Large current account deficits and neglected vulnerabilities

J. Daniel Aromí
IIEP UBA-Conicet, FCE UCA

January 23, 2019

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. The documented regularities are robust to changes in the specification and do not seem to be explained by efficient learning dynamics. 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, financial interdependencies and the stability of economic perceptions.

[1] See, for example, Sachs 1981, Heymann 1994, Kaminsky et al. 2003, Reinhart & Rogoff 2009, Milesi-Ferretti & Razin 1996, Blanchard & Giavazzi 2002, Edwards 2004, Bernanke 2005, Obstfeld & Rogoff 2007.

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 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 instances of large current account deficits. The study intends to measure the extent to which the risks associated with large current account deficits are properly incorporated 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 percentile 10 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 thresholds for the identification of large deficits. In extended analyses, it is observed that the reported regularity is not present 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. These results suggest that the excessive persistence in forecasts is a feature specifically linked to instances of large deficits.

A second set of analyses provides evidence on the extent to which these surprising reversals are associated with neglected vulnerabilities. This evaluation is needed since deficit reversals not unambiguously linked to negative scenarios. Reversals could reflect postive unexpected developments such as better terms of trade or expanded productive capacities.[2] Using a comprehensive database of macroeconomic forecasts, it is

[2]For example, large oil discoveries are associated to reversing patterns in current account balances that do not involve traumatic events (Arezki et al. 2017).

established that large current account deficits are followed by negative surprises in GDP growth. More specifically, when percentile 10 is used as a threshold, large current account deficits anticipate a 4.2% increment in the mean difference between forecasted and realized 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. Hence, the surprisingly fast reversals are not reflecting unexpected increments in the value of local production. The evidence points to surprisingly low levels of aggregate economic activity.

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

Extended analysis shows that neglected vulnerabilities are also detected in the case of private GDP growth forecasts. This result reinforces the conclusion that the documented systematic errors are manifested by an ample set of economic actors and analysts. Also, out of sample exercises suggest that efficient learning processes cannot satisfactorily explain the systematic forecast errors. Therefore, it is reasonable to conjecture that the documented anomalies are likely to persist. Finally, while the documented association between large current account deficits and vulnerability neglect is very robust, the intensity of negative news is particularly strong following instances of high credit growth and investment expansions. This evidence points at two specific channels of exposure to risk that seem to be unattended: excessive activity in the financial sector and uncertainty regarding future profitability of investment projects.

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 resulting from 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 by economic actors.

The findings reported in this work are consistent with 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). 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 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 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 with 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 vulnerability neglect. Extended analysis is 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's Historical Forecasts Database. A large collection of forecasts produced by International Monetary Fund's staff is distributed through this database. This study uses 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 and five-year-ahead GDP forecasts. April 2018 World Economic Outlook Database is the source of additional information on realized current account balances. The sampled countries are given by 46 advanced and emerging economies.[3]

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[4] 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 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 opinion: The Wall Street Journal and The Economist.[5] 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

[3]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.

[4]www.tradingeconomics.com

[5]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.

has proven useful in related exercises.[6]

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

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

. Table 1 provides descriptive statistics corresponding to the data used in the analyses presented below.

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 data reported in the WEO in t+2. 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 study exercise is developed. In this preliminary exercise, large current account deficits are identified as instances in which the current account balance is below the 10th percentile. More specifically, for each country and each April's WEO release, the realized current account balance for the previous year is compared to percentile 10. This 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 1 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 the current year (year 0) are, on average, close to realizations observed in the previous year (year -1). 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 are observed when the speed of correction is evaluated. 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 forecast and realization is above 2% of GDP.

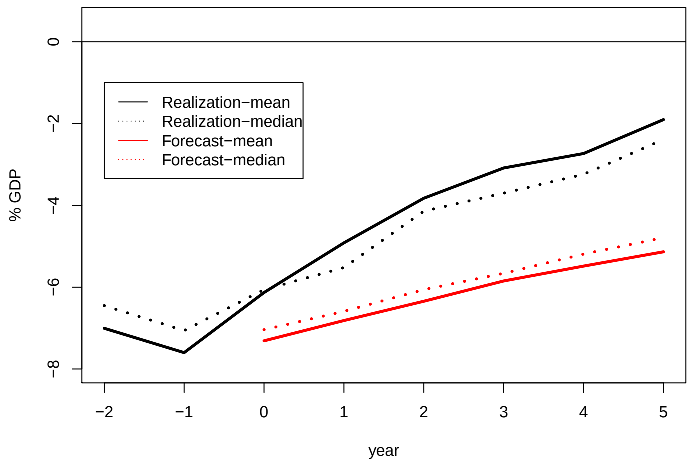

Figure 1: Current account balance conditional on large current account deficits.
Notes: Large current account deficits are identified in year 0 if the current account balance for year -1 is below percentile 10.

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. First, 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. This percentile, p_t^x, is computed using historic information on realizations.[8] 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 coun-

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

try 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: $fe^k_{ct} = \sum_{j=1}^{k} ca_{ct+j} - ca^t_{ct+j}$. Given these definitions, following Baron & Xiong (2017), the empirical model used to estimate conditional forecast errors is given by:

$$fe^k_{ct} = \alpha^k_x + \beta^k_x I_{(ca_{ct-1}<p^x_t)} + u_{ct} \tag{1}$$

Where $I_{(ca_{ct-1}<p^x_t)}$ is a dummy variable indicating large current account deficits and u_{ct} is an error term. This moles with a panel structure allows for the estimation of dually clusteres standard errors.

Table 2 reports the estimated values for the parameter of interest, β^k_x, 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 with 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 deficits are reversed is significantly faster than what forecasters anticipate.

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

		[1] $< p_t^{25}$	[2] $< p_t^{10}$	[3] $< p_t^{5}$
	$\hat{\beta}_x^k$	0.009**	0.013***	0.015***
k=1		[2.17]	[3.16]	[2.63]
	# obs. $< p_t^x$	292	123	64
	$\hat{\beta}_x^k$	0.036**	0.061***	0.090***
k=3		[1.97]	[3.33]	[3.32]
	# obs. $< p_t^x$	96	41	23
	$\hat{\beta}_x^k$	0.041	0.111**	0.097**
k=5		[0.99]	[2.67]	[2.05]
	# obs. $< p_t^x$	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 following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Beyond the systematic errors previously documented, additional insights can be gained considering alternative models that postulate 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, systematic errors following large current account surpluses could be evaluated. More precisely, is it the case that, as in the case of large current account deficits, forecasters attribute excessive persistence conditional on large current account surpluses?

Table 3 shows the estimated coefficients for models in which these alternative specifications are considered. The estimations are reported for the case of a threshold equal to percentile 10, $x = 10$, 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. As in the case of the original specification, the association is not linear. While the strength of this link is weaker, the multivariate regression points to information transmitted by more distant deficits 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]
$I_{(ca_{ct-1}<p_t^x)}$	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]	
$I_{ca_{c[t-11,t-2]}<p_t^x}$	-	-	-	0.024***	-
				[2.71]	
$ca_{c[t-11,t-2]}$	-	-	-	-0.054	-
				[-0.21]	
$I_{(ca_{ct-1}>p_t^{100-x})}$	-	-	-	-	0.014
					[0.73]

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. The estimated models correspond to parameter values x=10 and k=3.

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 indication of unexpected negative scenarios. This is because the information transmitted by current account deficits is not necessarily negative (Heymann 1994, Blanchard & Giavazzi 2002). In principle, unanticipated reversals of large deficits could be explained by unexpected favorable events such as improvements in terms of trade or gains in productive capacities. These developments would lead to a surprising reduction in the difference between the value expenditures by residents and the value of local production. For example, Arezki et al. (2017) show that the discovery of large oil reserves leads to current account deficits that are later reversed as investments mature. Inattention to these dynamics can lead to surprising reversals in current account deficits. Similar observations would apply in the case of unattended mean reversion in commodity prices (Schwartz 1997). In 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 analyzed. The multiplicity of indicators allows for 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. Complementing the analysis of surprises in growth performance, additional evidence is provided evaluating associations between large current account deficits and subsequent asset returns and innovations in sentiment 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 identified using the criteria used in the preliminary evaluation of current account balance forecasts of the previous section. GDP forecasts at the time of event identification are compared to the realized trajectory.

Figure 2 shows mean and median computations associated with 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 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 arrival of negative surprises regarding economic growth.

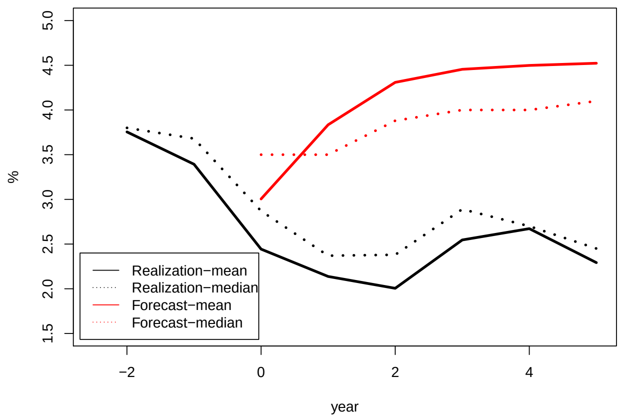

Figure 2: GDP growth conditional on large current account deficits.
Notes: Large current account deficits are identified in year 0 if the current account deficit for year -1 is below the 10th percentile.

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 the past distribution of current account balances. The growth forecast error for k-year-ahead forecasts is given by:

$$gfe_{ct}^{k} = \sum_{j=1}^{k} GDPgr_{ct+j} - GDPgr_{ct+j}^{t} \quad (2)$$

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

$$gfe_{ct}^{k} = \alpha_x^k + \beta_x^k I_{(ca_{ct-1} < p_t^x)} + u_{ct} \quad (3)$$

Table 4 reports the estimated values for the parameter of interest, β_x^k. In all cases, the estimated values are negative. In all but one case, the estimated parameters is significantly different from zero. These results indicate that large current account deficits are followed by smaller 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 to a reduciton of 4.2% in mean cumulative forecast errors.[9] In other words, after large current account deficits, surprises in GDP growth turn more negative. This evidence is consistent with neglected vulnerabilities. Negative surprises in GDP growth point to 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 deficits

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
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 following Thompson (2011). *, **, and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

[9] It must be noted that in addition to the reported conditional bias, the estimation of the model points to an unconditional overoptimism bias that, in the case of this specification, is slightly below 2%. This is consistent with previous findings in the literature. See for example Aromi (forthcoming).

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 associated to 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 (Elliot et al. 2005). The analyses will replicate the methodology used in the case of GDP growth forecasts. The only modification involves substituting the independent 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 $ret_{ct}^{k} = \sum_{s=1}^{k} r_{ct}$ with $k \in \{1, 3, 5\}$.

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 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 estimations corresponding to these alternative indicators. Panel A points to a negative association between large current account deficits and subsequent stock market returns. For a three-year-ahead horizon and percentile 10 threshold, instances of large current deficits are followed by cumulative returns that, on average, are 29.6% lower.[10] This association is also observed for different horizons and using alter-

[10]Under this specification, considering the estimated α, the mean cumulative return conditional on an

native thresholds to identify events.

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

		$< p_t^{25}$	$< p_t^{10}$	$< p_t^{5}$
A. Stock market returns				
k=1	$\hat{\beta}_x^k$	-0.060***	-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	-0.771***	-0.629
		[-1.36]	[-2.65]	[-0.86]

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.

Panel B in table 5 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,

event is -0.12. This mean value is hard to reconcile with any risk based explanation.

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. On average, large current account deficits are followed by the arrival of negative surprises or weaker assessments regarding economic prospects.

5 Extensions

In this section, three additional exercises are implemented. First, complementing the analysis of WEO growth forecasts, the performance of private consulting firms is evaluated. This exercise required the collection of private GDP growth forecast (mostly from Economist Intelligence Unit). Second, considering that the reported patterns could be explained by efficient learning dynamics, an out of sample exercise is carried out. This analysis sheds light on the extent to which the negative surprises could have been anticipated using historic information. A positive answer would point to the presence of systematic errors that are likely to persist. The exercise exploits a simple forecast model trained with data for the period 1969-1989. Finally, the third extension provides a more detailed characterization of the reported patterns. Information arrival following large current account deficits is analyzed distinguishing between different scenarios in which the events occurred. In this way, some evidence regarding unattended mechanisms is provided. In addition, these explorations serve as robustness tests of the previously reported results.

5.1 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 in the context of large current account deficits is valuable in the contexts of the current study.

Private forecasts were collected for a set events of large current account deficits. More specifically, forecasts associated to the events are 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.[11] After a time intensive search, the resulting database contains three-year-ahead forecasts associated to slightly more than 80% of the events.

Figure 3 provides a comparison of forecast errors associated to private forecasts and WEO forecasts. It is evident that both type of forecast display very similar properties and are strongly associated. Conditional on large current account deficits, in the case of private forecasts, the cumulative estimated mean error equals -0.065. For the matched sample, in the case of WEO forecasts, the estimated mean errors is -0.063. Additionally, the correlation coefficient for private and WEO forecast errors is 0.96. 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.

[11] In those few cases in which forecast from EIU where unavailable, forecasts were located searching other publications such as Far Eastern Economic Review and Oxford Analytica.

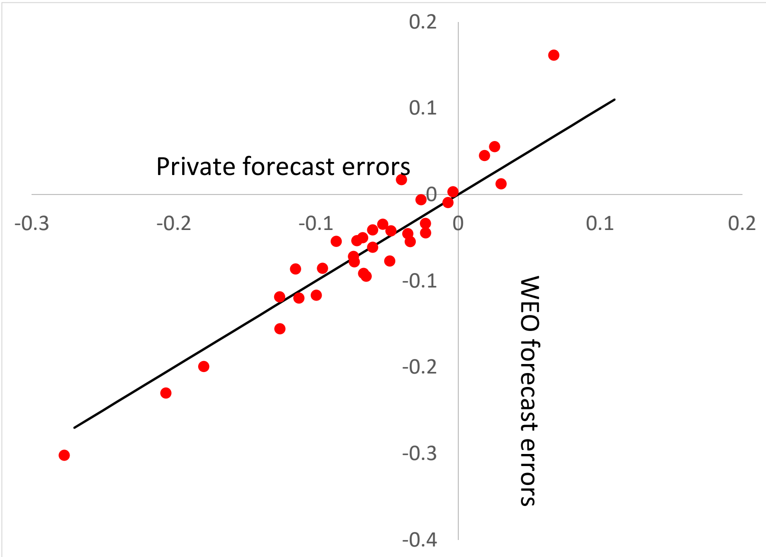

Figure 3: Growth forecast errors following Large Current Account Deficits

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

5.2 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 pasts forecasting practices, it also has implications regarding the information provided by incoming forecasts. Under inefficient forecasts, the documented systematic errors are likely to persist.

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:

$$g_{c[t,t+3]} = \alpha_0 + \alpha_1 g_{c[t-4,t-1]} + \alpha_2 g_{c[t-7,t-4]} + \beta I_{(ca_{ct-1}<p_t^{10})} + u_{ct} \tag{4}$$

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.[12] The fitted model is given by:

$$\hat{g}_{c[t,t+3]} = 0.056 + 0.096 g_{c[t-4,t-1]} + 0.291 g_{c[t-7,t-4]} - 0.041 I_{(ca_{ct-1} < p_t^{10})} \tag{5}$$

It is worth noting that the estimated coefficient of 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 evaluated computing mean forecast error, root mean squared error (RMSE) and mean absolute error (MAE). These indicators of forecast performance are also reported for WEO forecasts.

Table 6 shows that, conditioned on large current account deficits, there is a sharp contrast between the performance of WEO forecasts versus forecasts resulting from the trained model. The mean error of model forecasts is, in absolute value, 6% smaller than WEO mean forecast error. Additionally, according to the metrics of accuracy (RMSE and MAE), model forecasts perform better thatn expert forecasts. In contrast, in the absence of large current, the difference between mean forecast errors is smaller and WEO forecasts are slightly more accurate.

[12] While the training dataset covers information the period 1969-1989, the fitness of the model is assessed considering the accuracy of forecasts generated in years 1975-1986.

Table 6: **Performance of trained model vs WEO forecast**

	Trained Model	WEO
Large CA deficit		
Mean Forecast Error	-0.005	-0.066
RMSE	0.072	0.095
MAE	0.052	0.072
No large CA deficit		
Mean Forecast Error	-0.002	-0.019
RMSE	0.071	0.063
MAE	0.052	0.044

This exercise indicates that vulnerabilities associated with current account deficits could have been anticipated using historical information. Additionally, it suggests that the documented systematic errors cannot be explained in a satisfactory manner by learning dynamics under efficient use of available information. As a consequence, it is reasonable to conjecture that unattended vulnerabilities are likely to persist.

5.3 Exploring different types of episodes

As indicated in the introduction, assessing vulnerabilities associated to large current account deficits requires contemplating multiple aspects. The anomalies documented above could be the result of a similar level of inattention to multiple mechanisms through which vulnerabilities emerge. Alternatively, there might exist a particular subset of relevant mechanisms that are unattended. The identification of relevant mechanisms that are unattended is valuable from the perspective of forecasters, policymakers and, also, for the evaluation of the information content of expert opinions.

To advance the understanding of unattended channels, large current account deficits will be characterized according to likely exposure to particular mechanisms. A set of variables will be used to proxy for the relevance of different channels in different events. For example, the fiscal deficit will be used to proxy for vulnerabilities associated to deterioration in the government financial position. 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. Continuing with the previous example, if government finances constitute a key unattended mechanism, negative surprises should be particularly intense when large current account deficits are accompanied by large fiscal deficits.

Seven variables are used to proxy for exposure to risks associated to different channels. First, one aspect to be evaluated is persistence of large current account deficits. Persistence can be linked to gradual deterioration that, in the case of neglect, can lead to important negative surprises. The value of the current account deficit 4 years before event identification will be used as proxy for the activation of this channel. Second, the emergence of large current account deficits can be associated to an increment in expenditures in capital goods. As long as the productivity and profitability associated to these goods is unknown, the economy is exposed bad realizations of these variables (Heymann 1994). Increments in the investment ratio (from year $t-4$ though year $t-1$) is used to proxy for exposure to this type of risk.[13]

Risks associated to 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). Two indicators will be used to characterize different financial aspects. To proxy for exposure to risky expansions of the financial system, the rate of growth of domestic credit to the private sector, measured as a % of GDP, is incorporated to the set of variables (Kaminsky & Reinhart 1999).[14] Matching the forecast window size, cumulative growth is computed from year $t-4$ though year $t-1$. In a related perspective, it is noted that foreign direct investment is considered a preferable form of deficit financing. It is considered to be a more stable source of funds that limits the exposure to fluctuations in financial markets (Frankel & Rose 1996, Dell'Ariccia et al. 2008). To characterize the form in which the deficit is financed, the net flow of direct investment, as a percentage of the current account balance, is incorporated as a second indicator of financial conditions.[15]

Government deficits have been traditionally considered a factor of external crises

[13]Investment ratios correspond to those reported in the WEO database.
[14]The data on credit growth is from the World Development Indicators provided by the World Bank.
[15]The indicator is computed using data from IMF's Balance of Payment statistics.

(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.[16] Real exchange rate appreciations have also been linked to difficulties originating in the external front (Calvo et al. 1993, Ghosh et al. 2015, Ghosh et al. 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. Finally, countries with different level of development can be conjectured to be exposed to different risks or vulnerabilities. For example, differences in business cycle properties have been reported by Aguiar & Gopinath (2007). Also, the associated difference in the institutional environment can be thought to have an impact on deficit sustainability. Having these concerns in mind, per capital GDP is the final variable to be incorporated.[17]

The median values of the latest realization of the selected variables on event identification date are shown in table 7. 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 and associated to increments in the investment ratio and accelerations in credit growth. Also, large current account deficits are less frequent in the case of wealthier economies. There is no important differences between events and no-event in the case of budget deficits and real exchange rate appreciations.

[16]The information corresponds to that reported in the WEO database.
[17]GDP per capita statistics are from the Penn World Table.

Table 7: Median values of proxy variables

Condition	Event	No Event
Previous CA Balance (t-4)	-0.041	-0.002
Inv. ratio growth (t-4 vs t-1)	0.011	-0.003
Credit growth (t-4 vs t-1)	0.161	0.056
Net Dir.Inv. (% CA Balance)	0.281	-
GDP per capita	0.167	0.361
Gov. net lending/borrowing (% of GDP)	-0.024	-0.024
RER appreciation (t-4 vs t-1)	0.067	0.047

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.

To likely activation of a given mechanism, events are classified using the median of the corresponding variable as a threshold. Table 8 reports the mean value of the cumulative growth forecast errors for each of the resulting subsamples. A first inspection shows that negative surprises are a robust property. That is, mean forecast errors are lower than -3.6% in each of the 14 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 can only be ascertained in the case of investment ratio growth and credit growth. In the most prominent case, it is observed that while the mean growth forecast error is -0.036 when credit growth is below the median, it equals -0.089 for events in which credit growth is above the median. This association can be linked the literature on credit expansions and vulnerability neglect (Baron % Xiong 2017, Kindleberger 1978). While with a lower level of statistical significance, investment booms are also linked to more negative surprises. This association is compatible with disregard for uncertainty in the profitability of expenditures in capital goods.

While the differences are not statistically significant, more intense negative errors are observed for persistent deficits and for events accompanied by real exchange rate appreciations. In the case of government deficits, more negative surprises are observed in the case of smaller budget deficits. This association suggests that, in relative terms, the channel associated to budget balances is contemplated in the assessments of risks in contexts of large current account deficits. Finally, mean forecast errors are very similar when events are grouped considering wealth levels and net inflow of direct investment.

Table 8: Growth forecasts errors following Large Current Account Deficits

Condition	Below Median	Above Median	Difference
Previous CA Balance (t-4)	-0.064	-0.043	0.021
Inv. ratio growth (t-4 vs t-1)	-0.041	-0.066	-0.025*
Credit growth (t-4 vs t-1)	-0.036	-0.089	-0.053***
Net Dir.Inv. (% CA Balance)	-0.064	-0.053	0.011
GDP per capita	-0.053	-0.060	-0.007
Gov. net lending/borrowing (% of GDP)	-0.048	-0.073	-0.025
RER appreciation (t-4 vs t-1)	-0.042	-0.064	-0.021

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.

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. These systematic errors are compatible with neglected vulnerabilities. This interpretation is supported by a diverse set of indicators that establish a link between large current account deficits and the subsequent arrival of negative surprises. The evidence is documented for the case of GDP growth, stock returns and a sentiment metric. Additional analyses indicate that these regularities are not explained by efficient learning dynamics and are observed for a diverse set of events.

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. Complementary, 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:

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.

Aromi (forthcoming). Medium term forecasts: experts vs. simple models. International Journal of Forecasting.

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.

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.

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. 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.

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

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.

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.

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.

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

Sachs, J. D. (1981). The current account in the eacroeconomic adjustment process.

Schwartz, E. S. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. The journal of finance, 52(3), 923-973.

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.