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Large current account deficits and neglected vulnerabilities

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Abstract

Using a sample covering 46 advanced and emerging economies over 1990-2017, it is found that large current account deficits are reversed significantly faster than what forecasters anticipate. In addition, large current account deficits are followed by negative surprises in economic growth, low asset returns and drops in sentiment. These regularities are observed for advanced and emerging economies. Analyses for different sample periods do not point to a gradual reduction in the reported patterns. These findings are indicative of systematic neglect of vulnerabilities and have implications for the understanding of past economic events and the design of macro-prudential policies.

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 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 and the likelihood of a change in the perceptions that dominate international financial markets.

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 to 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 macroeconomic events, such as crises, and for the design of macro-prudential policies.

In this work, a database covering 46 advanced and emerging economies between 1990 and 2017 is used to characterize expectations and macroeconomic trajectories around large current account deficits. The study intends to measure the extent to which the risks associated to large current account deficits are properly incorporated

[1] See for example Heymann 1994, Reinhart & Rogoff 2009, Milesi-Ferretti & Razin 1996, Blanchard & Giavazzi 2002, Edwards 2004, Sachs 1981, Bernanke 2005, Obstfeld & Rogoff 2007.

by analysts and economic actors. With this objective, a large collection of macroeconomic forecasts is evaluated. This dataset is complemented with information from asset markets and indicators of economic sentiment.

The first set of results shows that large current account deficits are followed by systematic errors in current account balance forecasts. Conditional on large current account deficits, forecasted deficits are significantly larger than realized deficits. For example, when the 10th percentile is used to identify large deficits, average forecast errors over the following three years add up to 6.1% of GDP. These surprisingly fast reversals are observed for different forecast horizons and under different definitions of large deficits. Forecasts associated to excessive persistence seems to a property that is specific of instances of large deficits. The reported regularity is not observed in the case of large current account surpluses. Additionally, when a linear association between past current account balances and subsequent forecast errors is evaluated, no significant link is found.

A second set of analyses provides evidence on the extent to which these surprising reversals are associated to neglected vulnerabilities. Using a comprehensive database of macroeconomic forecasts, it is established that large current account deficits are followed by negative surprises in GDP growth. More specifically, when the 10th percentile is used as a threshold, large current account deficits are associated to a 4.2% increment in the mean difference between three-year-ahead cumulative growth forecasts and corresponding realizations. This type of association is verified for different forecast horizons and thresholds. This evidence is compatible with forecasts that do not reflect vulnerabilities in an adequate manner.

The analyses of GDP growth forecasts, are complemented with the evaluation of other indicators that provide further evidence on disregarded risks. It is found that large current account deficits are followed by lower stock market returns and drops in market sentiment as inferred from economic press content. Using a 10th percentile threshold to identify the events and a three-year-ahead forecast horizon, mean cumulative stock market returns are 29.6% lower and the mean sum of changes in sentiment equals 0.9 standard deviations. These regularities constitute additional evidence consistent with overlooked risks.

The presence of systematic errors in assessments of future macroeconomic scenarios has implications for the understanding of macroeconomic events. For example, macroeconomic crises can be understood as the result of a combination of exogenous shocks, wrong incentives and misperceived exposures to risk. The evidence reported in this work suggests that neglected vulnerabilities have an important role in the explanation of crises. Relatedly, this evidence is also relevant for the design of macro-prudential economic policies. In particular, it suggests that policies intended to alleviate problems with incentives to take too much risk need to be complemented with policies that consider the likely disregard of vulnerabilities.

The findings reported in this work are consistent with a growing 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). 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).

This work is also related to theoretical contributions that have proposed models in which cognitive limits and associated simplified representations and noisy perceptions result in expectations that are unable to reflect available information in an adequate manner (Maćkowiak et al. 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 to naive projection of previous trajectories (Hirshleifer et al. 2015), disregard of mean reverting processes (Beshears et al. 2012) and categorical reasoning (Mullainathan 2002).

The paper is organized as follows. In the next section the data used in the analyses is described. Section 3 reports the regularities regarding surprising reversals of large current account deficits. Section 4 provides evidence consistent with the existence of vulnerabilities neglect. Some robustness exercises are shown in the following section. Concluding remarks are presented in section 6.

2 Data

The main source of data for this study is the World Economic Outlook Historical Forecasts Database. International Monetary Fund's staff forecasts are distributed through this database. This study uses current account balance forecasts corresponding to the World Economic Outlook April release 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 and five-year-ahead GDP forecasts. World Economic Outlook Historical Forecasts Database is the source of additional information on realized current account balances. The sampled countries are given by 46 advanced and emerging economies.[2]

In addition to WEO's forecasts, 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

[2]Sampled countries are: Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Ecuador, Egypt, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Thailand, Turkey, United Kingdom, United States, Uruguay and Vietnam. The sampled countries represent approximately 80% of world GDP over the sample period.

[3]www.tradingeconomics.com

country c is given by the difference of the log of the index for years t and $t-1$: $r_{ct} = log(p_{ct}) - log(p_{ct-1})$.

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 opinions: 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]

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 to 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 to 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 to the country. The strings of text associated to country c and year t are merged resulting in a list of words labeled K_{ct}. This 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 to more optimism.

In the third step, the original index is converted to obtain an indicator of changes in sentiment. With this objective, the variation 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: $sent^k_{ct} = \sum_{j=1}^{k} cs_{ct+j}$. Table 1 provides descriptive statistics corresponding to the data used in the analyses presented below.

[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).

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

Table 1: Descriptive statistics

Activity Indicator	Obs.	Mean	St. Dev.	Min	Max
Current Account Balance					
Realization	1281	0.001	0.055	-0.144	0.309
One-year-ahead forecast	1281	-0.002	0.050	0.157	0.267
Three-year-ahead forecast	1281	-0.003	0.046	-0.177	0.266
Five-year-ahead forecast	1279	-0.003	0.044	-0.152	0.251
GDP growth					
Realization	1281	0.031	0.036	0.185	0.263
One-year-ahead forecast	1281	0.036	0.019	-0.053	0.099
Three-year-ahead forecast	1281	0.039	0.017	-0.004	0.107
Five-year-ahead forecast	1281	0.039	0.018	-0.65	0.100
Other variables					
Stock market returns	1046	0.049	0.351	-1.847	1.345
Changes in Sentiment	1035	0.056	1.374	-5.866	5.457

Note: Data from the April releases of the WEO's Historical Forecasts Database for the period 1990-2017. Realizations data correspond to real-time data as reported two years after in the same database. Yearly stock market returns correspond to S&P's Global Equity Indices.

3 Large current account deficits and surprising reversals

In this section, current account balance forecasts and realizations are analyzed. As a preliminary analysis, before implementing a formal statistical model, a simple event analysis exercise is developed. In this perliminary exercise, large current account deficits are identified as instances in which the current account balance is below the 10th percentile. This percentile corresponds to a computation using the complete database. Having identified the set of events, the mean forecast is computed for the event year and the following five years. This trajectory is compared to the mean trajectory of realizations.

Figure 1 shows the trajectories around the event year (year 0). Both lines display positive slopes, that is, large current account deficits are gradually corrected and are expected to be corrected. Also, mean forecasts for the current year (year 0) are close to realizations observed in the previous year (year -1). On the other hand, for all year 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 lines suggest that the differences between forecast and realizations are economically significant. Independently of the forecast horizon, the mean difference between forecasts and realizations is approximately 2% of GDP.

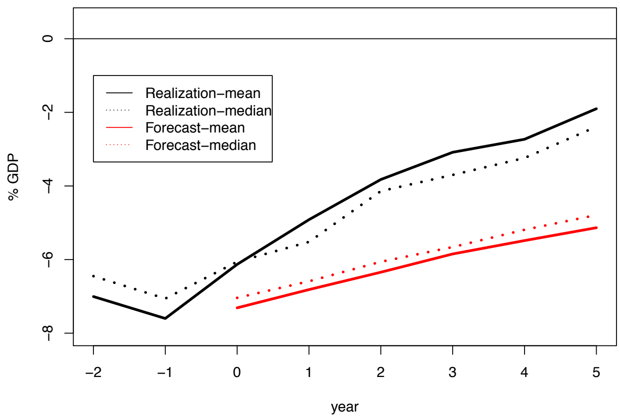

Figure 1: Current account balance conditional on large current account deficits. Notes: Large current account deficits are identified as instances in which the current deficit for period t-1 is below the 10th percentile.

An empirical model is proposed to implement a careful analysis 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. First, given a parameter $x \in \{1, 50\}$, for each sample year t, the x-th percentile is computed using information on realized current account deficits that is available at the time in which forecasts are released in year t. A large current account deficit is identified in year t and country c if the latest available value for current account balance ca_{ct-1} is below the x-th percentile that is computed using historic information on realizations.[7] In the analyses presented below, three values are considered for the parameter x: 5, 10 and 25.

Let ca_{ct} represent the current account balance, as a percentage of GDP, for country c and year t and let $ca_{ct}^{t'}$ represent the forecast for this indicator released in year t'. Then, the cumulative k-year-ahead forecast error is given by: $fe_{ct}^{k} = \sum_{j=1}^{k} ca_{ct+j} - ca_{ct+j}^{t}$. Given these definitions, following Baron & Xiong (2017), the empirical model used to estimate conditional forecast errors is given by:

[7] The methodology mimics the empirical strategy implemented in Baron & Xiong (2017) to identify large credit expansions.

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

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

Table 2 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. In the case of a 10th percentile threshold and three-year-ahead forecasts, large current account deficits are associated to cumulative forecast errors that are 6.1% higher. These results are consistent with the insights provided by the informal event analysis exercise. The speed at which current account balances are reversed is significantly faster than what forecasters anticipate.

Table 2:
Mean forecast errors conditional on large current account deficit

		[1] $> 25\%$	[2] $> 10\%$	[3] $> 5\%$
	$\hat{\beta}_x^k$	0.009**	0.013***	0.015***
k=1		[2.17]	[3.16]	[2.63]
	# obs. $> x$	292	123	64
	$\hat{\beta}_x^k$	0.036**	0.061***	0.090***
k=3		[1.97]	[3.33]	[3.32]
	# obs. $> x$	96	41	23
	$\hat{\beta}_x^k$	0.041	0.111**	0.097**
k=5		[0.99]	[2.67]	[2.05]
	# obs. $> x$	48	22	12

Notes: This table reports estimates from the panel regression model specified in equation 1. t-statistics in brackets are computed from standard errors dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Having identified systematic errors conditional on large current account deficits, additional insights can be gained considering alternative models that contemplate different associations between past values of the current account balance and subsequent forecast errors. One motivation for these additional analyses is that the model presented in equation (1) might be misspecified. In particular, it could be conjectured that there exists a linear association between past realizations and forecast errors. Also, it is of interest to check whether there exists an association with more distant realizations of the current account. For example, the association with realizations of the current account balance in the previous 10 years could be evaluated. Finally, it is of interest to check whether after large current account surpluses a systematic forecast errors as those observed following large deficits are observed. That is, is it the case that, conditional on large current account surpluses, forecasters attribute excessive persistence to the dynamic process?

Table 3 shows estimated coefficient for models in which these alternative specifications are considered. The estimations are reported for the case of a threshold equal to the 10th percentile, $x = 10$, and three-year-ahead forecasts, $k = 3$. Similar results are observed in the case of alternative specifications. First, according to columns 2 and 3, there is no linear association between realized current account balances and forecast errors. Column 4 shows that an association can be detected when current account realizations over the previous 10 year period are considered. This association is not linear. While the strength of this link is weaker, the multivariate regression points to information that does not completely overlap with that transmitted by the latest realized deficit. Finally, the case of large current account surpluses is evaluated using an identification strategy that mirrors the strategy used in the case of large current account deficits. Column 5 shows that, conditioning on large current account surpluses, no systematic forecast error is detected. In summary, the collected evidence points to a single anomaly: surprisingly fast reversals of large current account balances.

Table 3: Forecast errors

	[1]	[2]	[3]	[4]	[5]
$I_{(ca_{ct-1}<x)}$	0.061***	-	0.068***	0.060**	0.063***
	[3.33]		[3.37]	[2.47]	[3.47]
ca_{ct-1}		-0.091	0.084	0.106	-
		[-0.52]	[0.50]	[0.47]	
$I_{ca_{c[t-11,t-2]}>x}$	-	-	-	0.024***	-
				[2.71]	
$ca_{c[t-11,t-2]}$	-	-	-	-0.054	-
				[-0.21]	
$I_{(ca_{ct-1}>100-x)}$	-	-	-	-	0.014
					[0.73]

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

4 Evidence on neglected vulnerabilities

The detection of systematic forecast errors reported in the previous section constitutes an anomaly from the perspective of forecasting performance. Nevertheless, it must be noted that surprisingly fast reversals of current account deficits are not necessarily an indicator of the realization of surprisingly negative scenarios. This is because the information transmitted by current account deficits is not necessarily negative (Heymann 1994). In principle, unanticipated reversals of large deficits could be explained by unexpected favorable events such as improvements in the terms of trade or gains in productive capabilities. These developments would lead to a surprise reduction in the difference between current expenditures and current incomes. For example, Arezki et al. (2017) show that the discovery of large oil reserves leads to current account deficits that are later reversed as productive investments mature. Inattention to these dynamics can lead to surprising current account deficits reversals. Similar observations apply to the case of unattended mean reversion in commodity prices (Schwartz 1997). On other words, further analysis is needed to secure a more precise interpretations of the previous findings.

To resolve this ambiguity, in this section, three indicators are exploited to provide a more informative characterization of events around large current account deficits. First, a comprehensive dataset of GDP growth forecasts will be used to evaluate surprises in growth forecasts subsequent to large current account deficits. A systematic link between large deficits and negative surprises in GDP growth could be interpreted as a strong indication of vulnerability neglect. Beyond surprises in growth performance, complementary evidence is generated inspecting asset market dynamics and the evolution of sentiment as reflected in the economic press.

4.1 Growth forecast and current account deficits

WEO's Historical Forecast Database allows for a valuable analysis of the direction 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 informal event study exercise. Large current account deficits are given by instances in which, at the time of forecast release, the previous year current account balance is below the 10th percentile. The 10th percentile is computed using the complete dataset.

Figure 2 shows mean and median computations associated to the simple 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. For the five years that follow the event, the difference is approximately 2%.

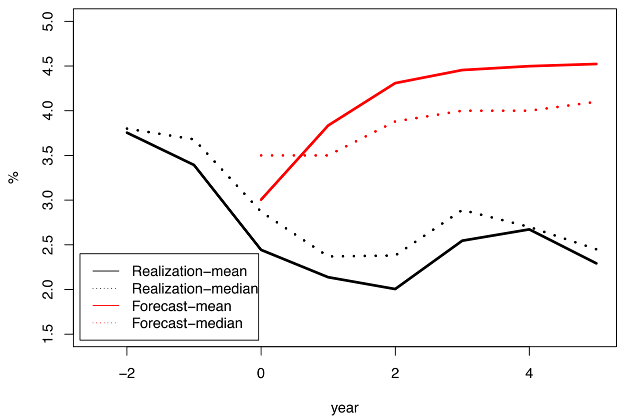

Figure 2: GDP growth conditional on large current account deficits.
Notes: Large current account deficits are identified as instances in which the current deficit for period t-1 is below the 10th percentile.

As in the case of the current account balance, this preliminary exercise is complemented by a formal evaluation using non-overlapping forecast periods and identifying large deficits using exclusively past current account balance frequencies. Growth forecast errors for k-year-ahead forecast errors are defined as: $gfe^k_{ct} = \sum_{j=1}^{k} GDPgr_{ct+j} - GDPgr^t_{ct+j}$ 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:

$$gfe^k_{ct} = \alpha^k_x + \beta^k_x I_{(ca_{ct-1}<x)} + u_{ct} \tag{2}$$

Table 4 reports the estimated values for the parameter of interest, β^k_x. Indicating large current account deficits are followed by larger differences between forecast and expectations, in all cases, the estimated values are negative. The estimated parameter is significantly different from zero in all but one case. Considering a three-year-ahead forecast horizon and the 10th percentile as a threshold, cumulative mean forecast errors are 4.2% larger subsequent to large current account deficits. In other words, large current account deficits anticipate more negative surprises in GDP growth. This evidence is consistent with neglected vulnerabilities. Negative surprises in GDP growth point the realization of negative scenarios that were not adequately considered at the time of forecast release.

Table 4: Mean growth forecast errors conditional on large current account deficit

		$> 25\%$	$> 10\%$	$> 5\%$
k=1	$\hat{\beta}_x^k$	-0.012***	-0.013***	-0.015***
		[-3.47]	[-3.77]	[-3.31]
k=3	$\hat{\beta}_x^k$	-0.041***	-0.042***	-0.057**
		[-4.06]	[-3.17]	[-2.34]
k=5	$\hat{\beta}_x^k$	-0.045***	-0.043*	-0.013
		[-2.91]	[-1.71]	[-0.31]

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

4.2 Asset markets 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 in instances of large current account deficits. Thanks to heterogeneity in the type of variable and the source of the data, these additional evaluations serve as significant robustness tests of the previously reported regularities. The analyses will replicate the methodology used in the case of GDP growth forecasts simply using an alternative 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 negative 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 where $k \in \{1, 3, 5\}$.

An alternative indicator of opinions regarding economic prospects results from summarizing information reported in the press. The underlying conjecture is that information in the press is reflective of a broader consensus that goes beyond the opinions held by journalists. This is a plausible conjecture and 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.

Table 5 shows the results of the analysis corresponding to these alternative indicators. Panel A point to a negative association between large current account deficits and subsequent stock market returns. For a three-year-ahead horizon and a

10th percentile threshold, instances of large current deficits are followed by cumulative returns that, on average, are 29.6% lower. This evidence is also observed for different horizons and using alternative thresholds to identify events.

Panel B in table 5 shows that large current account deficits are followed by lower sentiment. In the 3 year that follow the event, in the case of a 10th percentile threshold, the cumulative standardized change in sentiment is estimated at -0.925. As in the case of GDP forecast errors, stock returns and changes in sentiment display patterns that are indicative of unattended vulnerabilities.

Table 5: Asset returns and sentiment after large current account deficits

		$> 25\%$	$> 10\%$	$> 5\%$
A. Stock market returns				
k=1	$\hat{\beta}_x^k$	-0.060***	-0.109***	-0.131*
		[-2.71]	[-2.74]	[-1.74]
k=3	$\hat{\beta}_x^k$	-0.125	-0.296**	-0.320*
		[-1.15]	[-2.26]	[-1.69]
k=5	$\hat{\beta}_x^k$	-0.208	-0.425***	-0.268
		[-0.98]	[-5.01]	[-1.33]
B. Change in sentiment				
k=1	$\hat{\beta}_x^k$	-0.105	-0.350***	-0.404**
		[-1.32]	[-3.18]	[-2.27]
k=3	$\hat{\beta}_x^k$	-0.468	-0.925***	-0.900**
		[-1.50]	[-5.02]	[-2.38]
k=5	$\hat{\beta}_x^k$	-0.566	-0.0771***	-0.629
		[-1.36]	[-2.65]	[-0.86]

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

5 Extensions and robustness tests

More insights regarding the previously reported exercises are gained estimating more flexible models of the associations between large current account deficits and subsequent news flows. These extended analyses allow for more precise assessments regarding the circumstances in which neglected vulnerabilities are to be expected.

In addition, these variations serve as robustness tests of the previous results.

Two extensions are considered. The first alternative responds to likely differences between advanced and emerging economies in terms of the presence of surprising reversals and neglected vulnerabilities.[8] The extension involves allowing for different parameters for advanced economies and emerging economies. For each sample year, economies are classified as advanced (emerging) if its GDP per capita for that year is above (below) 50% of U.S. GDP per capita.

A second extension considered in this section involves allowing for different associations during different sample periods. More specifically, the sample is divided between the early sample and the late sample using year 2002 as the last year of the early sample. In addition to constituting a robustness test, this specification intends to capture whether there is any evidence associated to learning dynamics. It could be conjectured that surprising reversals and neglected vulnerabilities decline or disappear with time as analysts and economic agents learn from past mistakes.

In table 6 the results associated to implementing these alternative evaluations are reported. The reported estimations correspond to a three-year-ahead horizon and a 10th percentile threshold. Panel A shows that, in general terms, the evidence on neglected vulnerabilities is documented for both types of countries. In the case of GDP forecast and changes in sentiment statistically significant association with the expected sign are observed. In the case of current account balances and stock market returns, the estimated coefficients are of the expected sign and economically significant, but, in each case, significance is observed in only one of the country groups. In the case of current account balance forecasts, systematic errors are significant only in the case of emerging economies. In the case of stock market returns, significantly lower returns are observed in the case of advanced economies.

Panel B in table 6 reports the evidence regarding associations for different sample periods. In all cases, the estimated coefficients are consistent with the values expected under neglected vulnerabilities. For example, in the case of current account forecast errors, the mean value estimated for each sample period is significantly higher after large current account deficits. In most cases, the parameters estimated for different sample periods exhibit similar magnitudes. At must be noted that, in the case of the late sample period, all the estimated associations are statistically significant and the estimated parameters do not point to declines in the intensity of the regularities. These observations are inconsistent with learning dynamics that result in the gradual elimination of the anomalies.

[8]Differences in business cycle properties have been reported, for example, in Aguiar & Gopinath (2007).

Table 6: Robustness tests

	fe^k_{ct}	gfe^k_{ct}	ret^k_{ct}	$sent^k_{ct}$
A. By level of development				
$\hat{\beta}^A_x$	0.043	-0.065**	-0.345***	-1.02**
	[1.60]	[-3.53]	[-3.73]	[-2.11]
$\hat{\beta}^E_x$	0.066***	-0.035**	-0.273	-0.896***
	[3.54]	[-2.05]	[-1.55]	[-4.70]
B. By sample period				
$\hat{\beta}^{ES}_x$	0.068**	-0.037	-0.277	-0.647**
	[2.51]	[-1.55]	[-1.19]	[2.31]
$\hat{\beta}^{LS}_x$	0.053*	-0.049***	-0.312***	-1.505***
	[1.75]	[-3.25]	[-2.72]	[-8.08]

Notes: The reported estimations correspond to a three-year-ahead horizon and a 10th percentile threshold. t-statistics in brackets are computed from standard errors dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

6 Conclusions

This study documents regularities regarding news arrival following large current account deficits. The analysis of a large collection of forecasts indicates that current account reversals are, on average, surprisingly fast. This systematic errors are compatible with neglected vulnerabilities. This interpretation is supported by a diverse set of indicators that point to an association between large current account deficits and the arrival of negative surprises. This evidence is documented for the case of GDP growth, stock returns and a sentiment metric. Additional analysis indicate that these regularities are observed during different sample periods and in the case of advanced and emerging economies.

These results have implications for the understanding of relevant macroeconomic events such as crises associated to current account deficit reversals. In addition, the presence of patterns consistent with neglected vulnerabilities should inform the design of macroprudential policies. Beyond moral hazard and the associated strategic exposure to risks, policy makers have to contemplate the systematic inability to assess vulnerabilities in an accurate manner.

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