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Media Sentiment and International Asset Prices

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I N T E R N A T I O N A L   M O N E T A R Y   F U N D

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Media Sentiment and International Asset Prices

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Abstract

We assess the impact of media sentiment on international equity prices using more than 4.5 million Reuters articles published across the globe between 1991 and 2015. News sentiment robustly predicts daily returns in both advanced and emerging markets, even after controlling for known determinants of stock prices. But not all news-sentiment is alike. A local (country-specific) increase in news optimism (pessimism) predicts a small and transitory increase (decrease) in local returns. By contrast, changes in global news sentiment have a larger impact on equity returns around the world, which does not reverse in the short run. We also find evidence that news sentiment affects mainly foreign – rather than local – investors: although local news optimism attracts international equity flows for a few days, global news optimism generates a permanent foreign equity inflow. Our results confirm the value of media content in capturing investor sentiment.

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I. Introduction

The amount financial and economic news has increased dramatically over the past 20 years. The rise of real time news-wire such as Reuters and Bloomberg has also greatly increased the speed at which news travel across the world. Beyond providing information, journalists also choose to portray events related to asset market variations using tonal words that could intrinsically affect investors' investment decisions. This paper explores the impact of such media sentiment on equity prices.

Using more than 4.5 million Reuters articles published across the globe between 1991 and 2015, we find that news tone – our measure of news sentiment - robustly predicts daily returns in both advanced and emerging markets, even after controlling for known determinants of stock prices. However, not all news has the same impact. Local (country-specific) news optimism (or pessimism) only affects equity returns temporarily, i.e. for a few days. By contrast, changes in global news sentiment have a larger impact on equity returns around the world that does not reverse in the short run, suggesting a novel and arguably stronger source of sentiment-driven asset price fluctuations. Combining our news sentiment indices with daily equity flows from mutual funds investing in sixteen EMs between 2007 and 2015, we find an effect strikingly close to that of stock returns: although local news optimism attracts equity flows for a few days only, global sentiment optimism attracts them permanently. However, this effect is driven by the (net) asset demand of foreign funds domiciled outside of the country rather than local funds domiciled in the country, suggesting that news tone affects prices mostly through its effect on foreign investors' sentiment.

Our paper is constructed as follows. Using the fraction of positive and negative words in each article to capture the tone of news published, we first construct a daily news-based sentiment index for 25 advanced and emerging countries between 1991 and 2015. We then estimate the response of equity prices to sentiment shocks using Jordà's (2005) local projection method. We first estimate the effect of US news sentiment on US equity returns and compare our results to existing studies on the US such as Tetlock (2007). We then test whether these results extend to all countries, after controlling for known sources of predictability in international equity returns, both locally and globally (e.g. commodity prices, VIX etc.). Overall, we find panel estimates to be close to the US benchmark. Positive sentiment shocks also imply a significant impact on equity returns of 10 basis points that partially reverses after a few days, confirming that the effect of news sentiment on asset prices is a pervasive phenomenon that is not limited to the US.

Since a large fraction of news articles in our corpus refer to multiple countries, we then explore whether sentiment shocks are mainly driven by local (country-specific) news, or by global news having an impact on a country. To isolate the effect of local news from that of global news, we start by recomputing the daily sentiment index for each country after having excluded articles that mention any other country than the country of interest, allowing us to capture the sentiment in genuinely local news. Second, we augment our specifications with a daily "global news sentiment index" extracted from the original cross-country sentiment indices, allowing us to control for the tone of news published in the world every day. We find that the effect of local sentiment shocks is still significant and transitory. However, 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 returns around the world and do not reverse in the short run (i.e. at least 3 weeks). In our sample, sudden changes in optimism (or pessimism) in global news generate a permanent increase (decrease) of 25 basis points - roughly five times the size of the local sentiment shock – that reaches its peak slowly after ten to fifteen days, both in Advanced Economies (AEs) and in Emerging Markets (EMs).

Finally, we extend our analysis to international equity flows. Using daily equity flows from a very large number of international equity mutual funds investing in sixteen EMs between 2007 and 2015, we explore the response of capital flows to both local and global news sentiment shocks. 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 sentiment optimism generates a permanent equity inflow peaking after two weeks. Using the official domicile of each fund as a proxy for the location of investors, we then contrast the response of local and foreign equity funds. Although funds located outside the country respond strongly to news sentiment, the response from local funds is muted, suggesting that news tone affects prices mostly through its impact on foreign investors' sentiment.

We close the paper by investigating further the properties of global news sentiment. We report three interesting findings. First, the effect of global news sentiment is state-dependent: the impact of global news sentiment is four times stronger in global "bear" markets than in global "bull" markets, suggesting that investors are more sensitive to news tone during global market downturns. Second, we find that the global news sentiment index explains more of the variance in equity returns across the world than other typical measures of global risk aversion, such as the VIX. Although VIX shocks have a stronger impact on equity markets around the world, they are also much less frequent than shocks captured by the global news sentiment index, which arguably captures a much broader set of events than the VIX, especially when it comes to periods of global market optimism. Finally, we investigate the kind of news that drive sudden changes in global news sentiment. In general, global news sentiment is driven by multi-country news, which are broader, longer and with a stronger tonality than local news articles. However, the content of those news varies significantly with the direction of the global news sentiment index: when the global news sentiment index is strongly positive, the corpus of news in the world tilts towards positive financial and corporate news in advanced AEs, especially in the US. By contrast, the coverage tilts strongly towards economic and political news in EMs when the global news sentiment index goes into negative territory, suggesting that the drivers of global market rallies differ from those of global sell-offs.

Overall, our findings are robust to a variety of tests and extensions. Importantly, we show that results are stable over time and across countries (EMs and AEs), are not driven by extreme values or crisis events (such as the Global Financial Crisis) or by the presence of key countries – such as the US – in the sample. They are also robust to an alternative measure of sentiment based on a "Term Frequency - Inverse Document Frequency" ("TF-IDF") weighting of words. Since we control for the number of articles published every day, the effect we capture is also unlikely to capture the volume of news, as opposed to its tone.

Taken together, our results are consistent with shocks to investors sentiment, affecting both advanced and emerging countries, during which local news and their tone affect investor sentiment and prices momentarily before returning to their fundamental values. From a theoretical perspective, this finding is consistent with the presence of noise (or liquidity) traders (DeLong et al (1990), Campbell (1993)). Although we are not able to identify which theory prevails, using capital flows data reveals that such traders are more likely to be foreigners than locals. The response of equity prices to global news sentiment shocks is, however, more ambiguous. The longer and more permanent impact on world stock markets is consistent with global news containing genuinely new (good or bad) information on global fundamentals that is only slowly incorporated into stock prices. An alternative explanation is that sudden changes in global news sentiment are strong enough to cause drifts in investors' sentiment that do not reverse in the short run, even in the absence of new "hard" information about fundamentals. The fact that global news shocks have a stronger impact in troubled times, when investors are more anxious, support this interpretation (Garcia, 2013).

This paper relates to the growing body of research investigating the link between the news media, investor sentiment, and asset prices, in particular Tetlock (2007) and Garcia (2013). We contribute to this literature in several ways. To our knowledge, we are the first to assess the link between news sentiment and equity returns in a large sample of advanced countries and emerging countries using a large dataset of news.[2] Extending the analysis to other countries allows us to isolate the contribution of global sentiment and highlight its differential effect. Finally, we are the first to assess the effect of sentiment shocks on high frequency capital flows data. Beyond validating the results obtained on prices, our results cast a light on *who* are the investors most sensitive to sudden changes in sentiment. More generally, we are closely connected to the vast empirical literature on investor sentiment that has focused on how to measure investor sentiment and to quantify its effects on a variety of financial market outcomes (See Baker and Wurgler (2007) for a review). With respect to that literature, we confirm the value of media text (and tone) in in capturing investors' sentiment.

[2] 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 results also contribute to the vast literature documenting the strength – and rise – of co-movement 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, (2013), Puy (2016), Claessens, Cerutti and Puy (2015)). Most of the debate has focused on the importance of global (or external) factors for (local) asset price movements, and the role of foreign investors in propagating shocks across countries. Broadly speaking, our results support the view that external events matter and are in general stronger than local factors. In particular, global news sentiment contributes significantly to global asset prices co-movement, through its impact on international investors' behavior. However, we do not find evidence that this phenomenon has increased over time or affects more EMs than AEs.

Finally, from a technical perspective, we are connected to the recent and fast-growing literature that links textual information to both economic and financial outcomes (see Gentzkow, Kelly, and Taddy (2017) for a review). Among many others, Baker, Bloom, and Davis (2016) develop an index of economic policy uncertainty from US newspaper articles, showing that it forecasts declines in investment, output, and employment.[3]Using daily Internet search volume from millions of households in the US, Da, Engelberg and Gao (2015) found that the volume of queries related to household concerns (e.g., "recession," "unemployment," and "bankruptcy") could predict short-term return reversals, temporary increases in volatility, and mutual fund flows out of equity funds and into bond funds.

The rest of the paper is constructed as follows. Section II presents the data used in this paper, and the text analysis we use to construct sentiment measures. Section III presents the empirical framework and key results. Section IV provides further results on the properties of the global news sentiment index. Section V reports extensions and robustness. The last section concludes.

[3] Our results are orthogonal to the various EPU indexes constructed by Baker, Bloom and Davis (2016). Results available on request.

II. Data description

The paper uses three main data sources: (i) articles to construct country-specific news-sentiment indexes (ii) asset prices and related high-frequency financial variables (such as trading volumes or liquidity measures) and (iii) capital flows data. We detail them in turn.

A. News articles and Sentiment measures

1. News articles

Our dataset of news articles was acquired from Factiva, a leading provider of news archives. We focused on articles published by Reuters in English, as it offers the most consistent coverage over time and across countries. Each article contains a timestamp, a title, a main text, as well as topics and locations tags generated by Factiva using a proprietary algorithm. We selected all the articles tagged with either “Economic News” or “Financial Market News”, as well as with at least one of the countries included in our sample. Our dataset contains close to 4.5 million daily articles covering 25 countries - 9 Advanced Economies (AEs) and 16 Emerging Markets (EMs) - from 1991 to 2015.

Summary tables and figures reporting (i) the start (and end) of the news coverage by country (ii) the number of articles by country and (iii) the main topics covered in our corpus are provided in Appendix. Overall, the articles we use cover a wide range of economic news (economic policy, government finance etc..), financial news (commodity markets, equity markets, forex etc..), corporate news and political news. The distribution of topics is similar in AEs and in EMs. Quantitatively, US-related articles represent one fourth of our sample (200 articles per day).[4] The distribution of non-US country tags is more balanced, with an average of 97,000 articles per country over the whole sample (20 articles per day).

2. News-Sentiment measures

To measure sentiment, we use pre-existing dictionaries of tonal words. Given the range of topics covered in our corpus of news, we first combine dictionaries of positive and negative words compiled by Loughran and McDonald (2011) for financial texts and by Young and Soroka (2012) for political and economic texts. Next, for each word in a dictionary (e.g. “lose”), we collect all of its inflections (“losing”, “loser”, “lost”, “loss”, etc.) that are present in our corpus and include them in the dictionary, obtaining a list of 7,217 negative words and 3,250 positive words. Table 1 reports the most frequent tonal words in our corpus, illustrating that the most frequent positive and negative words we selected reflect the sentiment typically associated with economic or financial outcomes.

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[4] Note that articles can tag multiple location and topics at the same time. See Appendix for details and next section for an example.

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

Positive Word	Fraction Of Positive Words	Fraction Of Articles	IDF
strong	0.107	0.118	2.135
gains	0.099	0.104	2.265
well	0.082	0.103	2.271
good	0.065	0.077	2.561
help	0.061	0.074	2.603
recovery	0.056	0.058	2.850
highest	0.044	0.053	2.935
agreement	0.043	0.042	3.179
assets	0.042	0.042	3.159
positive	0.041	0.051	2.973
better	0.041	0.053	2.932
gained	0.041	0.049	3.007
boost	0.040	0.054	2.914
leading	0.039	0.052	2.957
confidence	0.036	0.039	3.255
gain	0.035	0.042	3.159
agreed	0.034	0.042	3.179
stronger	0.032	0.042	3.172
worth	0.032	0.039	3.239
opening	0.032	0.041	3.199

Negative Word	Fraction Of Negative Words	Fraction Of Articles	IDF
crisis	0.088	0.069	2.675
losses	0.072	0.069	2.677
deficit	0.071	0.044	3.132
weak	0.070	0.070	2.656
limited	0.063	0.062	2.774
concerns	0.063	0.067	2.705
decline	0.050	0.052	2.960
weaker	0.048	0.049	3.007
poor	0.047	0.049	3.017
unemployment	0.045	0.030	3.493
lost	0.045	0.048	3.034
fears	0.041	0.045	3.109
dropped	0.040	0.045	3.095
slow	0.039	0.042	3.162
negative	0.039	0.040	3.225
problems	0.037	0.039	3.233
worries	0.037	0.040	3.210
hard	0.036	0.039	3.234
recession	0.035	0.032	3.457
loss	0.033	0.032	3.441

Note: This table presents the most frequent positive (negative) words in our corpus of news articles. The first column reports the weight of each word as a share of all positive (negative) words. The second reports the fraction of articles in which it appears. The third column reports its inverse document frequency (IDF), which is defined below.

Source: Dictionaries come from Loughran and McDonald (2011) and Young and Soroka (2012). News articles come from Factiva.com.

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, t_{ij} is the number of occurrences of word i, and w_{ij} is the weight associated with word i. In the baseline case, we take $w_{ij} = 1$, each word contributing to the sentiment measure proportionally to its frequency of occurrence in an article. However, it is well established that the distribution of words in the English language follows a Zipf's law, with most words appearing infrequently while a small number of words are being used very frequently.[5] In a robustness check, to smooth the differences in word frequency naturally occurring in the English language, we allow each word to contribute to the sentiment index proportionally to its "Term Frequency - Inverse Document Frequency" ("TF-IDF"). In this case, we have:

[5] For a broader discussion of Zipf's laws in economics, see Gabaix (2016).

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

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 gives more weight to words that appear more rarely across documents.

To illustrate our dictionary-based approach to measuring sentiment, here is an example of an article in our corpus in which the tonal words are underlined.[6] It suggests that although our sentiment measure s_j does not capture all 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

After computing the sentiment of each article s_j, we obtain a daily sentiment index for each country c by taking the average of s_j across articles published in any given day that contain country c in its location tags.

B. Asset prices and related variables

We explore the impact of news-sentiment measures on stock market returns. Equity returns are computed using the country's main stock market index. Returns are computed in local currency to isolate the effect of sentiment on the local stock market from its effect on the exchange rate. Daily world returns, which are used as a global control, are computed using the Dow Jones World Index. The final coverage, along with the list of indexes and sources used to compute equity returns is reported in the Appendix.

[6] This article's main location tag is Argentina and one of the topic tags is "Economic News".

To proxy for market liquidity, we also collect daily equity trading volumes reported by local stock exchanges. Following Campbell, Grossman, and Wang (1993) and Tetlock (2007), we compute the detrended log of daily trading volume, using the rolling average of the past 60 days of log volume as the trend. Similarly, we measure stock market volatility by first de-meaning each daily stock return, squaring this residual and then subtracting the past 60-day moving average of the squared residual.

Finally, we use (i) the S&P Goldman Sachs Commodity index to measure daily changes in commodity prices (in %) and (ii) the CBOE VIX to proxy for global volatility.

C. Capital flows

We assess the impact of news sentiment shocks on capital flows using daily equity fund flows from EPFR. The EPFR global dataset, which tracks the asset allocation of equity and debt funds domiciled in developed countries and key offshore financial centers, has become an important source of high-frequency capital flows.[7] Because of its extensive industry coverage and quality, the EPFR global has been widely used recent academic contributions on funds behavior (e.g., Raddatz and Schmukler (2012), Jotikasthira et al. (2012), Fratzscher (2012), and other references therein).[8] In policy circles, fund flows reported by EPFR have been increasingly used as a (high frequency) proxy for foreign capital inflows, especially in Emerging Markets.[9]

In practice, we use the "equity country flows" data set, which reports, every day, the estimated amount of equity funding in US dollars that came (or left) each country, each day, because of international funds' portfolio reallocation. Overall, our dataset of equity flows covers 16 emerging markets between 2005 and 2015.[10] After estimating the effect of sentiment shocks

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[7] Its coverage has increased significantly over time, reaching currently a wide industry and geographic coverage. As of 2013, the EPFR global was collecting information from more than 29,000 equity funds and 18,000 fixed-income funds representing US$20 trillion of assets invested in over 80 advanced economies and EMs.

[8] 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 EPFR and CRSP datasets.

[9] Most funds followed by the EPFR global dataset (i) are located in advanced economies and (ii) account for a significant share of the external funding received by EMs. As a result, country flows dataset has proved to be a good (high frequency) proxy of total gross inflows in (or out) of emerging countries. For instance, Miao and Pant (2012) showed that EPFR fund flows correlate well with BOP recorded capital flows into EMs.

[10] We focus on EMs for two reasons. First the EPFR data coverage is generally much higher for EMs than for AEs, so the correlation between EPFR equity flows and equity flows measured by the IMF Balance of Payments is higher for EMs. Using the fund's domicile in the EPFR database to distinguish foreign vs. local funds is also more accurate when focusing on EMs. A high number of funds investing in AEs are domiciled in regional tax

on the total equity inflow (or outflow) into (or out of) the country, we then distinguish the behavior of local and foreign equity funds using the official domicile of the fund.[11]

III. News, Sentiment and Equity Returns

A. Empirical framework

Except when otherwise noted, we estimate the (cumulative) response of asset prices to daily sentiment shocks using Jordà's (2005) local projection method, both for individual and panel regressions. This choice is mainly driven by the uncertainty surrounding the timing, strength and linearity of the responses in asset prices to news shocks in our sample, which spans both AEs and EMs over more than 25 years. In this context, a flexible estimation method that is more robust to misspecification than typical VARs is desirable. In practice, we estimate the following model:

Equation (1)

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

where $Cum\_R_{i,t,t+h}$ designates the cumulative equity returns in country i between day t and t+h (in %), $\mu_{i,h}$ captures country-fixed effects, $R_{i,t}$ denotes the (daily) equity return in %, $GoodNews_{i,t}$ denotes the (normalized) value of the news-based sentiment index, $Art_{i,t}$ denotes the number of articles published, $Vlm_{i,t}$ denotes the de-trended log-trading volumes proxying for market liquidity, $Vol_{i,t}$ denotes our proxy for market volatility; $Glob_t$ denotes global controls - such as daily world equity returns (in %), VIX or changes in commodity prices (in %) - used to capture other sources of global news; and $D_{i,t}$ denotes a set of outlier and day-of the week dummies. We report results using the equal weighting scheme to create the sentiment index (defined as s_j above) and report results derived using the TF-IDF weighting scheme in Appendix (see also robustness section). Our results are not sensitive to this definition however.

heavens (e.g. Luxembourg for European funds) which makes them foreign from the point of you of many AEs, even though they are local funds. This problem is much less present for EMs.

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

Consistent with Tetlock (2007) and Garcia (2013), this model allows us to test whether optimism in the news published *today* (or in the last few days) can predict *future* returns after controlling for all known sources of predictability for up to J=8 days. For instance, 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, whereas measures of (detrended) volatility proxy for the influence of several other market frictions that can affect prices in the short run. Finally, dummies in the vector *D* make sure our results are not driven by outliers (e.g. crisis) or predictable spikes in returns, which typically occur at the beginning or the end of the week.

This specification deviates from Tetlock (2007) in several ways, however. First, we control for the number of articles published each day, allowing us to differentiate between the volume of news and its (average) tone.[12] Second, we include global proxies - global returns or yields, VIX and change in commodity prices - to capture global co-movement, ensuring that our sentiment index is not only capturing shocks that are known to affect asset prices around the world. Third, we estimate the cumulative response of returns up to 20 days (as opposed to 5 trading days for Tetlock (2007)).

We estimate this equation using OLS and lags up to 8 days. Since the error term in the local projection framework follows a moving average process of order *h-1* by construction however, standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator. 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).[13]

B. <u>Results – Benchmark</u>

To compare our results with the seminal work of Tetlock (2007) and help the interpretation of subsequent panel regressions, Figure 1.A reports regression results on the US only, i.e. using US news only and (daily) US Dow Jones Industrial Index returns between 1991 and 2015.[14] Our estimation is based on 6,260 observations, against 4,000 in the original paper. Interestingly, although our set-up varies in a few ways compared to Tetlock (2007), we find very similar

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[12] The number of articles used to estimate sentiment can vary with the definition of sentiment (unweighted, TF-IDF etc..) or when performing robustness checks. We adjust the number of articles accordingly, so that the number of articles always correspond to the definition of sentiment used.

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

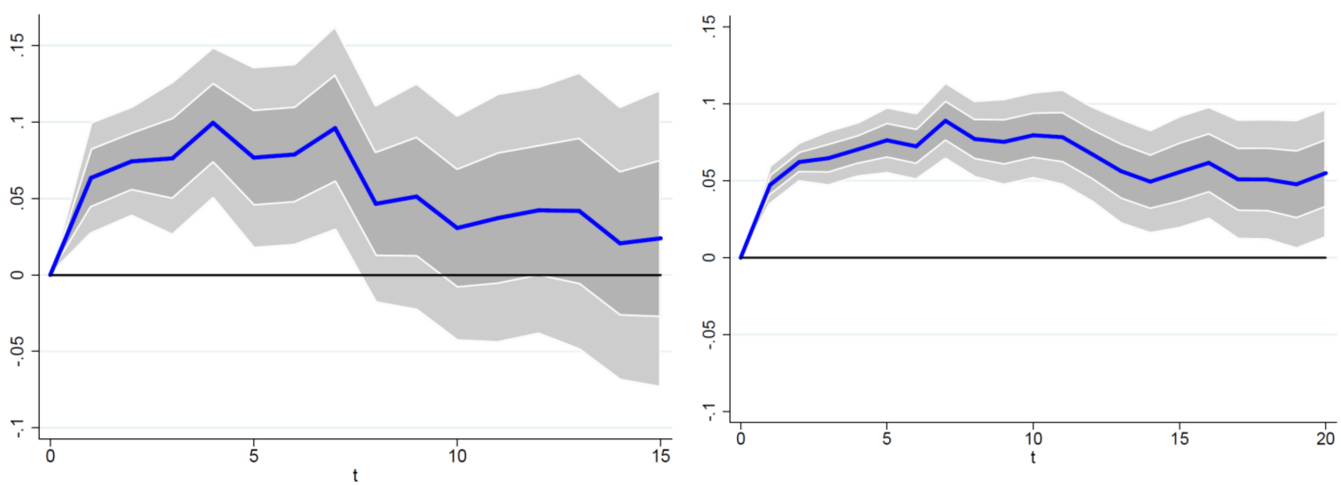
[14] More specifically, we replicate Equation (1) in Tetlock (2007).

results. Good news – measured by a one standard positive deviation in sentiment – generate positive but transitory returns. The response peaks slightly below 10 basis points and is not statistically different from zero after one calendar week.[15]

Figure 1.B generalizes the regression performed for the US to a panel context. In line with equation (1), we control for global events using the global daily return of the World Dow Jones Index, the daily VIX and daily changes in commodity prices to control for residual global co-movement and typical shocks that affect returns around the world. To ensure that our results are not driven by extreme values, we also control for outliers in both returns (using dummies) and regressors (winsorizing variables at 0.05%). All regressions also include day-of the week fixed effects. Our estimation is based on 101,170 observations in a panel covering 25 countries. Interestingly, the panel results are close to the US benchmark. We find that the effect of news sentiment on asset prices is a pervasive phenomenon that is not limited to the US. A positive sentiment shock implies a positive and economically significant increase in equity returns. Although the magnitude of the impact at the peak is similar to the US – with a peak estimated at 9 basis points – the reversal is not complete however. We obtain a similar result when we remove the US from the sample, indicating that the result is not driven by the US.

Figure 1 – Benchmark Results – Equity Returns

Figure 1.A - US only | Figure 1.B – Panel Full Sample



Note: t denotes the number of days after the shock. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.

C. Global vs. Local News Sentiment

[15] In Tetlock (2007), a one-standard deviation change in pessimism was generating a drop of 8.1 basis points in Dow Jones returns the next day. This negative impact was (almost) completely reversed by the end of the trading week.

Two types of articles constitute our corpus: local news and multi-country news. About 60% of our corpus consists of local news (i.e. ~2.5 million), which only mentions one country and convey rather specialized content. A typical example of local news is the article reported in section 2, discussing labor market laws in Argentina.[16] By contrast, the remaining 40% of our corpus contains articles discussing multiple countries. A typical multi-country news is the article about "Fears of Brazilian devaluation hit emerging markets" reported in Appendix, which mentions multiple countries and their interrelations.[17] The presence of multi-country news mechanically increases the co-movement of our country-level 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 of a country excluding any article mentioning any other country. This highly restrictive filter removed 1.5 million articles across countries (see Appendix),[18] allowing us to only focus on genuinely local (country-specific) news.[19] Second, we extract a common factor ("global news sentiment") from our initial sentiment series using a Kalman filter. We then include the global news sentiment index in our regression, allowing us to contrast the effect of local and global news and to control for residual cross-country correlation in sentiment indices that was not properly purged by our filter based on location tags.

More specifically, we now estimate the following model:

Equation (2)

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

Figure 2 presents the results using these two alternatives. Figure 2.A reports results for the full sample, whereas Figure 2.C and 2.D report results for AEs and EMs, respectively.

[16] Other recent headlines that would typically qualify as purely local articles are as follows: "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.

[17] 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.

[18] The share of local news is reported on the histogram showing the distribution of topics in our corpus of news.

[19] As expected, cross country-correlations in sentiment also decreases substantially once we purge "multi-country" news and restrict attention to local news.

As expected, we find that controlling for the global sentiment affects the size and shape of the response of the local news sentiment (in blue), the cumulative response being roughly twice smaller (5 basis points, as opposed to 10 in the previous estimates, see Figure 1.B). 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.[20] Broadly speaking, these results confirm the existence of pure “sentiment” shocks, affecting both advanced and emerging countries, during which the tone of local news affect investor sentiment and prices momentarily before returning to their fundamental values. From a theoretical perspective, this finding is consistent with the presence of noise (or liquidity) traders (DeLong et al (1990), Campbell (1993)).

In sharp contrast, we find that global news sentiment shocks have a stronger and permanent effect on returns (in green). We estimate a total permanent impact around 25 basis points - roughly 5 times the size of the local sentiment shock - which is reached after 10 to 15 days. Importantly, this result is only marginally affected by the exclusion of the GFC from our sample. This longer and permanent impact on world stock markets suggests that global news contain genuinely new information about fundamentals that is only slowly incorporated into stock prices. An alternative explanation is that sudden changes in global news sentiment are strong enough to cause drifts that do not reverse in the short run, even in the absence of new “hard” information about fundamentals.

[20] The median absolute deviation in our sample is 70 basis points, for both AEs and EMs. This suggests a non-trivial economic impact of sentiment shocks of roughly the same magnitude for both emerging and advanced countries.

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

Figure 2.A – Panel Full Sample

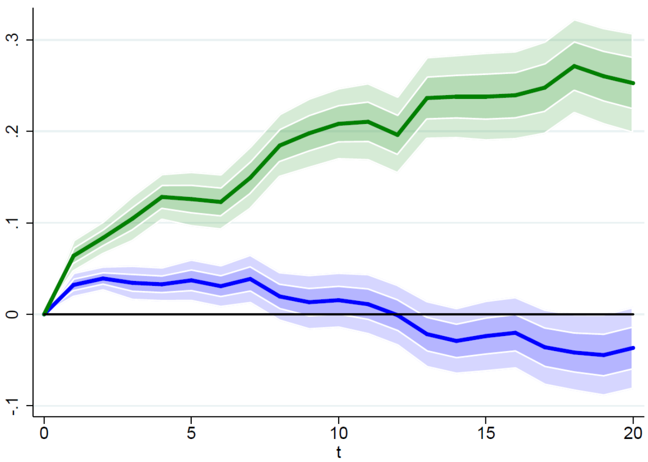


Figure 2.B – Panel – excl. GFC

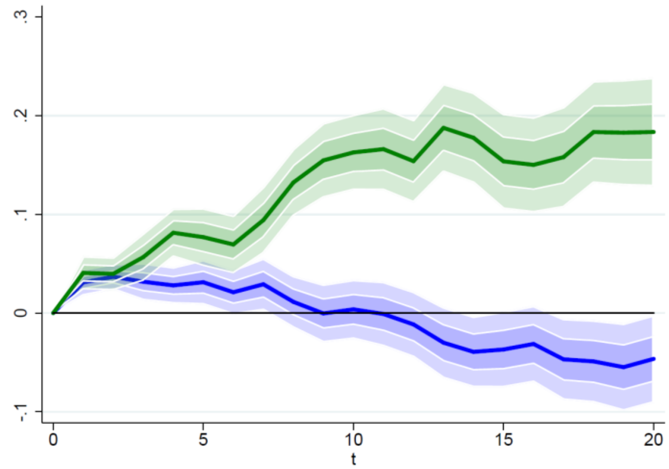


Figure 2.C – Advanced Economies

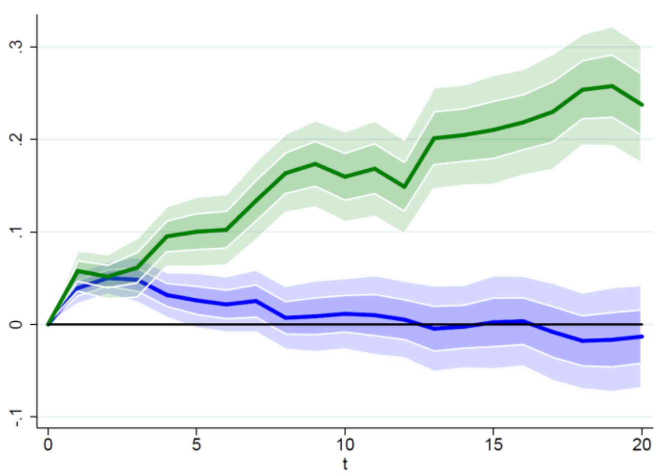
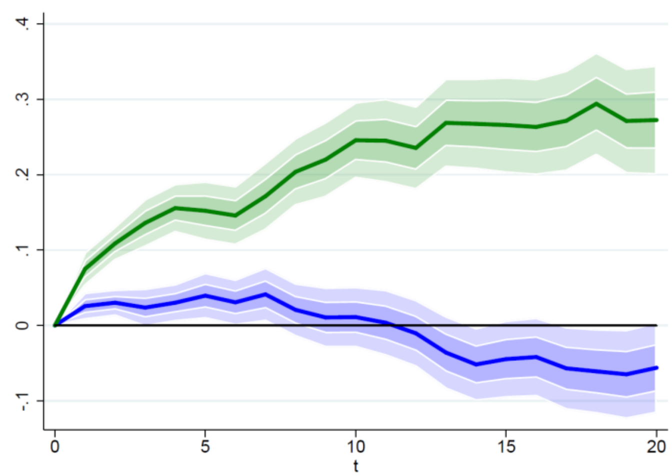


Figure 2.D – Emerging Markets



Note: t denotes the number of days after the shock. The blue line reports the cumulative response of equity prices to local news sentiment shocks. The green line reports the cumulative response to global news sentiment shocks. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.

D. News Sentiment and Capital Flows

We now extend of our empirical framework to capital flows data. Using daily equity flows from international mutual funds tracked by EPFR between 2005 and 2015 for 16 EMs, we find a very similar response of equity fund flows to sentiment shocks. Empirically, we estimate the following model, which is a direct application of our framework to equity flows (rather than prices). Our sample is smaller than for prices however (23,720 observations), since we are not able to go as far back in time (2005, as opposed to 1991).

Equation 3

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

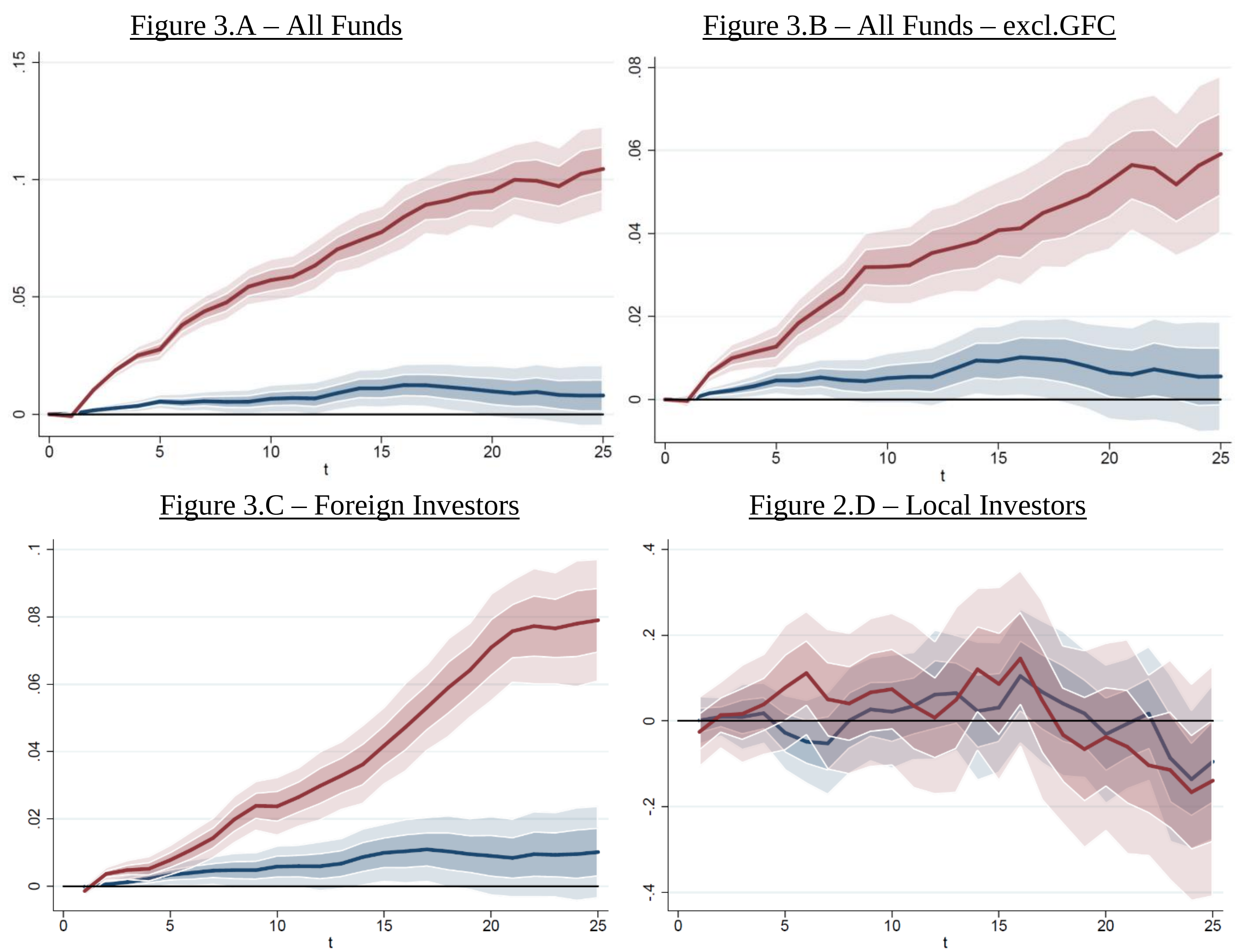
$Cum_{F_{i,t,t+h}}$ designates the cumulative equity (fund) flows in country *i* between day *t* and *t+h* (expressed in % of the initial allocation of capital at time *t-1*), $\mu_{i,h}$ captures country-fixed effects, $F_{i,t-j}$ denotes lagged daily flows, $R_{i,t}$ denotes lagged (daily) equity return in %, $GoodNews_{i,t}$ denotes the (normalized) value of the news-based sentiment index (local or global), $Art_{i,t}$ denotes the number of articles published, $Vlm_{i,t}$ denotes the de-trended log-trading volumes proxying for market liquidity, $Vol_{i,t}$ denotes our proxy for market volatility; $Glob_t$ denotes global controls – including the daily world equity returns (in %), the VIX, changes in commodity prices (in %) and daily returns in the MSCI EM index - used to capture other sources of global news; and $D_{i,t}$ denotes a set of outlier and day-of-the week dummies.

Figure 3 reports our results. Overall, we find very similar responses between prices and flows. Although local news optimism attracts equity fund flows, it does so only temporarily. We estimate a statistically significant cumulative increase at the peak of 0.01%.[21] However, we cannot exclude a full reversal after a week (at the 5% significance level). Optimism in global news, however, generate a larger and permanent inflow of equity in all EMs in our sample, which peaks after 2 weeks around 0.1% (Figure 3.A). This result is also robust to the exclusion of the GFC (Figure 3.B). After breaking flows between local and foreign investors however, we find that these results are almost entirely driven by foreign investors, i.e. investors domiciled outside of the country (Figure 3.C). By contrast, the response of local equity investors is not significantly different from zero at all horizons and for both types of shocks (at 5% significance level).[22]

[21] 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, 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 equity flows in our sample is around 0.01%.

[22] The amount of local funds in EMs covered by EPFR increases significantly after 2010 in the database, allowing us to estimate their response more precisely. Using only post-2010 data strengthens our results however. The response of foreign investors in unchanged, while the response of local investors becomes even flatter.

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



Note: t denotes the number of days after the shock. The blue line reports the cumulative response of equity flows to local news sentiment shocks. The red line reports the cumulative response to global news sentiment shocks. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.

IV. A further look at the Global News Sentiment Index

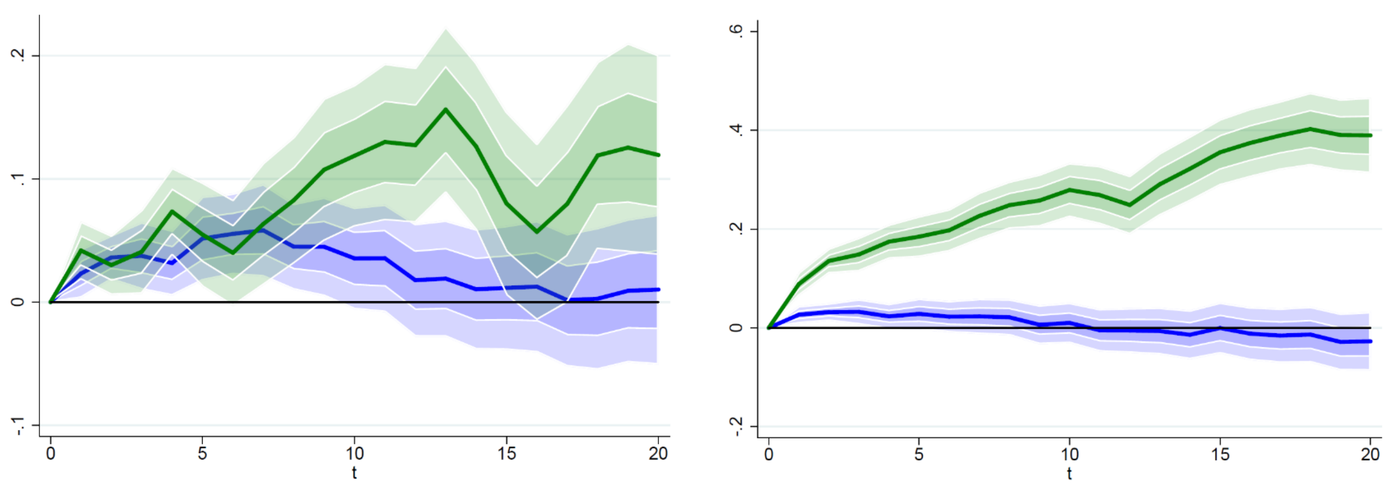
This section provides further results on the properties of the global news sentiment index. We highlight three key findings. First, the effect of global news sentiment is stronger when the global equity market is down, suggesting that investors are more reactive to good (and bad) global news during times of global market stress. Second, after comparing the global news sentiment index with the VIX, we find that the former captures a broader set of events than the latter. Innovations in the global news sentiment index also explain more of the variance in equity returns across the world than innovation in the VIX. Third, the composition of news varies with the direction of the global news sentiment index, which casts light on the kind of news that drive global stock market rallies (or sell-off). We document these findings in turn.

A. State dependence

We compare the effect of global news sentiment shocks in bull and bear global markets. Bull (Bear) markets are defined as periods during which the global equity market – measured by the Dow Jones World Index – is above its trend. Overall, we find that the impact of global sentiment shocks are roughly four times stronger in global bear markets (Figure 4), a magnitude similar to that in Garcia (2013). However, this asymmetry is not true for local news-sentiment shocks.[23]

Figure 4 – State dependence

Bull Market | Bear Markets



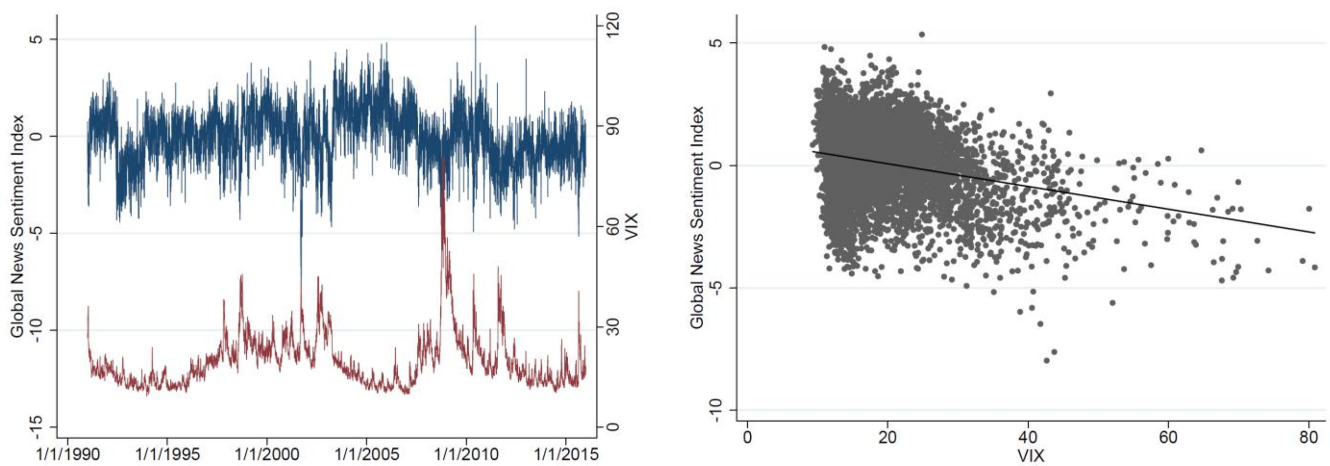
Note: t denotes the number of days. The blue line reports the cumulative response of equity prices to local news sentiment shocks. The green line reports the cumulative response to global news sentiment shocks. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.

[23] Local news shocks are not bigger when conditioning on the local (or global) market being low.

B. Comparison with VIX

How does the global news sentiment compare with another typical measure of global risk aversion, such as the VIX? Figure 5 plots global news sentiment index against 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 they both capture episode of heightened market stress. However, in many instances, movements in global sentiment are not matched by changes in the VIX. In particular, good news is not well captured by the VIX, which is a better proxy of global market turmoil than global market optimism. Overall, this suggests that the global sentiment index captures news that are not captured by the VIX.

Figure 5 – Global News Sentiment vs. VIX



Note: The left panel plots the VIX (in red – right axis) against Global News Sentiment (in blue – left axis). A scatterplot version of the same graph is reported on the right.

Using equation 2, we estimate that a one standard deviation shock in the VIX has a 1% impact on equity markets around the world, roughly six times the impact of a one-standard deviation shocks in global news sentiment (Figure 6.A). However, VIX shocks of that magnitude also happen much less often. Consequently, global news sentiment shocks account for more variance than VIX shocks at most horizons (Figure 6.B).

Figure 6 – Global News Sentiment Shocks vs VIX

Figure 6.A – Quantitative Impact

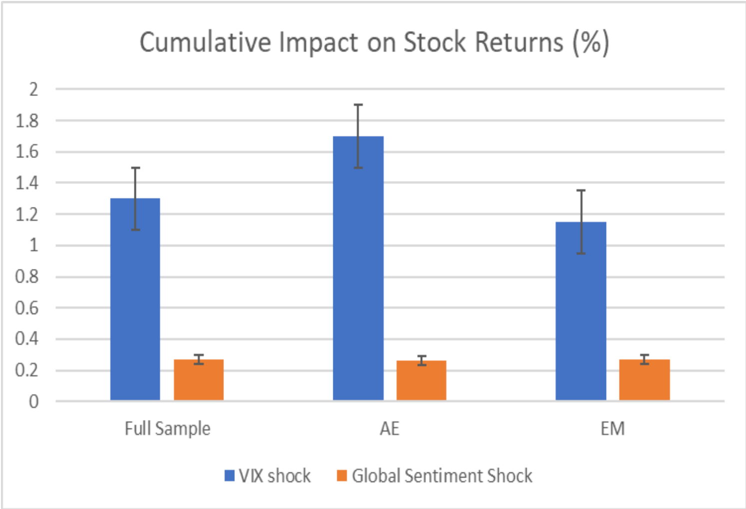
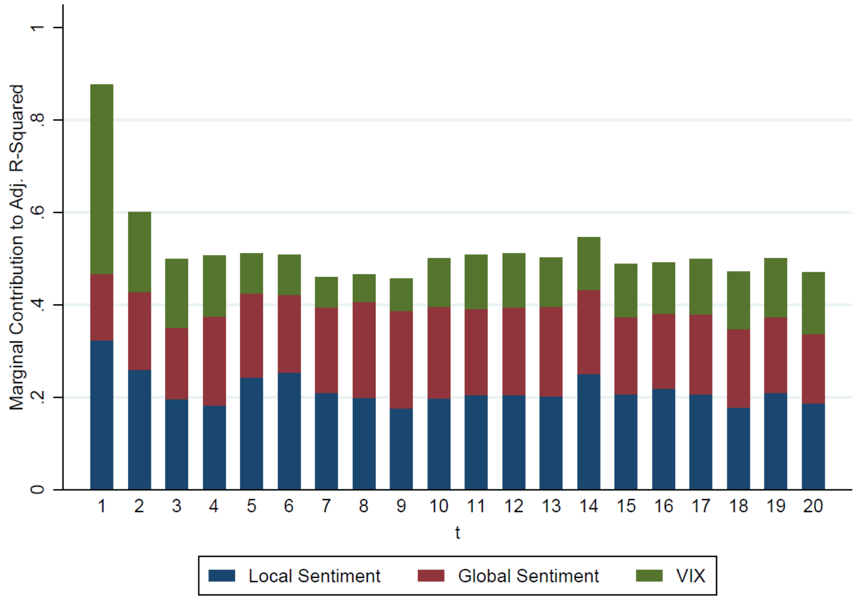


Figure 6.B – Variance Decompositions

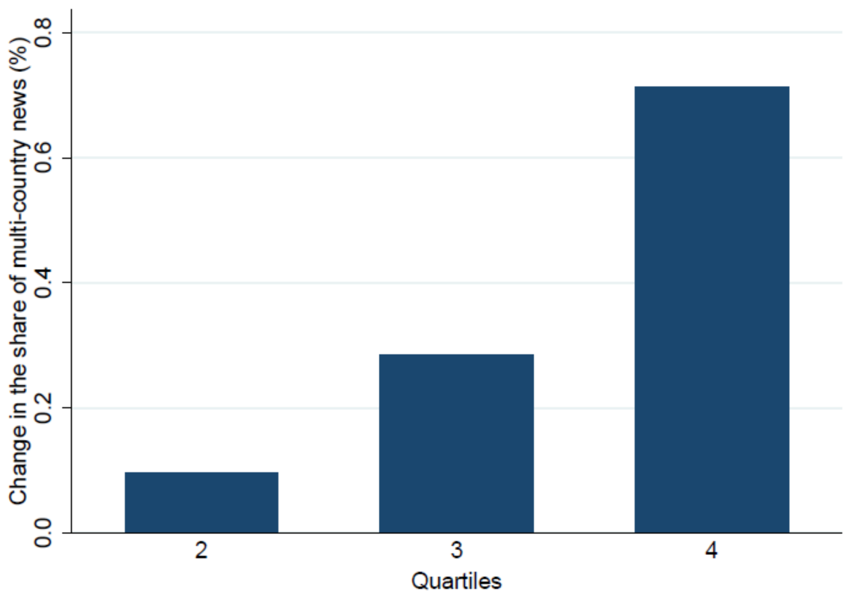


Note: Results are all based on equation 2. Figure 6.A reports the cumulative impact on future equity prices of a VIX shock today, using local projections. Figure 6.B decomposes the increase in Adjusted R-squared at different horizons after the introduction of local news sentiment, global news sentiment and the VIX, respectively. t denotes the number of days.

C. News Coverage

What kind of news drives global news sentiment? As expected, global news sentiment is, in general, driven by multi-country news. Figure 7 shows the share of multi-country news increases significantly when the global news sentiment takes more extreme values, either positively or negatively. Interestingly, we also find that multi-country news articles are different from local news. They are longer, broader in scope and more tonal than local news articles. On average, we estimate that they are roughly twice as long, cover twice as many topics and use twice as many "tonal words" – positive or negative - than their local counterparts.[24] They also make use of more extreme language than local news articles.[25]

Figure 7 – Multi-Country News and Global News Sentiment



Note: Figure 7 reports the change in share of multi-country news coverage as a function of the (absolute) value of the global news sentiment (reported by quartiles). The share of multi-country news increases when the global news sentiment takes more extreme values.

We also find that the drivers of global market rallies differ from those of global sell-offs. After comparing the relative weight of news topics and location in periods of high (or low) global sentiment to their average over the whole sample, we find that the composition of news varies significantly with the direction of the global news sentiment index. When the global news

[24] The stronger tonality of multi-country news is there even after controlling for the size of the article. Regression results on request.

[25] Based on the TFIDF measure – which captures more unusual words. This effect is also robust to controlling for the size of the article.

sentiment index is strongly positive, the corpus of news tilts towards positive financial and corporate news in advanced AEs, especially in the US – with the notable exception of Greece related news, which are overrepresented in periods of low global sentiment. In contrast, the coverage tilts strongly towards economic and political news in EMs when the global news sentiment index goes into negative territory (Figure 8).

V. <u>Robustness and Extensions</u>

Overall, our findings are robust to a variety of tests and extensions. First, they are relatively stable over time and across countries (EMs and AEs), suggesting that the effect is not driven by a single episode or by any distinct group of countries. Reflecting 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.* (2018)). Other important contributions have also emphasized the high sensitivity of emerging markets to the global financial cycle, at least compared to AEs (e.g. Rey (2013), Cerutti, Claessens and Puy (2015)). 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 EMs than AEs (See Appendix).

Our results are also not driven by extreme values or crisis – such as the Global Financial Crisis (GFC), or by key countries – such as the US.[26] Finally, they are robust to an alternative measure of sentiment based on a Term Frequency - Inverse Document Frequency (TF-IDF) weighting of words, which is also widely used in the literature (See Appendix).

VI. <u>Conclusion</u>

Using a new set of news articles around the world, we revisit the effect of news sentiment on asset prices around the world between 1991 and 2015. Extending the scope of the existing literature allows us to qualify several existing results on the link between the media, investor sentiment and stock returns, while deriving new ones. *Inter alia*, we find that news sentiment has a pervasive impact on (short term) equity prices around the world. However, we also find local news have a very different impact than global news. Finally, we cast light on the role of foreign investors in transmitting sentiment shocks. Overall, our results contribute to the vibrant academic literature on the role of the media as propagator of sentiment shocks and highlight its role in driving international co-movement in asset prices.

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[26] Results without the US on request.

Figure 8– Global News Sentiment and News Coverage

Figure 8.A – Locations

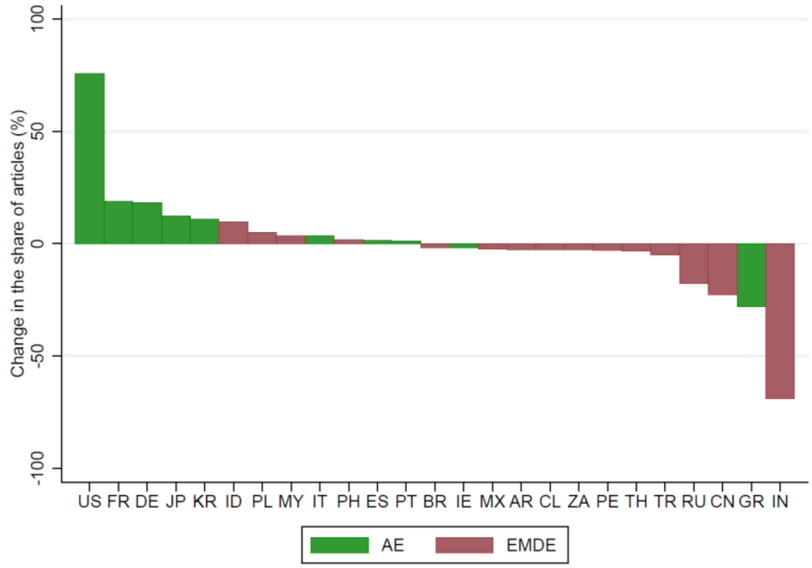
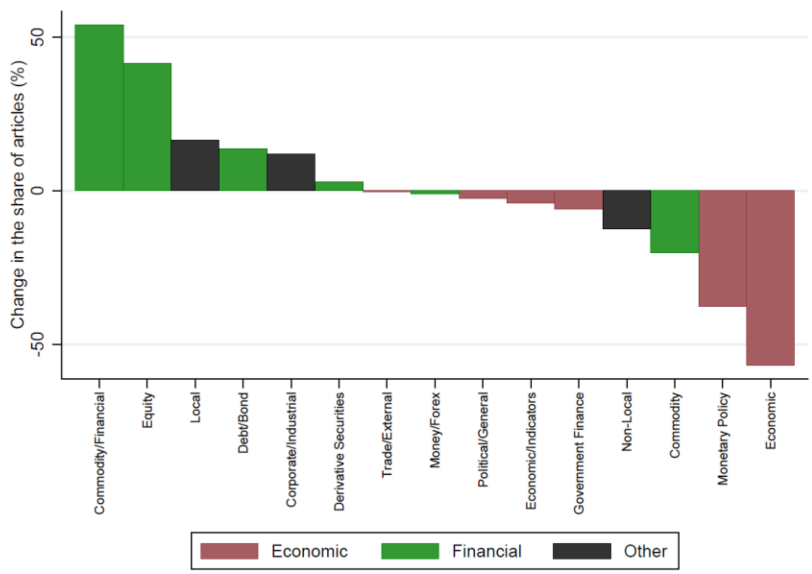


Figure 8.B – Topics



Note: Figure 8.A and 8.B compares the change in news coverage during periods of high global sentiment relative to periods of low global sentiment. Figure 8.A reports the change in each country's share of articles during periods of high global sentiment relative to the country's share of articles over the entire sample. Figure 8.B reports the change in each topic's share of articles during periods of high global sentiment relative to the topic's share of articles over the entire sample.

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Appendix

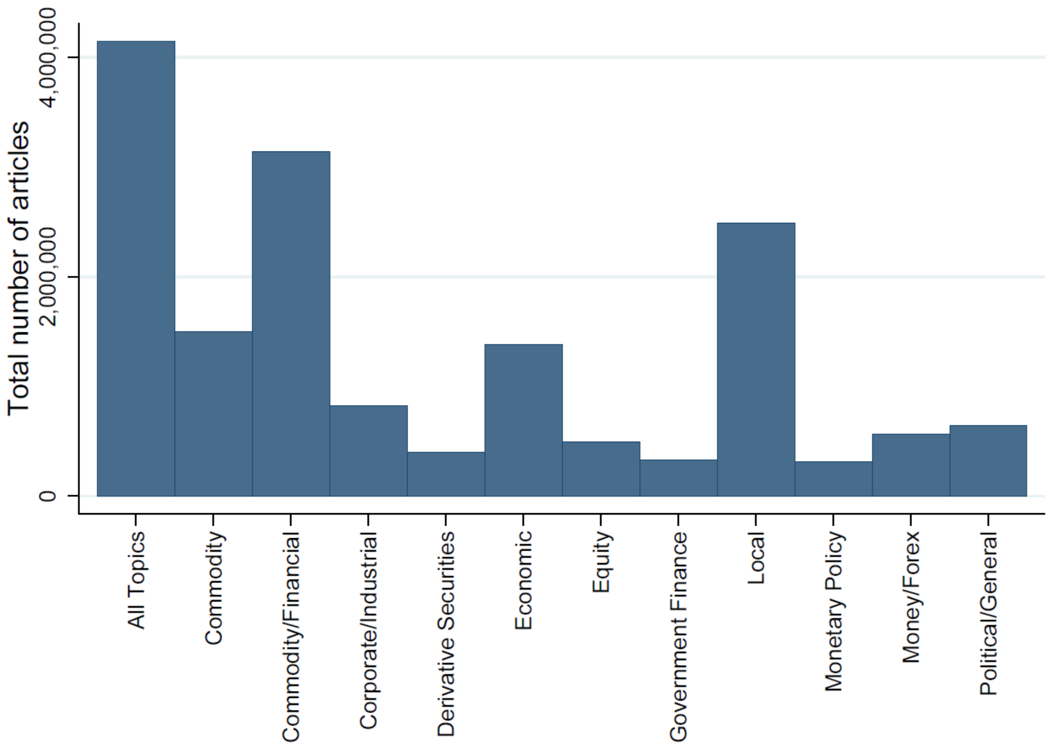
I- News articles – Stylized facts

a. Country and Time Coverage

Country	News_Start	News_Stop	# Articles	Average per day
United States	1/1/1991	12/31/2015	1815542	201.41
France	1/2/1991	12/31/2015	139927	17.31
Germany	1/2/1991	12/31/2015	229059	26.24
Italy	1/2/1991	12/30/2015	87530	11.33
Japan	1/1/1991	12/30/2015	274804	31.66
Greece	1/9/1991	12/31/2015	60824	9.1
Ireland	1/7/1991	12/30/2015	28194	4.76
Portugal	1/3/1991	12/29/2015	32162	5.45
Spain	1/2/1991	12/30/2015	56418	7.86
Turkey	1/2/1991	12/31/2015	46728	6.58
South Africa	1/2/1991	12/31/2015	77318	10.54
Argentina	1/2/1991	12/31/2015	51287	7.12
Brazil	1/2/1991	12/31/2015	87488	11.69
Chile	1/8/1991	12/28/2015	24095	3.7
Mexico	1/2/1991	12/31/2015	69558	9.26
Peru	1/3/1991	12/31/2015	17348	2.97
India	1/2/1991	12/31/2015	356683	40.34
Indonesia	1/2/1991	12/31/2015	87550	10.98
Korea	1/3/1991	12/31/2015	100153	11.91
Malaysia	1/2/1991	12/30/2015	99394	12.26
Philippines	1/2/1991	12/30/2015	55460	7.08
Thailand	1/2/1991	12/29/2015	82555	10.44
Russia	12/30/1991	12/31/2015	111540	14.81
China	1/2/1991	12/31/2015	245913	27.69
Poland	1/1/1991	12/30/2015	64998	9.29

Note: This table reports the distribution of country tags in our corpus of articles.

b. <u>Main Topics covered – All countries</u>



<u>Note:</u> This figure reports the most frequent topics tagged in our corpus of news articles. A very similar distribution of topics is observed across AEs and EMs. "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 (see 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 II)

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

c. 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

II- Asset Prices Coverage

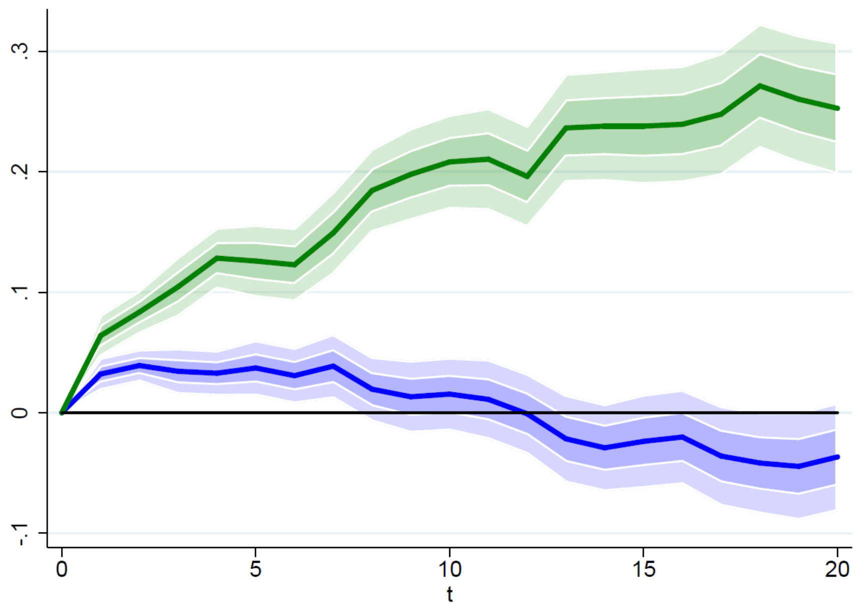
a. Stock Indices

Country	Sample_Start	Sample_End	Stock Index
Argentina	1/2/1991	12/31/2015	ARGENTINA MERVAL - PRICE INDEX
Brazil	1/2/1991	12/31/2015	BRAZIL BOVESPA - TOT RETURN IND
Chile	1/2/1997	12/30/2015	CHILE SANTIAGO SE GENERAL (IGPA) - PRICE INDEX
China	1/2/1991	12/31/2015	SHANGHAI SE COMPOSITE - PRICE INDEX
Germany	1/2/1997	12/31/2015	DAX 30 PERFORMANCE - PRICE INDEX
Spain	1/2/1997	12/31/2015	IBEX 35 - PRICE INDEX
France	1/1/1997	12/31/2015	FRANCE CAC 40 - PRICE INDEX
Greece	1/2/1997	12/31/2015	ATHEX COMPOSITE - PRICE INDEX
Indonesia	1/2/1991	12/31/2015	IDX COMPOSITE - PRICE INDEX
Ireland	1/2/1997	12/30/2015	IRELAND SE OVERALL (ISEQ) - PRICE INDEX
India	1/2/1991	12/31/2015	S&P BSE (SENSEX) 30 SENSITIVE - PRICE INDEX
Italy	1/2/1997	12/30/2015	FTSE MIB INDEX - PRICE INDEX
Japan	1/1/1991	12/31/2015	NIKKEI 225 STOCK AVERAGE - PRICE INDEX
Korea	1/3/1991	12/31/2015	KOREA SE COMPOSITE (KOSPI) - PRICE INDEX
Mexico	1/2/1991	12/31/2015	MEXICO IPC (BOLSA) - PRICE INDEX
Malaysia	1/2/1991	12/31/2015	FTSE BURSA MALAYSIA KLCI - PRICE INDEX
Peru	1/2/1997	12/31/2015	S&P/BVL GENERAL(IGBVL) - PRICE INDEX
Philippines	1/2/1991	12/30/2015	PHILIPPINE SE I(PSEi) - PRICE INDEX
Poland	1/1/1997	12/31/2015	WARSAW GENERAL INDEX - TOT RETURN IND
Portugal	1/2/1997	12/30/2015	PORTUGAL PSI-20 - PRICE INDEX
Russia	12/30/1991	12/31/2015	RUSSIA RTS INDEX - PRICE INDEX
Thailand	1/2/1991	12/30/2015	BANGKOK S.E.T. - PRICE INDEX
Turkey	1/2/1991	12/31/2015	BIST NATIONAL 100 - PRICE INDEX
United States	1/1/1991	12/31/2015	DOW JONES INDUSTRIALS - PRICE INDEX
South Africa	1/1/1997	12/31/2015	FTSE RAFI

III- Robustness and Extensions

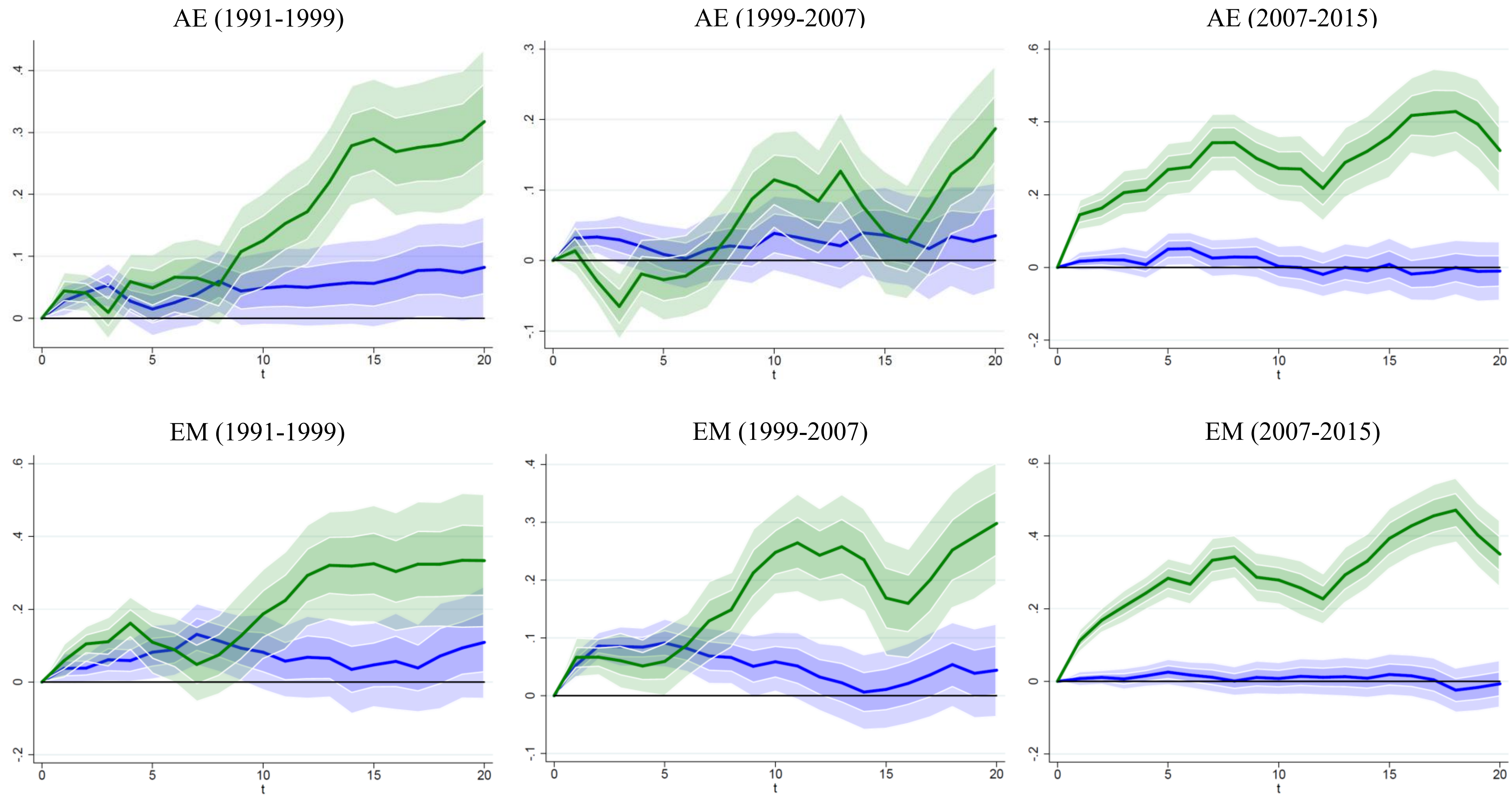
Figure 8 and 9 reports robustness checks and extensions derived using equation 2. Figure 8 plots the response of local asset prices to local and global news sentiment using TF-IDF measures of news sentiment. Results are only provided for the full sample (mirroring Figure 2.A) but are unchanged when excluding the GFC or restricting attention to AEs or EMs. Figure 9 plots the response across time and groups of countries using the standard measure of sentiment.

Figure 8 - Panel with TF-IDF sentiment



Note: t denotes the number of days after the shock. The blue line reports the cumulative response of equity prices to local news sentiment shocks. The green line reports the cumulative response to global news sentiment shocks. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.

Figure 9 – Benchmark results - Country and Time Split



Note: t denotes the number of days. The blue line reports the cumulative response of equity prices to local news sentiment shocks. The green line reports the cumulative response to global news sentiment shocks. Standard errors are always corrected for serial auto-correlation and heteroskedasticity using a Newey and West (1987) estimator.