Financial Cycles, U.S. Monetary Policy, and Media Tone*

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May 2019

Abstract

In this paper, I study the impact of changes in international media tone on synchronized fluctuations in financial aggregates (also known as financial cycles) across 29 advanced and emerging market economies. Media tone captures how news articles frame economic and financial information, which may in turn affect investors' risk preferences. I construct a global media tone index using methods from natural language processing and a database of 8 million news articles. Results indicate that global media tone is strongly correlated with an underlying common factor in stock prices, bond yields, and credit growth across countries. Controlling for macroeconomics fundamentals and policy actions, I find that U.S. monetary policy is the most important driver of the global financial cycle, while media tone accounts for a relatively sizeable fraction of its variance.

Keywords: Financial cycles; asset prices; credit cycles; media tone; investor sentiment, natural language processing

JEL classification: E32; E44; F30; F42; G15; G41

*I am very grateful to my advisor Kei-Mu Yi and my committee Bent Sørensen and David Papell for their guidance and support. I am also thankful to German Cubas, Dietrich Vollrath, Chris Murray, Radek Paluszynski, Fan Wang, and to participants at the University of Houston's Macroeconomics Workshop and the Third Year Workshop for their many helpful discussions and comments.

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1 Introduction

The 2003–2007 credit and housing booms and following financial disruptions in the form of asset price busts and credit crunches resulted in the deepest economic crisis since the Great Depression. The crisis was particularly destructive in magnitude and breadth as it affected many countries and financial markets simultaneously. However, clusters of countries experiencing joint fluctuations or cycles in financial activity is not unique to the Great Recession (see Reinhart & Rogoff (2008)). Common shocks or spill-over effects can lead to multiple countries experiencing comovement in their financial markets—a phenomenon dubbed as global financial cycles (Claessens, Kose, & Terrones (2011); Rey (2013a); Borio (2014)).

Rey (2013b) documents that symptoms of the global financial cycle can go from benign to excess credit creation and large asset price bubbles. Miranda-Agrippino & Rey (2015) show that one of the determinants of the global financial cycle is the U.S. monetary policy, which affects capital flows, credit growth, and bank leverage in the international financial system. However, symptoms of financial cycles may also involve bouts of "irrational exuberance or pessimism" (Cerutti, Claessens, & Rose (2017)). In particular, studies have found that this could be driven by the tone or frame of communication, which influences investors' risk preferences and in turn is reflected in volatility of prices and allocations in financial markets (see, for example, Schmeling & Wagner (2019); Fraiberger, Lee, Puy, & Rancier (2018)).[1]

In this paper, I examine the role of media tone in driving global financial cycles. In particular, I assess the impact of a world media tone index, in addition to key macroeconomic fundamentals and policy actions in accounting for synchronized fluctuations in financial aggregates across countries. The availability of real-time economic and financial news from common sources (for example, Reuters, Bloomberg, and Financial Times) allows market participants to access the same information in news articles across many countries. Thus, the framing of economic and financial events in international news articles can generate a common media tone that may simultaneously impact financial markets in a number of advanced and emerging market economies.

I proceed as following. I first construct a new dataset on stock prices, bond yields, and domestic credit for 29 Advanced Economies (AEs) and Emerging Market Economies (EMs) over the

[1]Framing refers to the idea that economics agents tend to draw different conclusions from information depending on how it is presented to them (Mas-Colell, Whinston, & Green (1995); Tversky & Kahneman (1984)).

period 1999–2018. The dataset combines stock indices, long-term bond yields, and credit growth rates obtained from the Bloomberg database and IMF's International Financial Statistics (IFS) at monthly frequency. Using this dataset, I employ a multi-level factor analysis approach to estimate three types of common factors: (1) a global financial factor that captures common variation in all financial variables and all countries, (2) financial variable-specific factors that capture common variation in each financial variable across all countries (for example, a global stock price factor), and (3) country-specific factors that are common to all financial variables within a country (for example, a US financial factor that captures comovement in credit, bonds and equities in the United States).

My results indicate that a common global factor explains a large fraction of the variation in financial aggregates across countries, indicating the existence of a global financial cycle. In particular, the global financial factor accounts for, on average, 37.2 percent of the year-over-year variation in stock prices, bond yields, and domestic credit across countries. However, considerable heterogeneity exists in the results across countries and financial variables. For example, the global financial factor captures 60 percent of the variation in stock market indices across countries, while it explains approximately 20 percent of the variation in bond yields and domestic credit. Additionally, for advanced economies such as Singapore and Norway, the variation in stock prices accounted for by the global factor is higher than average, whereas for emerging markets the corresponding estimate is smaller. Financial variable- and country-specific factors appear to be less important on average, except in the case of capturing comovement in bond yields across advanced economies.

After establishing empirically the existence of a global financial cycle, I proceed to assess the sources of its fluctuations. I use a variance decomposition to compute the percentage of fluctuations in the global financial cycle due to a global media tone index and other driving forces (including monetary policy, fiscal policy, productivity, and oil prices). To construct the global media tone index, I use a large database of newspaper articles in combination with techniques from natural language processing. The newspaper database contains approximately 8 million news articles from many sources such as Reuters, Financial Times, and The Wall Street Journal. I count number of words in each article that are classified as either positive or negative in the Loughran & McDonald (2011) financial dictionary.[2] A monthly global media tone is created by aggregating articles at the monthly level.[3]

[2]The Loughran & McDonald (2011) dictionary employs a large sample of 10-Ks to develop world lists that reflect tone in financial text.

[3]Python's Natural Language Toolkit (NLTK) is used to implement the counting algorithm.

The results indicate that global media tone index moves closely with the global financial factor—correlation is 0.44 between the two indices. Because the tone index is based on newspaper articles, it may also capture information on actual market conditions. Therefore, I narrow down the newspaper articles by retaining only articles that communicate information on monetary policy, fiscal policy, productivity, and oil prices.[4] Additionally, I order the global media tone index last when estimating the variation in the global financial cycle due to different driving forces. I find that the orthogonalized media tone index explains an incremental variation of 3.29 percent in the global financial factor, which is sizeable relative to the contribution of other key predictors such as oil prices. Moreover, the results indicate that U.S. monetary policy is the most important driver of the global financial cycle.

The remainder of the paper is structured as follows. Section 2 constructs the global financial cycle by employing a factor model. Section 3 uses textual analysis to extract the global media tone index from the newspaper data. Section 4 decomposes the variance of the global financial cycle in parts due to different drivers including the global media tone. Section 5 concludes.

2 International Financial Cycles

I start by exploring the existence of joint fluctuations in financial activity across multiple countries and financial markets using a multi-level factor model. In particular, I estimate the underlying common component of monthly financial market data on stock prices, long-term bond yields and domestic credit obtained from the Bloomberg database and IMF for a number of Advanced Economies (AEs) and Emerging Markets (EMs) over the period 1999–2018. A similar broad view that integrates multiple financial series to define the global financial cycle is employed by Ha, Kose, Otrok, & Prasad (2017) to study spillovers between macroeconomic and financial cycle for the G7 countries. The broad definition of the global financial cycle follows the idea of using multiple aggregates to study business cycles versus using a single variable, for example, output or industrial production (Claessens et al. (2011)).

2.1 Multi-level Factor Model

The following multi-level factor model is used to characterize the global financial cycle

[4] The Dow Jones newspaper database tags news articles according to topics, which I use to filter articles.

$$
\begin{aligned}
Y_t &= BF_t + \epsilon_t && (1) \\
\epsilon_{t-1} &= \Psi(L)\epsilon_{t-1} + u_t, \qquad E_t(u_t u_t') = \Omega && (2) \\
F_t &= \Phi(L)F_{t-1} + \nu_t, \qquad E_t(\nu_t \nu_t') = I_K && (3)
\end{aligned}
$$

where Y_t is a vector of observed variables of length N countries $\times$ M financial variables. The vector F_t is set of $K < N$ latent factors that capture all comovement in the observed data. In particular, the F_t vector is composed of three types of common factors: a global financial factor that is common to all financial variables and all countries, financial variable-specific factors that are common to each financial variable and all countries (for example, a global stock price factor), and country-specific factors common to all financial variables within a country (for example, a US factor that captures comovement in credit, bonds and equities in US).

The idiosyncratic component ϵ_t follows an independent autoregressive process of order q where $\Psi(L)$ is a diagonal lag polynomial matrix and the covariance matrix Ω is diagonal. To incorporate dynamics into the factor structure, the vector F_t is set to follow an autoregressive process of order p. This allows the past values of each factor to affect the current values of the observed variables. For example, today's stock prices will be influenced by both the present and the past values of, say, the global financial factor. $\Phi(L)$ is a diagonal lag polynomial matrix that defines the dynamics of the latent factors and I_K is an identity matrix. If $\Phi(L)$ is a a diagonal matrix, the latent factors will evolve independently of each other. In other words, there are no spillovers from, for example, the global stock market factor to the global financial factor and vice versa.

B is an $N \times K$ matrix of factor loadings. The elements of B capture the impact the underlying factors on the observed variables, Y_t. Imposing zero restrictions on B gives the dynamic factor model a block-specific structure.[5] This allows us to interpret the factors as global, variable-specific and country-specific factors. For instance, in a two-country case, we can write the factor model

[5] Dynamic factor models with block-specific structure are also known as multi-level factor models or dynamic hierarchical factor models. A criticism of factor models is that the estimation of factors from a large panel of variables does not take advantage of the data structure and, thus, the estimated factors are hard to interpret. The multi-level factor model mitigates this concern (see Moench et al. (2013)).

with zero restrictions on the B matrix as following

$$\begin{bmatrix} \Delta S_t \\ \Delta B_t \\ \Delta C_t \\ \Delta S_t^* \\ \Delta B_t^* \\ \Delta C_t^* \end{bmatrix} = \begin{bmatrix} \beta_S & \gamma_S & 0 & 0 & \theta_S & 0 \\ \beta_B & 0 & \gamma_B & 0 & \theta_B & 0 \\ \beta_C & 0 & 0 & \gamma_C & \theta_C & 0 \\ \beta_S^* & \gamma_S^* & 0 & 0 & 0 & \theta_S^* \\ \beta_B^* & 0 & \gamma_B^* & 0 & 0 & \theta_B^* \\ \beta_C^* & 0 & 0 & \gamma_C^* & 0 & \theta_C^* \end{bmatrix} \begin{bmatrix} f_t^{global} \\ f_t^{Stocks} \\ f_t^{Bonds} \\ f_t^{Credit} \\ f_t^{Country} \\ f_t^{Country*} \end{bmatrix} + \begin{bmatrix} \epsilon_S \\ \epsilon_B \\ \epsilon_C \\ \epsilon_S^* \\ \epsilon_B^* \\ \epsilon_C^* \end{bmatrix}$$

where $l.h.s$ represent the stocks (S), bonds (B) and credit (C) observable data for home and foreign country and $r.h.s$ shows the three types of factors—global (f_t^{global}), variable-specific (f_t^{Stocks}, f_t^{Bonds}, f_t^{Credit}) and country-specific ($f_t^{Country}$, $f_t^{Country*}$)—and the corresponding factor loadings. It can be seen that the observed data across all countries and financial variables load on to the common global factor, f_t^{global}, while only the observed data specific to each financial variable and country load on to their variable- and country-specific factors.

2.2 Estimation

The estimation in the above model differs slightly from the usual dynamic factor model since it has a block-specific structure. These are also known as Dynamic Hierarchical Factor models or multi-level factor models (see Moench, Ng, & Potter (2013)). One criticism of factor models is that the estimated factors are hard to interpret. Factors estimated from a large panel of data do not take advantage of the data structure. The multi-level factor mode mitigates this concern. For example, in the above model, the international stock market factor, f_t^{stock}, is estimated by removing the information in the data that is already captured by the global factor, f_t^{global}.

Different methods are available to estimate factors in model (1). Three methods are presented in Jackson, Kose, Otrok, & Owyang (2015): (1) the Bayesian approach of Otrok & Whiteman (1998), (2) the Bayesian state space approach of Kim & Nelson (1998) and (3) a frequentist principal components analysis (PCA) approach. Different methods have different advantages. For instance, the principle component approach is convenient to use when the number of observed variables is large while the Bayesian State-space approach of Kim and Nelson is more appropriate when the number of estimated factors is small. The Bayesian Otrok-Whiteman approach, which is less widely used in the literature, is generally good for a large number of factors and observed variables. I will employ the PCA approach to estimate the factors. Since PCA is a non-parametric techniques, it does not take into account the dynamics of the latent factors as described in (3).

The frequentist principle component approach can be modified to estimate the factors with the block-specific structure of model (1). The estimation involves the following steps:

1. Extract the first factor, f_t^{global}, with its associated factor loadings β_{global}, from the entire dataset ($T \times N$).

2. Letting Y_{n_m} for $n_m = 1, \ldots, m$ correspond to the observable series which load upon the second-level factor m, and adjust the data to remove the first factor: $\tilde{Y}_{n_m} = Y_{n_m} - \beta_{global} f_t^{global}$. Then extract the principle component from this set $\tilde{Y}_{n_m}$.

3. A similar adjustment is done to obtain the third factor.

2.3 Global Financial Factor, Asset Prices and Domestic Credit Growth

Figure 1 plots the estimated global financial factor, f_t^{global}, with asset prices and domestic credit for US and India in the top and bottom panels, respectively. The global factor captures major world financial events: the dot-com crash from early 2000 to late 2002, the 2003–2007 global economic expansion, the financial crisis of 2007–2008 and the subsequent recovery, the European debt crisis beginning in early 2010, the 2015–16 global stock market sell-off and the late 2018 bear market.

The first plot in the top panel of figure 1 compares the global financial factor with the US S&P 500 growth rate and US 10-year government bond yields. The global financial factor appears to track the fluctuations in US stock and bond market data closely with correlations of 0.79 and 0.67, respectively. The global financial factor follows the sharp decline in stock prices and US government bond yields during the dot-com bubble crisis as a result of stock sell-off and an increase in demand for safe-haven assets. Moving along the timeline, joint fluctuations in the two financial markets are clear—a decline in stock prices are typically accompanied with a drop in bond yields and vice versa. During periods of expansions, such as the period between 2002–2007, bond and stock assets trade inversely as they compete for savings. Stock price rallies in such periods result in higher bond yields as households save in riskier assets that are more sensitive to economic growth. During the 2007-09 Great Recession and European Debt crisis, the global factor falls sharply as the global economy contracted. The US S&P 500 index and bond yields decline as well. Bond yields for India are less correlated with the global factor during the early period but have co-moved more closely with the

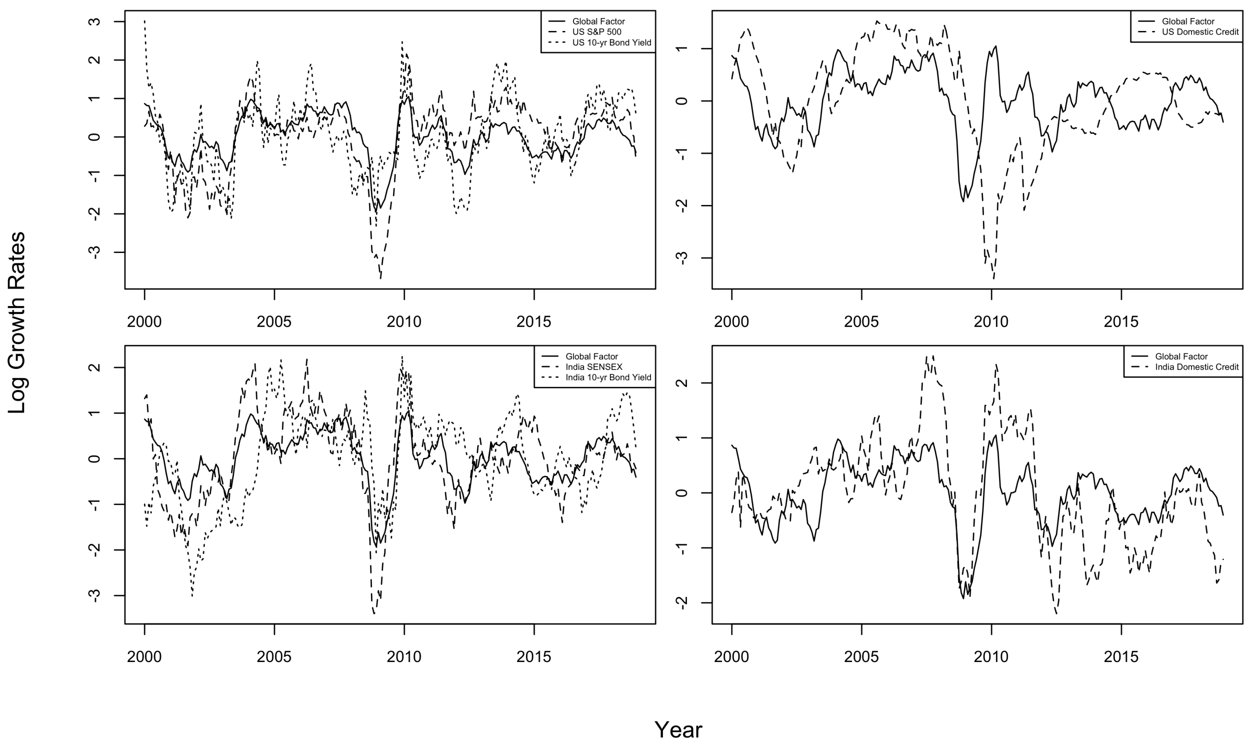


Figure 1: Global Financial Factor with US and India asset prices and domestic credit growth 2000–2018

global financial factor since 2005 as shown by the first plot in the bottom panel of figure 1.[6] The correlation of domestic credit series with the global financial factor for both countries is weaker compared to the asset prices as can be seen by the second plots in the top and bottom panel of figure 1.

2.4 Advanced Economies versus Emerging Markets

Figure 2 plots the global financial factor with the three different financial variables for all advanced economies and emerging markets. The grey band in each plot captures the extremes for each financial variable. For example in the first plot for stock prices for advanced economies, we can see that the grey band is narrow and follows the global financial factor closely indicating that the

[6] This is most likely a result of weaker linkages of the bond market (relative to India's benchmark stock market Index) with the global financial system during this period. Economic liberalization in India, which included deregulation of markets and more greater foreign investment, was initiated in 1991 as a result of IMF and World Bank conditions for a $500 million bail out package. The reforms were continued by the Bharatiya Janata Party (BJP) government from 1999–2004.

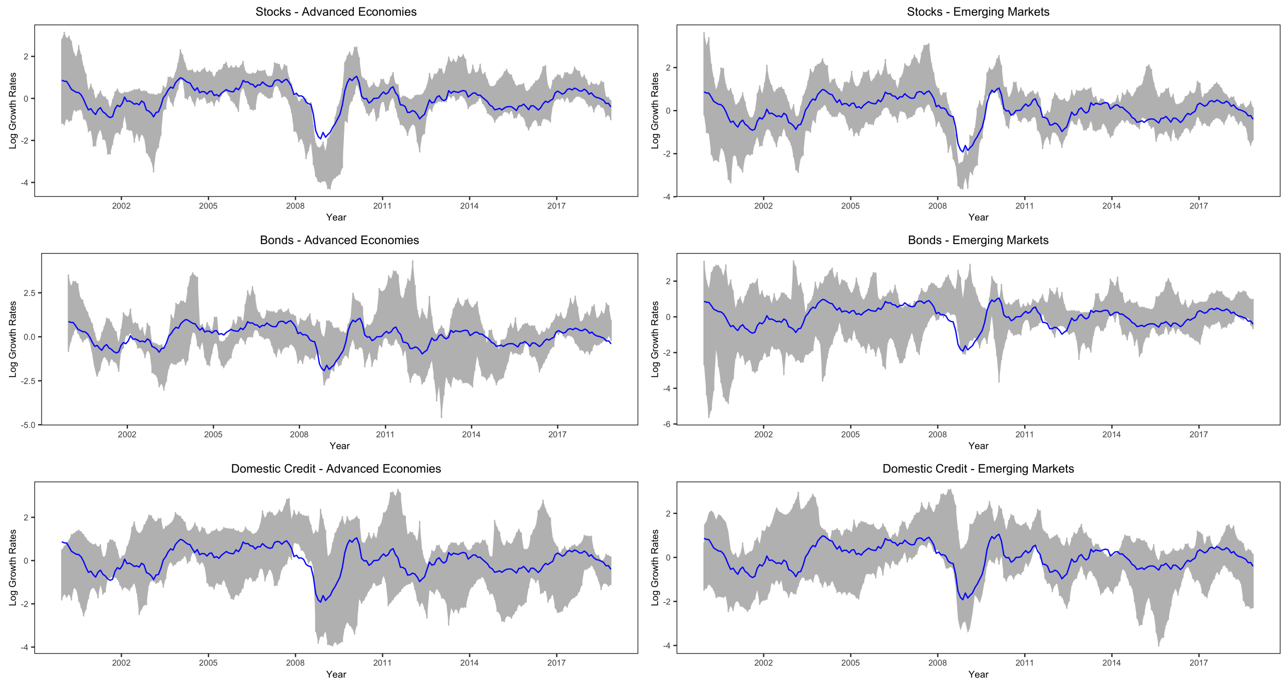


Figure 2: Financial Markets in Advanced Economies and Emerging Markets 2000–2018

the common factor indeed drives a large percentage of the variation in stock prices across most advanced economies. Comparing this result with the emerging markets' stock prices (second plot in the top panel of figure 2), it can be seen that role of a common global factor in driving stock markets has increased since roughly 2005 as the width of the grey band has decreased.

The bond yields are more spread out compared to the stock prices around the global financial factor. For advanced economies the grey band becomes wider starting roughly 2009-10 while for the emerging markets the bond yields vary more across countries in the earlier years. Domestic credit is much more spread out relative to the stock prices and bond yields for both advanced and emerging markets.

2.5 Variance Decompositions for Financial Variables

In order to take a closer look at the importance of the global financial factor in driving financial markets across countries, I do a variance decomposition. In particular, I divide the variation in each of the stock, bond and credit data series captured by the common global factor, market-specific factor, country-specific factor and an idiosyncratic term. The results of this exercise are shown in Table 1.

It can be seen that the global financial factor captures on average 60 percent of the variation in the stock market indices. For advanced economies such as Singapore and Norway, the stock price variation captured by the global financial factor is above 60 percent while in emerging markets the role played by the global factor is smaller on average. The remaining variation is mostly captured by the idiosyncratic term with the market- and country-specific factors only playing a minor role. The global factor captures approximately 20 percent of the variation for bond yields and domestic credit. The market- and country-specific factors play a more important role in the bond markets for advanced economies. The idiosyncratic term captures the remaining variation for both bond yields and domestic credit.

3 Global Media Tone Index

In order to construct the global media tone index, I use a database of newspapers articles. The data contains about 8 million articles from different sources, namely, Reuters, Financial Times and Wall Street Journal. I employ techniques from text analysis to analyze the articles in order to create a tone score for each article. This is done by counting the number of positive and negative words in each article using Loughran & McDonald (2011) financial dictionary.[7] Higher values imply a more positive tone and vice versa. A monthly global media tone is created by aggregating articles at the monthly level. The tone index is shown in Figure 3. The correlation between the tone index and the global factor is 0.44. It broadly follows the global financial factor but is relatively more noisy.

The "tone" index created using the newspaper articles contains actual information about economic fundamentals and policy actions as well. In order to separate out the pure article tone from the constructed index, I will keep the residual of the index after regressing it on other predictors as discussed in Section 4.

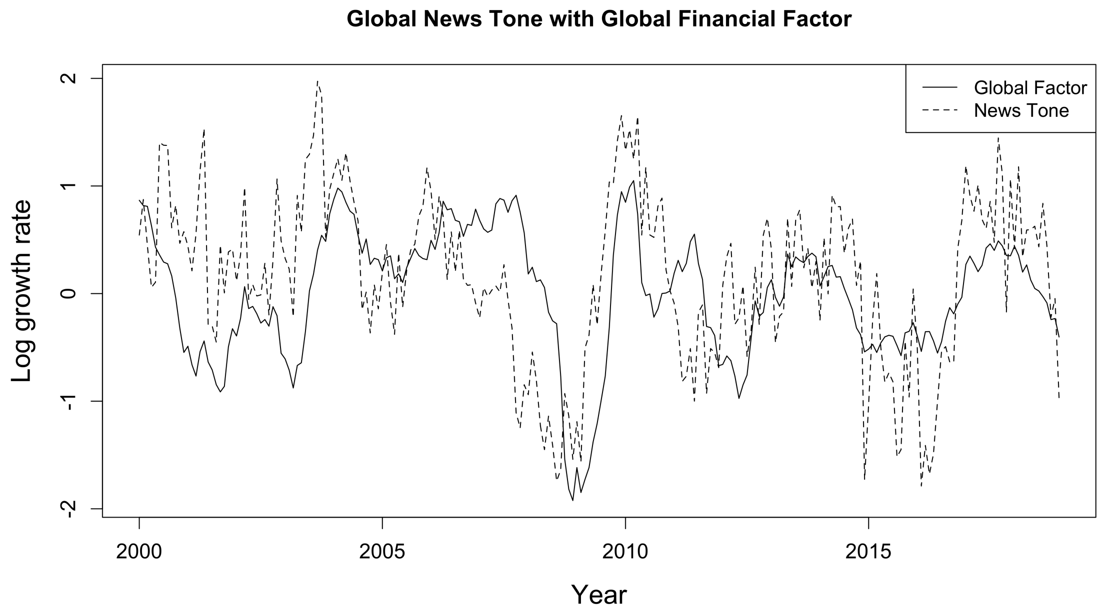
4 What drives the global financial cycle?

In section 3, we found evidence that a large percentage of the variation in financial variables across advanced economies and emerging markets is accounted by an underlying common factor. The

[7]Pre-constructed dictionaries used in text analysis define positive and negative words by conduction surveys. For example a word is presented to the survey participants and they respond whether the word has a negative or positive connotation in their opinion.

Country	Stocks				Bonds				Credit			
	Global	Market	Country	Idiosync	Global	Market	Country	Idiosync	Global	Market	Country	Idiosync
Australia	70.4	14.6	0.6	14.4	60.3	35.7	0.2	3.8	34.4	3.5	0.2	61.9
Austria	66.3	7.2	1.3	25.2	23.0	4.0	55.3	17.7	19.2	1.9	0.3	78.7
Belgium	52.4	34.3	0.2	13.1	19.9	2.5	51.2	26.3	11.2	2.9	5.3	80.7
Canada	73.6	5.2	0.1	21.1	34.4	20.3	4.9	40.4	53.2	1.0	0.2	45.5
Finland	59.5	8.7	2.0	29.8	28.9	7.8	0.0	63.3	0.3	10.7	2.4	86.6
France	65.3	22.2	4.6	7.9	32.1	4.0	0.0	63.9	21.3	12.3	2.3	64.1
Germany	63.8	20.3	2.5	13.4	46.7	9.0	0.0	44.4	7.8	5.4	2.9	84.0
Iceland	43.7	9.2	0.0	47.0	1.9	20.2	2.3	75.6	43.5	1.5	0.2	54.7
Italy	63.2	19.3	0.2	17.3	3.8	43.4	2.9	49.9	12.5	8.2	0.2	79.1
Japan	51.5	2.8	0.9	44.8	30.6	6.9	9.3	53.3	6.3	2.4	1.1	90.2
Netherlands	62.2	2.3	1.1	34.4	32.0	52.7	3.7	11.6	18.5	10.6	1.1	69.9
New Zealand	34.1	17.5	3.3	45.0	49.1	5.4	6.6	38.9	29.8	3.5	0.3	66.4
Norway	74.9	3.9	8.1	13.1	22.2	21.6	9.7	46.5	22.8	3.1	0.9	73.2
Portugal	80.6	0.2	0.4	18.8	0.0	20.2	5.4	74.4	15.2	22.0	2.1	60.7
Singapore	75.5	9.6	3.3	11.6	22.6	2.3	66.7	8.5	14.5	1.6	7.4	76.5
Spain	72.5	3.7	3.9	19.9	6.4	29.1	3.9	60.7	13.8	9.6	0.9	75.7
Switzerland	56.5	4.1	18.3	21.0	47.9	15.5	1.0	35.6	7.8	4.2	0.2	87.8
UK	66.3	6.0	8.5	19.2	46.7	25.1	1.2	27.0	39.3	1.9	2.1	56.7
USA	62.9	3.6	15.0	18.6	45.4	0.3	5.1	49.2	0.7	0.8	0.9	97.6
Brazil	63.2	0.4	3.0	33.4	17.1	0.1	3.6	79.1	31.9	0.1	7.4	60.6
China	28.8	0.8	0.0	70.4	12.8	0.3	0.0	86.9	1.9	1.7	11.5	84.8
Hungary	55.5	1.2	0.1	43.2	5.2	29.6	0.1	65.1	16.4	6.5	0.6	76.5
India	68.4	0.2	0.4	31.0	17.6	0.1	14.7	67.5	31.8	0.0	0.4	67.7
Malaysia	63.1	0.0	0.2	36.7	9.3	0.0	0.1	90.6	6.1	0.1	0.0	93.8
Phillipines	36.2	2.8	1.6	59.4	6.8	0.1	0.1	93.0	2.4	4.1	24.2	69.3
Poland	78.9	0.8	0.1	20.2	9.2	0.4	0.3	90.0	17.5	15.6	1.6	65.2
Russia	50.0	1.0	0.1	48.9	0.8	0.1	9.5	89.6	23.3	6.1	0.0	70.6
South Africa	60.9	1.0	0.8	37.3	4.0	0.3	1.2	94.5	23.2	2.7	0.2	73.9
South Korea	52.0	0.8	0.2	47.1	25.9	3.8	0.0	70.3	38.6	0.4	4.2	56.8
AEs	62.9	10.2	3.9	22.9	29.1	17.2	12.1	41.6	19.6	5.6	1.6	73.2
EMs	55.7	0.9	0.6	42.8	10.9	3.5	3.0	82.7	19.3	3.7	5.0	71.9
Average	60.4	7.0	2.8	29.8	22.8	12.4	8.9	55.8	19.5	5.0	2.8	72.7

Table 1: Variance Decompositions for Financial Variables



main question that this study aims to answer is whether media tone plays a role in driving this co-movement beyond what can be explained by economic fundamentals and policy actions. In order to investigate this I regress the global financial factor on monetary policy, fiscal policy, productivity, oil prices and global media tone:

$$f_t^{global} = \beta_M f_{Monetary,t} + \beta_F f_{Fiscal,t} + \beta_P f_{Productivity,t} + \beta_O f_{Oil,t} + \beta_N f_{News,t} + \epsilon_t,$$

where $f_{Monetary,t}$ is a common factor for monetary policies (policy rates) for G7 countries, $f_{Fiscal,t}$ is a common factor for fiscal policies (government tax revenue and spending) for G7 countries, $f_{Productivity,t}$ is a common factor for productivity (labor productivity) for G7 countries, $f_{Oil,t}$ is a common factor for oil prices (WTI, Brent, Dubai) and $f_{News,t}$ is the global media tone index.

I apply the variance operator on both sides of this equation to decompose the variance of the estimated global financial cycle into parts that are due to monetary policy, fiscal policy, productivity, oil prices and global media tone. The predictors on the $r.h.s$ are orthogonalized by regressing the second variable on the first and keeping the residuals as the orthogonalized predictor. I continue in this manner to orthogonalize all predictors. Thus, the orthogonalized global media tone index contains only information above and beyond what is already captured by the other predictors. Because the media tone index is constructed by taking only news articles on monetary policy, fiscal

Table 2: Variance Decomposition for the Global Financial Cycle

Drivers	$f_{Monetary,t}$	$f_{Fiscal,t}$	$f_{Productivity,t}$	$f_{Oil,t}$	$f_{News,t}$
Percentage	36.90	5.02	9.97	4.44	3.29

policy, productivity and oil prices, therefore, the residual can be interpreted as the pure measure for media tone.

The results of the variance decomposition are reported in Table 2. Monetary policy and changes in G7 productivity are two most important drivers of the global financial cycle, accounting for 36.9 and 9.97 percent of its variation, respectively. The media tone index captures 3.29 percent of the variation in the global financial cycle beyond what is accounted by other predictors. The magnitude of the variation explained by the media tone index is substantial when compared to the contribution of other important drivers of financial markets such as oil prices.

5 Conclusion

This paper evaluates the role of a global media tone generated by news articles in driving synchronized fluctuations in financial aggregates across countries. The availability of real-time economic and financial news across the globe allows market participants to access common information. Framing of information in these articles can influence investors' risk preferences across multiple countries simultaneously, which is reflected in joint variation in prices and allocations in financial markets.

My methodology involves using a multi-level factor model to estimate a global financial factor that captures comovement in financial variables across 29 advanced and emerging market economies. The variance of the estimated global financial factor is then decomposed into parts that are due to monetary policy, fiscal policy, labor productivity, oil prices, and the global media tone index. The global media tone index is constructed using a word counting approach implemented on a large database of newspaper articles.

The results indicate the existence of a common global factor that explains, on average, 37.2 percent of the variation in financial aggregates across countries. I find that U.S. monetary policy is most important in accounting for fluctuations in the global financial cycle. Moreover, my findings suggest that the global media tone index explains a sizeable fraction of synchronized movements in financial markets when compared to the contrubution of other drivers such as oil prices.

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