting two years before the year of identification of the event (year 0). This trajectory is generated using the same event study methodology used to describe GDP forecast and realizations in section 3.[11] The cyclical component is positive in the years that precede event identification. By year 0, the event identification year, the cyclical component falls but remains positive. During these early years, GDP is more that 1% above trend levels. After following a downward trajectory, the cyclical component becomes slightly negative in years 3 through 5. To evaluate the timing of this pattern appropriately, it is worth noting that events are identified in year 0 based on current account deficits corresponding to year -1. That is, according to the mean trajectory, starting from the year in which large deficits took place (year -1), it takes four years for GDP to fall below its trend.

In summary, growth slowdowns fail to provide information that can be used to anticipate anomalies. Also, on average, GDP is above trend during the early stages of the events. Only in the late stages of the episodes does GDP fall slightly below its trend. This evidence favors two related interpretations. First, negative growth shocks do not seem to be the drivers of the documented anomalies that follow large current account deficits. Second, this evidence suggests that the anomalies reported in this study can, in part, be explained by experts that fail to recognize the transitory nature of expansions in economic activity.

[11] Confidence intervals were computed through resampling techniques. More specifically, given the original database with n episodes, 500 new databases with n observations are generated by resampling, with replacement, from the original dataset.

Figure 4: Cyclical component of GDP



Notes: Growth slowdowns are identified in year 0 if the cyclical component of GDP for year -1 is below percentile 10. The cyclical component is expressed as percentage deviation of HP filtered GDP trend. Dotted lines indicate 95% bootstrap confidence intervals.

4.3 Credit expansions

The financial system can be the source of negative shocks. In addition, it can play a role as an amplification mechanism of negative shocks. Risks associated with financial developments constitute a traditional issue in the context of large current account deficits (Kaminsky & Reinhart 1999, Frankel & Rose 1996, Dell'Ariccia et al. 2008, David et al. 2016). Also, it is worth noting that credit expansions have been linked to neglected vulnerabilities (Baron & Xiong 2017, Minsly 1977, Kindleberger 1978).

Motivated by these observations, this subsection evaluates anomalies linked to credit growth and the relationship with the anomalies reported in the previous section. Credit expansion episodes are evaluated in terms on their ability to anticipate systematic errors in GDP growth forecasts. Also, anomalies associated with credit expansions and large current account deficits are evaluated jointly through a simple empirical model. This exercise is used to test whether the simultaneous occurrence of both types of episodes are followed by particularly intense negative surprises.

Credit expansions are identified according to the evolution of domestic credit to the private sector as a % of GDP.[12] Let cr_{ct} be the credit ratio for country c in year t then, the cumulative rate of growth of credit as a fraction of GDP over h years is given by $\Delta^h cr_{ct} = cr_{ct}/cr_{ct-h} - 1$. Following the methodology used in the previous exercises, instances of credit expansion are identified evaluating whether the rate of growth exceeds percentile x. More specifically, the threshold percentile used to identify credit booms is 75. Large current account deficits are identified using percentile 25. Then, the empirical model with all regressors is given by:

$$gfe^3_{ct} = \alpha^k_x + \beta^{ca}_{25} I_{(ca_{ct-1}<p^{25}_t)} + \beta^{cr}_{75} I_{(\Delta^h cr_{ct-1}>p^{75}_t)} + \beta^I I_{(ca_{ct-1}<p^{25}_t \ \& \ \Delta^h cr_{ct-1}>p^{75}_t)} + u_{ct} \quad (7)$$

That is, three year ahead forecast errors are conditional on credit expansions and large current account deficit episodes. To identify credit expansions two window lengths are considered: 3 years and 5 years.

As shown in table 7, in the case of univariate models, credit growth is shown to anticipate systematic negative surprises. That is we find evidence that is consistent with forecasts that do not incorporate the information transmitted by credit expansions in an accurate manner. The estimated coefficients are smaller than those estimated for the case large current account deficits. When episodes of large current account deficits and the interaction term are incorporated a more detailed description emerges. In the absence of large current account deficits, credit expansions do not to carry much information regarding systematic errors. In contrast, in scenarios of large current account deficits, credit expansions communicate information regarding systematic errors. In those scenarios, credit expansions are associated with a substantial increment in the size of the negative surprise in GDP growth. More specifically, conditioning on both types of events, results in a drop of more than 8% in mean forecast errors. According to these results, analyst are not able to assess in a adequate manner the heightened risks associated with credit expansions.

[12]The data on credit growth is from the World Development Indicators provided by the World Bank.

Table 7: Credit expansions

		3-year Cred. Exp.		5-year Cred. Exp.	
	[1]	[2A]	[2B]	[3A]	[3B]
$\hat{\beta}^{ca}_{25}$	-0.043***	-	-0.044***	-	-0.036***
	[6.7]		[3.8]		[4.8]
$\hat{\beta}^{cr}_{75}$	-	-0.022**	-0.004	-0.035***	-0.015**
		[2.0]	[0.9]	[4.2]	[2.3]
$\hat{\beta}^{I}$	-	-	-0.033***	-	-0.033**
			[3.5]		[2.2]

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

4.4 Private forecasts

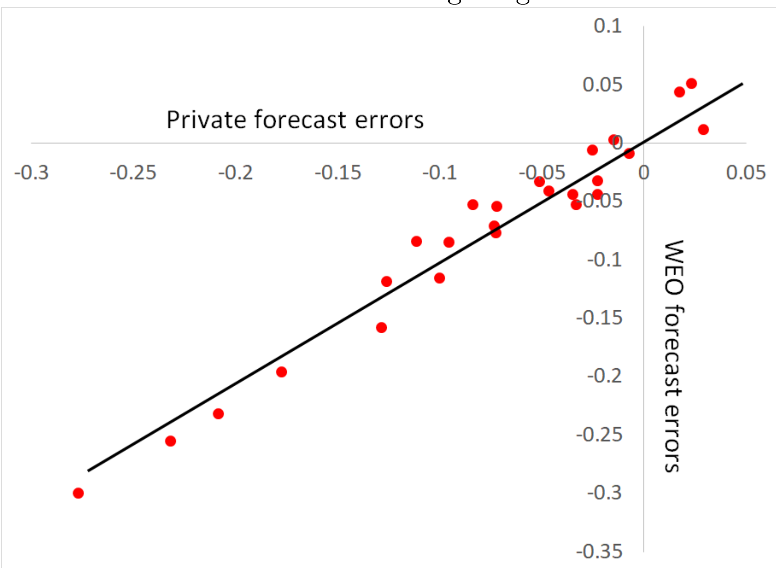
The evidence reported above indicates that vulnerability neglect in scenarios of large current account deficits is a widespread phenomenon. It is manifested by asset prices, the tone of press content and macroeconomic forecasts. In this subsection, as a additional evaluation of the extent to which these systematic errors are widespread, a collection of private macroeconomic forecasts are evaluated and compared to WEO forecasts. While previous evidence suggests that there are important similarities between forecasts released by different analysts (Loungani 2001, Gavin & Mandal 2001), a specific evaluation of their performance following large current account deficits is valuable in the context of the current study.

Private forecasts were collected for a set events of large current account deficits. More specifically, events correspond to those identified using percentile 10 as threshold and three-year-long non-overlapping windows. The construction of these alternative database involved inspecting publications of private consulting firms. Due to availability reasons, most of the forecasts correspond to those released by the Economist Intelligence

Unit.[13] After a time intensive search, the resulting database contains three-year-ahead forecasts associated with 25 events.

Figure 5 provides a comparison of forecast errors associated with private forecasts and WEO forecasts for this smaller set of events. It is evident that both types of forecast display very similar properties and are strongly correlated. Conditional on large current account deficits, in the case of private forecasts, the cumulative estimated mean error equals -0.0776. For the matched sample, in the case of WEO forecasts, the estimated mean errors is -0.0783. Additionally, the correlation coefficient for private and WEO's forecast errors is 0.981. Summarizing, the evaluation of private forecasts provide additional evidence consistent with vulnerabilities neglect. It also shows that the intensity of the systematic errors is very similar for different types of economic analysts.

Figure 5: Growth forecast errors following Large Current Account Deficits



Note: Cumulative forecast errors conditioned on Large CA Deficit. Three-year-ahead forecast horizon ($k = 3$). Percentile 10 threshold ($x = 10$).

[13]In a few cases forecast from EIU where unavailable but, forecasts from alternative sources were identified inspecting other publications such as Far Eastern Economic Review and Oxford Analytica.

4.5 Out of sample forecasts

As noted by Batchelor (2007), systematic errors do not necessarily imply that forecasts are inefficient. These systematic errors could be observed in the case in which analysts learn to make forecasts in new or changing environments. This distinction does not only lead to different evaluations of pasts forecasting practices, it also has implications regarding the information provided by incoming forecasts. Errors associated with efficient learning processes are expected to be corrected with the arrival of new data. In contrast, errors linked to inefficient use of information might prove quite persistent.

To evaluate whether efficient learning can explain the documented systematic errors an out of sample forecast exercise is implemented. A simple growth forecasting model is proposed:

$$g_{c[t,t+3]} = \alpha_0 + \alpha_1 g_{c[t-4,t-1]} + \alpha_2 g_{c[t-7,t-4]} + \beta_x I_{(ca_{ct-1}<p_t^x)} + u_{ct} \tag{8}$$

Where $g_{c[t',t'+3]}$ indicates cumulative GDP growth from year t' through year $t'+3$. In this model, GDP growth in the subsequent three year period is a function of lagged GDP growth and a dummy variable that indicates large current account deficits. This model is trained using GDP growth and current account balance data for the period 1969-1989.[14]

The first panel in table 8 reports the fitted models for different values of the threshold percentile. It is worth noting that the estimated coefficient for the large current account deficit dummy is negative and economically significant. Importantly, the coefficient estimated using 1976-1989 data is similar to the systematic error conditional on large current account deficits shown in the previous section. This is the first piece of evidence suggesting that neglected vulnerabilities could have been anticipated contemplating past associations between current account balances and GDP growth trajectories.

The out of sample forecast exercise involves using the fitted model together with information available at the time of WEO forecast release. The testing sample is given by three-year-ahead windows from 1990 through 2014. The resulting forecasts are eval-

[14]The training dataset contains information corresponding to the period 1969-1989.Data prior to 1988 is from Penn World Table Mark 5 (Summer & Heston 1991). The model is trained generating three-year-ahead forecasts in years 1975 through 1986.

uated computing the mean forecast error, the root mean squared error (RMSE) and the mean absolute error (MAE). These indicators of forecast performance are also computed for WEO forecasts.

The second panel in table 8 describes the performance of trained models and experts. The statistics are computed for two scenarios at the time of forecast release: scenarios with large current account deficits and scenarios with no current account deficits. It is worth noting that, given real-time data availability, this split could have been by experts at the time of WEOs forecast release. The evidence indicates that relative forecasting performance varies when different scenarios are considered. Conditioned on large current account deficits, model forecasts perform better than WEO forecasts. The mean error of model forecasts is, in absolute value, smaller than WEO mean forecast error. Additionally, according to the metrics of accuracy (RMSE and MAE), model forecasts perform better than expert forecasts. In contrast, in the absence of large current account deficits, the difference between mean forecast errors is smaller and WEO forecasts are more accurate than model forecasts.

Table 8: Model vs WEO forecasts

	$x = 25$		$x = 10$		$x = 5$	
	Model	WEO	Model	WEO	Model	WEO
A. Fitted model						
$\hat{\alpha}_0$	0.056	-	0.054	-	0.053	-
$\hat{\alpha}_1$	0.176	-	0.167	-	0.171	-
$\hat{\alpha}_2$	0.221	-	0.216	-	0.218	-
$\hat{\beta}_x$	-0.022	-	-0.022	-	-0.049	-
B. Performance						
B.1 Large CA deficit						
Mean Forecast Error	-0.016	-0.059	-0.023	-0.064	-0.016	-0.087
RMSE	0.076	0.091	0.079	0.100	0.083	0.118
MAE	0.055	0.067	0.061	0.076	0.060	0.092
B.2 No large CA deficit						
Mean Forecast Error	0.021	-0.013	0.000	-0.019	0.000	-0.019
RMSE	0.067	0.054	0.069	0.059	0.069	0.060
MAE	0.050	0.040	0.049	0.043	0.049	0.043

This exercise indicates that vulnerabilities associated with current account deficits could have been anticipated using historical information. Hence, it suggests that the documented systematic errors cannot be explained in a satisfactory manner by learning dynamics under efficient use of available information. A plausible interpretation is that the documented anomalies are the result of a stable property of the process through which analysts and economic agents construct assessments. As a consequence, it could be conjectured that unattended vulnerabilities are likely to persist.

5 Conclusions

This study shows that large current account deficits are typically followed by the systematic arrival of negative news. This conclusion is supported by analysis of growth forecast errors, asset market returns and the evolution of press sentiment. The pattern is observable both in the case of advanced and emerging economies and is particularly noticeable when large current account deficits coincide with credit expansions. Also, the evidence indicates that large current account deficits are followed by surprisingly fast current account reversals. Additional analyses indicate that these regularities are not explained by efficient learning dynamics.

The documented regularities are relevant for the evaluation of the information content of asset prices and expert assessments. In addition, these results have implications for the understanding of relevant macroeconomic events such as crises associated with current account deficit reversals. Complementarily, the presence of patterns consistent with neglected vulnerabilities should inform the design of macro-prudential policies. Beyond moral hazard and the associated strategic exposure to risks, the documented regularities suggest that policy makers have to contemplate the widespread inability to assess vulnerabilities in an adequate manner.

References:

Adam, K., Kuang, P., & Marcet, A. (2012). House price booms and the current account. NBER Macroeconomics Annual, 26(1), 77-122.

Afrouzi, H, Kwon, S., and Ma, Y. (2020). A Model of Costly Recall. working paper, Columbia University.

Aguiar, M., & Gopinath, G. (2007). Emerging market business cycles: The cycle is the trend. Journal of political Economy, 115(1), 69-102.

Arezki, R., Ramey, V. A., & Sheng, L. (2017). News shocks in open economies: Evidence from giant oil discoveries. The quarterly journal of economics, 132(1), 103-155.

Aromí (2019). Medium term forecasts: experts vs. simple models. International Journal of Forecasting, 35(3), 1085-1099

Baron, M., & Xiong, W. (2017). Credit expansion and neglected crash risk. The Quarterly Journal of Economics, 132(2), 713-764.

Batchelor, R. (2007). Bias in macroeconomic forecasts. International Journal of Forecasting, 23(2), 189-203.

Bernanke, B. (2005). The global saving glut and the US current account deficit (No. 77). Board of Governors of the Federal Reserve System (US).

Beshears, J., Choi, J. J., Fuster, A., Laibson, D., & Madrian, B. C. (2013). What goes up must come down? Experimental evidence on intuitive forecasting. American Economic Review, 103(3), 570-74.

Blanchard, O., & Giavazzi, F. (2002). Current account deficits in the euro area: the end of the Feldstein-Horioka puzzle?. Brookings papers on economic activity, 2002(2), 147-186.

Calvo, G. A., Leiderman, L., & Reinhart, C. M. (1993). Capital inflows and real exchange rate appreciation in Latin America: the role of external factors. Staff Papers, 40(1), 108-151.

Cavallo, E., Eichengreen, B., & Panizza, U. (2018). Can countries rely on foreign saving for investment and economic development?. Review of World Economics, 154(2), 277-306.

Chinn, M. D., & Ito, H. (2007). Current account balances, financial development and institutions: Assaying the world "saving glut". Journal of international money and Finance, 26(4), 546-569.

Dell'Ariccia, M. G., Mauro, M. P., Faria, M. A., Ostry, M. J. D., Di Giovanni, J., Schindler, M. M., & Terrones, M. M. (2008). Reaping the benefits of financial globalization (No. 264). International Monetary Fund.

de Mello, L., Padoan, P. C., & Rousová, L. (2011). The Growth Effects of Current Account Reversals: THE ROLE OF MACROECONOMIC POLICIES. OECD Economic Department Working Papers, nr. 871.

Edwards, S. (2004). Financial openness, sudden stops, and current-account reversals. American Economic Review, 94(2), 59-64.

Elliott, G., Timmermann, A., & Komunjer, I. (2005). Estimation and testing of forecast rationality under flexible loss. The Review of Economic Studies, 72(4), 1107-1125.

Frankel, J. (2011). Over-optimism in forecasts by official budget agencies and its implications. Oxford Review of Economic Policy, 27(4), 536-562.

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. Journal of international Economics, 41(3-4), 351-366.

Gavin, W. T., & Mandal, R. J. (2001). Forecasting inflation and growth: do private forecasts match those of policymakers?. Business Economics, 36(1), 13-13.

Garcia, D. (2013). Sentiment during recessions. The Journal of Finance, 68, 1267-1300.

Gennaioli, N., Shleifer, A., & Vishny, R. (2012). Neglected risks, financial innovation, and financial fragility. Journal of Financial Economics, 104(3), 452-468.

Gentzkow, M., & Shapiro, J. M. (2010). What drives media slant? Evidence from US daily newspapers. Econometrica, 78(1), 35-71.

Ghosh, A. R., Ostry, J. D., & Qureshi, M. S. (2015). Exchange rate management and crisis susceptibility: A reassessment. IMF Economic Review, 63(1), 238-276.

Ghosh, A. R., Ostry, J. D., & Qureshi, M. S. (2016). When Do Capital Inflow Surges End in Tears?. The American Economic Review, 106(5), 581.

Greenwood, R., Hanson, S. G., Shleifer, A., & Sørensen, J. A. (2020). Predictable Financial Crises (Vol. 31, No. 20-130, pp. 3307-3343). Harvard Business School Working Paper.

Gruber, J. W., & Kamin, S. B. (2007). Explaining the global pattern of current account imbalances. Journal of international money and Finance, 26(4), 500-522.

Heymann, D. (1994). Sobre la interpretación de la cuenta corriente. Desarrollo Económico, 323-342.

Heymann, D., & Sanguinetti, P. (1998). Business cycles from misperceived trends. ECONOMIC NOTES-SIENA-, 205-232.

Hirshleifer, D., Li, J., & Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. Journal of Monetary Economics, 76, 87-106.

Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. American economic review, 89(3), 473-500.

Kaminsky, G. L., Reinhart, C. M., & Vegh, C. A. (2003). The unholy trinity of financial contagion. Journal of economic perspectives, 17(4), 51-74.

Kindleberger, C. P. (1978). Manias, panics, and crashes: A History of Financial Crises. New York: Basic Books.

López-Salido, D., Stein, J. C., & Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. The Quarterly Journal of Economics, 132(3), 1373-1426.

Loungani, P. (2001). How accurate are private sector forecasts? Cross-country evidence from consensus forecasts of output growth. International journal of forecasting, 17(3), 419-432.

Maćkowiak, B., & Wiederholt, M. (2015). Business cycle dynamics under rational inattention. The Review of Economic Studies, 82(4), 1502-1532.

Mann, C. L. (2002). Perspectives on the US current account deficit and sustainability. Journal of Economic Perspectives, 16(3), 131-152.

Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. The Quarterly Journal of Economics, 132(4), 1755-1817.

Minsky, H. P. (1977). The Financial Instability Hypothesis: A Restatement of Keynes and an Alternative to Standard Theory. Nebraska Journal of Economics and Business, 16, 5-16.

Milesi-Ferretti, G. M., & Razin, A. (1996). Current account sustainability: selected East Asian and Latin American experiences (No. w5791). National Bureau of Economic Research.

Milesi-Ferretti, G. M., & Razin, A. (2000). Current account reversals and currency crises: empirical regularities. In Currency crises (pp. 285-323). University of Chicago Press.

Mullainathan, S. (2002). Thinking through categories. UC Berkeley. Mimeo.

Obstfeld, M., & Rogoff, K. (2007). The unsustainable US current account position revisited. In G7 current account imbalances: Sustainability and adjustment (pp. 339-376). University of Chicago Press.

Summers, R., & Heston, A. (1991). The Penn World Table (Mark 5): an expanded set of international comparisons, 1950–1988. The Quarterly Journal of Economics, 106(2), 327-368.

Pierri, D., Rojas, M., Lambi, M. (2020). The empirical dimension of oberborrowing. Serie Documentos de Trabajo del IIEP.

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. Review of economics and statistics, 84(2), 371-376.

Reinhart, C. M., & Rogoff, K. S. (2009). This time is different: Eight centuries of financial folly. Princeton University Press.

Sachs, J. (1983). The current account in the macroeconomic adjustment process. In Long-Run Effects of Short-Run Stabilization Policy (pp. 15-27). Palgrave Macmillan, London.

da Silveira, R. A., Sung, Y., & Woodford, M. (2020). Optimally Imprecise Memory and Biased Forecasts.

Tetlock, Paul (2007). Giving content to investor sentiment: The role of media in the stock market. Journal of Finance, 62, 1139-68.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. Journal of financial Economics, 99(1), 1-10.

Appendix A: Fall WEO's Forecasts In the main text, the analysis considered WEO's growth forecast and WEO's real-time data for the Spring release. Table A1 below reports that the anomaly is also found in the case of WEO's Fall release forecasts. As expected, as forecasters are able to collect more information, a reduction in the size of the anomaly can be observed.

Table A1: Mean growth forecast errors conditional on large current account deficits

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
k=1	$\hat{\beta}_x^k$	-0.011***	-0.011***	-0.013***
		[3.7]	[3.2]	[3.5]
k=2	$\hat{\beta}_x^k$	-0.022***	-0.017***	-0.029***
		[3.2]	[2.7]	[2.9]
k=3	$\hat{\beta}_x^k$	-0.037***	-0.026***	-0.044**
		[3.5]	[2.9]	[2.5]
k=4	$\hat{\beta}_x^k$	-0.032***	-0.039***	-0.045*
		[3.5]	[5.4]	[1.7]
k=5	$\hat{\beta}_x^k$	-0.037**	-0.049**	-0.021*
		[2.0]	[2.1]	[4.3]

Notes: t-statistics in brackets are computed from standard errors dually clustered on country and time following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Appendix B: Additional characterization of episodes

To shed more light on possible mechanisms, large current account deficits are analyzed under different contexts. A set of variables will be used to proxy for the relevance of different channels. The intensity of negative news will be assessed for different values of these indicators. If there is a relevant channel that is particularly unattended then, the associated proxy variable is expected to be strongly informative regarding subsequent negative surprises.

Five variables are used to proxy for exposure to risks associated to different channels. First, one aspect to be evaluated is the persistence of large current account deficits. The value of the current account deficit 4 years before event identification will be used to measure persistence. Second, investment booms are considered. Increments in the investment ratio (from year $t-4$ though year $t-1$) is used to proxy for investment booms.[15] Foreign direct investment is considered a preferable, more stable, form of deficit financing (Frankel & Rose 1996, Dell'Ariccia et al. 2008). The net flow of direct investment, as a percentage of the current account balance, is used to characterize deficit financing.[16] Government deficits have been traditionally considered a factor of external crises (see, for example, the influential framework proposed in Krugman 1979). Responding to this traditional perspective, government net lending/borrowing is incorporated to the set of proxy variables.[17] Real exchange rate appreciations have also been linked to difficulties originating in the external front (Calvo et al. 1993, Ghosh et al. 2015,2016). As a result, real exchange appreciation from year t-4 through year y-1 is incorporated to the set of variables. Real exchange rates are computed against the US dollar using data from the World Economic Outlook database.

The median values of the latest realization of the selected variables on event identification date are shown in table A2. To allow for an analysis informed by a larger quantity of events, percentile 20 was used as the threshold. Similar results are observed under alternative parameter choices. According to the descriptive statistics, large current account deficits are typically persistent, associated to increments in the investment ratio, larger budget deficits and more intense appreciations.

[15] Investment ratios correspond to those reported in the WEO database.

[16] The indicator is computed using data from IMF's Balance of Payment statistics.

[17] The information corresponds to that reported in the WEO database.

Table A2: Median values of proxy variables

Condition	Event	No Event
Previous CA Balance (t-4)	-0.040	-0.006
Inv. ratio growth (t-4 vs t-1)	0.011	-0.001
Net Dir.Inv. (% CA Balance)	0.225	-
Gov. net lending/borrowing (% of GDP)	-0.033	-0.026
RER appreciation (t-4 vs t-1)	0.066	0.044

Note: Large current account deficits (events) are identified using percentile 20 as a threshold. Net direct investment flows, as a fraction of the current account balance, are not computed for no-event dates since changes in the sign of the current account balance difficult the interpretation of the median value.

Table A3 reports the mean value of the cumulative growth forecast errors for each of the resulting colllection of events. The main message that results from this analysis is that the anomaly is a very robust finding. That is, on average, forecast errors are below -4.3% in each of the 10 subsamples evaluated. In terms of the associations with the value of the selected variables, most of the differences are in the expected direction but, statistically significant differences are only observed in the case of RER appreciations.

Table A3: Growth forecasts errors following Large Current Account Deficits

Condition	Below Median	Above Median	Difference
Previous CA Balance (t-4)	-0.071	-0.051	0.020
Inv. ratio growth (t-4 vs t-1)	-0.055	-0.069	-0.014
Net Dir.Inv. (% CA Balance)	-0.065	-0.052	0.013
Gov. net lending/borrowing (% of GDP)	-0.054	-0.078	-0.024
RER appreciation (t-4 vs t-1)	-0.043	-0.081	-0.038*

Note: Mean cumulative errors for 3-year-ahead forecasts and percentile 20 threshold. Averages do not add up to the same value since, in some cases, due to missing data, some events are not considered. *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.