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Media sentiment and international asset prices☆

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ABSTRACT

We investigate the relationship between media sentiment and international equity prices using a new dataset of 4 million news articles published between 1991 and 2015. Three key results emerge. First, news sentiment robustly predicts future daily returns around the world. However, we find a sharp contrast between the effect of local news and that of global news: whereas local news optimism (pessimism) predicts a small and transitory increase (decrease) in local equity returns, global news sentiment has a larger impact on returns that does not reverse in the short run. Second, news sentiment affects local prices mainly through the investment decisions of foreign—rather than local—investors. Third, large variations in global news sentiment predominantly happen in the absence of new information about fundamentals, suggesting that movements in global sentiment capture variations in investors sentiment. Taken together, our findings illustrate the key role played by foreign news and investors sentiment in driving local asset prices.

1. Introduction

This paper formally investigates the link between media sentiment and equity prices around the world, focusing on the following questions. First, does news sentiment predict international equity returns, and can we isolate the effect of foreign news from that of country-specific news? Second, what type of investors are reacting to news sentiment? Third, does news sentiment capture new information about economic fundamentals, or rather "animal spirits" fueled by journalists (Shiller (2015))?

Using 4 million Reuters articles published around the world between 1991 and 2015, we highlight three key results. First, in line with previous studies, we find that news tone—our measure of news sentiment—robustly predicts future daily returns both in

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advanced economies (AE) and in emerging markets (EM) even after controlling for known determinants of stock prices. However, not all news has the same impact. Changes in local (country-specific) news sentiment have a small and temporary impact on local equity returns that is reversed after a few days. By contrast, changes in global news sentiment have a much larger impact on equity returns around the world that is not reversed in the short run.

Second, by analyzing daily equity flows from international mutual funds between 2008 and 2015, we find an effect that is strikingly close to that of stock returns: although local news optimism attracts equity flows for a few days only, global sentiment optimism attracts them more permanently. This effect is entirely driven by the (net) asset demand from foreign funds domiciled outside of the country rather than local funds domiciled in the country, indicating that news tone predominantly affects local equity prices through the investment decisions of foreign investors.

Third, we find that large variations in global news sentiment typically happen in the absence of new information about fundamentals in core countries (e.g. the US, the Eurozone, or China). We also find that global news sentiment shocks have a stronger impact (i) in troubled times, when investors are more anxious, and (ii) on the allocation of international Exchange Traded Funds (ETFs), whose investors tend to pay little attention to the fundamentals of countries these funds ultimately invest in. Taken together, these results show strong empirical support for the existence of animal spirits shocks at a global level.

Our core empirical strategy relies on estimating the response of equity prices to sentiment shocks using Jordà (2005)'s local projection method. First, we construct news sentiment indices for 25 advanced and emerging countries at a daily frequency using using a bag-of-words method. We then quantify the effect of variations in US news sentiment on US equity returns, finding estimates similar to those obtained in previous studies (e.g. Tetlock (2007)). Next, we test whether these results extend to all countries, controlling for known sources of predictability in international equity returns both locally and globally. Overall, the magnitude of our panel estimates is close to the US benchmark: a one standard deviation increase in news sentiment is associated with an increase in equity returns of around 9 basis points that partially reverses after a few days, indicating that the effect of news sentiment on asset prices is a pervasive phenomenon that is not limited to the US.

To further investigate what drives this partial reversal, we then isolate the effect of local news from that of global news. We recompute the sentiment index of each country after excluding any article mentioning any other country, allowing us to capture the sentiment of purely local news. We also construct a global news sentiment index capturing the tone of news published in the world every day. While the effect of local sentiment shocks is still significant, its magnitude is roughly cut in half, peaking around 4.5 basis points before vanishing after a week. By contrast, global news sentiment shocks have a stronger impact on equity returns that does not reverse in the short run (i.e. at least 3 weeks). A one standard deviation increase in global news optimism (or pessimism) generates a permanent increase (decrease) of around 45 basis points that reaches its peak slowly after ten to fifteen days, both in AE and in EM alike. These findings are robust to a variety of tests and extensions: they remain stable over time and across countries, they are not driven by extreme values, crisis events or by having the US in our sample, and they are not sensitive to varying the bag-of-words model used to compute the sentiment index.

To uncover which type of investors drive these movements in equity prices, we then extend our analysis to international equity flows. Using data on daily flows from international equity mutual funds between 2008 and 2015, we explore how funds' allocations react to changes in local and global news sentiment. Overall, we find a very similar response to that of stock returns: although local news optimism attracts equity fund flows for a few days only, global optimism generates an inflow that peaks after three weeks. Using the official domicile of each fund as a proxy for its location, we also find that while foreign equity funds strongly respond to changes in news sentiment, the response from local funds is muted, suggesting that news tone affects prices mostly through foreign investors.

From a theoretical perspective, our results suggest that local news affect investors sentiment, leading to temporary variations in asset prices resulting from the investment decisions of either noise or liquidity traders (Long et al. (1990), Campbell et al. (1993)). We also find that such traders are more likely to be foreigners than locals. We also uncover evidence on the nature of global news sentiment shocks. In theory, the longer and more sustained response of equity prices to global news sentiment shocks could indicate that global news convey new information on fundamentals that is slowly incorporated into local asset prices (Veldkamp (2011)). Alternatively, the tone of global news could induce swings in investors sentiment—or so-called "animal spirits"—leading to movements in local asset prices occurring even though no new information on the state of the world economy has emerged (Shiller (2015)). Although distinguishing these two hypotheses is difficult, we present indirect evidence favoring the latter. First, while measures of macroeconomic surprises in major economies correlate with the global news sentiment, they only capture 19% of its total variance.[1] Furthermore, our results are robust to the inclusion of these surprise measures as controls in our estimations, suggesting that global investor sentiment rather than global news shocks about macroeconomic fundamentals drive our results. We also find that global news sentiment shocks have a stronger impact in troubled times when investors are more anxious: the impact of global news sentiment is four times stronger in global "bear" markets than in global "bull" markets (Garcia (2013)). Finally, we find that global news sentiment shocks have a stronger impact on investors who tend to be much less informed about fundamentals. More specifically, the investment response of Exchange Trade Funds (ETFs) to a change in global news sentiment is roughly three times as large as the response of active funds. Taken together, these results strengthen the view that the global sentiment shocks capture variations in investors sentiment that are are not arbitraged away in the short run (Shleifer and Vishny (1997)). They are silent, however, on why those shocks happen and matter empirically. Although theories based on a variety of frictions could account for the results we get, they are also consistent with rational expectations and a frictionless environment (Colacito et al. (2018)).

Given the large impact of global news sentiment shocks on international asset prices, we close the paper by investigating its properties in more details. First, we find that global news sentiment shocks explain a larger portion of the variance in

[1] Macroeconomic surprises are measured by the difference between actual data releases and the Bloomberg survey median.

international equity returns than those of the VIX. Although both indices capture the same spikes in risk aversion during times of high financial market stress, our index tracks a much broader set of events than the VIX, especially when it comes to periods of global market optimism. We also show that our key results are robust to introducing the Economic Policy Uncertainty index (EPU) in our estimation (Baker et al. (2016)), suggesting that changes in global news sentiment are not driven by variations in the uncertainty expressed in economic news. This finding holds also when we include our own news uncertainty index, built using our own set of news, in the estimation.

Our results contribute to two main branches of the literature. The first is the vast literature documenting the strength—and rise—of co-movements in asset prices and capital flows (Fratzscher (2012), Raddatz and Schmukler (2012), Jotikasthira et al. (2012), Ghosh et al. (2014), Broner et al. (2013), Rey, 2015, Puy (2016), Cerutti et al. (2019)). Our results on the long-lasting impact of global sentiments on flows and returns also relates our paper to the literature on the effect global growth news shocks on international portfolio reallocation and returns (Colacito et al. (2018)). Most of the debate has focused on the importance of global (or push) factors for (local) asset price movements, and on the role of foreign investors in propagating shocks across countries. A growing consensus has emerged on the importance of foreign factors rather than local ones in explaining asset price movements. Particular attention has been paid to the existence of a global financial cycle with a strong impact on asset prices in EM (Rey (2015)). Our results support this view, global news having a strong impact on local asset prices through international investors. However, we are the first to explore these questions using cross-country news data at such high frequency, allowing us to disentangle the effect of local news from that of global news, and bridging the gap between prices and quantities which are typically analysed separately. Local news sentiment can serve as a proxy for sudden changes in local conditions—or "pull" factors—that we find to be affecting both asset prices and flows, a result that is missing from studies only relying on macroeconomic proxies.[2] We also introduce a new index of global news sentiment that captures more events than the VIX, thereby offering a better proxy for "push" factors.

Our findings also relate to the growing body of research investigating the link between the news media, investors sentiment, and asset prices (Tetlock (2007), Garcia (2013), Manela and Moreira (2017), Calomiris and Mamaysky (2019)). We contribute to this literature in several ways. To our knowledge, we are the first to assess the link between news sentiment and high-frequency equity returns in a large sample of AE and EM using a large dataset of news articles. Until now, the literature had largely focused on the US using a relatively small sample of news. For instance, Garcia (2013) and Tetlock (2007) use one column in one newspaper per day to capture US news sentiment, representing roughly 30,000 and 3000 articles respectively. For the US only, we use 1.8 million articles. Our work also complements Calomiris and Mamaysky (2019), who assess the predictive power of (i) topic-specific sentiment, frequency, and unusualness (entropy) of word flow (ii) on monthly and one-year ahead stock market outcomes in 51 countries. In contrast, we focus on the very short run impact of news tone, exploring very different questions, i.e. the differential effect of local and global news and the channels through which news propagate. Going beyond the US and using media articles across countries allows us to estimate the relative contribution of local and foreign news to local equity returns for the first time. The use of a vast scope of news also extends previous contributions that have focused exclusively on financial news, complementing recent contributions showing the importance of policy news in driving asset prices (Baker et al. (2019)).

We are also the first to assess the effect of news sentiment on high frequency capital flows data, casting light on the speed at which flows respond to news. For instance, the protracted response of international equity flows in response to global news sentiment shocks is consistent with Albuquerque et al. (2005), who found that US investors build and unwind foreign equity positions gradually. Our results also shed light on the type of investors who are the most sensitive to sudden changes in news sentiment. The overreaction of ETFs complements recent findings showing how ETFs amplify the global financial cycle, especially in EM (Williams et al. (2018)). Finally, we are closely connected to the vast empirical literature that has focused on measuring investors sentiment and quantifying its effects on a variety of financial market outcomes (see Baker and Wurgler (2007) for a review). Our findings strengthen the view that the news media plays a key role in capturing investors' sentiment. We also provide new sentiment measures that are transparent, easy to replicate, and readily available for researchers and practitioners alike. The high frequency and large cross-sectional coverage of our measures make them particularly attractive for vast range of applications.[3]

Finally, from a technical perspective, we contribute to the recent and fast-growing literature that links textual information to both economic and financial outcomes (see Gentzkow et al. (2017) for a review). Among many others, Baker et al. (2016) develop an index of economic policy uncertainty from US newspaper articles, showing that it forecasts declines in investment, output, and employment. Using daily internet search volume from millions of households in the US, Da et al. (2014) find that the volume of queries related to economic issues (e.g. "recession," "unemployment," and "bankruptcy") can predict short-term return reversals, temporary increases in volatility, and mutual fund flows out of equity and into bond funds. Recently, Croce et al. (2020) use news diffused through Twitter to quantify the exposure of major financial markets to news shocks about global contagion risk accounting for local epidemic conditions. Among other things, they show how constructing news-based indices from Twitter accounts of major newspapers may be a free-of-any-charge alternative data source for future studies.

[2] For instance, the capital flows literature finds little to no role for local conditions—usually measured by domestic output growth—in affecting gross equity flows dynamics (see, among others, Forbes and Warnock (2012) or Cerutti et al. (2019) and references therein).

[3] Both country-specific and global news sentiment indices are available on the authors' websites. Although our analysis stops in 2015, that data is available until December 2019.

The rest of the paper is constructed as follows. Section 2 presents our data our news sentiment measures. Section 3 presents our empirical framework and our key findings. Section 4 provides further results on the properties of the global news sentiment index. Section 5 reports extensions and robustness checks. The last section concludes.

2. Data description

Our empirical analysis relying on three main data sources: (i) a dataset of news articles, (ii) a dataset of asset prices, trading volumes, and volatility measures, and (iii) a dataset of capital flows. We detail them in turn.

2.1. News articles and sentiment measures

2.1.1. News articles

Our dataset of news comes from Factiva.com. Each article is annotated with topics and geographic tags generated by Factiva using a proprietary algorithm. We focused on English articles published by Reuters between 1991 and 2015 and tagged with either "economic news" or "financial market news" as well as with one of the 25 countries in our sample—9 AE and 16 EM. Summary statistics of our news dataset are provided in Appendix Table A1. Overall, our dataset covers a wide range of economic topics (e.g. economic policy, government finance, etc.), financial topics (e.g. commodity markets, equity markets, forex, etc.), as well as corporate and political news (Appendix Fig. A1). The distribution of topics is similar in AE and in EM. On average, 201.4 US-related articles were published each day, representing 42% of our sample.[4] The distribution of articles across non-US countries is relatively balanced, averaging at 99,479 articles per country over the whole sample. For non-US countries, 13.8 articles were published each day on average.

2.1.2. News-sentiment measures

To measure news sentiment, we use a "bag-of-words" model, allowing us to reduce complex and multi-dimensional text data into a single number.[5] First, we combine existing lists of positive and negative words found in financial texts by Loughran and Mcdonald (2011) and in texts related to economic policy by Young and Soroka (2012). We then expand our lists by including the inflections of each word: for example, the word "lose" belongs to the negative list, hence we also include the words "losing", "loser", "lost", "loss", etc., leading to a final list of 7217 negative words and 3250 positive words. Table 1 shows the most frequent tonal words in our corpus.

Next, we define the sentiment of an article j as:

$$s_j = \frac{\sum_i w_{ij} p_{ij} - \sum_i w_{ij} n_{ij}}{\sum_i w_{ij} t_{ij}},$$

where p_{ij} is the number of occurrences of positive word i in article j, n_{ij} is the number of occurrences of negative word i in article j, t_{ij} is the number of occurrences of word i in article j, and w_{ij} is the weight associated with word i in article j. In our baseline estimates, we take $w_{ij} = 1$, allowing each word to contribute to the sentiment measure proportionally to its frequency of occurrence. In a robustness check, we let each word contribute to the sentiment measure proportionally to its "Term Frequency–Inverse Document Frequency" (TF-IDF, Manning et al. (2008)) by taking:

$$w_{ij} = \log\left(\frac{N}{N_i}\right),$$

where N is the number of articles in the corpus and N_i is the number of articles in which word i is present. Hence, this weighting smoothes out differences in word frequency naturally occurring in the English language by giving more weight to words that appear more rarely across documents.[6] Finally, we explore, in appendix and as a robustness, a version of our index where only negative words are counted. However, we emphasize at this stage that none of the key results depends on the way we define sentiment at the article level.

To illustrate our sentiment measure, we show the example of an article in which tonal words are highlighted in bold,[7] indicating that although our sentiment measure does not capture all of the nuances in the text, it provides a good indication of its overall tone:

[4] Note that an article can be tagged with multiple locations and topics. See the next section for an example and Appendix Figure 29 for details.

[5] See Gentzkow et al. (2017) for more details on the analysis of text data in the social sciences.

[6] It is well established that the distribution of words in the English language follows a power law. For a broader discussion on power laws in Economics, see Gabaix (2016).

[7] This article contains the tags "Argentina" and "Economic News".

Table 1
Most frequent positive (left) and negative (right) words. *Source:* Words lists come from Loughran and Mcdonald (2011) and Young and Soroka (2012). News articles come from Factiva.com.

Positive word	Fraction of positive words	Fraction of articles	IDF	Negative word	Fraction of negative words	Fraction of articles	IDF
Strong	0.107	0.118	2.135	Crisis	0.088	0.069	2.675
Gains	0.099	0.104	2.265	Losses	0.072	0.069	2.677
Well	0.082	0.103	2.271	Deficit	0.071	0.044	3.132
Good	0.065	0.077	2.561	Weak	0.070	0.070	2.656
Help	0.061	0.074	2.603	Limited	0.063	0.062	2.774
Recovery	0.056	0.058	2.850	Concerns	0.063	0.067	2.705
Highest	0.044	0.053	2.935	Decline	0.050	0.052	2.960
Agreement	0.043	0.042	3.179	Weaker	0.048	0.049	3.007
Assets	0.042	0.042	3.159	Poor	0.047	0.049	3.017
Positive	0.041	0.051	2.973	Unemployment	0.045	0.030	3.493
Better	0.041	0.053	2.932	Lost	0.045	0.048	3.034
Gained	0.041	0.049	3.007	Fears	0.041	0.045	3.109
Boost	0.040	0.054	2.914	Dropped	0.040	0.045	3.095
Leading	0.039	0.052	2.957	Slow	0.039	0.042	3.162
Confidence	0.036	0.039	3.255	Negative	0.039	0.040	3.225
Gain	0.035	0.042	3.159	Problems	0.037	0.039	3.233
Agreed	0.034	0.042	3.179	Worries	0.037	0.040	3.210
Stronger	0.032	0.042	3.172	Hard	0.036	0.039	3.234
Worth	0.032	0.039	3.239	Recession	0.035	0.032	3.457
Opening	0.032	0.041	3.199	Loss	0.033	0.032	3.441

Notes: This table presents the most frequent positive (negative) words in our corpus. For each panel, the first column reports the number of occurrences of each positive (negative) words relative to all occurrences of positive (negative) words, the second reports the fraction of articles in which the word appears, and the third column reports its inverse document frequency (IDF), which is defined below.

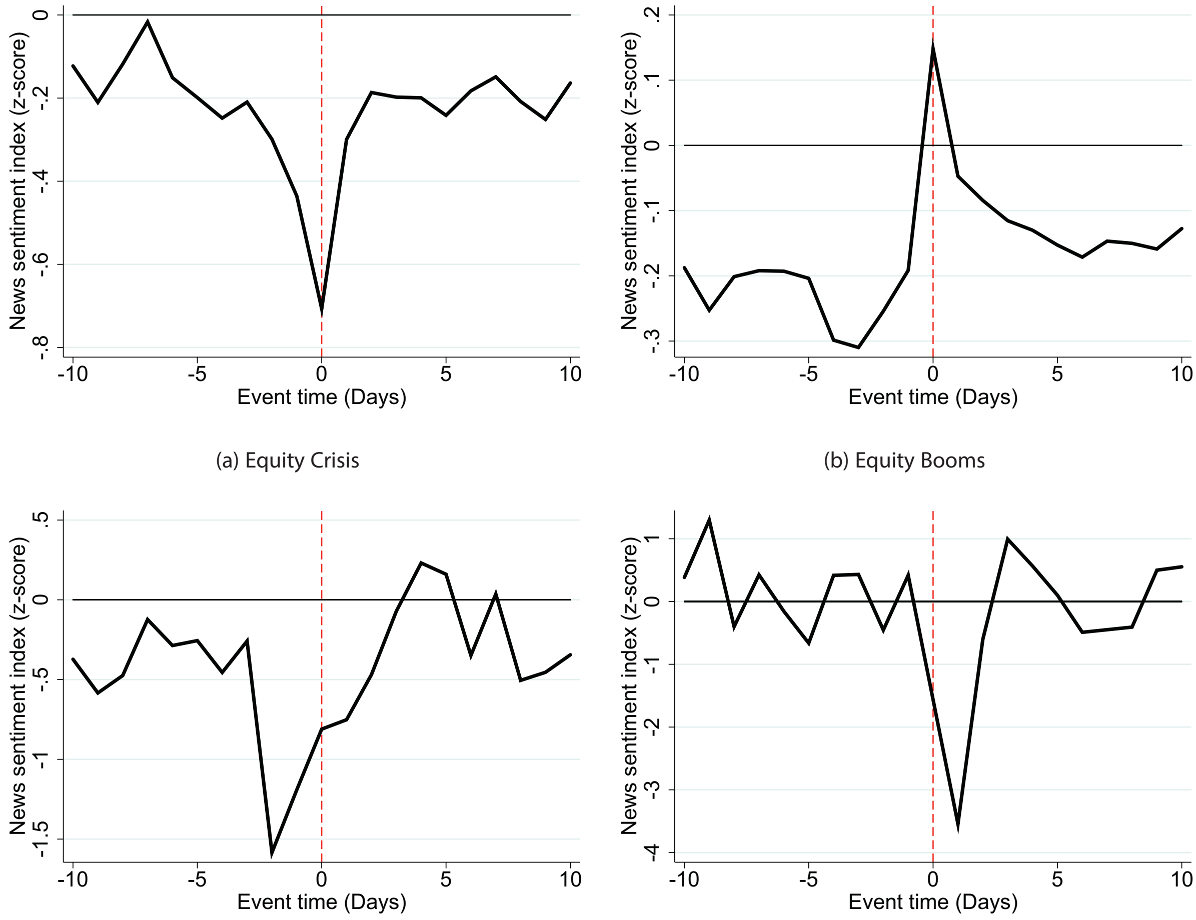
Title: Argentina's Peronists defend Menem's labor reforms.
Timestamp: 1996-09-02
Text: BUENOS AIRES, Sept 2 (Reuters)—The Argentine government Monday tried to counter **criticisms** of President Carlos Menem's proposals for more **flexible** labor laws, **arguing** that not just workers would contribute to new **unemployment** insurance. Menem **angered** trade unions, already in **disagreement** over his fiscal **austerity** programs, by announcing a labor reform package Friday including **suspending** collective wage deals and replacing **redundancy** payouts with **unemployment** insurance.
Topics: Labor/Personnel Issues, Corporate/Industrial News, Economic/Monetary Policy, Economic News, Political/General News, Labor Issues, Domestic Politics.
Locations: Argentina, Latin America, South America.

Next, we compute a daily sentiment index for each country by taking the average sentiment across articles that are tagged with the country's name. Finally, we normalize each country sentiment index by computing its z-score.

2.1.3. Sentiment indices—stylized facts

Table A4 in Appendix reports standard statistics about the cross country (raw) sentiment indices. Overall, we find that the the mean and the median of news indices are negative, reflecting the fact that our dictionary of tonal words contains more negative words. We also find very little difference in the properties of the indices across advanced and emerging markets, or among emerging markets. Unsurprisingly, we also find that the news sentiment index takes values that are, on average, higher in "good" times (See Fig. A10). The latter is true whether we define good times using real variables (e.g. when GDP growth is positive) or financial (strong equity market performance).

To give more intuition about the index, Fig. 1 also reports the behaviour of the news sentiment index around key economic and financial events. We first plot, in the upper panels, the daily news sentiment index around equity crisis (Panel A) and booms (Panel B); where we define crisis or booms as daily variations of the local equity index greater than 3 standard deviation (on either side). As expected, we find that news sentiment collapses (or improves drastically) around equity busts (booms). We also zoom in on specific events that occurred in advanced and emerging markets. Panel C reports the behaviour of the US sentiment index around September 15, 2018 when Lehman brothers filed for Chapter 11 bankruptcy, while Panel D reports the behaviour of the China sentiment index around June 13, 2015 when the China's stock market bubble popped. In both cases, we also find that the news sentiment index tracks closely those events and reacts as expected.



(a) Equity Crisis

(b) Equity Booms

(c) U.S. Lehman Brothers' Failure

(d) China Stock Market Crash

Fig. 1. Sentiment indices around key economic and financial events. *Notes:* This figure plots the behaviour of the sentiment index around selected events. In all panels, the sentiment index has been expressed as z-scores, in units of standard deviations away from the average within each country. The top two panels of this figure report the behaviour of the sentiment index around equity busts (Panel A) and booms (Panel B), where we define crisis or booms as daily variations of the local equity index greater than 3 standard deviation (on either side). Panel C reports the behaviour of the sentiment index for the U.S. around September 15, 2018 when Lehman brothers filed for Chapter 11 bankruptcy. Panel D reports the behaviour of the sentiment index for China around June 13, 2015 which began with the popping of China's stock market bubble.

2.2. Asset prices and related variables

Daily equity returns are computed using each country's main stock market index, and world equity returns are computed using the Dow Jones World Index. Summary statistics of the dataset used to compute equity returns are reported in the Appendix Table A3. To proxy for market liquidity, we also collect daily equity trading volumes reported by local stock exchanges. Following Campbell et al. (1993) and Tetlock (2007), we compute the de-trended daily log trading volume using a rolling average of the past 60 days to define the trend. Next, we compute stock market volatility by (i) de-meaning each daily stock return, (ii) taking the square of this residual, and (iii) subtracting the past 60-day moving average of the squared residuals. Finally, we use (i) the S&P Goldman Sachs Commodity index to measure daily percentage changes in commodity prices, and (ii) the CBOE VIX to proxy for global volatility.

2.3. Capital flows

Finally, we collected data on daily equity fund flows from EPFR Global, which contains information on the asset allocation of a large number of international equity funds at high frequency. As of 2013, EPFR contained information on more than 29,000 equity funds and 18,000 fixed-income funds, representing US$20 trillion of assets invested in over 80 AE and EM. Because of its extensive industry coverage and quality, EPFR Global has widely been used in recent academic contributions on funds behaviour (e.g., Raddatz and Schmukler (2012), Jotikasthira et al. (2012), Fratzscher (2012), and other references therein). The EPFR dataset has been found to be a reliable data source. Comparing TNAs (Total Net Assets) and monthly returns of a subsample of EPFR funds to CRSP mutual fund data, Jotikasthira et al. (2012) found only minor differences between the EPFR and the CRSP dataset. In policy circles, fund flows reported by EPFR have increasingly been used as a high-frequency proxy for foreign capital inflows especially in EM. Most funds followed by EPFR Global are (i) located in AE and (ii) account for a significant share of the external funding received by EM. As a result, the country flows dataset has proved to be a good proxy of total gross inflows in (or out) of EM. For instance, Pant and Miao (2012) showed that EPFR fund flows correlate well with BOP capital flows into EM. We focused on the "equity country flows" dataset, which reports the estimated daily amount of equity funding in US dollars that entered or left each country due to international funds' portfolio reallocation. Our dataset of equity flows covers 16 EM between 2008 and 2015.[8]

3. News, sentiment and equity returns

3.1. Empirical framework

Unless otherwise noted, we estimate the cumulative response of asset prices to daily sentiment shocks using Jordà (2005)'s local projection method. This choice is motivated by the uncertainty surrounding the timing, the strength, and the shape of the response of asset prices to news sentiment shocks in our sample spanning AE and EM over more than 25 years. In this context, it is desirable to use an estimation method that is more flexible and robust to misspecification than typical VARs. More specifically, we estimate the following model:

$$\begin{aligned} Cum_{R_{i,t,t+h}} = {} & \alpha_h + \mu_{i,h} + \sum_{j=1}^{J} \theta_j^h R_{i,t-j} + \sum_{j=1}^{J} \beta_j^h GoodNews_{i,t-j} + \sum_{j=1}^{J} \tau_j^h Art_{i,t-j} \\ & + \sum_{j=1}^{J} \gamma_j^h Vlm_{i,t-j} + \sum_{j=1}^{J} \delta_j^h Vol_{i,t-j} + \sum_{j=1}^{J} \rho_j^h Glob_{t-j} + D_{i,t}^h + \varepsilon_{i,h}^t, \end{aligned} \tag{1}$$

where $Cum_{Ri,t,t+h}$ is the cumulative equity return in country i between day t and $t+h$, $\mu_{i,h}$ is the country fixed effect, $R_{i,t}$ is the equity return, $GoodNews_{i,t}$ is the standardized news sentiment index, $Art_{i,t}$ is the article count, $Vlm_{i,t}$ is the de-trended log-trading volume, $Vol_{i,t}$ is a proxy for market volatility, $Glob_t$ are global controls—daily world equity returns, the VIX, and daily changes in key commodity prices—and $D_{i,t}$ is a set of outliers and day-of-the-week dummies. We estimate Eq. (1) using ordinary least squares and we only report the main coefficient of interest β_1^h (Fig. 2) for simplicity.[9]

Our model allows us to test whether news sentiment at time t can predict cumulative future returns after controlling for known sources of predictability for up to $j = 8$ days. Lagged returns control for market microstructure phenomena that can generate auto-correlation in observed daily returns (e.g. bid-ask bounce, nonsynchronous trading, and transactions costs). Trading volumes capture the effects of changes in market liquidity, and measures of market volatility account for the influence of other market frictions affecting prices in the short run. Finally, a vector of dummies ensures that our results are not driven by outliers (e.g. crisis) or predictable spikes in returns, which typically occur at the beginning or at the end of a week.[10]

Our specification deviates from Tetlock (2007) in several ways. First, we control for the number of articles published each day, allowing us to distinguish between the volume of news and their tone. Second, we include global proxies—global returns or yields, VIX and change in commodity prices—to capture global co-movements, ensuring that our sentiment index is not entirely capturing shocks that are known to affect asset prices around the world.[11] Third, we estimate the cumulative response of returns up to 20 days ahead as opposed to 5 trading days for Tetlock (2007).

3.2. Results—benchmark

To compare our results with the seminal work of Tetlock (2007), Fig. 2.a reports regression results for the US, using US news and US Dow Jones Industrial Index returns between 1991 and 2015.[12] Our estimation is based on 6016 observations against 4000

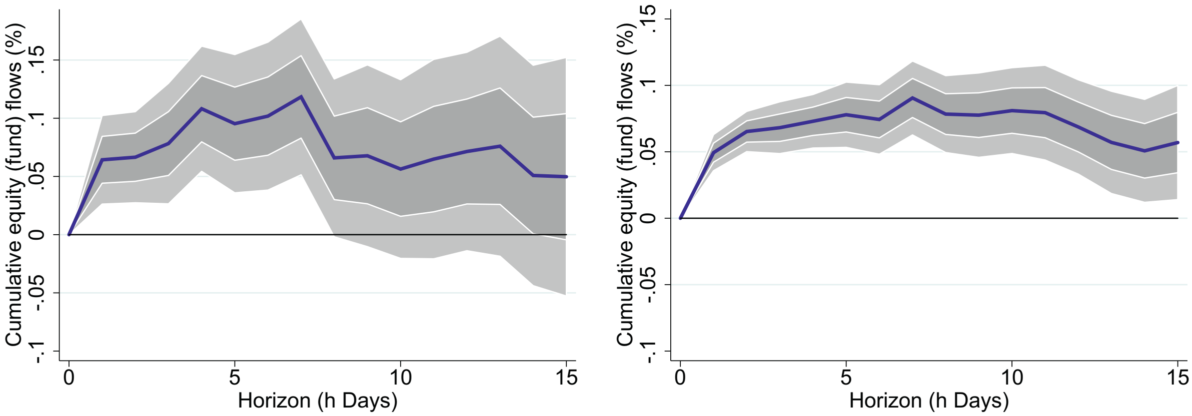
[8] We focus on EM for two reasons. First, the EPFR coverage is generally much higher for EM than for AE, so the correlation between EPFR equity flows and equity flows measured by the IMF Balance of Payments is higher for EM. Using the fund's domicile in the EPFR database to distinguish foreign vs. local funds is also more accurate when focusing on EM. A high number of funds investing in AE are domiciled in regional tax heavens (e.g. Luxembourg for European funds) which makes them technically foreign from the point of view of many AE, even though they are local funds. This problem is much less prevalent for EM.

[9] Since the error term in the local projection framework follows a moving average of order $h-1$, standard errors are always corrected for serial auto-correlation and heteroskedasticity. In addition, since the local projections suffer an efficiency loss that increases with the horizon h, we include the residual from the estimation at horizon $h-1$ in the regression at horizon h, as suggested by Jordà (2005). Adding the residual from the regression for horizon $h-1$ also addresses a potential bias identified in Teulings and Zubanov (2014).

[10] We control for outliers by introducing dummy variables equal to one if the cumulative equity returns for a given projection horizon is above (or below) six standard deviations away from the average for each country. We use outlier dummies to make sure that our results are not entirely driven by a few extreme events. However, our results are not sensitive to this assumption. In fact, all of our results are economically and statistically stronger when those dummies are not included. These results are available upon request.

[11] Similar to the use of outlier dummies, using global controls actually *weakens* our results. The size and statistical significance of all of the effects we estimate improves when taking these controls out.

[12] More specifically, we replicate Eq. (1) in Tetlock (2007).



(a) US Only

(b) Panel Full Sample

Fig. 2. Benchmark results—equity returns. *Notes:* The solid line shows the cumulative response of equity prices to a news sentiment shock h-days ahead estimated using Eq. (1). The x axis denotes the number of days after the shock. The dark and light shaded areas indicate the 90% and 95% confidence intervals, respectively. For Fig. 2a, standard errors are corrected for serial correlation and heteroskedasticity using the Newey and West estimator. For Fig. 2b, standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator. In both panels, the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

in the original paper. Interestingly, although our sample of news and our specification deviate from Tetlock (2007), we find very similar results. Good (bad) news—measured by a one standard deviation increase in sentiment—generate positive (negative) but transitory returns. The response peaks at 11.8 basis points and is not statistically different from zero after one calendar week. This is close to Tetlock (2007), who found that a one standard deviation increase in news pessimism generates a 8.1 basis points drop in Dow Jones returns the next day, before being completely reversed by the end of the trading week.

Fig. 2.b presents the results when we extend our estimation across countries. As specified in Eq. (1), we control for global events using the World Dow Jones Index returns, the VIX, and changes in commodity prices to control for global co-movements and typical shocks that affect returns around the world. Our estimation is based on 102,665 observations in a panel covering 25 countries. Interestingly, we find that the panel results are close to the US benchmark: a positive news sentiment shock leads to a positive and economically significant increase in equity returns with a peak at 9.1 basis points, indicating that the effect of news sentiment on asset prices is a pervasive phenomenon that is not limited to the US. However, although the magnitude of the impact at the peak is similar to that of the US, we do not observe a reversal anymore. We obtain a similar result when we remove the US from the sample, indicating that the presence of the US in the sample is not driving the results.

3.3. Global vs. local news sentiment

Two types of articles constitute our corpus: local news and multi-country news. Fig. A1 shows that about 58.0% of articles in our corpus (i.e. 2.5 million articles) consists of local news tagged with only one country and conveying country-specific information. A typical local article is the one discussing labor market laws in Argentina reported in Section 2[13] By contrast, the remaining 42% of our corpus contains articles discussing multiple countries. A typical multi-country article is one reported in Appendix Fig. A2 entitled "Fears of Brazilian devaluation hit emerging markets", which mentions multiple countries and their interrelations.[14] The presence of multi-country news mechanically increases the co-movement between our country-specific sentiment indices, suggesting that our previous estimates confound the impact of local and multi-country news.

To distinguish the sentiment conveyed in local news from that of multi-country news, we first re-compute the daily news sentiment index of each country by excluding any article mentioning any other country. This highly restrictive filter removes 1.8 million articles across countries (Appendix Fig. A1), allowing us to only focus on genuinely local (country-specific) news. Second, we extract a common factor ("global news sentiment") from our initial sentiment series using a Kalman filter. Formally, we estimate the following single (latent) factor model in the spirit of Stock and Watson (2016):

$$
\begin{aligned}
S_{i,t} &= P_i F_t + u_{i,t} \\
F_t &= A_1 F_{t-1} + A_2 F_{t-2} + \ldots + v_t \\
u_{i,t} &= C_1 u_{i,t-1} + C_2 u_{i,t-2} + \ldots + e_{i,t},
\end{aligned}
$$

[13] Other recent headlines that would qualify as purely local news are the following: "Inflation in Philippines a Faultline for Duterte's 'Build, Build, Build' Ambition" (05/31/2018); Socialist chief Pedro Sanchez set to become Spain's Prime minister" (05/31/2018); "Slovenia central bank forecasts steady growth despite global risks (10/22/2018)". Their content can be consulted online.

[14] Location tags include: Argentina, Asia, Brazil, Central America, Chile, Emerging Market Countries, Central/Eastern Europe, Europe, Indonesia, Latin America, Russia, South America, Southeast Asia, United Kingdom, CIS Countries, Western Europe.

where $S_{i,t}$ refers to the news sentiment index in country i on day t, F_t is the (unobserved) global news sentiment factor at time t, and P_i is the country-specific factor loading. In practice, we use an $AR(8)$ for the factor structure and estimate the model using Maximum Likelihood. We then include the global sentiment index in our regressions, allowing us to contrast the effect of local news from that of global news. Properties of the global news sentiment index are discussed in Section 4. More specifically, we estimate the following model:

$$\begin{aligned} Cum_{R_{i,t,t+h}} &= \alpha_h + \mu_{i,h} + \sum_{j=1}^{J}\theta_j^h R_{i,t-j} + \sum_{j=1}^{J}\gamma_j^h Vlm_{i,t-j} + \sum_{j=1}^{J}\delta_j^h Vol_{i,t-j} \\ &+ \sum_{j=1}^{J}\beta_{g,j}^h Global\_GoodNews_{i,t-j} + \sum_{j=1}^{J}\beta_{l,j}^h Local\_GoodNews_{i,t-j} \\ &+ \sum_{j=1}^{J}\tau_j^h Art_{i,t-j} + \sum_{j=1}^{J}\rho_j^h Glob_{t-j} + D_{i,t}^h + \varepsilon_{i,h}^t. \end{aligned} \tag{2}$$

Fig. 3 presents the results. Fig. 3.a reports results for the full sample of countries, whereas Fig. 3.c and d reports results for AE and EM respectively. Fig. 3.b reports results for all countries excluding the year between September 2008 and 2009, ensuring that our results are not driven by the Global Financial Crisis (GFC). As expected, we find that controlling for the global sentiment

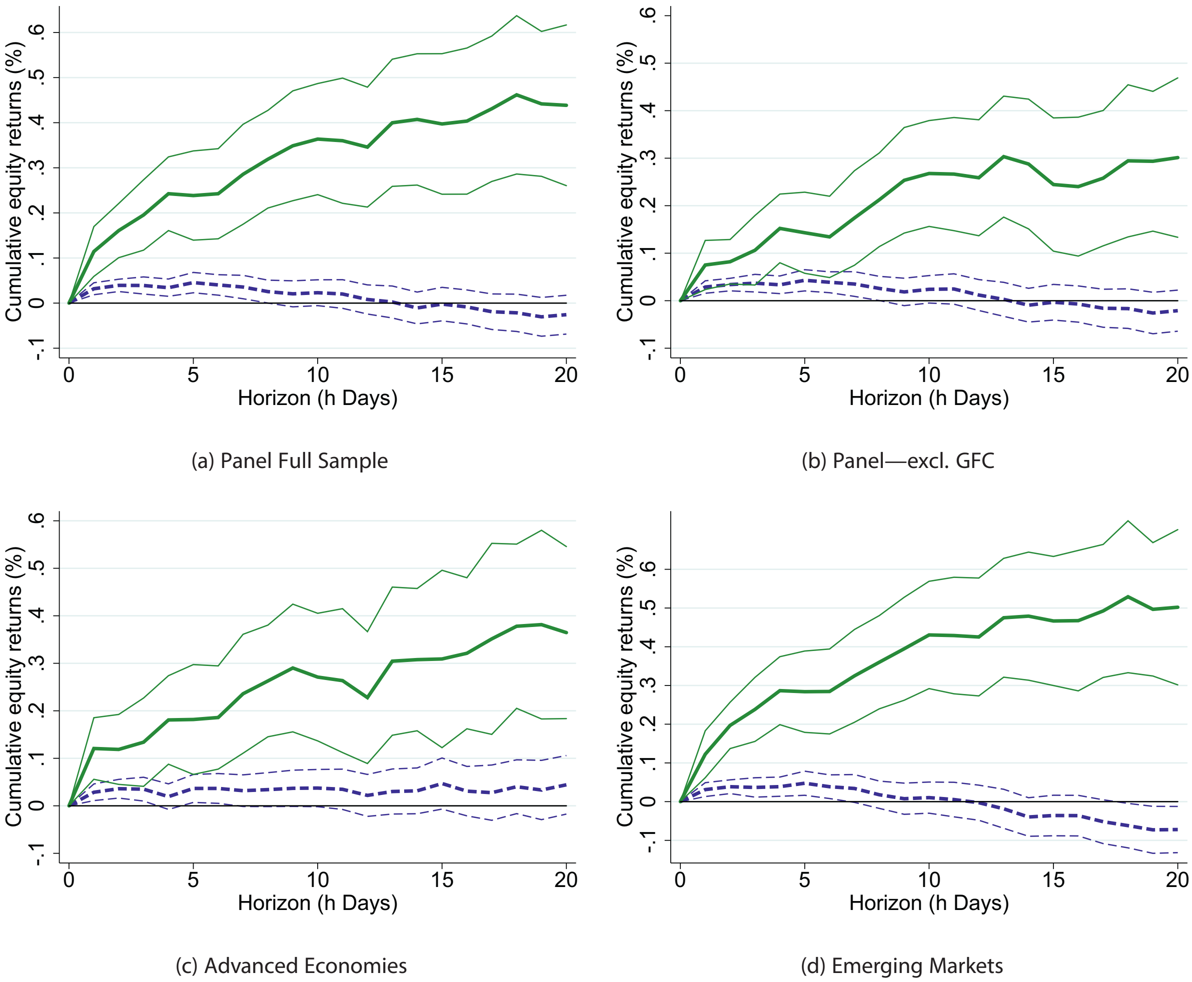


Fig. 3. Global vs. local sentiment shocks—equity returns. *Notes:* Each thick line shows the cumulative response of equity prices to a news sentiment shock h-days ahead estimated using Eq. (2). The x axis denotes the number of days after the shock. The dotted thick blue line reports the cumulative response of equity prices to local news sentiment shocks. The solid thick green line reports the cumulative response to global news sentiment shocks. The thinner lines around each thick line indicate the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

affects the size and the shape of the response to local news sentiment shocks, the cumulative response being roughly twice smaller (4.5 basis points, as opposed to 9.1 in the previous estimates). More importantly, while we did not see a full reversal after 15 days in the previous estimates, the gains now completely vanish after a week. Quantitatively, sentiment shocks are still economically significant however.[15] These results suggest that the tone of local news affects investors sentiment and equity prices momentarily before returning to their fundamental values, consistent with the presence of noise or liquidity traders (Long et al. (1990), Campbell et al. (1993)).

In sharp contrast, we find that global news sentiment shocks have a larger and more sustained impact on equity returns (Fig. 3), peaking at about 46.2 basis points—about 10 times larger than the response to local sentiment shocks—after 15 to 20 days. This result is only marginally affected by the exclusion of the GFC from our sample, with a peak around 30 basis points (i.e 6 times larger). The sustained impact on world stock markets could indicate that global news contain genuinely new information about fundamentals that is only slowly incorporated into stock prices around the world. However, an alternative explanation is that sudden changes in global news sentiment are strong enough to cause drifts in equity prices that do not reverse in the short run, even in the absence of new information about fundamentals. We explore these two hypotheses further in the next section.

3.4. News sentiment and capital flows

Next, we extend our empirical framework to capital flows data using daily equity flows from international mutual funds tracked by EPFR between 2008 and 2015 for 16 EM. More specifically, we now estimate the following model:

$$\begin{aligned} Cum_{F_{i,t,t+h}} = {} & \alpha_h + \mu_{i,h} + \sum_{j=1}^{J} \theta_j^h F_{i,t-j} + \sum_{j=1}^{J} \eta_j^h R_{i,t-j} + \sum_{j=1}^{J} \gamma_j^h Vlm_{i,t-j} + \sum_{j=1}^{J} \delta_j^h Vol_{i,t-j} \\ & + \sum_{j=1}^{J} \beta_{g,j}^h Global\_GoodNews_{i,t-j} + \sum_{j=1}^{J} \beta_{l,j}^h Local\_GoodNews_{i,t-j} \\ & + \sum_{j=1}^{J} \tau_j^h Art_{i,t-j} + \sum_{j=1}^{J} \rho_j^h Glob_{t-j} + D_{i,t}^h + \varepsilon_{i,h}^t. \end{aligned} \tag{3}$$

$Cum_{F_{i,t,t+h}}$ is the cumulative equity flow in country i between day t and $t+h$ (expressed in % of the initial allocation of capital at time $t-1$), $\mu_{i,h}$ is the country-fixed effect, $F_{i,t-j}$ is the lagged equity flow, $R_{i,t}$ is the lagged equity return, $Local\_GoodNews_{i,t}$ ($Global\_GoodNews_{i,t}$) is the standardized value of the local (global) news sentiment index, $Art_{i,t}$ is the article count, $Vlm_{i,t}$ is the de-trended log-trading volume, $Vol_{i,t}$ is our proxy for market volatility, $Glob_t$ are global controls—daily world equity returns, the VIX, changes in commodity prices, and daily returns in the MSCI EM index—and $D_{i,t}$ is a set of outliers and day-of-the-week dummies.

Fig. 4 reports our results. Overall, we find that the response of equity flows is strikingly similar to that of stock prices. Although local news optimism attracts equity fund flows, it does so only temporarily. We estimate a statistically significant cumulative increase peaking at 0.01%.[16] We also cannot reject a full reversal after two weeks at the 5% significance level. Furthermore, optimism in global news generate a larger and more sustained inflow in all EM in our sample, peaking at about 0.15% after 3 weeks (Fig. 4.a). This result is also robust to the exclusion of the GFC (Fig. 4.b).

By distinguishing between flows coming from local and from foreign investors, we find that these results are almost entirely driven by foreign investors, i.e. funds domiciled outside of the country (Fig. 4.c). For instance, we contrast the behaviour of funds investing in Argentina and domiciled in Argentina, with the behaviour of funds investing in Argentina but domiciled abroad. By contrast, the response of local equity investors is not significantly different from zero at 5% significance level, for all horizons and for both types of news sentiment shocks.[17]

4. Investigating the global news sentiment index

4.1. Comparison with other metrics

Prompted by having estimated such a large effect of global news sentiment shocks on equity prices, we now turn to investigating the properties of the global news sentiment index further. Fig. 5.a compares variations in global news sentiment and in the VIX. Not surprisingly, the two are negatively correlated (−0.27) and spikes in VIX are always matched by a significant and synchronized drop in global news sentiment, suggesting that both indices capture episode of heightened market stress. However, in many instances, movements in global sentiment are not matched by changes in the VIX. Good news, in particular, are not well captured by the VIX, which is a better proxy of global market turmoil than of global market optimism. This is confirmed when

[15] The median absolute deviation in our sample is about 5.5 basis points, both for AE and EM.

[16] Percentages are expressed as a ratio of Asset Under Management before the shock happens (at $t-1$). So a 0.01% increase in country c means that the equity fund industry tracked by EPFR, as a whole, increased its stock of equity assets in country c by 0.01%. This magnitude is economically significant since the average mean deviation of daily equity flows in our sample is around 0.01%.

[17] The amount of local funds in EM covered by EPFR significantly increased after 2010, allowing us to estimate their response more precisely. Using data from 2010 onwards reinforces our results: the response of foreign investors is unchanged, while the response of local investors becomes even flatter.

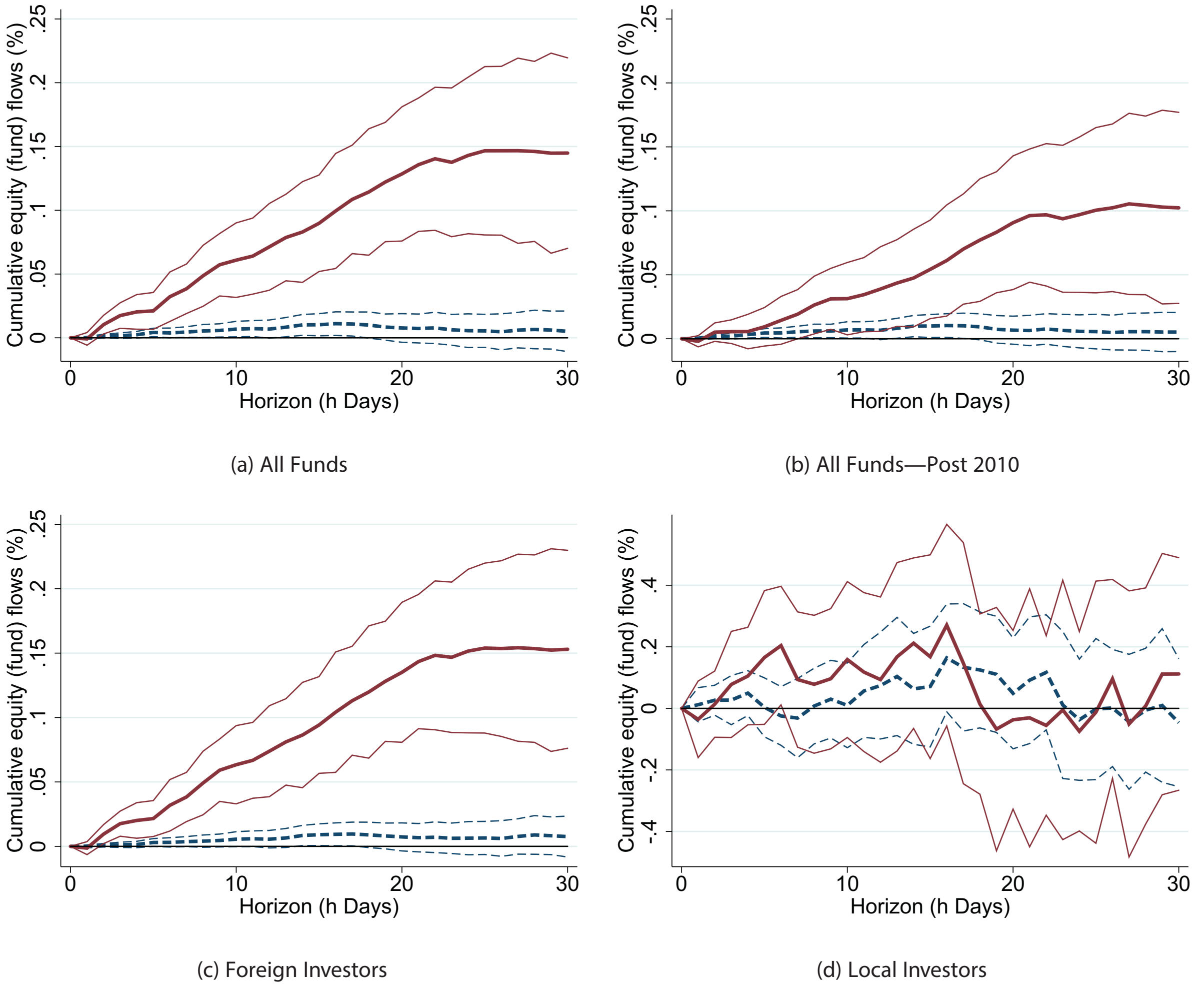
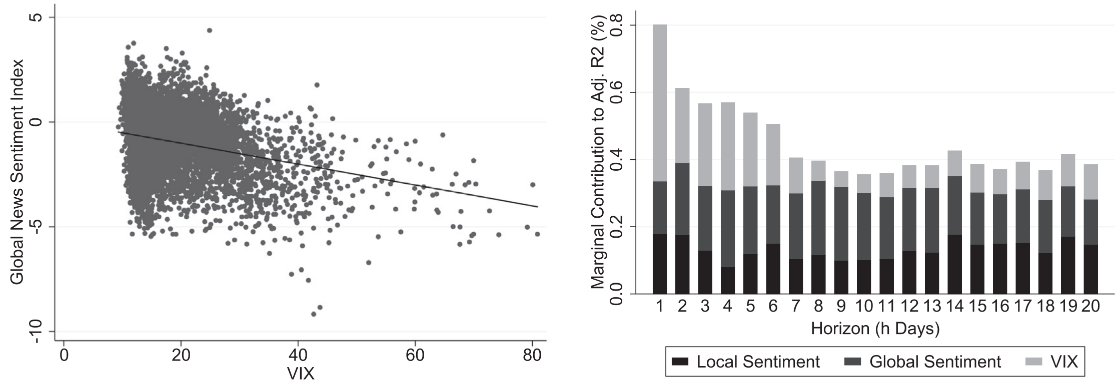


Fig. 4. Global vs. local sentiment shocks—equity flows. *Notes:* Each thick line shows the cumulative response of equity fund flows to a news sentiment shock *h*-days ahead estimated using Eq. (3). The *x* axis denotes the number of days after the shock. The dotted thick blue line shows the cumulative response of equity flows to local news sentiment shocks. The solid thick red line reports the cumulative response to global news sentiment shocks. The thin lines around each thick line represents the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011). Estimates are based on 19,555 observations.

looking at the difference in correlations between the VIX and the global news sentiment index in good and bad times. During global "bull" equity markets—defined as periods during which the global equity market is above its trend—the correlation between the VIX and the global sentiment index is close to zero. However it rises to −0.31 during global "bear" markets, i.e. when the global equity market drops below its trend.[18] Using Eq. (2), we also show that global news sentiment shocks account for a larger fraction of the variance in equity returns than VIX shocks at most horizons (Fig. 5.b.).

We also compare the global news sentiment to measures of uncertainty. First, we include the US Economic Policy Uncertainty Index (EPU) from Baker et al. (2016) as an additional control in Eq. (2). Appendix Fig. A5 shows that our results remain unchanged, suggesting that the effect we capture is not explained by the uncertainty about US policy reported in the news. Second, we show that the global news sentiment does not reflect the uncertainty expressed in the news more generally. To show this, we estimate a news uncertainty index by counting the fraction of uncertainty related words in each article. We then include our country-specific news uncertainty index in Eq. (2) as an additional control, finding that our results remain unchanged (Appendix Fig. A6).

[18] The trend is constructed using a two-sided HP filter with a smoothing parameter of 129,600, set using the Ravn and Uhlig (2002) rule for monthly data. Appendix Fig. A8 reports the actual period defined as global bear and bull markets, respectively.



(a) Correlation (b) Variance Decomposition

Fig. 5. Global News Sentiment vs. VIX. *Notes:* Panel A of this figure shows the global news sentiment index against the VIX; Panel B decomposes the increase in adjusted R-squared at different horizons after the introduction of the local news sentiment, the global news sentiment, and the VIX in Eq. (2) respectively. *h* denotes the number of days in the projection horizon.

4.2. Global news sentiment: fundamentals or sentiment?

Next, we aim to uncover the nature of global news sentiment shocks, exploring two competing hypotheses. The first hypothesis ("fundamental hypothesis") is that the global news index captures genuinely new information on the fundamentals of the economy that are slowly incorporated into equity prices (Veldkamp (2011)). Alternatively, the "sentiment hypothesis" suggests that the tone of news articles could induce swings in investors sentiment—or so-called "animal spirits"—leading to variations in asset prices, even though no new information on the state of the economy has come up (Shiller (2015)).

To test the "fundamental hypothesis", we use the Citigroup Economic Surprise Index (CESI), which captures deviations between actual macroeconomic data releases and the Bloomberg survey median in key countries. We regress our global news sentiment index on economic data surprises in the US, the Euro Area, China, and the G10 countries, which are available at daily frequency since 2003. Although they are all positively correlated with the global news sentiment index—i.e. higher sentiment implying data releases being better than expected—they only account for 19% of the variance in the global news sentiment (Table 2).

More importantly, Appendix Fig. A7 shows that our main results remain unaffected by introducing these economic surprise measures in our estimations, indicating that global news sentiment shocks do not simply capture new information on economic fundamentals. The fact that only 19% of the variance in global news sentiment is captured, per se, does not imply a lack of new information on fundamentals. This could simply be explained by measurement error in the global news sentiment index. If this was the case however, the result would disappear when introducing directly data surprises in the estimations.[19] This is not the case. Appendix Fig. A7 shows that our results on the impact of global news (magnitude and shape) remain unaffected when introducing economic surprise measures. An alternative story is that the data surprise indices we use actually miss some important information on fundamentals that are actually picked up by the global news index. However, this is rather implausible since it is based on the Bloomberg consensus forecasts covering the US, the Euro Area, China and the G10 countries.

Next, we assess the "sentiment hypothesis" using three approaches. First, under this hypothesis, one would expect the global news sentiment to have a disproportionate impact in periods during which investors sentiment is more volatile (Garcia (2013). Hence, we compare the effect of global news sentiment shocks on equity prices in global bull and in bear markets using Eq. (2). Bull (bear) markets are defined as periods during which the global equity market—measured by the Dow Jones World Index—is above (below) its trend. We find that the impact of global sentiment shocks are roughly four times stronger in global bear markets (Fig. 6.a), a magnitude very similar to that in Garcia (2013).

Second, one would also expect investors who are more sentiment-driven to overreact to global news sentiment shocks relative to those driven by "hard" information about fundamentals. Using the heterogeneity in mutual funds, we compare ETFs to non-ETFs (or active Funds), as investors in ETFs tend to be much less informed about the underlying fundamentals of the assets it contains (Fig. 6.a). We find that in response to a one standard deviation change in global news sentiment, ETF funds increase their position in by 0.2% across countries on average. In contrast, the response of active funds is between two and three times smaller. Although it is highly probable that both channels co-exist in practice, our results suggest that empirically (and historically) global sentiment shocks capture more often variations in investors sentiment that are not arbitraged away in the short run, rather than genuinely new information about global fundamentals.

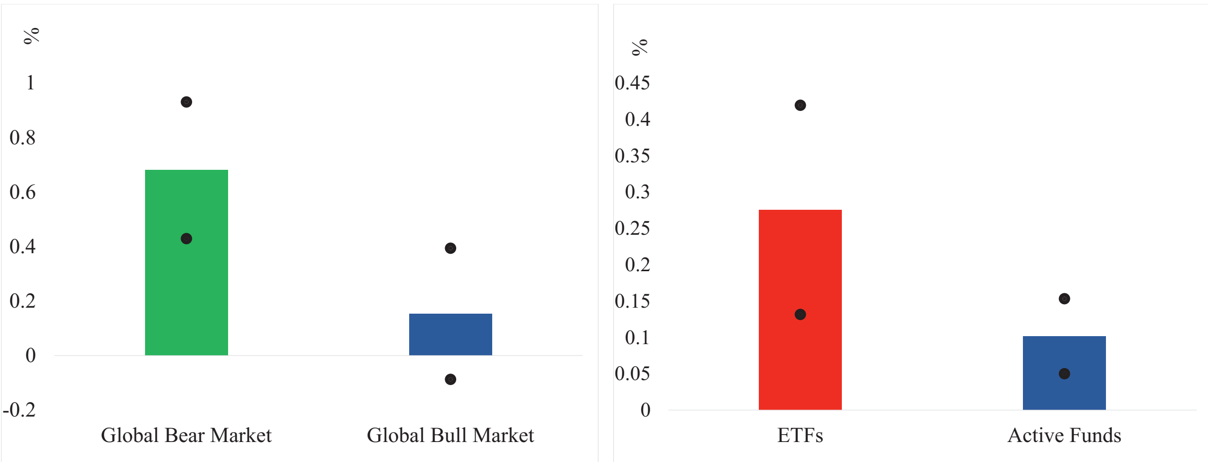
Third, we extend the model in Eq. (2) to analyse the impact of news sentiment on currencies. We use daily FX indexes for each country/currency as our left hand side variable (instead of equity returns). Each index is defined by the amount of a foreign

[19] If all the information on world macro fundamentals is correctly captured by data surprises, and there is no sentiment channels, then the global news sentiment index would only pick up noise and its impact on equity prices would disappear.

Table 2
Global news sentiment and economic surprises.

	Global news sentiment index				
	(1)	(2)	(3)	(4)	(5)
CESI_USD	0.006 ***				0.012 ***
	(0.001)				(0.002)
CESI_EUR		0.010 ***			0.018 ***
		(0.000)			(0.001)
CESI_CNY			0.007 ***		0.004 ***
			(0.000)		(0.000)
CESI_G10				0.017 ***	−0.026 ***
				(0.001)	(0.004)
N	3349	3348	3112	3349	3087
R^2	0.03	0.13	0.05	0.10	0.19

Notes: The Citigroup Economic Surprise Indices (CESI) are defined as the weighted historical standard deviations of data surprises (actual releases vs. Bloomberg survey median). A positive reading implies that economic releases have, on average, beaten the Bloomberg consensus. *CESI_USD*, *CESI_EUR*, *CESI_CNY*, *CESI_G10* refer to macroeconomic data surprises captured by the US, Europe, China and G10 indexes, respectively. Robust standard errors are in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.



(a) Global News Sentiment Impact (Equity Prices)

(b) Global News Sentiment Impact (Funds' Allocation)

Fig. 6. Fundamentals vs. sentiment hypothesis. *Notes:* The left panel compares the cumulative effect of global news sentiment shocks on equity prices in global bear vs. global bull markets. The effect is reported at its peak (i.e. after $h = 20$ days). The trend is constructed using a two-sided HP filter with a smoothing parameter of 129,600, set using the Ravn and Uhlig (2002) rule for monthly data. Results are based on Eq. (2). The right panel compares the impact of a global news sentiment shocks on ETFs vs. Non-ETFs (or active) funds' allocation at the peak of the projection horizon (i.e. after $h = 20$ days). Percentages are expressed as a ratio of Asset Under Management before the shock happens (i.e. at $t - 1$). Results are derived using Eq. (3). In both cases, dots indicate the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

currency X necessary to purchase one US dollar, implying that when the index goes down, the currency appreciates against the dollar. Data on daily FX indexes are taken from the BIS. Fig. A11, in appendix, reproduces Fig. 3, but using results from the FX model. Panel A shows the effect of a (positive) shock to global news sentiment on all currencies in our sample. Panel B does the same after excluding the GFC period. Panel C restricts attention to reserve currencies (Yen, Pound, Euro), while Panel D shows the response of non-reserve currencies only (EM currencies).

Results using currencies generally corroborate our main findings on equities, both qualitatively and quantitatively. Panel A shows that all currencies tend to appreciate against the dollar when global sentiment improves, and that the effect does not reverse in the short run, which is consistent with our findings on equity returns. This finding persists even after removing the GFC period from our sample. We also find that this effect is mainly driven by EM currencies. When global sentiment improves (deteriorates), all EM currencies strongly appreciate (depreciate) against the dollar – i.e. FX index goes down (up) – see Panel D. This result mirrors precisely the strong impact of global news sentiment shocks on capital flows to emerging markets that we identify in Section 3.4 It also confirms our interpretation of the global news sentiment shock, i.e. that bullish (bearish) global sentiment

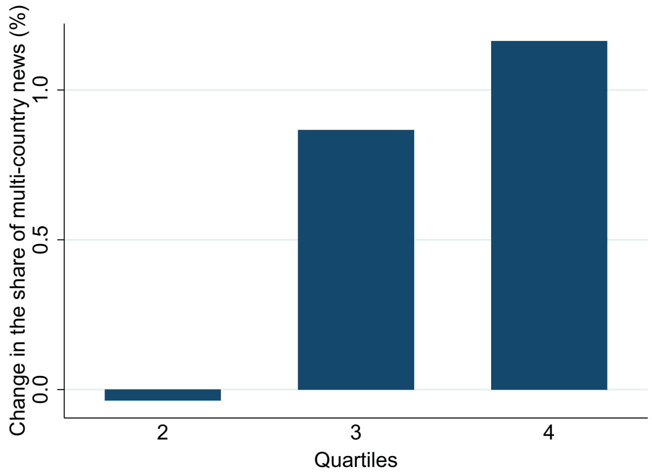


Fig. 7. Multi-country news and global news sentiment. *Notes:* This figure shows the change in the share of multi-country news as a function of the absolute value of the global news sentiment (reported by quartile). The share of multi-country news increases when the global news sentiment takes more extreme values.

captures an improvement (deterioration) in global investors' risk appetite, generating capital inflows to (outflows from) EMs and driving up (down) EM currencies.

The lack of diversification when it comes to the response of both flows, prices and currencies to global news sentiment across emerging markets, is striking. Assuming new information about global fundamentals comes, one would expect different markets to respond differently. The large sample of EMs we cover include countries that vary extensively in size, fiscal position, monetary policy or trade exposure. Still global news shock seem to affect all of them in a very uniform way. This undifferentiated response is much more consistent with waves of market optimism/pessimism with little regard to fundamentals.

4.3. News coverage

We close the paper by documenting some stylized facts about which type of article constitute the global news sentiment. As expected, the global news sentiment is mainly driven by multi-country news. Fig. 7 shows that the share of multi-country news increases significantly when the global news sentiment takes more extreme values. Interestingly, we also find that multi-country news are different from local news: they tend to be longer, broader in scope, and more tonal than local news. They are also about twice as long, covering about 50% more topics and using almost three times as many tonal words than their local counterparts. They also make use of more rare words than local news.[20]

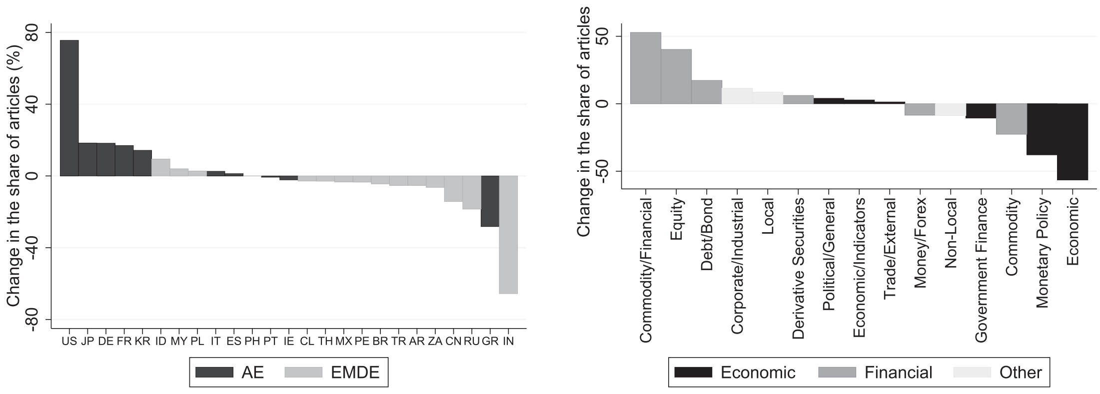
Importantly, we emphasize that global news or multi country news can reflect events that, in essence, are country-specific. However, since those events have important implications for the rest of the world, they end up being tagged on multiple countries and ultimately affect global news sentiment. For instance, events such as a the 9/11 terrorist attack in the US, or rumors of default in Argentina during the 2001 financial crisis, are technically country-specific. However, their vast implications for the rest of the world will be reflected in news in other countries, generating contagion in news sentiment. Empirically, this implies that this kind of events/news will be absorbed by our global news index, and will therefore not be attributed to the local news sentiment index. In other words, the local news index moves only with country-specific news that do not have any impact on other countries. Such local news are typically “small news” that are much narrower in scope, of shorter length, and much less tonal.

We also find that the distribution of news topics varies with the level of the global news sentiment index. When the global news sentiment index is strongly positive, the corpus of news tilts towards positive financial and corporate news in advanced AE, especially in the US—with the notable exception of news focusing on Greece, which are over-represented in periods of low global news sentiment. In contrast, the coverage strongly tilts towards economic and political news in EM when the global news sentiment index goes into negative territory (Fig. 8b).

5. Additional robustness tests

Overall, our findings are robust to a variety of tests and extensions. First, they are stable over time and across countries (AE and EM), suggesting that our estimates are not driven by a single episode or by any distinct group of countries. Owing to the rapid rise in international financial integration, recent research has pointed to a general increase in global financial synchronization over the past two decades (e.g. Bruno and Shin (2014), Obstfeld (2015), Jordà et al. (2019)). Other important contributions

[20] These effects hold after controlling for the length of each article. Regression results are available upon request.



(a) Locations

(b) Topics

Fig. 8. Global news sentiment and news coverage. *Notes:* This figure compares the change in news coverage during periods of high global news sentiment relative to periods of low global news sentiment. Panel A reports the change in each country's share of articles during periods of high global news sentiment relative to the country's share of articles over the entire sample. Panel B reports the change in each topic's share of articles during periods of high global news sentiment relative to the topic's share of articles over the entire sample.

have also emphasized the high sensitivity of EM to the global financial cycle, at least compared to AE (e.g. Rey (2015), Cerutti et al. (2019)).

Although we find that global news sentiment has a stronger impact than local news sentiment, we do not find evidence that the effect of global news is significantly stronger now than in the 90's, or that it affects more EM than AE (Appendix Fig. A4). We find however that the response of local asset prices to global news sentiment shocks is more precisely estimated in the most recent part of the sample, i.e. after 2007. The presence of the GFC in that sub-sample could easily explain the homogeneous response we get compared to the earlier part of the sample. Alternatively, the vast changes observed in international financial market integration over the last 30 years could also account for that fact. In particular, equity markets' integration was (i) more limited, on average and (ii) much more heterogeneous, in the 90's than it was over the last 10 years. Finally, the coverage of our dataset of news was less extensive in the 1990s. One would therefore expect stronger and more homogeneous effects of global shocks in the most recent part of the sample.

Finally, our results are also not driven by extreme values or crisis – such as the GFC, or by key countries—such as the US. They are also robust to an alternative specification on the news sentiment index in which each word is weighted by its TF-IDF (Appendix Fig. A3). Finally, all our key results are robust to using different clustering techniques for the standard errors. To illustrate this, Fig. A9 re-estimates Fig. 3.a and b using both Driscoll and Kraay (1998) and double-clustered standard errors (by country and time). Overall, our results are unchanged.

6. Conclusion

Using a new dataset of news articles focusing on 25 countries, we explore the link between between the news media, investors sentiment, and stock returns around the world between 1991 and 2015. Taken together, our results show that news sentiment has a pervasive impact on short-term equity prices and equity flows around the world. We uncover a novel key difference between the effect of local news sentiment from that of global news sentiment. While local news sentiment have only a small and transitory impact, global news have a larger and more protracted effect. We demonstrate that the effect of global news sentiment is not driven by macroeconomic surprises. Our results also cast light on the role of foreign investors in transmitting sentiment shocks, and in particular that of passive uniformed investors (ETFs). The potentially large implications of our results for models of international asset prices and international capital flows are left to further research.

Declaration of Competing Interest

None.

Appendix A. Appendix

A.1. Stylized facts

Table A1
Country and time coverage.

Country	AE/EM	News Start	News End	# Articles	Average per day
United States	AE	1/1/1991	12/31/2015	1,815,542	201.41
France	AE	1/2/1991	12/31/2015	139,927	17.31
Germany	AE	1/2/1991	12/31/2015	229,059	26.24
Italy	AE	1/2/1991	12/30/2015	87,530	11.33
Japan	AE	1/1/1991	12/30/2015	274,804	31.66
Greece	AE	1/9/1991	12/31/2015	60,824	9.10
Ireland	AE	1/7/1991	12/30/2015	28,194	4.76
Portugal	AE	1/3/1991	12/29/2015	32,162	5.45
Spain	AE	1/2/1991	12/30/2015	56,418	7.86
Turkey	EM	1/2/1991	12/31/2015	46,728	6.58
South Africa	EM	1/2/1991	12/31/2015	77,318	10.54
Argentina	EM	1/2/1991	12/31/2015	51,287	7.12
Brazil	EM	1/2/1991	12/31/2015	87,488	11.69
Chile	EM	1/8/1991	12/28/2015	24,095	3.70
Mexico	EM	1/2/1991	12/31/2015	69,558	9.26
Peru	EM	1/3/1991	12/31/2015	17,348	2.97
India	EM	1/2/1991	12/31/2015	356,683	40.34
Indonesia	EM	1/2/1991	12/31/2015	87,550	10.98
Korea	EM	1/3/1991	12/31/2015	100,153	11.91
Malaysia	EM	1/2/1991	12/30/2015	99,394	12.26
Philippines	EM	1/2/1991	12/30/2015	55,460	7.08
Thailand	EM	1/2/1991	12/29/2015	82,555	10.44
Russia	EM	12/30/1991	12/31/2015	111,540	14.81
China	EM	1/2/1991	12/31/2015	245,913	27.69
Poland	EM	1/1/1991	12/30/2015	64,998	9.29
Non-US	AE/EM	1/1/1991	12/31/2015	2,486,986	13.79
Total	AE/EM	1/1/1991	12/31/2015	4,302,528	22.72

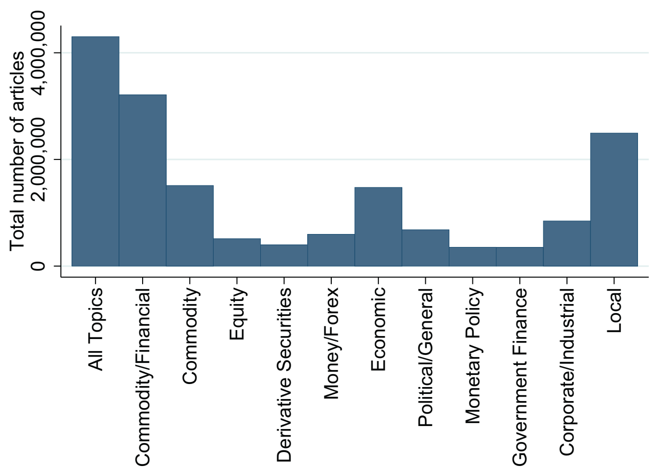


Fig. A1. Main topics covered—all countries. *Notes:* This figure reports the most frequent topics tagged in our corpus of news articles. A very similar distribution of topics is observed across AE and EM. “Commodity/Financial Markets” news and “Economics News” are used as primary tags, so they will automatically be used when one of their sub-tag is used (Table A2 below). Note that tags do not represent a partition of our sample of articles since articles can be tagged across several categories at the same time (see example in Section 2).

Table A2
Sub-tags under each primary tag.

Commodity & financial markets news	Economic news
Commodity markets	Economic & Monetary Policy
Equity Markets	Government Finance
Money and Forex	Economic Performance
Derivative Securities	Trade and External Payments

Title: Fears of Brazilian devaluation hit emerging markets

Timestamp: 1998-09-11

Text: LONDON, Sept 11 (Reuters)—Emerging market currencies braced for further knocks on Friday amid fears that Brazil might give in to devaluation pressure and unleash a fresh onslaught around the globe. The rouble continued to gain ground in thin trade amid hopes of an imminent end to Russia's political deadlock. But the Hungarian forint and Polish zloty slid on global bearishness after Thursday's huge stock market falls in Latin America.
Most Asian currencies held steady, helped by the firmer yen as the dollar sagged on President Bill Clinton's political woes and speculation about an impending U.S. interest rate cut. The Indonesian rupiah rebounded from Thursday's sharp fall. With the market discounting the near-certainty that Russia's parliament would approve Yevgeny Primakov as prime minister later on Friday, attention focused mainly on whether Brazilian markets would see another hammering after Thursday's collapse. "It's like a tidal wave waiting offshore, and everybody's hoping it'll go in the other direction. If it hits Rio it'll hit everywhere else," said Nigel Rendell, an emerging markets strategist at Santander Investment Bank in London. A huge exodus of dollars on Thursday from Brazil's foreign exchange markets, estimated at over $2 billion, panicked the key Sao Paulo stock market into a plunge of nearly 16 percent, its biggest one-day drop for nearly 11 years. The rout sparked similar slides across the region and fed general fears of a world economic slowdown, prompting steep market falls in Japan and Hong Kong early on Friday. Latin American currencies are little traded in London, and analysts said the market was waiting for direction from Wall Street's opening and the start of New York currency trade. As an early indication of sentiment, the region's most liquid unit, the Mexican peso, lost further ground from New York's closing levels. By 1215 GMT it was 10.65 bid to the dollar, just off Thursday's historic low of 10.685. Brazil, heavily dependent on capital inflows to support a pronounced short- term debt burden, has come under particular pressure from the flight investment capital from emerging markets. The central bank hiked its key interest rate overnight by 20 points to nearly 50 percent to try to halt the massive outflows. Analysts say it is touch and go whether Brazil will devalue the real before presidential elections on October 4, although officials have repeatedly denied devaluation is on the cards. "It does think it is likely. The only question is whether it will come before or after the election," said David Boren, an emerging market strategist at Daiwa Europe in London. Analysts say Brazil still has enough reserves—now around $50 billion—to continue propping up the real but delaying what many see as the inevitable may leave the country financially depleted and less able to engineer an orderly devaluation in uncertain global market conditions. If Brazil devalues, it will almost certainly spark a fresh wave of pressure on emerging market currencies worldwide. Analysts said Argentina would be among the first in line, although the country had sufficient reserves in relation to its money supply to defend its currency board system. "With market focus on possible devaluations in Latam, China's currency stance may again come under market scrutiny," Standard Chartered Bank said on Friday in a note to clients. China has vowed not to devalue, and news on Thursday of a 23 percent rise in the country's trade surplus in the first eight months of the year eased selling pressure on the yuan to the extent that the central bank was spotted buying dollars. Analysts said Hong Kong's currency board would also come under more pressure if the real fell. Other potential victims included South Africa and even the stronger Central European countries such as Poland and Hungary, possibly forcing Budapest to widen its 4.5 percent wide trading band for the forint. The forint was glued with to the bottom of its target band on Friday. The zloty also swung sharply lower and was was quoted only 1.31/1.03 percent above its target basket parity at 1215 GMT, compared with Thursday's fixing of 3.97 percent above parity. The rouble firmed to around 10.5 bid to the dollar from late Thursday levels of 12.5, buoyed partly by hopes of some political stability. But volume remained very thin, and analysts said the rally was unlikely to last

Fig. A2. Global news—an example.

as the new government looked set to print money to clear wage and pension arrears.
FOREX MARKET SNAPSHOT. The following is a snapshot of emerging markets currency rates. * ASIA AFX=) * Chinese yuan CNY=) at 8.279 vs 8.2798 on Thursday * New Taiwanese dollar TWD=) 34.47 vs 34.4 * Indonesian rupiah IDR=) 11,600 vs 11,900 * Thai baht THB=TH) at 40.65 per dollar vs 40.7 * Philippine peso PHP=) 43.4 per dollar vs 43.6 * South Korean won KRW=) at 1,365 per dollar vs 1,367 * Indian rupee INR=) 42.41 per dollar vs 42.4 * EUROPE EUROPEFX= * Russian rouble RUB=) on MICEX Selt electronic trading system at 10.51/13.15 per dollar vs average rate of 12.375 on Thursday. EMTA indicative rate at 11.238. * Zloty 1.31 percent above target basket parity vs 3.97 percent at Thursday's fixing. * Mark/Czech crown DEMCZK=) at 18.03 bid vs 17.838 * Hungarian forint DEMHUF=) unchanged from Thursday at 2.25 percent below parity against a target basket * Slovak crown DEMSKK=) fixed at 5.35 percent below target basket vs 5.80 percent on Thursday * Ukrainian hryvnia UAH=) unchanged at 3.10 per dollar * Romanian leu ROL=) at 9,045 per dollar vs 9,025 * AFRICA AFRICAFX= & MIDEAST MEFX=) * Israeli shekel ILS=) 3.8508 bid on dollar from Thursday's 3.8568 * South African rand ZAR=) 6.3 per dollar vs 6.2555 * Kenyan shilling KES=) at 59.8 per dollar vs 59.9 * LATIN AMERICA LATAMFX= * Mexican peso MXN=) at 10.65 per dollar vs 10.48 * Brazil's real BRL=) at 1.1786 per dollar vs 1.1789 * Venezuela bolivar VEB=) unchanged at 586.9 per dollar. (C) 1998.

Topics: Money/Forex Markets, Foreign Exchange News, Commodity/Financial Market News

Locations: Africa, Argentina, Asia, Brazil, Central America, China, Emerging Market Countries, Eastern Asia, European Union Countries, Central/Eastern Europe, Europe, Hong Kong, Hungary, Indonesia, Japan, Latin America, Mexico, North America, Poland, Russia, South Africa, South America, Southeast Asia, Southern Africa, United Kingdom, United States, Arizona, CIS Countries, Western U.S., Western Europe

Fig. A2 ***(continued)***

Table A3
Asset prices coverage—stock indices.

Country	Sample start	Sample End	Index
Argentina	1/1/1991	12/31/2015	ARGENTINA MERVAL
Brazil	1/2/1991	12/30/2015	BRAZIL BOVESPA
Chile	1/1/1991	12/31/2015	CHILE SANTIAGO SE GENERAL (IGPA)
China	1/2/1991	12/31/2015	SHANGHAI SE COMPOSITE
France	1/2/1991	12/31/2015	FRANCE CAC 40
Germany	1/2/1991	12/30/2015	DAX 30 PERFORMANCE
Greece	1/2/1991	12/31/2015	ATHEX COMPOSITE
India	1/2/1991	12/31/2015	S&P BSE (SENSEX) 30 SENSITIVE
Indonesia	1/3/1991	12/30/2015	IDX COMPOSITE
Ireland	1/2/1991	12/31/2015	IRELAND SE OVERALL (ISEQ)
Italy	1/4/1993	12/30/2015	FTSE MIB INDEX
Japan	1/1/1991	12/31/2015	NIKKEI 225 STOCK AVERAGE
Korea	1/3/1991	12/30/2015	KOREA SE COMPOSITE (KOSPI)
Malaysia	1/2/1991	12/31/2015	FTSE BURSA MALAYSIA KLCI
Mexico	1/2/1991	12/31/2015	MEXICO IPC (BOLSA)
Peru	1/2/1991	12/31/2015	S&P/BVL GENERAL (IGBVL)
Philippines	1/2/1991	12/29/2015	PHILIPPINE SE INDEX (PSEI)
Poland	4/16/1994	12/30/2015	WIG20 INDEX
Portugal	12/31/1992	12/31/2015	PORTUGAL PSI-20
Russia	1/2/1995	12/31/2015	MXRU INDEX
South Africa	7/3/1995	12/31/2015	JALSH INDEX
Spain	9/6/1991	12/31/2015	IBEX 35
Thailand	1/2/1991	12/30/2015	BANGKOK S.E.T.
Turkey	1/2/1991	12/31/2015	BIST NATIONAL 100
United States	1/2/1991	12/31/2015	DOW JONES INDUSTRIALS

Table A4
Summary statistics of the sentiment index—by country.

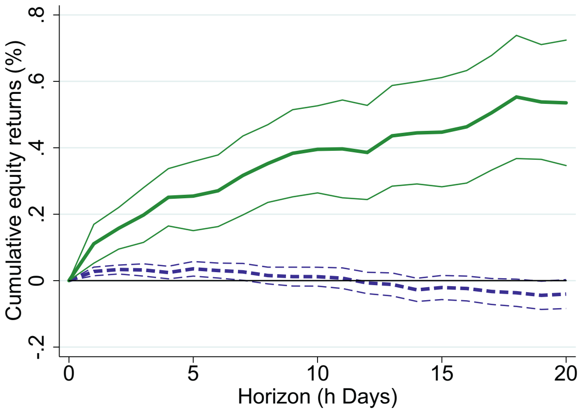
Country	Variable	N	Mean	SD	Min	p25	Median	p75	Max
AR	Sentiment	6485	−0.0064	0.0218	−0.1463	−0.0174	−0.0042	0.0064	0.1250
BR	Sentiment	6950	−0.0058	0.0186	−0.1908	−0.0154	−0.0044	0.0047	0.0952
CL	Sentiment	5695	−0.0041	0.0276	−0.1405	−0.0200	−0.0022	0.0130	0.1250
CN	Sentiment	8604	−0.0022	0.0150	−0.1200	−0.0095	−0.0014	0.0055	0.1512
DE	Sentiment	8365	−0.0056	0.0167	−0.1667	−0.0138	−0.0046	0.0035	0.1277
ES	Sentiment	6415	−0.0044	0.0253	−0.1547	−0.0179	−0.0018	0.0107	0.1554
FR	Sentiment	7573	−0.0054	0.0194	−0.1429	−0.0148	−0.0039	0.0051	0.1549
GR	Sentiment	5989	−0.0049	0.0266	−0.1493	−0.0193	−0.0014	0.0112	0.1270
ID	Sentiment	7446	−0.0033	0.0199	−0.1333	−0.0134	−0.0030	0.0074	0.1091
IE	Sentiment	4411	−0.0023	0.0284	−0.1695	−0.0181	0.0000	0.0143	0.1346
IN	Sentiment	8493	0.0034	0.0195	−0.1713	−0.0039	0.0031	0.0112	0.1493
IT	Sentiment	7140	−0.0051	0.0232	−0.1538	−0.0169	−0.0031	0.0085	0.1268
JP	Sentiment	8345	−0.0039	0.0147	−0.1304	−0.0113	−0.0035	0.0037	0.1795
KR	Sentiment	7776	−0.0040	0.0203	−0.1379	−0.0140	−0.0023	0.0074	0.1148
MX	Sentiment	6788	−0.0028	0.0243	−0.1591	−0.0154	−0.0009	0.0114	0.1034
MY	Sentiment	7506	−0.0043	0.0153	−0.1692	−0.0114	−0.0034	0.0037	0.0833
PE	Sentiment	4509	−0.0016	0.0280	−0.2295	−0.0158	0.0000	0.0141	0.1505
PH	Sentiment	6747	−0.0039	0.0232	−0.2041	−0.0164	−0.0029	0.0088	0.1250
PL	Sentiment	6296	−0.0017	0.0219	−0.1442	−0.0126	0.0000	0.0106	0.2000
PT	Sentiment	4649	−0.0039	0.0271	−0.2353	−0.0182	−0.0031	0.0121	0.1091
RU	Sentiment	7055	−0.0043	0.0178	−0.1411	−0.0133	−0.0026	0.0056	0.1458
TH	Sentiment	7464	−0.0031	0.0192	−0.1352	−0.0123	−0.0023	0.0069	0.1385
TR	Sentiment	6355	−0.0020	0.0246	−0.2857	−0.0152	0.0000	0.0133	0.1290
US	Sentiment	8825	−0.0030	0.0124	−0.1210	−0.0080	−0.0016	0.0033	0.0896
ZA	Sentiment	6809	−0.0067	0.0233	−0.1707	−0.0193	−0.0055	0.0072	0.1004
AE	Sentiment	61,712	−0.0043	0.0211	−0.2353	−0.0141	−0.0028	0.0062	0.1795
EM	Sentiment	110,978	−0.0032	0.0213	−0.2857	−0.0135	−0.0018	0.0081	0.2000
Total	Sentiment	172,690	−0.0036	0.0212	−0.2857	−0.0138	−0.0022	0.0074	0.2000

Notes: This table reports summary statistics about the (raw) daily sentiment indices for each country. *Sentiment* denotes our baseline measure of news sentiment. The AE and EM rows report summary statistics by country groups; the Total row reports summary statistics across all countries in our sample.

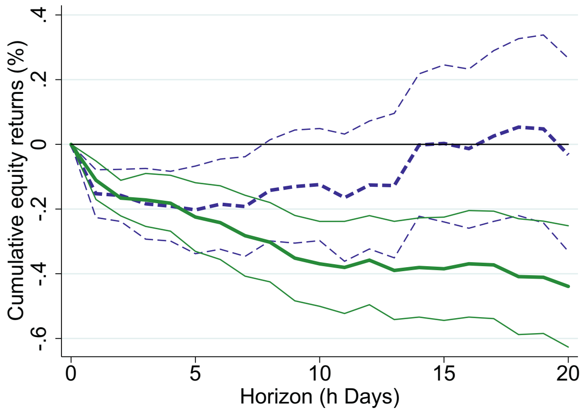
A.2. Robustness and extensions

Figs. A3 and A4 report robustness checks and extensions derived using Eq. (2). Fig. A3, panel A, plots the response of local asset prices to local and global news sentiment using TF–IDF measures of news sentiment. Results are only provided for the full sample (mirroring Fig. 3a) but are unchanged when excluding the GFC or restricting attention to AE or EM. We also report results when using only the share of negative words in the article—out of all tonal words (Panel B). We do so to check that positive words do not offset negative words within the same expression, leading potentially to a downward bias in our estimates. For instance, although the expression "higher unemployment" is clearly negative, its impact on an article tone would be neutralized in our benchmark measure, since it is the sum of a positive and a negative word. Results, however are generally unchanged. The shape and magnitude of the impact of local news sentiment is identical, suggesting that our results are not driven by measurement error. Similarly, the long lasting impact of global news is unchanged. However, the size of the impact increases slightly, suggesting that, if anything, our estimates of the impact of global news sentiment could have suffered from a downward bias. This, however, reinforces our conclusion that global news are a major driver of asset prices.

Fig. A4 plots the response across time and groups of countries using the standard measure of sentiment. Fig. A5, Fig. A6, and Fig. A7 re-estimates Fig. 3.a while controlling for the US Economic Policy Uncertainty (EPU) Index, our uncertainty index, and the Citigroup Economic Surprise Index (CESI), respectively. Fig. A9 re-estimates Fig. 3.a and b under the Newey-West and double-clustered standard errors. Fig. A10 reports the average and median values of the (raw) sentiment index during various definitions of good and bad times.



(a) TF–IDF sentiment



(b) Negative share of tonal words

Fig. A3. Panel with TF–IDF sentiment and negative share of tonal words. *Notes:* Results in panel A are derived using Eq. (2) and using the updated version of news sentiment based on TF–IDF weights. Results in panel B use a measure of news sentiment based on only the share of negative words in the article out of all tonal words. Lines plot the cumulative response of equity prices to a news sentiment shock *h*-days ahead. The *x* axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

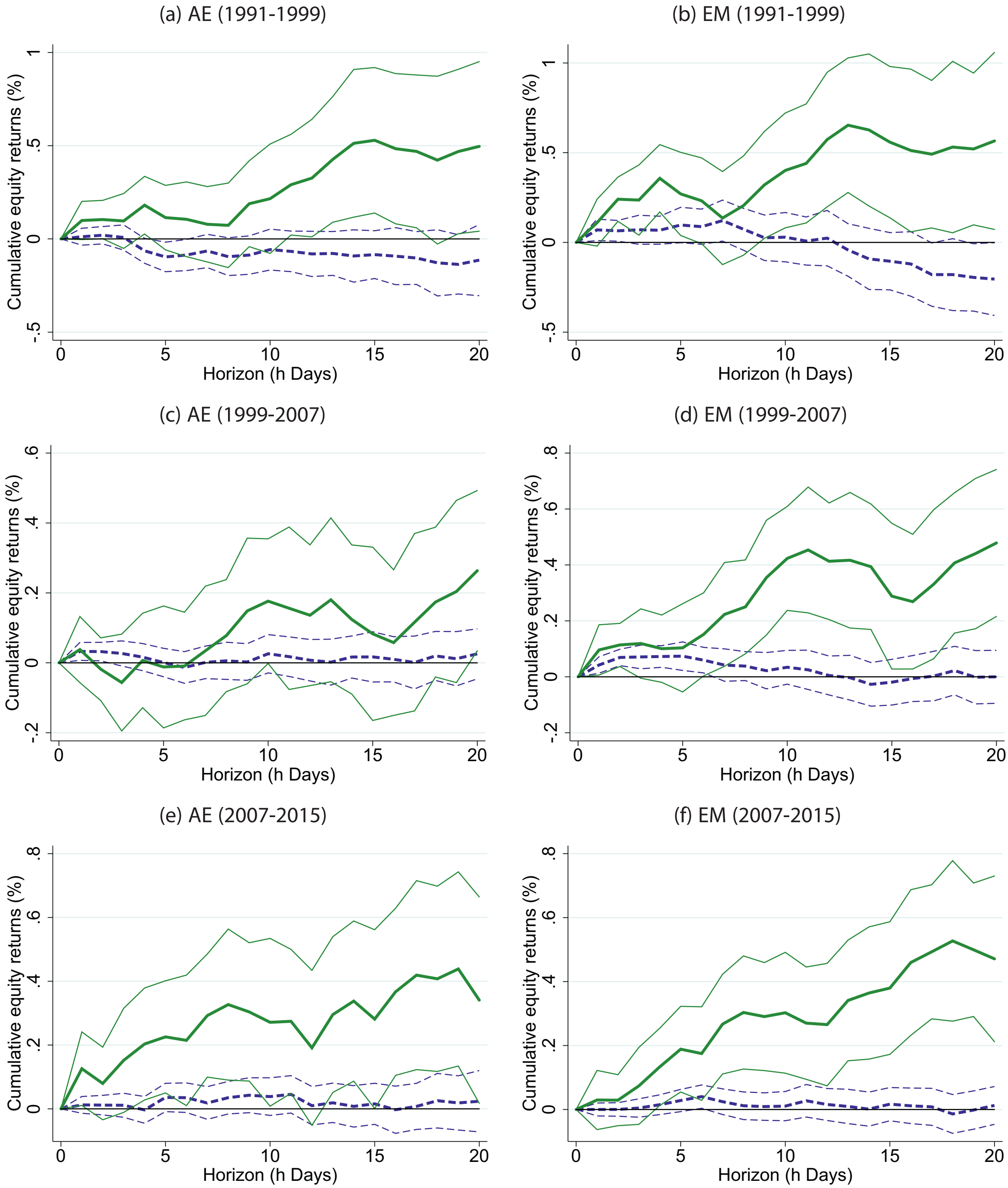


Fig. A4. Benchmark results—country and time split. *Notes:* Results are derived using Eq. (2) for subsamples split by the income group of the countries (AE or EM) and the time period covered (1991–1999, 1999–2007, and 2010–2015). Lines plot the cumulative response of equity prices to a news sentiment shock *h*-days ahead. The *x* axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

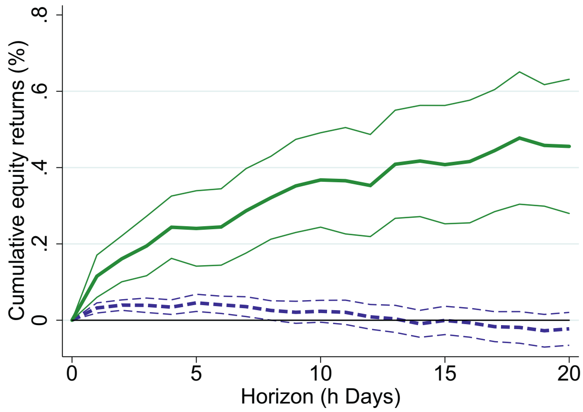


Fig. A5. Panel controlling for US EPU. *Notes:* Results are derived by introducing the US Economic Policy Uncertainty (EPU) Index from Baker et al. (2016) into Eq. (2) as an additional control. Lines plot the cumulative response of equity prices to a news sentiment shock *h*-days ahead. The *x* axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

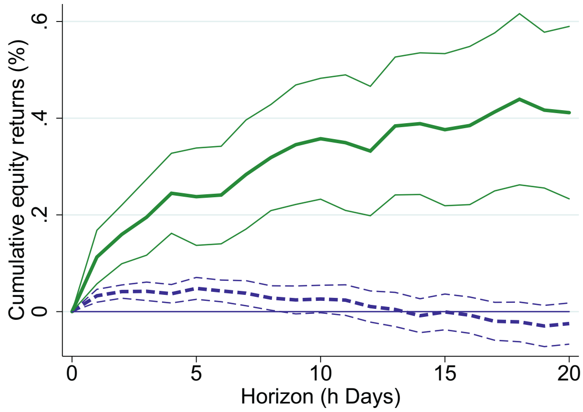


Fig. A6. Panel controlling for uncertainty index. *Notes:* Results are derived by introducing a (country-specific) news uncertainty index into Eq. (2). Mirroring the approach we use to measure news tone, we compute news uncertainty by computing the fraction of uncertainty related words in each article every day. Lines plot the cumulative response of equity prices to a news sentiment shock *h*-days ahead. The *x* axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

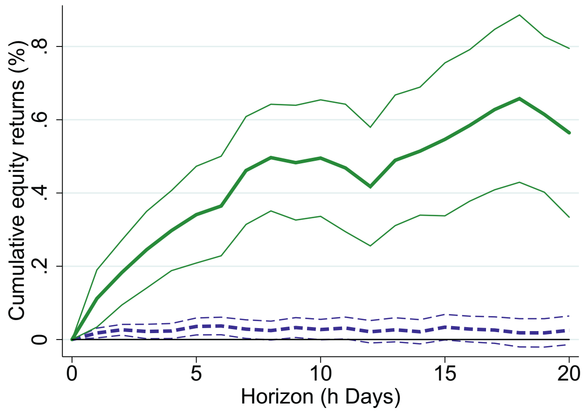


Fig. A7. Panel controlling for the Citigroup Economic Surprise Index (CESI). *Notes:* Results are derived by introducing the Citigroup Economic Surprise Index (CESI) for the US, the Euro Area, China and the G10 countries into Eq. (2). The Citigroup Economic Surprise Index (CESI), which are available in daily frequency since 2003, captures deviations between the actual macro-data releases and the Bloomberg survey median in key countries. Lines plot the cumulative response of equity prices to a news sentiment shock *h*-days ahead. The *x* axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

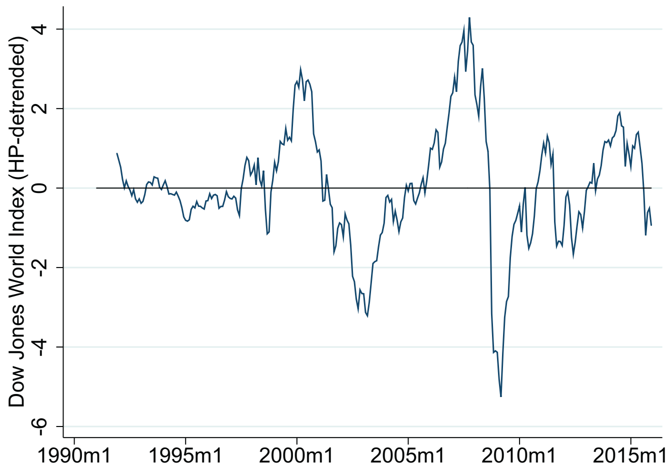
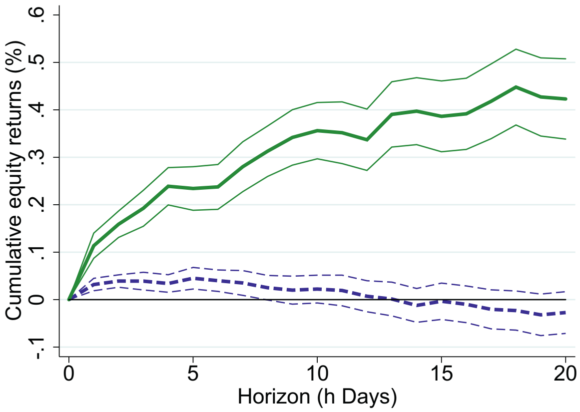
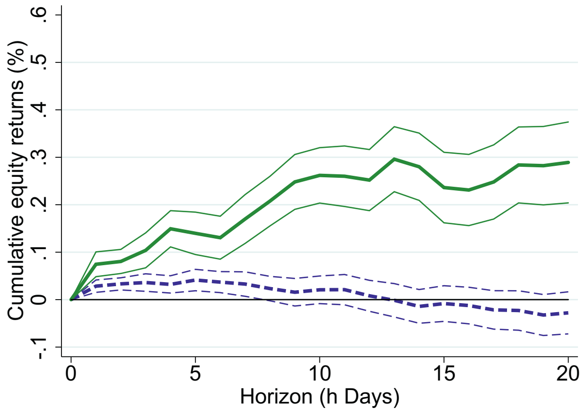


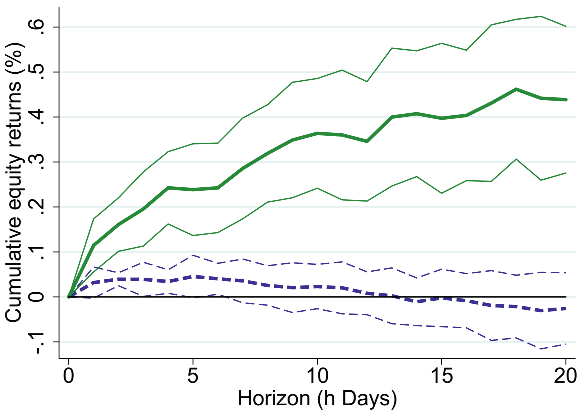
Fig. A8. Definition of global bull and bear markets. *Notes:* Bull (Bear) markets are defined at the monthly frequency as periods during which the global equity market—measured by the Dow Jones World Index—is above (below) its trend. The trend is constructed using a two-sided HP filter with a smoothing parameter of 129,600, set using the Ravn and Uhlig (2002) rule for monthly data.



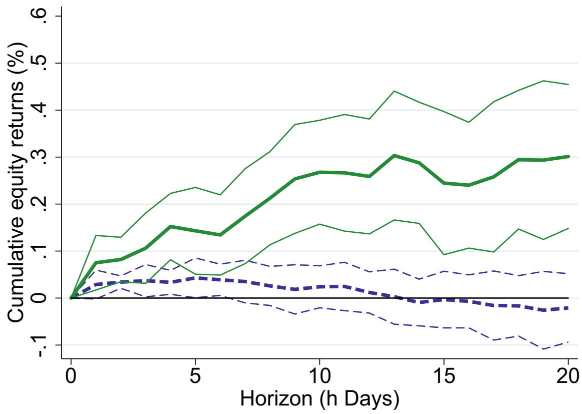
(a) Panel Full Sample
(Newey-West)



(b) Panel—excl. GFC
(Newey-West)



(c) Panel Full Sample
(Double-Clustered)



(d) Panel—excl. GFC
(Double-Clustered)

Fig. A9. Fig. 3.a and b estimated under alternative standard errors. *Notes:* This figure re-estimates Fig. 3.a (left panel) and 3.b (right panel) under Newey-West (top panel) and double-clustered (bottom panel) standard errors. Results are derived using Eq. (2) for the full sample of countries (left panel) and a subsample excluding the GFC (right panel). Lines plot the cumulative response of equity prices to a news sentiment shock h-days ahead. The x axis denotes the number of days after the shock. The blue thick-dotted line reports the cumulative response of equity prices to local news sentiment shocks. The green thick-solid line reports the cumulative response to global news sentiment shocks. The thinner lines around each impulse response report the 95% confidence intervals. The Newey-West Standard errors are corrected for serial correlation and heteroskedasticity with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011). Double-cluster robust standard errors (bottom panel) are clustered by country and time.

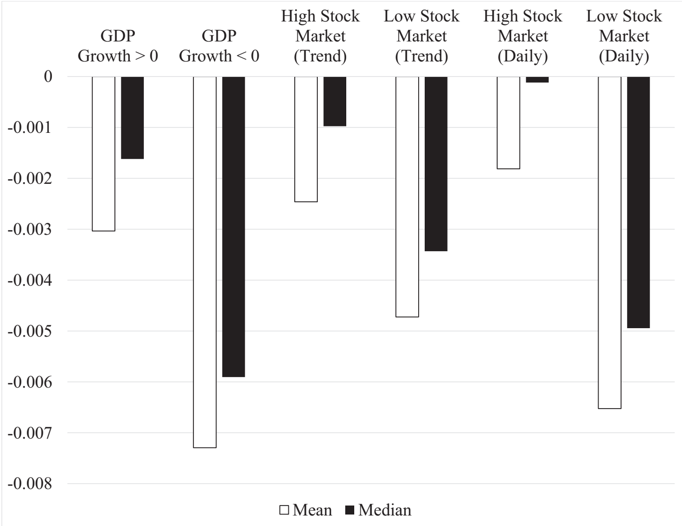


Fig. A10. Behaviour of the news sentiment index—good vs. bad times. *Notes:* This figure reports the average and median values of the (raw) sentiment index using various definitions of good and bad times. The first two columns split the sample based on periods where a country's real GDP growth has been positive (or negative). The third and fourth columns split the sample based on each country's stock market index being above or below its trend, where the trend is constructed using a two-sided HP filter with a smoothing parameter of 129,600, set using the Ravn and Uhlig (2002) rule for monthly data. The last two categories split the sample based on whether the country's daily stock market return has been positive or negative.

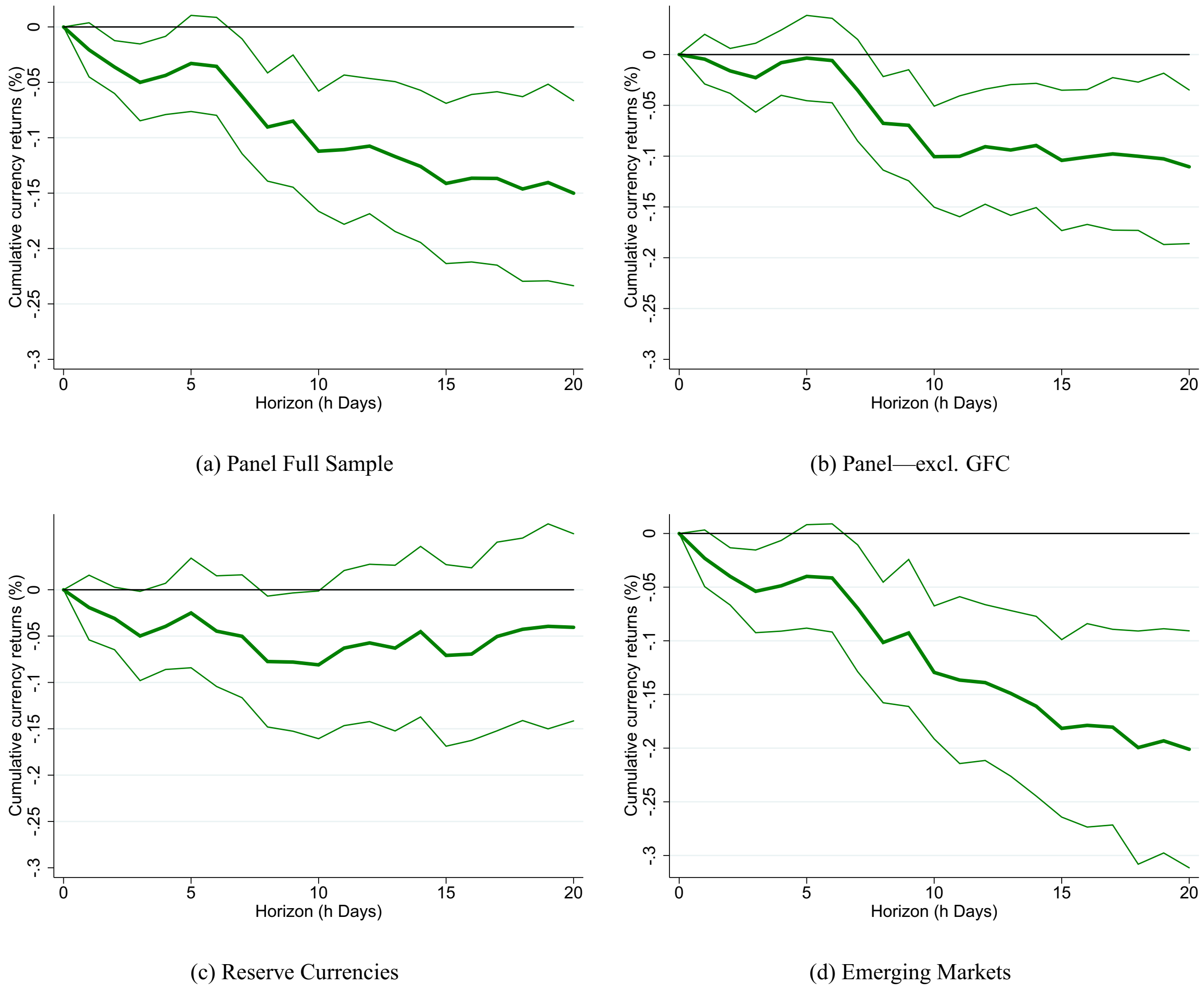


Fig. A11. Global sentiment shocks and currency returns. *Notes:* Each thick line shows the cumulative response of US dollar exchange rates to a global news sentiment shock *h*-days ahead estimated using Eq. (2). The *x* axis denotes the number of days after the shock. The solid thick green line reports the cumulative response to global news sentiment shocks. The thinner lines around each thick line indicate the 95% confidence intervals. Standard errors are corrected for general forms of cross-sectional and temporal dependence using the Driscoll and Kraay (1998) estimator; the autocorrelation structure under this specification has been set to have a truncation lag equal the projection horizon *h*, as suggested by Jordà (2005) and Kilian and Kim (2011).

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