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MEDIA SENTIMENT AND INTERNATIONAL ASSET PRICES

Samuel P. Fraiberger
Do Lee
Damien Puy
Romain Rancière

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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.

Samuel P. Fraiberger
World Bank
1818 H Street, NW
Washington, DC 20433
samuel.fraiberger@nyu.edu

Do Lee
Department of Economics
New York University
19 West 4th Street, 5th Floor
New York, NY 10012
dql204@nyu.edu

Damien Puy
International Monetary Fund
700 19th Street NW
Washington, DC 20431
dpuy@imf.org

Romain Rancière
Department of Economics
University of Southern California
Los Angeles, CA 90097
and NBER
ranciere@usc.edu

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 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 2007 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.[1] 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 10 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.[2] While the effect of local sentiment shocks is still significant, its magnitude is roughly cut in half, peaking around 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 25 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 2007 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 two weeks. Using the official domicile of each fund as a proxy for its location,

[1] Details are provided in Section 2.
[2] Details are provided in Section 3.

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, Shleifer, Summers and Waldmann (1990), Campbell, Grossman and Wang (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 20% of its total variance.[3] 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 twice as large as the response of active funds. Taken together, these results strengthen the view that global sentiment shocks capture variations in investors sentiment that are are not arbitraged away in the short run (Shleifer and Vishny (1997)).

Given the large impact of global news sentiment shocks on international asset prices, we close

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

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 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, Bloom and Davis (2016)), suggesting that changes in global news sentiment are not driven by variations in the uncertainty expressed in economic news.[4]

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, Lundblad and Ramadorai (2012), Ghosh, Qureshi, Kim and Zalduendo (2014), Broner, Didier, Erce and Schmukler (2013), Rey (2015), Puy (2016), Cerutti, Claessens and Puy (2019)).[5] 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, especially in EM and small open economies.[6] 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.[7] 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.

[4]This finding holds also when we include our own news uncertainty index in the estimation.

[5]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, Croce, Gavazzoni and Ready (2018)).

[6]See, for instance, the ongoing debate on the existence and strength of a global financial cycle, and its impact on asset prices in EM (Rey (2015).

[7]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).

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.[8] 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. 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, Bloom, Davis and Kost (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, Bauer and Schneider (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, Converse and Levy-Yeyati (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. [9]

Finally, from a technical perspective, we contribute to the recent and fast-growing literature

[8]This literature has 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 3,000 articles respectively. For the US only, we use 1.8 million articles. Our work 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.

[9]Both local and global news sentiment indices are available on the authors' websites. Although our analysis stops in 2015, data are available until December 2019.

that links textual information to both economic and financial outcomes (see Gentzkow, Kelly and Taddy (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.[10] Using daily internet search volume from millions of households in the US, Da, Engelberg and Gao (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.

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.A. News articles and Sentiment measures

2.A.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 Figure A1). The distribution of topics is similar in AE and in EM. 200 US-related articles were published each

[10] Our results are orthogonal to the various EPU indexes constructed by Baker et al. (2016). See Section 4..

day, representing one fourth of our sample.[11] The distribution of articles across non-US countries is relatively balanced, averaging at 97,000 articles per country over the whole sample. For non-US countries, 20 articles were published each day.

2.A.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.[12] 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 7,217 negative words and 3,250 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, Raghavan and Schütze (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

[11] Note that an article can be tagged with multiple locations and topics. See the next section for an example and Appendix Figure A2 for details.

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

Table 1. Most frequent positive (left) and negative (right) words

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.

Source: Words lists come from Loughran and Mcdonald (2011) and Young and Soroka (2012). News articles come from Factiva.com.

the English language by giving more weight to words that appear more rarely across documents.[13]

To illustrate our sentiment measure, we show the example of an article in which tonal words are highlighted in bold[14], 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:

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.B. 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

[13] 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).

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

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.C. 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.[15] Because of its extensive industry coverage and quality, EPFR Global has widely been used in recent academic contributions on funds behavior (*e.g.*, Raddatz and Schmukler (2012), Jotikasthira et al. (2012), Fratzscher (2012), and other references therein).[16] In policy circles, fund flows reported by EPFR have increasingly been used as a high-frequency proxy for foreign capital inflows especially in EM.[17] 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 2005 and 2015.[18]

[15]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.

[16]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.

[17]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.

[18]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.

3. News, Sentiment and Equity Returns

3.A. 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 $Cum_{R_{i,t,t+h}}$ 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 equation (1) using ordinary least squares and we only report the main coefficient of interest β_1^h (Figure 1) for simplicity.[19]

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

[19] 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) and Teulings and Zubanov (2014). Adding the residual from the regression for horizon $h-1$ also addresses a potential bias identified in Teulings and Zubanov (2014).

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.[20]

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.[21] Third, we estimate the cumulative response of returns up to 20 days ahead as opposed to 5 trading days for Tetlock (2007)).

3.B. Results – Benchmark

To compare our results with the seminal work of Tetlock (2007), Figure 1.A reports regression results for the US, using US news and US Dow Jones Industrial Index returns between 1991 and 2015.[22] Our estimation is based on 6,260 observations against 4,000 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 slightly below 10 basis points and is not statistically different from zero after one calendar week.[23]

Figure 1.B presents the results when we extend our estimation across countries. As specified in equation (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 101,170 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 basis points, indicating that the effect of news sentiment on asset prices is a pervasive

[20] 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.

[21] 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.

[22] More specifically, we replicate Equation (1) in Tetlock (2007).

[23] In Tetlock (2007), a one standard deviation increase in news pessimism generates a 8.1 basis points drop in Dow Jones returns the next day. This effect is almost completely reversed by the end of the trading week.

Figure 1. Benchmark Results – Equity Returns

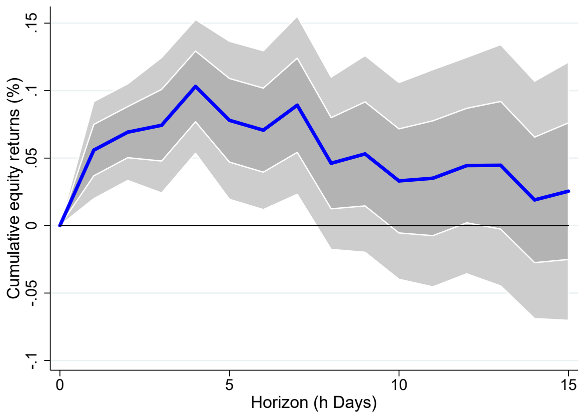


Figure 1.A. US Only

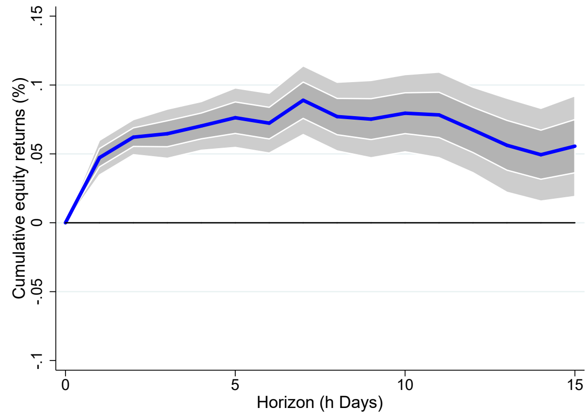


Figure 1.B. Panel Full Sample

Notes: The solid line shows the cumulative response of equity prices to a news sentiment shock h-days ahead estimated using equation (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. Standard errors are corrected for serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

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.C. Global vs. Local News Sentiment

Two types of articles constitute our corpus: local news and multi-country news. About 60% 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.[24] By contrast, the remaining 40% of our corpus contains articles discussing multiple countries. A typical multi-country article is one reported in the Appendix entitled "Fears of Brazilian devaluation hit emerging markets", which mentions multiple countries and their interrelations.[25] The presence of multi-country news mechanically increases the

[24] 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.

[25] 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.

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 1.5 million articles across countries (Appendix Figure 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 (2011):

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

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 $AR(1)$ both for the factor and for the error term, and we 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.[26] More specifically, we estimate the following model:

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

Figure 2 presents the results. Figure 2.A reports results for the full sample of countries, whereas Figure 2.C and 2.D report results for AE and EM respectively. Figure 2.B reports results for all countries excluding the years 2008 and 2009, ensuring that our results are not driven by the Global

[26] Properties of the global news sentiment index are discussed in section 4.

Financial Crisis (GFC). As expected, we find that controlling for the global sentiment affects the size and the shape of the response to local news sentiment shocks, the cumulative response being roughly twice smaller (5 basis points, as opposed to 10 in the previous estimates). More importantly, while we did not see a full reversal after 20 days in the previous estimates, the gains now completely vanish after a week. Quantitatively, sentiment shocks are still economically significant however.[27] 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 (Figure 2), peaking at about 25 basis points — about 5 times larger than the response to local sentiment shocks — after 10 to 15 days. Importantly, this result is only marginally affected by the exclusion of the GFC from our sample. 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.

[27] The median absolute deviation in our sample is about 70 basis points, both for AE and EM.

Figure 2. Global vs. Local Sentiment Shocks – Equity Returns

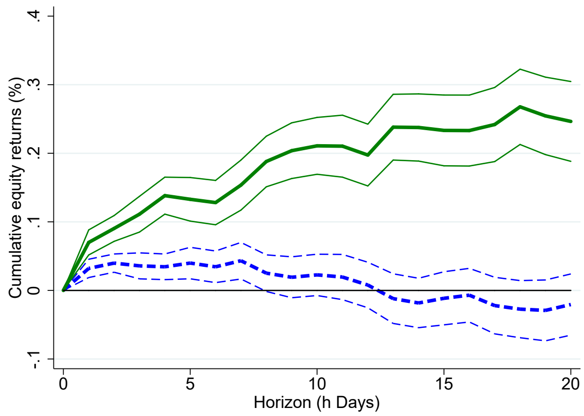


Figure 2.A. Panel Full Sample

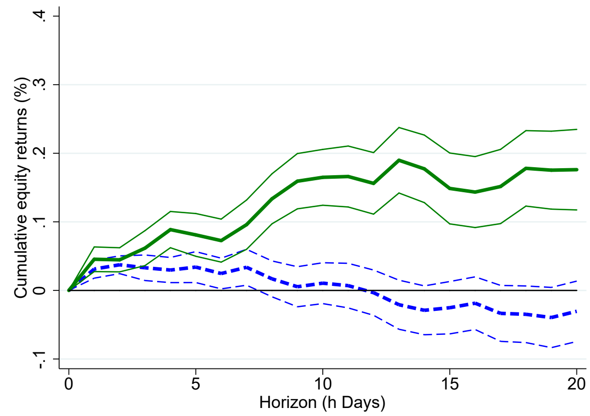


Figure 2.B. Panel – excl. GFC

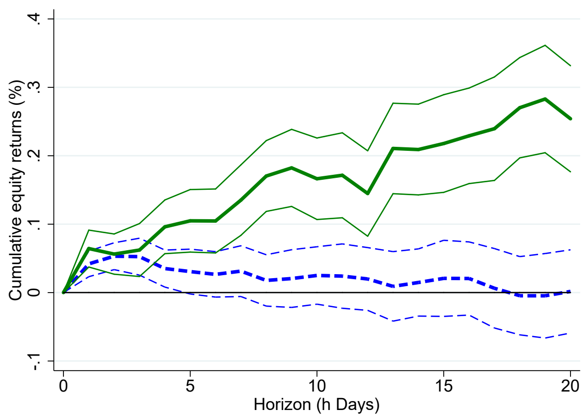


Figure 2.C. Advanced Economies

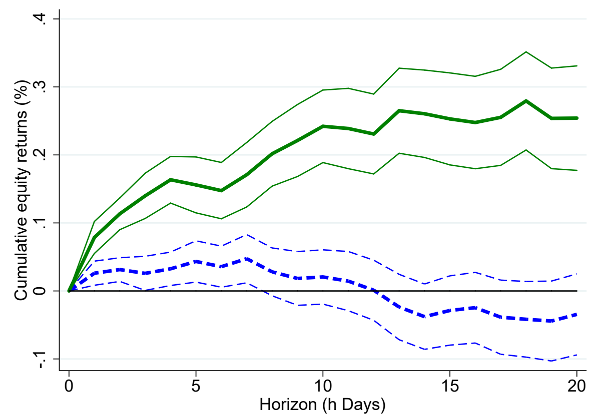


Figure 2.D. Emerging Markets

Notes: Each thick line shows the cumulative response of equity prices to a news sentiment shock h-days ahead estimated using equation (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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

3.D. 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 2005 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.

Figure 3 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%.[28] We also cannot reject a full reversal after a week 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 0.1% after 2 weeks (Figure 3.A). This result is also robust to the exclusion of the GFC (Figure 3.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 (Figure 3.C).[29] 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.[30]

[28] 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%.

[29] For instance, we contrast the behavior of funds investing in Argentina and domiciled in Argentina, with the behavior of funds investing in Argentina but domiciled abroad.

[30] 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

Figure 3. Global vs. Local Sentiment Shocks -– Equity Flows

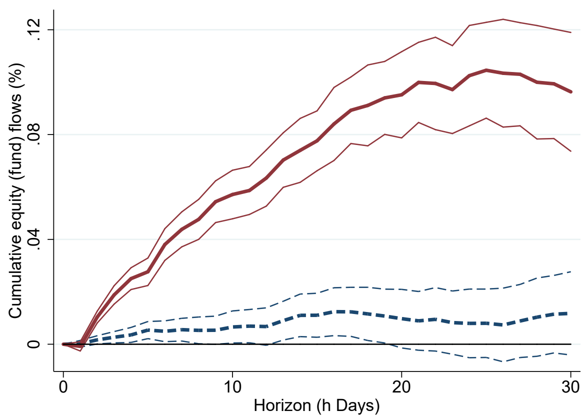


Figure 3.A. All Funds

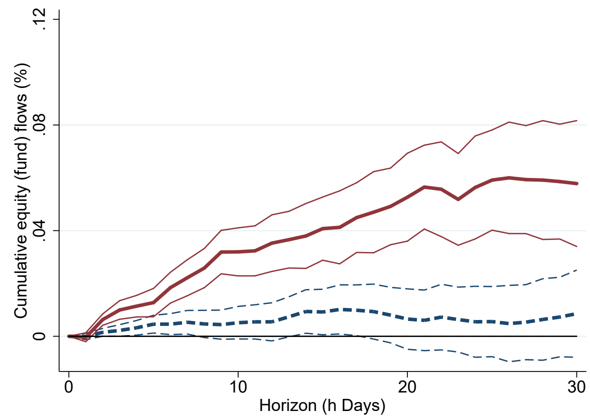


Figure 3.B. All Funds – excl. GFC

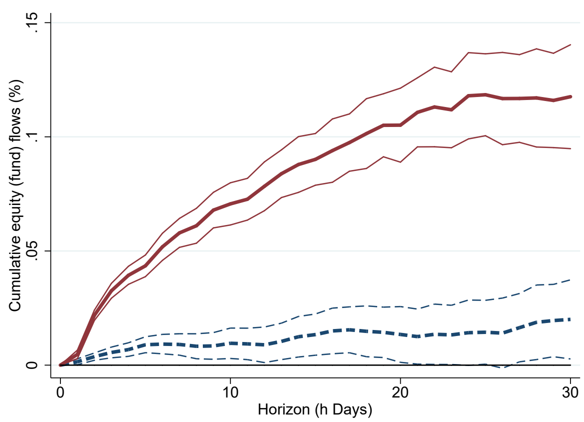


Figure 3.C. Foreign Investors

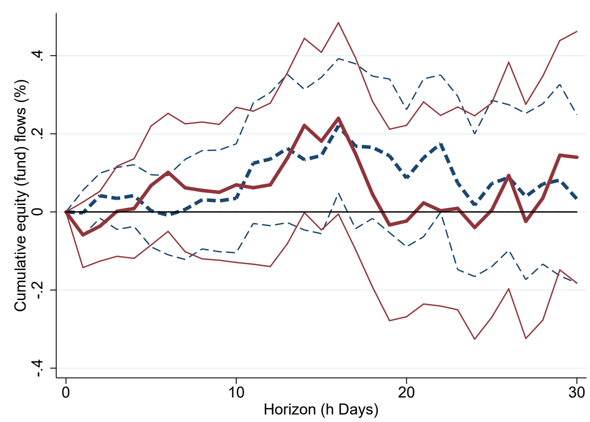


Figure 3.D. Local Investors

Notes: Each thick line shows the cumulative response of equity fund flows to a news sentiment shock h-days ahead estimated using equation (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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011). Estimates are based on 23,720 observations.

4. Investigating the Global News Sentiment Index

4.A. 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. Figure 4.A compares variations in global news sentiment and in the VIX. Not surprisingly, the two are negatively correlated (-0.35) 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. Using equation (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 (Figure 4.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 equation (2). Appendix Figure 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 equation (2) as an additional control, finding that our results remain unchanged (Appendix Figure A6).

4.B. 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 multi-country articles could convey 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" –

is unchanged, while the response of local investors becomes even flatter.

Figure 4. Global News Sentiment vs. VIX

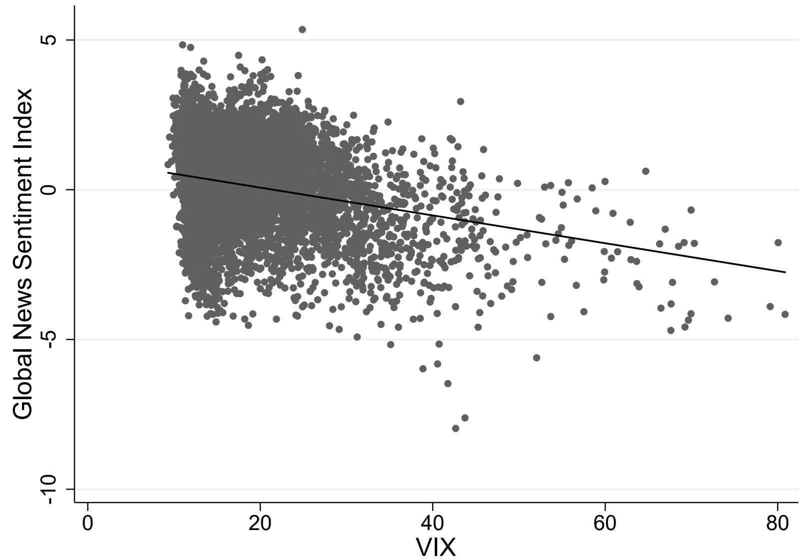


Figure 4.A. Correlation

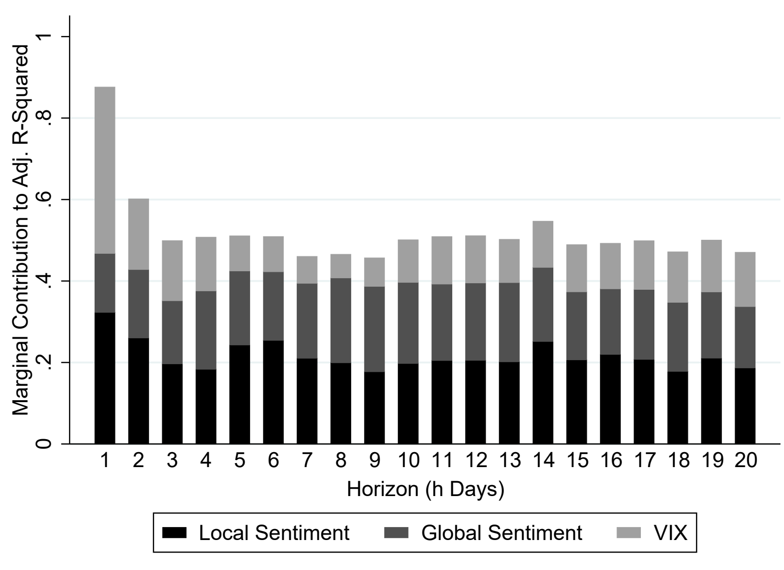


Figure 4.B. Variance Decomposition

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 equation (2) respectively. h denotes the number of days in the projection horizon.

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 Citi Index of Economic Surprises, 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 2001. 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 20% of the variance in the global news sentiment (Table 2). More importantly, Appendix Figure A7 shows that our main results remain unaffected by introducing these economic surprise measures, indicating that global news sentiment shocks do not simply capture new information on economic fundamentals.

Table 2. Global News Sentiment and Economic Surprises

	Global News Sentiment Index				
Variable	(1)	(2)	(3)	(4)	(5)
CESI_USD	0.006***				0.011***
	(0.001)				(0.002)
CESI_EUR		0.010***			0.017***
		(0.000)			(0.001)
CESI_CNY			0.007***		0.005***
			(0.000)		(0.000)
CESI_G10				0.017***	-0.026***
				(0.001)	(0.004)
N	3,349	3,348	3,112	3,349	3,087
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Next, we assess the "sentiment hypothesis" using two 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 equation (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.[31] We find that the impact of global sentiment shocks are roughly four times stronger in global bear markets (Figure 5.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 (Figure 5.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. Taken together, these results strengthen the "sentiment hypothesis", global sentiment shocks capturing variations in investors sentiment that are not arbitraged away in the short run.

4.C. 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. Figure 6 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 twice as many topics and using twice as many tonal words than their local counterparts. They also make use of more rare words than local news.[32]

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

[31] 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 Figure A8 reports the actual period defined as global bear and bull markets, respectively.

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

Figure 5. Fundamentals vs. Sentiment Hypothesis

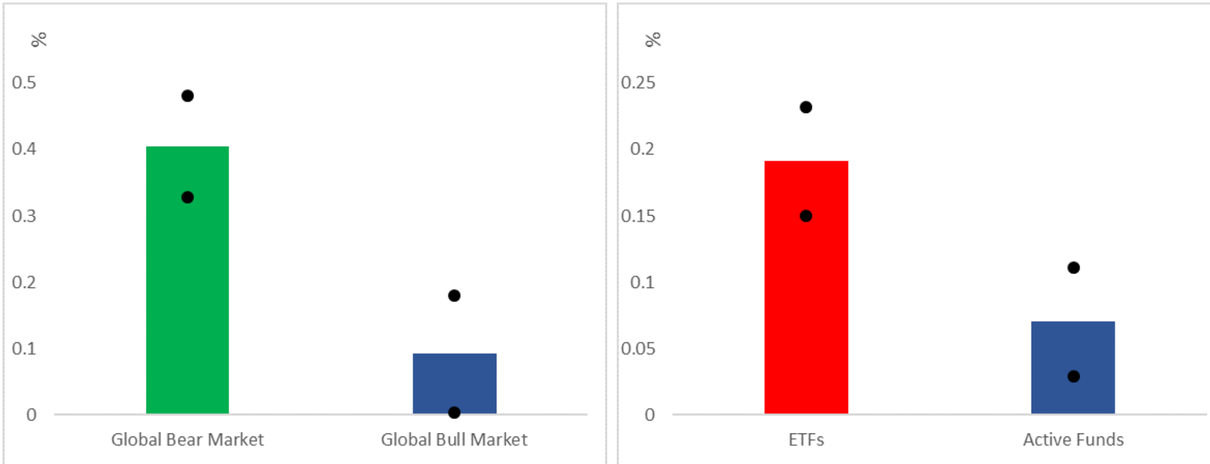
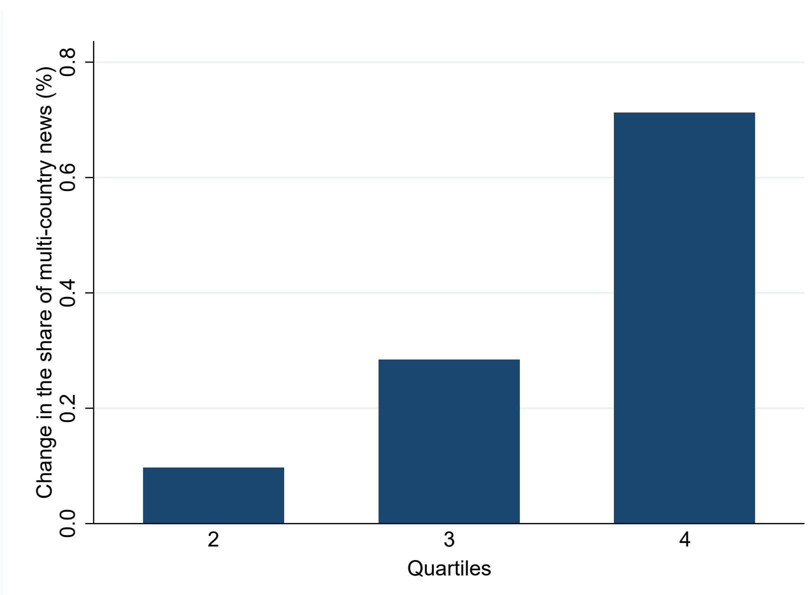


Figure 5.A. Global News Sentiment Impact (Equity Prices)

Figure 5.B. Global News Sentiment Impact (Funds' Allocation)

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 equation (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 equation (3). In both cases, dots indicate the 95% confidence intervals. Standard errors are corrected for serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure 6. 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.

when the global news sentiment index goes into negative territory (Figure 7).

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, Schularick, Taylor and Ward (2019)). Other important contributions 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 Figure A4).

Our results are also not driven by extreme values or crisis – such as the GFC, or by key countries – such as the US.[33] They are also robust to an alternative specification on the news sentiment index in which each word is weighted by its TF-IDF (Appendix Figure A3). Finally, all our key results are robust to using different clustering techniques for the standard errors. To illustrate this, Figure A9 re-estimates Figure 2.A and 2.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

[33]Results are available upon request.

Figure 7. Global News Sentiment and News Coverage

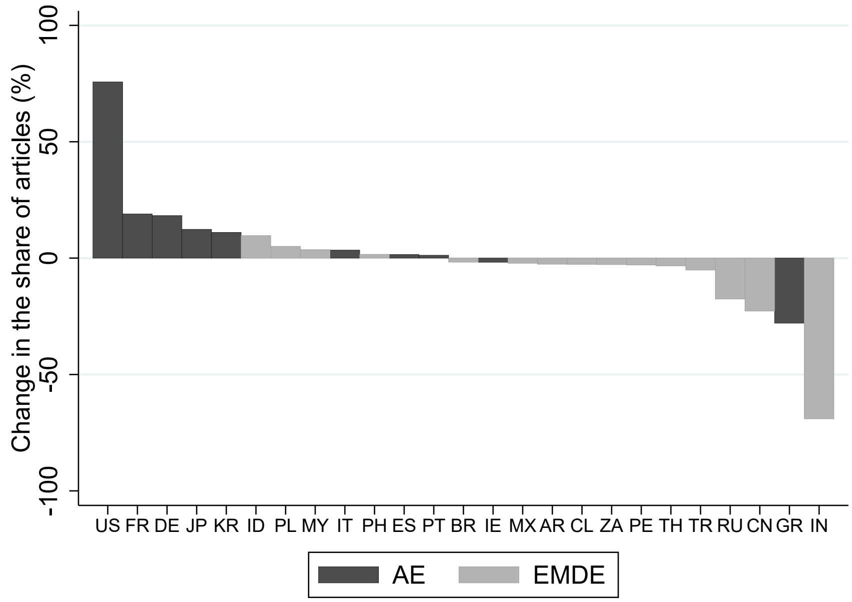


Figure 7.A. Locations

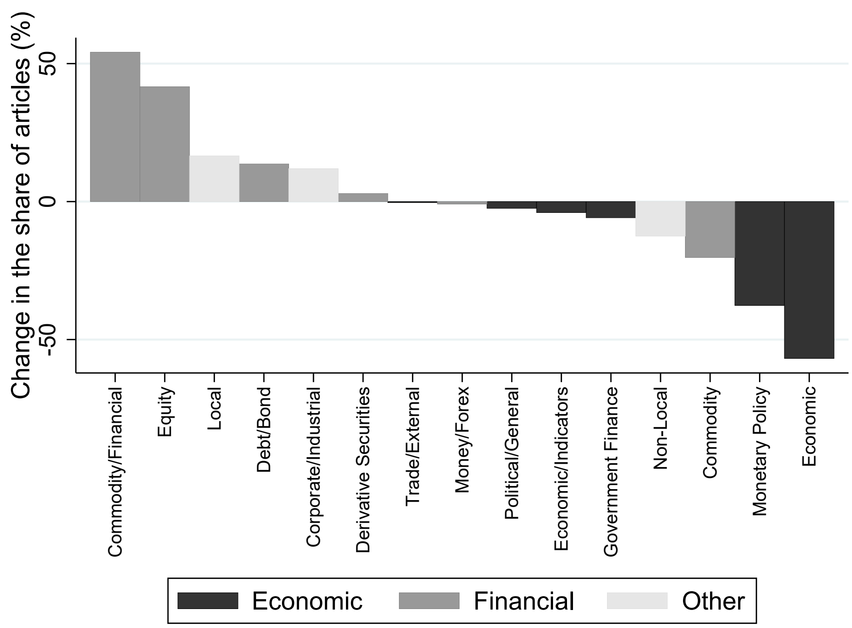


Figure 7.B. Topics

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.

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.

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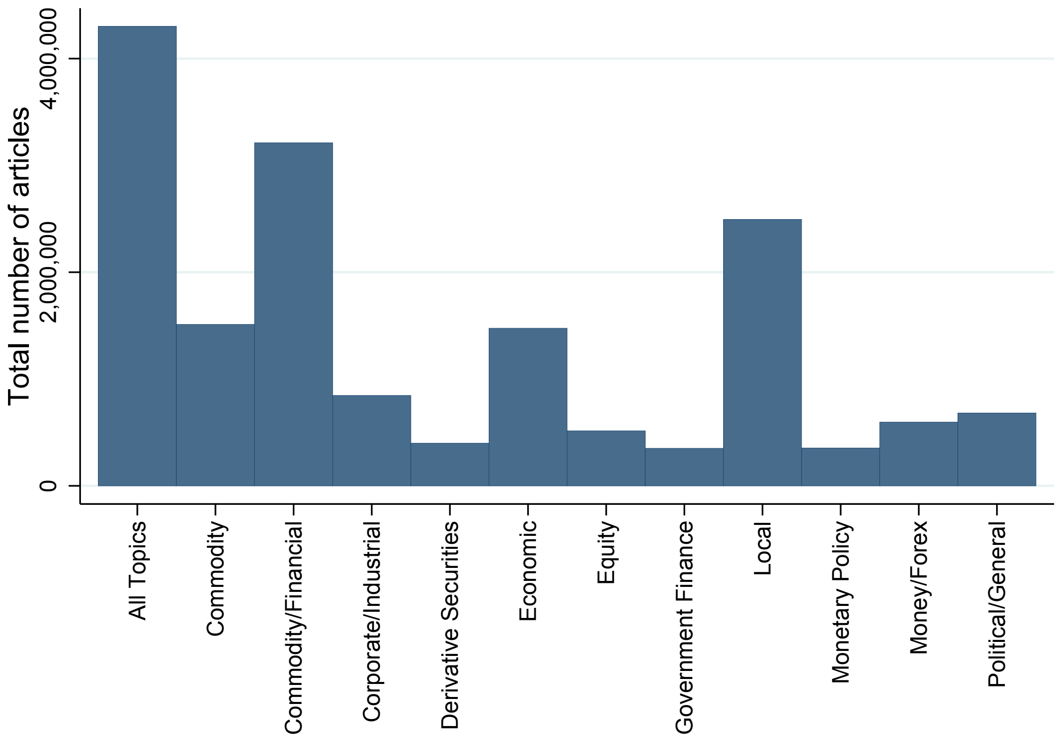
A Appendix

AA. Stylized Facts

Table A1. Country and Time Coverage

Country	AE/EM	News Start	News End	# Articles	Average per day
United States	AE	01/01/1991	12/31/2015	1,815,542	201.41
France	AE	01/02/1991	12/31/2015	139,927	17.31
Germany	AE	01/02/1991	12/31/2015	229,059	26.24
Italy	AE	01/02/1991	12/30/2015	87,530	11.33
Japan	AE	01/01/1991	12/30/2015	274,804	31.66
Greece	AE	01/09/1991	12/31/2015	60,824	9.1
Ireland	AE	01/07/1991	12/30/2015	28,194	4.76
Portugal	AE	01/03/1991	12/29/2015	32,162	5.45
Spain	AE	01/02/1991	12/30/2015	56,418	7.86
Turkey	EM	01/02/1991	12/31/2015	46,728	6.58
South Africa	EM	01/02/1991	12/31/2015	77,318	10.54
Argentina	EM	01/02/1991	12/31/2015	51,287	7.12
Brazil	EM	01/02/1991	12/31/2015	87,488	11.69
Chile	EM	01/08/1991	12/28/2015	24,095	3.7
Mexico	EM	01/02/1991	12/31/2015	69,558	9.26
Peru	EM	01/03/1991	12/31/2015	17,348	2.97
India	EM	01/02/1991	12/31/2015	356,683	40.34
Indonesia	EM	01/02/1991	12/31/2015	87,550	10.98
Korea	EM	01/03/1991	12/31/2015	100,153	11.91
Malaysia	EM	01/02/1991	12/30/2015	99,394	12.26
Philippines	EM	01/02/1991	12/30/2015	55,460	7.08
Thailand	EM	01/02/1991	12/29/2015	82,555	10.44
Russia	EM	12/30/1991	12/31/2015	111,540	14.81
China	EM	01/02/1991	12/31/2015	245,913	27.69
Poland	EM	01/01/1991	12/30/2015	64,998	9.29

Figure 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

Figure A2. Global News – An Example

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 Hong'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 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

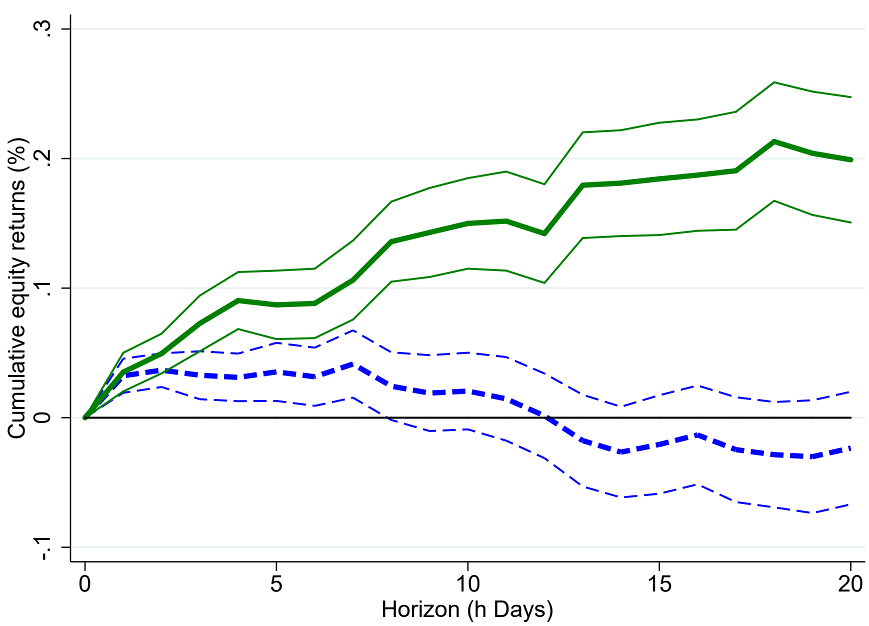
Table A3. Asset Prices Coverage – Stock Indices

Country	Sample Start	Sample End	Index
Argentina	01/02/1991	12/31/2015	ARGENTINA MERVAL - PRICE INDEX
Brazil	01/02/1991	12/31/2015	BRAZIL BOVESPA - TOT RETURN IND
Chile	01/02/1997	12/30/2015	CHILE SANTIAGO SE GENERAL (IGPA) - PRICE INDEX
China	01/02/1991	12/31/2015	SHANGHAI SE COMPOSITE - PRICE INDEX
Germany	01/02/1997	12/31/2015	DAX 30 PERFORMANCE - PRICE INDEX
Spain	01/02/1997	12/31/2015	IBEX 35 - PRICE INDEX
France	01/01/1997	12/31/2015	FRANCE CAC 40 - PRICE INDEX
Greece	01/02/1997	12/31/2015	ATHEX COMPOSITE - PRICE INDEX
Indonesia	01/02/1991	12/31/2015	IDX COMPOSITE - PRICE INDEX
Ireland	01/02/1997	12/30/2015	IRELAND SE OVERALL (ISEQ) - PRICE INDEX
India	01/02/1991	12/31/2015	S&P BSE (SENSEX) 30 SENSITIVE - PRICE INDEX
Italy	01/02/1997	12/30/2015	FTSE MIB INDEX - PRICE INDEX
Japan	01/01/1991	12/31/2015	NIKKEI 225 STOCK AVERAGE - PRICE INDEX
Korea	01/03/1991	12/31/2015	KOREA SE COMPOSITE (KOSPI) - PRICE INDEX
Mexico	01/02/1991	12/31/2015	MEXICO IPC (BOLSA) - PRICE INDEX
Malaysia	01/02/1991	12/31/2015	FTSE BURSA MALAYSIA KLCI - PRICE INDEX
Peru	01/02/1997	12/31/2015	S&P/BVL GENERAL(IGBVL) - PRICE INDEX
Philippines	01/02/1991	12/30/2015	PHILIPPINE SE I(PSEi) - PRICE INDEX
Poland	01/01/1997	12/31/2015	WARSAW GENERAL INDEX - TOT RETURN IND
Portugal	01/02/1997	12/30/2015	PORTUGAL PSI-20 - PRICE INDEX
Russia	12/30/1991	12/31/2015	RUSSIA RTS INDEX - PRICE INDEX
Thailand	01/02/1991	12/30/2015	BANGKOK S.E.T. - PRICE INDEX
Turkey	01/02/1991	12/31/2015	BIST NATIONAL 100 - PRICE INDEX
United States	01/01/1991	12/31/2015	DOW JONES INDUSTRIALS - PRICE INDEX
South Africa	01/01/1997	12/31/2015	FTSE RAFI

AB. Robustness and Extensions

Figure A3 and A4 reports robustness checks and extensions derived using equation (2). Figure A3 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 Figure 2A) but are unchanged when excluding the GFC or restricting attention to AE or EM. Figure A4 plots the response across time and groups of countries using the standard measure of sentiment. Figure A5, Figure A6, and Figure A7 re-estimates Figure 2.A while controlling for the US Economic Policy Uncertainty (EPU) Index, our uncertainty index, and the Citi Index of Economic Surprises, respectively. Figure A9 re-estimates Figure 2.A and 2.B under Driscoll and Kraay (1998) and double-clustered standard errors.

Figure A3. Panel with TF–IDF sentiment



Notes: Results are derived using Equation (2) and using the updated version of news sentiment based on TF–IDF weights. 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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure A4. Benchmark results – Country and Time Split

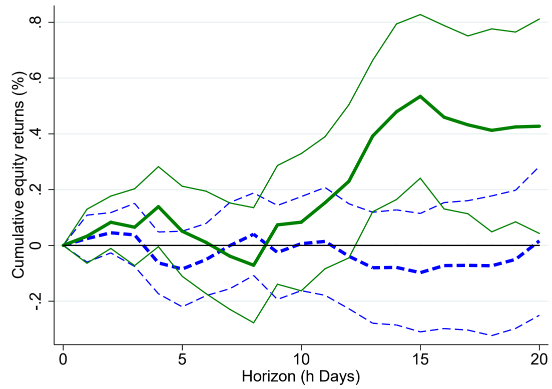


Figure A4.A. AE (1991-1999)

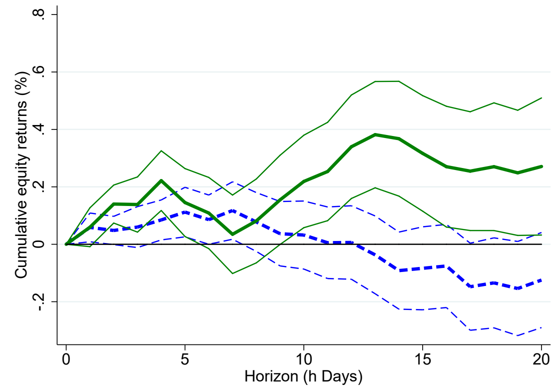


Figure A4.B. EM (1991-1999)

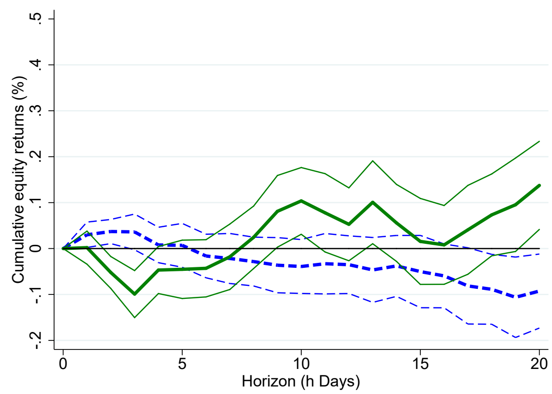


Figure A4.C. AE (1999-2007)

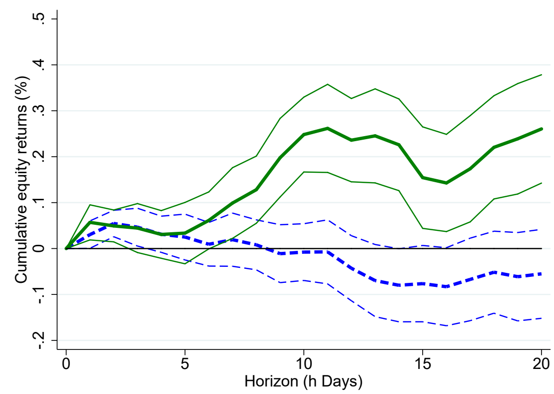


Figure A4.D. EM (1999-2007)

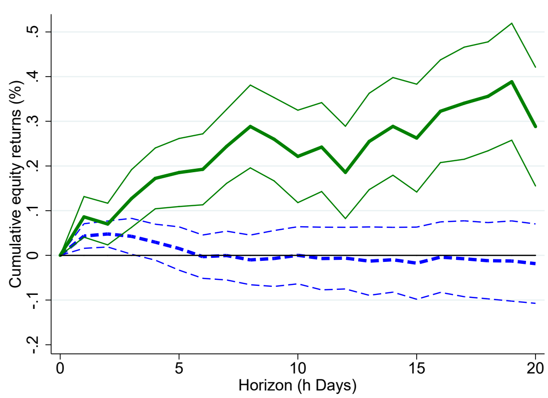


Figure A4.E. AE (2007-2015)

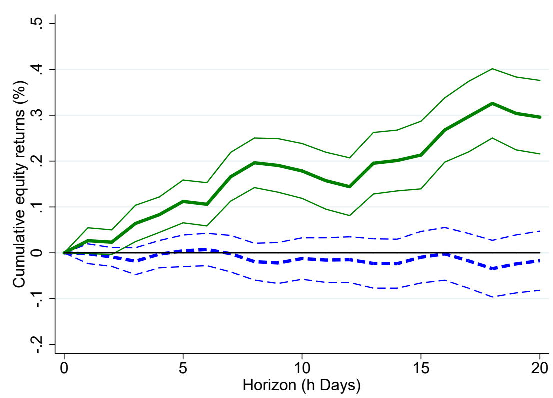
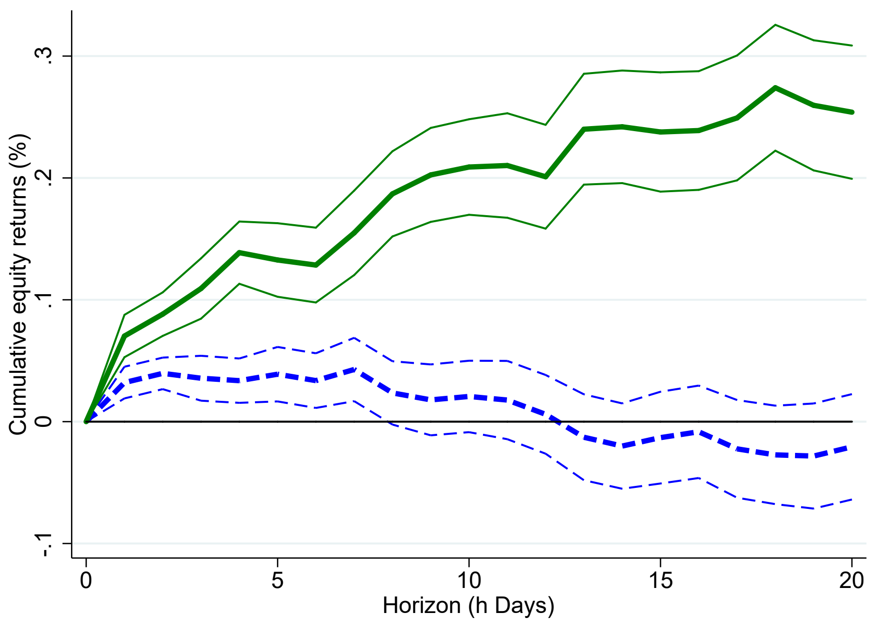


Figure A4.F. EM (2007-2015)

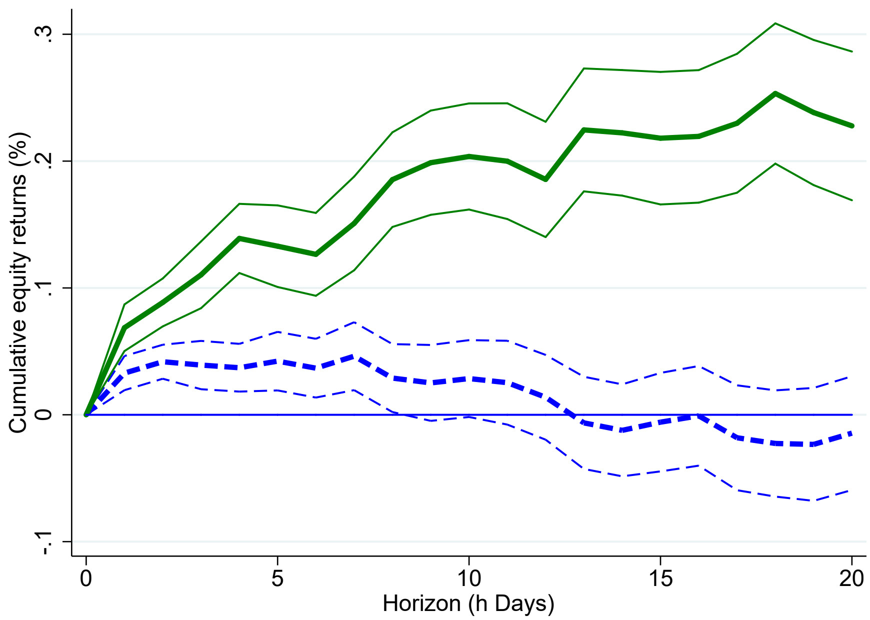
Notes: Results are derived using equation (2) for subsamples split by the income group of the countries (AE or EM) and the time period covered (1991-1999, 1999-2007, and 2010-2015). Lines plot the cumulative response of equity prices to a news sentiment shock h-days ahead. The x axis denotes the number 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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure A5. Panel controlling for US EPU



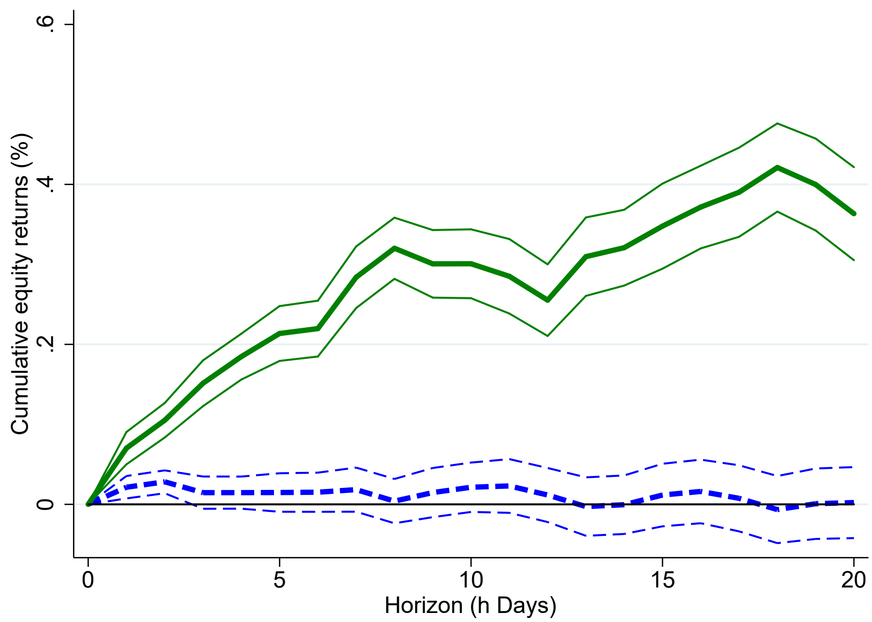
Notes: Results are derived by introducing the US Economic Policy Uncertainty (EPU) Index from Baker et al. (2016) into equation (2) as an additional control. Lines plot the cumulative response of equity prices to a news sentiment shock h-days ahead. The x axis denotes the number of days after the shock. 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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure A6. Panel controlling for uncertainty index



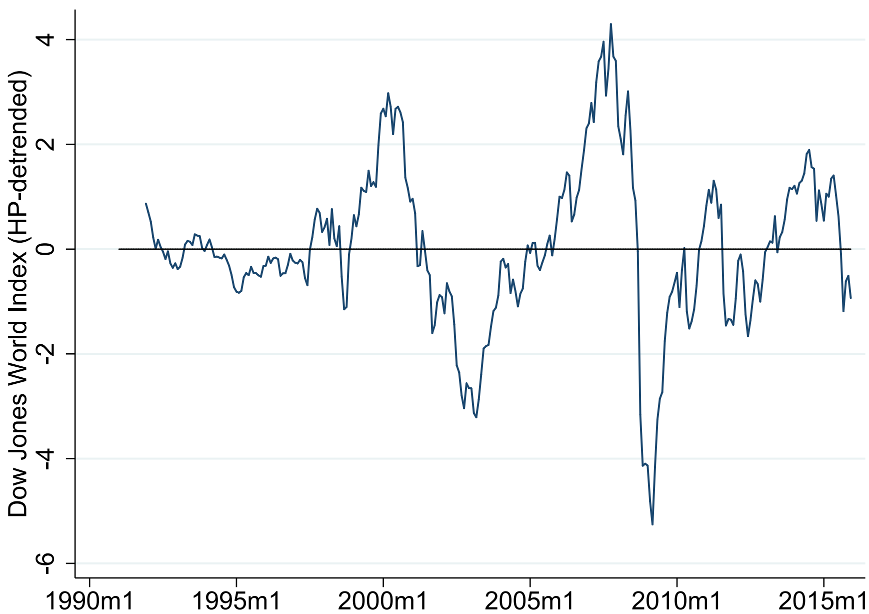
Notes: Results are derived by introducing a (country-specific) news uncertainty index into equation (2). Mirroring the approach we use to measure news tone, we compute news uncertainty by computing the fraction of uncertainty related words in each article every day. Lines plot the cumulative response 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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure A7. Panel controlling for the Citi Index of Economic Surprises



Notes: Results are derived by introducing the Citi Index of Economic Surprises for the US, the Euro Area, China and the G10 countries into equation (2). The Citi Index of Economic Surprises, which are available in daily frequency since 2001, 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 serial correlation and heteroskedasticity using the Newey and West estimator with the truncation lag set to equal the projection horizon h, as suggested by Jordà (2005) and Kilian and Kim (2011).

Figure 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.

Figure A9. Figure 2.A and 2.B estimated under alternative standard errors

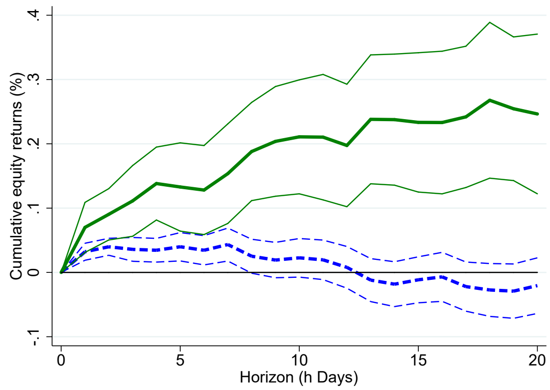


Figure A9.A. Panel Full Sample
(Driscoll and Kraay (1998))

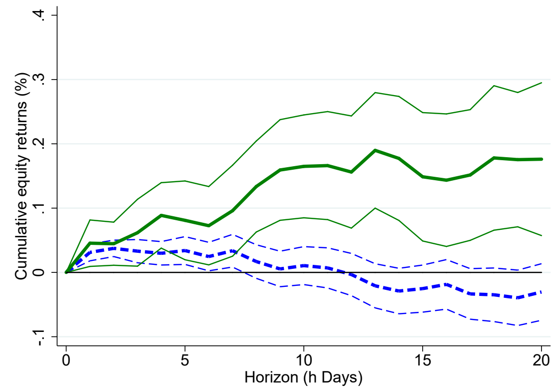


Figure A9.B. Panel – excl. GFC
(Driscoll and Kraay (1998))

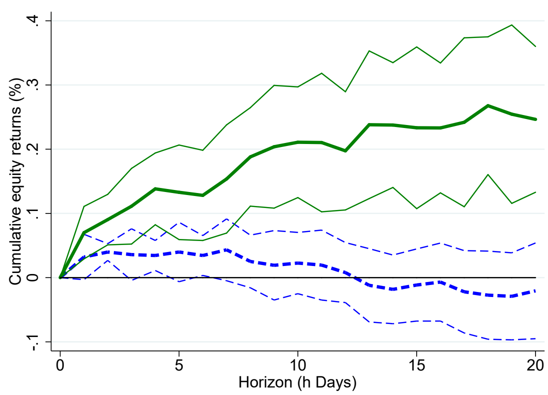


Figure A9.C. Panel Full Sample
(Double-Clustered)

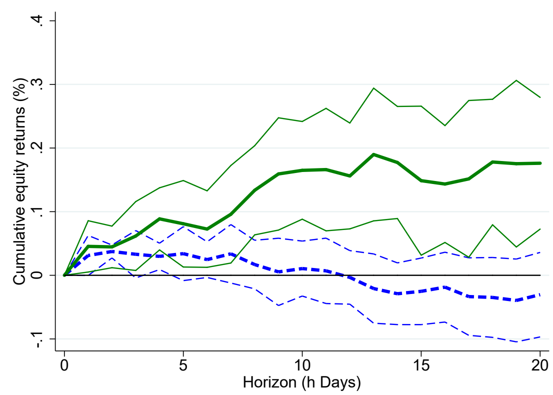


Figure A9.D. Panel Full Sample
(Double-Clustered)

Notes: This figure re-estimates Figure 2.A (left panel) and 2.B (right panel) under Driscoll and Kraay (1998) (top panel) and double-clustered (bottom panel) standard errors. Results are derived using equation (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 Driscoll and Kraay (1998) standard errors (top panel) are robust to general forms of cross-sectional and temporal dependence; 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). Double-cluster robust standard errors (bottom panel) are clustered by country and time.