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Tracking Chinese Vulnerability in Real Time Using Big Data

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Abstract[1]

In a recent paper, Robert Schiller (2017) commented that "as research methods advance, and as more social media data accumulate, textual analysis will be a stronger field in economics in the coming years. In line with this new field of research, we develop an indicator which allows us to track vulnerability sentiment in China in real time. In order to ensure robustness and depth, we use a combination of traditional macroeconomic and financial time series with textual analysis (sentiment data mining) using Big Data techniques.The index is composed by four different vulnerability dimensions (indebtedness concerns among highly leveraged state owned enterprises; a fast expansion of shadow banking activities, leading to an overall deterioration of credit conditions; risks of a potential correction in the housing market bubble; and speculative pressures in the exchange rate market.) These dimensions were carefully selected to reflect the developments on the ground in China, making this a highly specific and targeted indicator. We show that there is no systematic bias in information stemming from Mandaring and English media, but it is the latter the one more associated to the market risk measures thus confirming the existence of the information asymmetries in the emerging markets.

Key words: China, Vulnerability, Big Data, Sentiment Analysis, Information asymmetries

JEL classification: C55, C38, C43, D81.

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1. Introduction

The Nobel Prize winner Robert Shiller (2017) claimed that the use of new empirical research through textual analysis and Big Data should be extended empirically to analyze the role of narratives in Business Cycle Theory. In this paper, we build on this block of empirical research to analyze the role of narratives in the context of Chinese vulnerability sentiment. Rather than focusing on ways to measure economic activity sentiment (i.e. animal spirits); we develop an index to track Chinese vulnerability sentiment in real time using Big Data. This could help us to identify key vulnerabilities in China using risk narratives, which have the potential to become self-fulfilling or self-defeated.

Rather than focusing on a single risk, our China Vulnerability Sentiment Index (CVSI) is composed by four different vulnerability dimensions. These include indebtedness concerns among highly leveraged state owned enterprises; a fast expansion of shadow banking activities, leading to an overall deterioration of credit conditions; risks of a potential correction in the housing market bubble; and speculative pressures in the exchange rate market. The rationale for including these four dimensions of vulnerability is explained in Section 2.2. These dimensions were carefully selected to reflect the key vulnerability developments in China to assess the key risks faced by the Chinese economy.

The CVSI combines daily time series on sentiment from a Big Data database known as Global Database on Events Location and Tone (GDELT) with official statistics (hard data) and financial indicators in daily, weekly, monthly and quarterly frequencies, making it unique in its robustness and depth. The index is also unique in the sense that it enables us to track vulnerability and sentiment along a number of risk dimensions. To construct the overall index as well as the indices of each component, we use principal component analysis to reduce complex data sets to a lower dimension so as to reveal the most relevant underlying trends (Jolliffe, I.T., 2002).

The empirical results show that the information provided by the textual analysis, in combination with hard data, can be used to track the Chinese vulnerability sentiment in real time as well as contain some explanatory power over traditional market measures of risk as the risk premiums proxied by the Sovereign Credit Default Swap. Besides, the ability to disentangle the evolution of different vulnerability dimensions can aid investors and policymakers to formulate more nuanced views on the economy.

Finally, Big Data analysis allows us to check for the existence of a systematic bias in the narrative of different languages. As GDELT can distinguish between alternative sources of news (i.e those coming from Mandarin Chinese language sources and English language sources), we can trace the difference in the vulnerability sentiment of local (proxied by Mandarin) and global (proxied by English) news. Contrary to the common belief, our findings reveal that there is no systematic bias between English and Chinese media sentiment in in terms of vulnerability sentiment in China. However, our result shows that local media sources (i.e news in Chinese Mandarin text) have some leading-indicator properties over the English one. This is not surprising as local media should, offer a more complete view on the state of the economy. However, the key result lies on the fact that the higher correlation with market risk measures like the Chinese Sovereign Credit Default Swap (CDS) is for the global sentiment (English text). This could be the result of information asymmetries affecting the the pricing mechanism of liquid financial instrument in Emerging

Markets as the CD Swap mainly traded liquid financial centers and subject to margin calls. If this argument holds, the market indicators for risks could be affected by the language used in the major financial centers (Eyssell et al., 2012).

The paper is organized as follows: Section 2 motivates the reseach and defines the rationale for the components of the index. In Section 3, we describe the data, the sentiment algorithm as well as the used methology for contructing the indices. Section 4 presents the results as well as a robusteness check exercise to statistically justify the included variables in the anlysis using Bayesian Model Averaging technique, describes a monetary and fiscal policy index and its relation with the CSVI. Moreover, we disentangle the language effects according to the media source in the index. Section 5 concludes.

2. Assessing China’s vulnerability (motivation)

2.1. Motivation

China has become increasingly integrated in the global economy. The world can’t afford a crisis in China; just like China will be amongst the most severly impacted economies in case of another global financial crisis. In fact, a growing volume of literature has already examined implications of the moderation of Chinese growth on the global economy, including spillovers through a number of channels such as global trade (Drummond et al., 2013; Casanova et al., 2016), equities (Zhou et al., 2012) and investments (Ahua and Nabar, 2012; Lee et al. 2016). Inmediately after the crisis, the Chinese authorities implemented a RMB 4 trillion (USD 586 billion) fiscal stimulus package that would help to generate demand and boost global growth. Putting China’s ample coffers to good use provided a much needed spare wheel in times when the western world was immersed in the midst of a financial crisis that crippled investment and demand. It also enabled China to develop an important infrastructure package. However, the rapid pace of development in combination with a managed economy such as China’s, generated macroeconomic imbalances which still haunt policy makers to date.

As China is becoming increasingly integrated into the global financial system, the policy missteps can have repercussions for the global economy. For example, the Chinese stock market crash in 2015, which led to a 33% cumulative drop in the Shanghai stock index, triggered a 13% decline in US stocks, 17% in Europe stocks and 10% in Asian stocks. Moreover, the awkward mini-devaluation which followed the crash triggered competitive devaluations across a number of emerging markets in Asia and Latin America.Our index intends to capture these risks ahead of time, enabling both investors and policy makers to factor in the risks associated with China’s existing macroeconomic imbalances.

2.2. The index is composed by four different vulnerability dimensions

To assess the China´s vulnerability in detail, we have developed the index based on four risk dimensions that reflect the main macroeconomic imbalances in China. These dimensions, or components, were selected based on our assesemnet of what the main risk factors of the Chinese economy are, making this a highly specific and targeted indicator. More specifically, our index measures vulnerability and sentiment along four main dimensions:

1. **The Stated owned enterprises (SOE) vulnerability component**: This component captures the vulnerabilities associated with highly leveraged indebted SOEs. Total indebtedness in China has increased exponentially and is now equivalent to approximately 250% of GDP. Most of this debt is held by corporates, not household or the government. The surge in corporate indebtedness in China can be traced back to an increase in leveraging by SOEs, coinciding with the implementation of China’s huge post-financial crisis stimulus package (Huang 2014). There is some degree of controversy surrounding the sustainability of this debt overhang, especially given that many of these SOEs are “too big to fail” of deemed of “strategic importance”. What is certain is that excessively high debt levels could result in moderation of growth as the ability of these companies to continue to invest will be somehow constrained. Moreover, inefficiencies associated with the less than optimal allocation of resources mean that every new unit of new credit has a harder time finding a productive project to invest in. Over time, the consecuences of the economy could be quite

sizeable. In fact, if SOE liabilities have continued to climb despite falling productivity (see Moody`s 2016) this could put strain on bank balance sheets, requiring huge liquidity injection. The government is trying to steer the economy away from its dependency on debt by gradually removing its implicit guarantees on SOEs. This means that for smaller or regional SOEs could find themselves in a vulnerable position in case the cost of servicing their debt increases, as we have observed by the unusually large number of corporate defaults in the first quarter of 2017.

2. **The Housing bubble vulnerability component:** This component takes into account risks of a potential correction in the housing market bubble. China doesn't have mature stock markets neither developed pension systems so, for many households, housing and land has been the preferred investment vehicle. Aside fundamental factors (increasing incomes, household formation, urbanization and agglomeration) this trend has been exacerbated by a number of financial factors, including the collapse of the stock market in 2015, and excessive liquidity following from many years of loose monetary policy in China (Xu and Chen, 2012). Moreover, much of the economy itself is based on construction and real-estate development which directly and indirectly could account for near 30% of GDP. Not surprisingly, mortages have been one of the main drivers behind the increase in total credit. This has driven housing prices in China up, increasing the risk of a hard landing of the residential sector. A downturn could wreck havoc to the economy, leading to liquity issues in smaller banks which are more exposed to loans and leveraged buying (Koss, 2015).

3. **Shadow banking vulnerability component:** This component measures the fast expansion of shadow banking activities. An expansion of shadow banking could pose threats to the stability of China's financial institutions, leading to an overall deterioration of credit conditions (Li et al., 2014). Broader credit has soared, as measured by Total Social Financing (TSF), and is now equivalent to roughly 220% of GDP, up from just 206% in 2015. Higher levels of economy-wide leveraging have been fueled by bank lending to corporates, mortgages and corporate bond issuance. By contrast, the growth in "core" shadow banking activities included in TSF remains subdued. However, this moderation does not take into account "non-core" components such as the issuance of Wealth Management Products (WMPs), which have soared in recent months. China's shadow banking activities now account formore than 80% of GDP or RMB58 trillion according to estimates by Moody's (2016), having grown by 19% in the first half of 2016. If this situation continues indefinitely, it could lead to a worsening of credit conditions, leading to dire consequences in case of any shocks to onshore liquidity conditions.

4. **Exchange rate (FX) speculative pressure component:** This component accounts for speculative pressures in the exchange rate market. The RMB has been subject to depreciatory pressures since late 2014. This has led the authorities to expend a vast amount of sovereign resources to prop up the value of the currency. FX reserves dropped by USD1 trillion as a consequence, causing great pain to the authorities. As in the rest of the big Emerging Markets this component can be driven by idiosyncratic or global fianancial forces.

The fact that it is highly specific to the situation in China makes the CVSI unique compared to other initiatives that deploy standaridized methodologies across geographies. It also allows us to assess vulnerability and sentiment in a way which offers more granularity. China is a complex market and it will not be enough to talk about vulnerability in general terms. Some parts may be booming while risks mount in other areas, this is something which has significant implications for policymakers and investors alike.

3. A vulnerability sentiment index for the Chinese economy

3.1. The Data

In order to build these high frequency vulnerability components, we mix hard data (e.g. macroeconomic and financial vulnerability indicators), with high frequency soft data from the "*Global Database of Events, Language and Tone* (GDELT)", a big database created by Leetaru and Scrodt (2013)[2]. In such a way, we complement data from official statistics and market information with data in real time coming from news, which allows us to nowcast the official data and draw information from a new dimension, the emotional one. Thus we incorporate sentiments to the traditional analysys using hard and market data.

Figure 3.1.1 Hard data and sources

Indicator	Frequency	Source	Justification
Total Profits (SOEs)	Monthly	Ministry of Finance of the People's Republic of China	Vulnerability sentiment increases in case SOE profits decrease
Total Liabilities (SOEs)	Monthly	Ministry of Finance of the People's Republic of China	Vulnerability sentimented increases un case SOE liabilities increase
Mortgages as a percentage of total loans	Quarterly	The People's Bank of China	Vulnerability sentiment increases in case mortgages as a percentage of total loans increase
GICS housing index	Daily	Wind Information Service	Vulnerability increases if the price increases
Housing price index	Monthly	National Bureau of Statistics	Vulnerability increases if the price increases
New construction	Monthly	National Bureau of Statistics of the People's Republic of China	Vulnerability increases in new construction decreases
Real estate investment	Monthly	National Bureau of Statistics of the People's Republic of China	Vulnerability increases if real estate investments decrease
NPL ratio	Quarterly	China Banking Regulatory Commission	Vulnerability increases id NPL rations increase
Total social financing	Monthly	The People's Bank of China	Vulnerability increases if TSF increases
Entrusted loans	Monthly	The People's Bank of China	Vulnerability increases if the use of entrusted loand increases
Wenzhou Index	Daily	City of Wenzhou, Finance Bureau	Vulnerability increases as the Wenzhou Index increases
WMP yields	Weekly	Wind Information Service	Vulnerability increases with higher yields
Bank acceptance bill yields (6M Pearl River Delta)	Daily	Wind Information Service	Vulnerability increases withi higher yields
Foreign Exchange reserves	Monthly	The People's Bank of China	Vulnerability increases when FX reserves fall
USDCNY	Daily	Bloomberg	Vulnerability increases if the exchange rate depreciates
USDCNH	Daily	Bloomberg	Vulnerability increases if the exchange rate depreciates
O/N Hibor	Daily	Bloomberg	Vulnerability increases if O/N hibor rates spikes, pointing to tighter liquidity on intervention

Source: BBVA Research

2: Leetaru, Kalev and Schrodt, Phillip3 2013."Global Database of Events, Language, and Tone (GDELT)

The Hard data variables were selected to represent the four dimensions of risk outlined above. We rely on high frequency series (daily) wherever possible, in order to combine these with the soft data sentiment data from GDELT. There are several reasons for mixing different sources of information. First, relying exclusively on sentiment indicators could provide and excess of noise rather than signal. Second, sentiment related to some of the vulnerabilities can be the result of a third common factor (is economic growth). Thus, including factor analysis between hard and sentiment data will reassure us that the information steming fron sentiment is associated to any of the vulnerabilities. Finally, we mixed frequencies with all the sources pof information, including quarterly, monthly and weekly data converted into daily series and normalized for inclusion in the index. For the normalization, we used simple first normal form, substracting the average of the sample and then dividing by the standard deviation. A list of the official statistics and their sources can be found in Figure 3.1.1

For the soft sentiment data, we use GDELT[3], an open access database which pins down and processes news in broadcast, print and web media globally in over 100 languages on daily basis. GDELT The information is extracted from the media and systematized using PETRACH algorithm. As news articles are being parsed to build the GDELT database, different algorithms are run in order to assess the themes that a given piece of news was dealing with. Key words from different taxonomies and dictionaries are identified in the articles and thus a theme classification of the article is provided in the database. GDELT also identifies thousands of emotions, organizations, locations, counts, news sources and events across the world as well as the average tone of the analyzed news articles, this is, how positive or negative the wording of the article is (more details in Section 3.2).

Sentiment variables from GDELT are defined as the daily average tone of the news containing each particular theme. To delimit the scope of the news into the space desired for our analysis, some interaction series were also built, this is, the daily average tone of the news dealing with multiple of these themes. Specifically, the tone series regarding *Debt*, *Resource Misallocations,* and *Local Government* have been interacted with the theme on *State Owned Enterprises* to make sure the pieces of news included in analysis are indeed related to the State Owned Enterprises component of the index. The series selected for each of the components of the index are shown in Figure 3.1.2.

3: Further information can be found in the following link.

Figure 3.1.2. Included variables in the Index.

China Vulnerability Sentiment Index (CVSI)			
SOE Vulnerability Index (SOEI)	**Housing Bubble Vulnerability Index (HBI)**	**Shadow banking Vulnerability Index (SBI)**	**FX Speculative Pressure Index (FXI)**
Hard & Financial data			
Total.profits (M) Liabilties (M) **25%**	Mortages.loan (M) GICS.Housing.Index (M) Housing.Price (M) New.Construction (M) RealEst.Invest (M) **45%**	NPL.Ratio (M) TSF.Aggregate.New Increase (M) Entrusted.Loans (M) Wenzhou.Index (D) WMPs Acceptances (M) **35%**	Foreign.Reserves (D) CNY Exchange Rate (D) CNH Exchange Rate (D) HICNHON.Index (D) **40%**
Big data (GDELT) indicators in real time			
State_owned_enterprises (D) Resource_misallocs_&policy Failure (D) Resource_misallocs&SOEs (D) Institutional_reform_&_SOEs (D) Industry_policy (D) Industry_laws_and_regulations (D) Local_government_and_SOEs (D) Debt_and_SOEs (D) **75%**	Housing_policy_&_institutions (D) Housing_markets (D) Housing_prices (D) Housing_construction (D) Housing_finance (D) Land_reform (D) **55%**	Non_bank_financial_institutions (D) Asset_management (D) Bank_capital_adequacy (D) Financial_sector_instability (D) Banking_regulation (D) Infrastructure_funds (D) Financial_vulnerability_&_risks (D) Monetary_&_financial_stability (D) State_financial_institutions (D) **65%**	Currency_exchange_rate (D) Currency_reserves (D) Capital_account (D) Macroprudential_policy (D) Exchange_rate_policy (D) Illicit_financial_flows (D) **60%**

Source: BBVA Research

3.2. Measuring "Sentiment"

Both theoretical and empirical works have stressed that sentiments can influence agents decisions. The theoretical importance of sentiments in economics is far from new. Pigou (1927) believed that business cycle fluctuations are driven by expectations and entrepreneurs' errors of optimism and pessimism are crucial determinants of these fluctuations. Later, the seminal work by Keynes (1936) highlighted the importance of changes in expectations that are not necessarily driven by rational probabilistic calculations, but by what he labeled "animal spirits". More recently, Keynes's original hypothesis has been one of the salient features of the 1990-91 recession (Blanchard, 1993) while Angeletos and La'O (2013) develop a unique-equilibrium, rational-expectations, macroeconomic model which features "animal spirits", labeled sentiments. Shiller (2017) shows "narratives" can explain aggregate fluctuations though epidemic models.

There is also empirical literature which has stressed the importance of sentiment in economics. Angeletos, Collard and Dellas (2015) have quantified the importance of the variations in sentiment (or confidence) in macroeconomic DSGE models. They find that sentiment shocks lead to strong co-movement between employment, output, consumption and investment and that they account for around one half of GDP variance and one third of the nominal interest rate variance at business-cycle frequencies. Barsky and Sims (2012) found that this informational component forms the main link between sentiment and future activity in international business cycles. More recently, Recently Shapiro, Sudhoff, and Wilson (2017) show how the news sentiment measures outperform the University of Michigan and Conference board measures in predicting the federal funds rate, consumption, employment, inflation, industrial production, and the S&P500.

In this paper we measure sentiment vulnerability through textual search using sentiment analysis techniques. Sentiment analysis, also known as opinion mining, has been a challenging natural language processing or text mining problem. Due to development of digital news and its tremendous value for practical applications, there has been an explosive growth of both research in academia and applications in the industry (Liu, 2010). Shiller (2017) observes that textual search is a small but expanding area in economic research. Textual analysis has been used by economists, for example, to document changes in party affiliation (Kuziemko and Washington, 2015); political polarization (Gentzkow et al. 2016); and news and speculative price movements (Roll 1988; Boudoukh et al. 2013). Tetlock et al (2008) uses textual analysis to extract sentiment from corporate reports while Tetlock (2007) analyzes the sentiment in media. In the spirit of our work, Wang et al (2013) shows the existence of strong correlations between financial sentiment words in financial reports and the risk of companies. More recently, Shapiro, Sudhof and Wilson (2017) construct indexes measuring the economic sentiment embodied in newspaper articles.

There are two general approaches to quantify sentiment in text. The first is known as the “Bag of Words" or Lexical approach. It relies on a pre-defined dictionary (or set of dictionaries, one for each emotion) of words that are associated with that emotion. The second approach uses Natural Language Processing (NLP) tools, a subfield of computational linguistics which relies on machine learning techniques. NLP sentiment analysis attempts to extract emotional content from a set of text based both on word choice (lexicon) and the context (combinations and structure) of words. It estimates the emotional content of text using a predictive model that is trained on a large corpus of text containing a mapping between utterances and emotions.

The development of machine learning algorithms by computer scientists for natural language processing opens up the possibility of handling large unstructured text databases so as to quantify the content of raw text data (see for instance Blei et al., 2003).

To measure the tone or sentiment we rely on the Global Data on Events, Location, and Tone (GDELT) dataset and tools. As explained in Section 3.1, GDELT relies on hundreds of thousands of broadcast, print and online news sources from every corner of the globe in more than 100 languages. GDELT use “directional” word lists measuring words associated with positive and negative tone as proposed by more than 40 sentiment dictionaries and translating each article into English from more than 65 languages. GDELT uses NPL techniques to compute the average “tone” or sentiment of all documents containing one or more mentions of any particular theme we are looking for:

$$\text{Average tone} = \frac{\sum Positive\ words\ \ - \sum Negative\ words}{\sum Total\ words}$$

The score ranges from -100 (extremely negative) to +100 (extremely positive) but common values range between -10 and +10, with 0 indicating neutral. A neutral sentiment can be the result of a neutral language or a balancing of some extreme positive sentiments compensated by negative ones. Once negative and positive words are identified with each dictionary, we construct a tone variable based on the balance between the number of positive and negative words that appear in a given document divided by the total number of words included in the document.

3.2. Construction of the index: methodology

Vulnerability is a non-observable variable, meaning it is not possible to measure this quantitatively. However, if we assume that vulnerability in China is determined by the interaction of a set of observable variables, described in Section 3.1, we can approximate a measure of vulnerability sentiment by looking at the underlying pattern governing these correlated observable variables and their variances. In order to contruct the index, we deploy the use of Principal Component Analysis (PCA). PCA is a multivariate technique that enables us to reduce complex data sets to a lower dimension, revealing underlying trends by examining the variances associated to the principal component (Jolliffe, I.T., 2002). We also undertake PCA for the individual subcomponents, with the intention to disentangle different types of vulnerabilities, sometimes difficult to separate, which could be useful for identifying the sources which cause vulnerability and for policy making.

According to our calcultations, PCA explains the majority of the variance in the original data, making it a suitable approximation of vulnerability. The percentage explained variance by the first component for each index can be found on Figure 3.2.1. We define the CSVI as the underlying pattern from the set of variables grouped in the four components defined in Section 2.2 (SOE, HB, SB and FX):

$$CSVI = \mu_1 \mathrm{SOE} + \mu_2 \mathrm{HB} + \mu_3 \mathrm{SB} + \mu_4 \mathrm{FX} + \varepsilon$$

Figure 3.2.1. Percentage of explained variance by the first component in each case

Indices	% of explained variance by the first component
SOE Vulnerability Index	63.17
Housing Bubble Vulnerability Index	65.76
Shadow banking Vulnerability Index	59.53
FX Speculative Pressure Index	78.99
China Vulnerability Sentiment Index	**61.16**

Source: BBVA Research

Simultaneously, the four subcomonents summarize the main underlying trend related to state-owned enterprises, the housing sector, the shadow banking and FX pressures respectively in a single index. They are defined as follows:

$$\mathrm{SOE} = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_{10} x_{10} + \epsilon_1$$

$$\mathrm{HB} = \delta_1 y_1 + \delta_2 y_2 + \ldots + \delta_{11} y_{11} + \epsilon_2$$

$$\mathrm{S}B = \beta_1 z_1 + \beta_2 z_2 + \ldots + \beta_{15} z_{15} + \epsilon_3$$

$$FX = \rho_1 v_1 + \rho_2 v_2 + \ldots + \rho_{10} v_{10} + \epsilon_4$$

Where $(x_1, \ldots, x_{10})$ represent the variables included in the SOE component (see Figure 3.1.2); $(y_1, \ldots, y_{11})$ represent those for the housing bubble component (see Figure 3.1.2); $(z_1, \ldots, z_{15})$ shadow banking component (see Figure 3.1.2), and $(v_1, \ldots, v_{10})$ are the variables included in the FX speculative pressure component (see Figure 3.1.2). $\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4$ are the errors of each equation respectively.

Thus, in each case, we can define the weights of each variable in the components and in the overall index as following:

$$\omega_i = \frac{\sum_{j=1} \lambda_j X_{ji}}{\sum_{j=1} \lambda_j}$$

Where j is the first principal component, i is the number of variables in the index or sub-index, λ_j is the variance of the first principal component, X_{ji} is the eigenvector of the correlation matrix. Results are shown in Figure 3.2.2. Weights are balanced between components and also between variables in each component in most of the cases.

Figure 3.2.2. Relative weights of each variable and component in the overall index

Variable	Weights
Total profits	19.63
Institutional_reform_and_SOEs	12.37
Debt_and_SOEs	11.92
Local_government_and_SOEs	9.75
Industry_policy	9.50
Resource_misallocations_and_policy_failure	8.18
SOEs	7.15
Liabilities	10.62
Industry_laws_and_regulations	5.28
Resource_misallocations_and_SOEs	5.61
SOE Vulnerability Index	**29.18**

Variable	Weights
New Construction	16.37
mortages loan	14.57
Land_reform	12.62
Housing Price	11.60
Housing_construction	10.59
Housing_prices	10.05
Housing_policy_and_institutions	8.94
Housing_finance	7.83
Housing_markets	6.71
GICS Housing Index	0.36
Real Est. Investment	0.35
Housing Bubble Vulnerability Index	**26.05**

Variable	Weights
Wenzhou Index	16.58
WMP Yields	13.63
Infrastructure_funds	10.92
NPL Ratio	9.46
State_financial_institutions	8.95
Banking_regulation	7.28
Financial_vulnerability_and_risks	6.82
Asset_management	5.62
Financial_sector_instability	5.35
Bank_capital_adequacy	4.60
Non_bank_financial_institutions	4.35
Monetary_and_financial_stability	3.54
Acceptances	2.22
TSF Aggregate NewIncreased	0.57
Entrusted Loans	0.13
Shadow banking Vulnerability Index	**23.12**

Variable	Weights
Currency_exchange_rate	19.94
Exchange_rate_policy	17.95
Macroprudential_policy	15.33
HICNHON Index	13.84
CNY Curncy	11.92
Capital_account	10.05
CNH Curncy	8.73
Illicit_financial_flows	1.58
Foreign Reserves	0.60
Currency_reserves	0.06
FX Speculative Pressure Index	**21.64**

China Vulnerability Sentiment Index

Source: BBVA Research

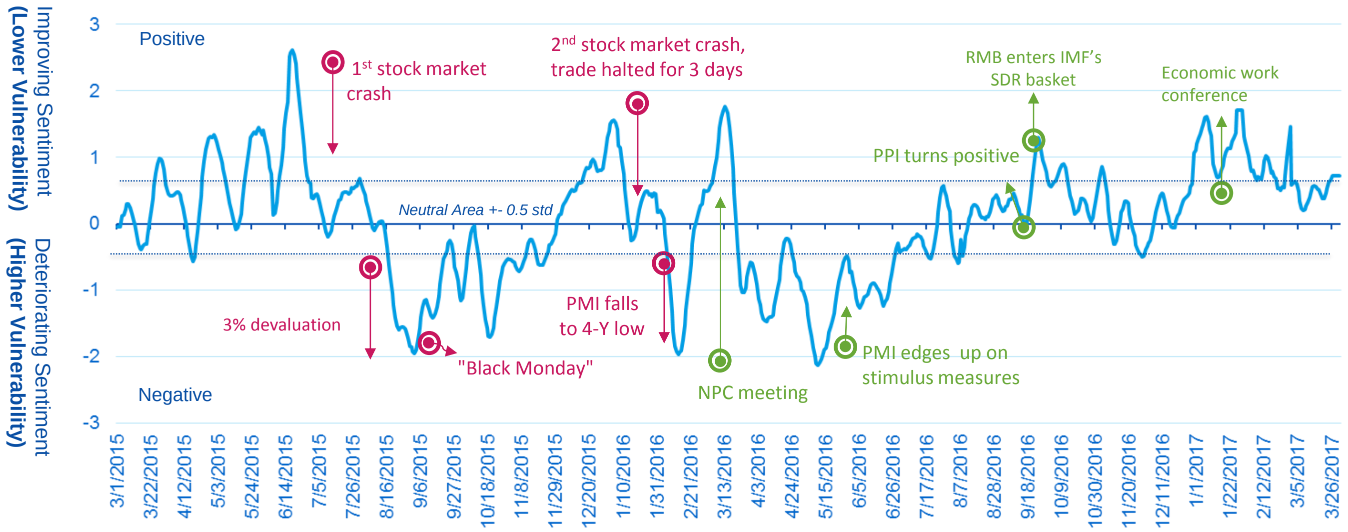
4. Results

4.1. The China Vulnerability Sentiment Index (CVSI) and its components

The CVSI index can be observed in Figure 4.1.1. The negative values reflect deteriorating in vulnerability sentiment, while positive values denote an improvement in sentiment. Neutral values can reflect a combination of two things: inherently neutral vulnerability and sentiment; or the balancing out of both positive and negative factors. The index captures the key risk events driving vulnerability sentiment in China. The CVSI shows a gradually improving vulnerability sentiment since the second half of 2016. This is in stark contrast to the sharp decline which can be observed in the second half of 2015 and the first half of 2016. During this period, the CVSI dipped quite steeply in mid-2015, refecting deteriorating vulnerability sentiment following from two stock market crashes and an ill-timed devaluation of the RMB. The series of stock market crashes ultimately resulted in a third of the value of the Shanghai Stock Exchange being wiped out in what is now referred to as “Black Monday”. Together with concernes surrounding high corporate debt levels, the bulk of which has been accrued by SOEs (see Section 2.2) and one-sided expectations of Yuan devaluation, the events of the summer of 2015 fueled fears of a potential collapse of the Chinese economy.

As this risky period would have potential implications on the global financial system, it’s not surprisingly that the risk narratives in global media deteriorated rapidly. Nevertheless, we see an inflexion point nearing the second half of 2016 and coinciding with the conclusion of the Chinese National Policy Committee meeting. During this event, authorities made clear their commitment to growth targets maintaining the compromise of reforms, adjusting the policy mix to more fiscal support combined with a tighter monetary policy stance and a stricter macro-prudential framework.

Figure 4.1.1. Chinese Vulnerability Sentiment Index (CVSI)
(Evolution of the “Tone” of main followed themes about vulnerability in China. Lower values indicate a deterioration of sentiment and higher vulnerability)

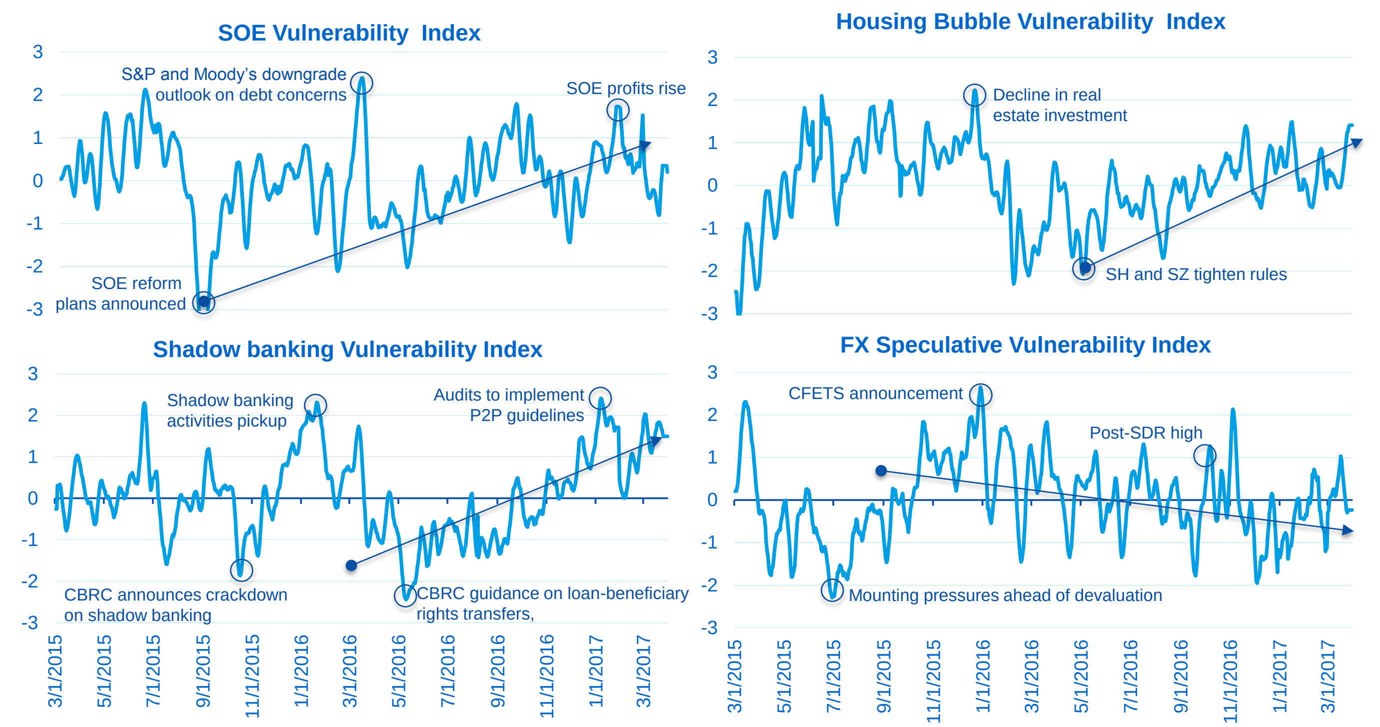


Source: www.gdelt.org and BBVA Research

The recovery observed in the general CVSI since the second half of 2016 has not been homogenous for all subcomponents (Figure 4.1.2). Our SOE component has edged up since the announcement of “supply side” reforms in the third quarter if 2015. Discussions surrpunding the restructuring of China’s titanic SOEs has been on the table since 2013. However on September 2015, China’s State Council issued a series of guidelines aimed at reforming the SOEs and boosting productivity through closures and mergers by 2020. The plans also included were annual targets for overcapacity reduction in the bloated steel and coal sectors. Through a combination of policy measures and external factors, targets for 2016 were exceeded with state media announcing that steel and coal was cut by 45 million tons and 250 million tons respectively contributive to a more positive narrative overall.

The overall indebtedness in the system remains very high at approximately 270% of GDP, so while the risk narratives seem to have stabilized lately and can be self-fulfilling, a future deterioration of the fundamentals subject to internal or external shocks may rasie concerns about the sustainability of this debt, thus making narratives self-defeating.Thus keeping alive good narratives for a prolongued period of time can lead to permanent positive moods which would allow the economy to move from a bad to a the good equilibrium (see Akerloff, G and Shiller,R., 2009)

Figure 4.1.2. Chinese Vulnerability Sentiment Index: Improving in 3/4 components
(Evolution of the “Tone” of main followed themes about vulnerability in China. Lower values indicate a deterioration of sentiment and higher vulnerability)



Source: www.gdelt.org and BBVA Research

The housing bubble index also reflects an improvement in vulnerability sentiment since the second half of 2016. Fears of an imminent housing bubble collapse in the beginning of 2016 were dissipated when authorities stepped up their effors to limit price increases in first-tier cities such as Shanghai, Shenzhen and Beijing, limiting the risks of rapid increasing prices and a posterior stronger correction. As prices moderated the index started a recovery from negative values to near neutral. In fact, prices in tier-1 cities have moderate since the start of 2017. Its not surprising that risk narrativesimproves as housing process increased while risk remain contained, at least for now. This is a reflection of the fact that the Chinese authorities have allowed prices to increase in order to support GDP while simultaneously intervening to contain asset price risks in major cities. Whether this move will prove successful over time or not remains to be seen.

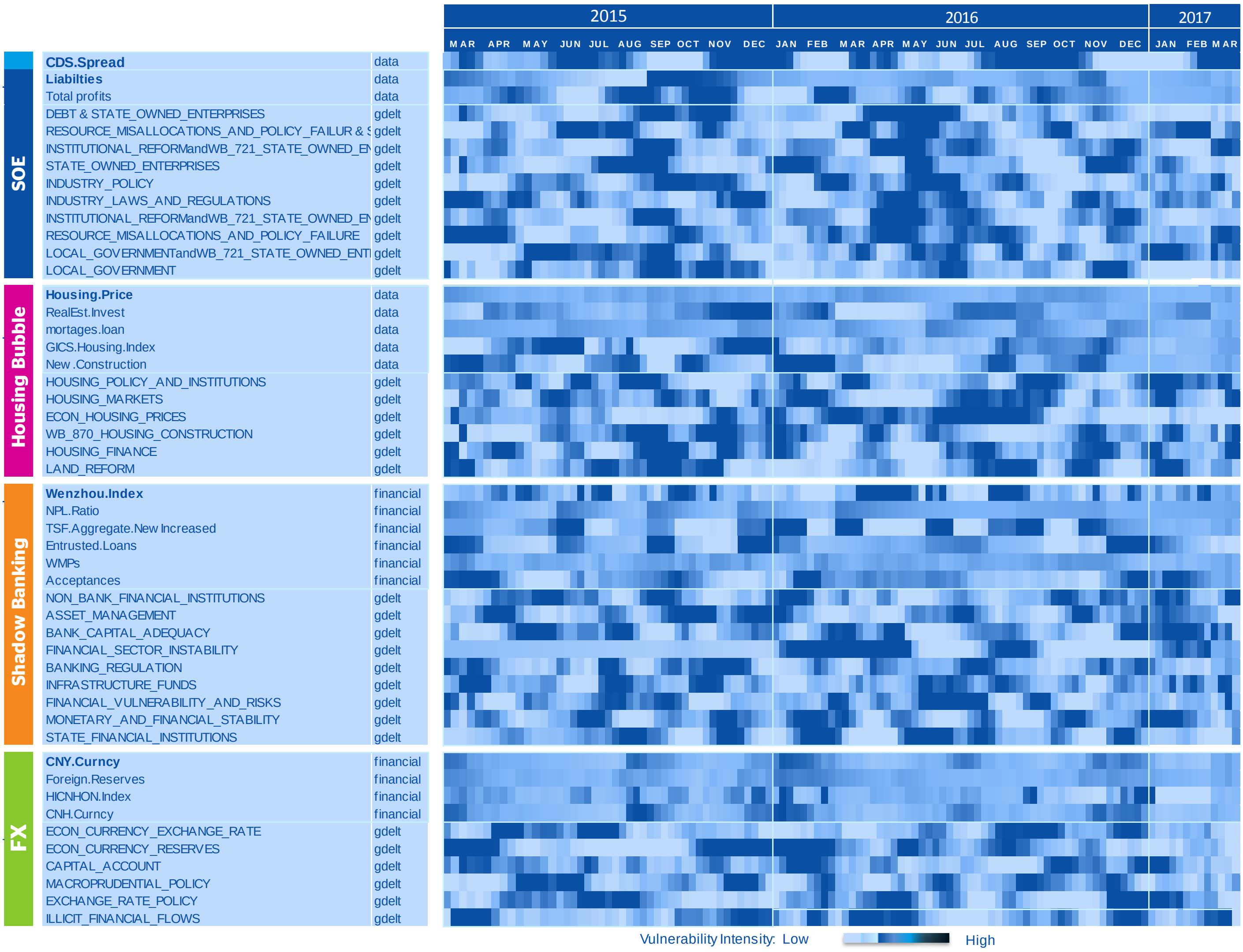
The shadow banking component reflects the most significant improvement in vulnerability sentiment. This is the result of the combination of tighter liquidity conditions and stricter regulatory scrutiny on the banks' off-balance-sheet activities will has restricted bank's incentive to engage in regulatory arbitrage, gradually dampening the fast-growing pace of shadow banking activities (Moody's, 2017). This may be a reflection of the China Banking Regulation Commission's (CBRC) latest crackdown on shadow banking activities launched around September 2016. These include measures to restrict issuance of WMPs, which continue to dominate the increase in shadown banking.

The only component where we do not observe an improvement is FX speculative pressures. This is due to the fact that, particularly during 4Q16, the RMB saw significant depreciatory pressures, leading to outflows and a depletion of FX reserves below the watershed level of 3 trillion USD. Much of this pressure has abated in 1Q17. The recovery in 1H17 can be traced back to a weaker USD, reflecting unwinding reflationary trades following from last year's presidential elections in the United States and expectations of less aggressive monetary policy tightening by the Federal Reserve. Moreover, stronger external demand has facilitated a recovery of Chinese exports in 2017, which has alleviated pressures on the current account – better terms of trade leading to a higher surplus in Q1.

4.2. Properties of the index

We find that high frecuency sentiment indicators can be used to nowcast vulnerability. This can be useful, for authorities, regulators and markets to adjust more timely and fine tune their decisions. In Figure 4.2.1, we show a heat map of the the weekly evolution ofrom GDELT from March 2015 to March 2017. The included variables in heatmap are scaled, centered and de-trended when necessary. We can observe that there are co-movement patterns in the data, with the crests and valleys of the series occurring within a couple of weeks of difference. This is especially noticeable in the GDELT series for the SOE and FX component where the series have a couple of pronounced changes of level. In the remaining series we can see more coincident and gradual sinusoid patterns. Furthermore, there seems that at worst the sentiment indicators are cpoincident wth some of them (SOE component) showing some ome leading properties.

Figure 4.2.1. Chinese Vulnerability Sentiment Index Color Map: Patterns and Co-movements



Source: BBVA Research

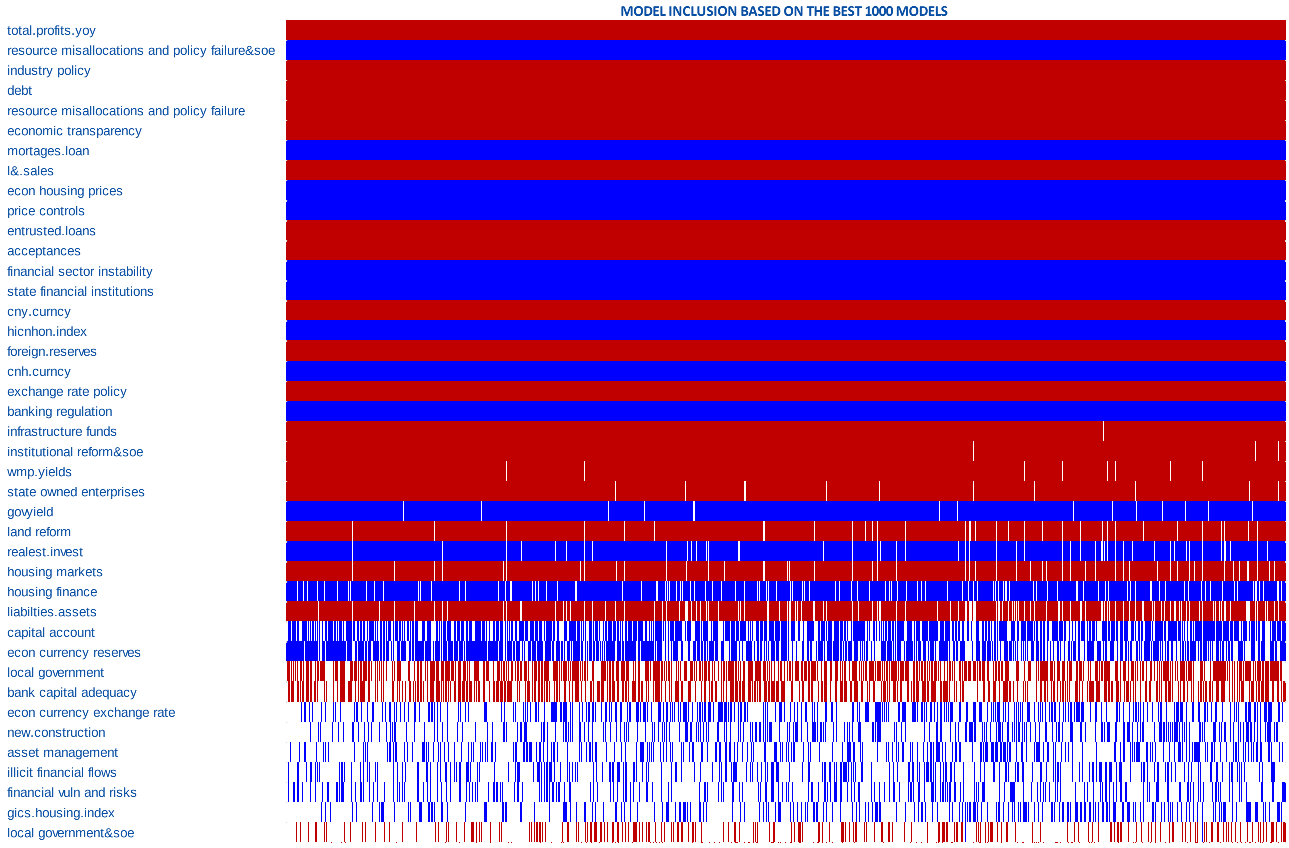
4.3. Robustness check

To check the robustness of the analysis we rely also on Bayesian techniques. Particularly, we run a Bayesian Model Averaging analysis (Hoeting et al., 1999), using as dependent variable the CDS spread of the five year Chinese bond (our market proxy for vulnerability). We test wether the set of our "a priori" selected variables will be including in amodel explaining market risk. In essence, we plot the posterior inclusion probability (PIP) of the variables using a difusse prior (a zero coefficient value or non inclusion).

The results of this analysis are presented in Figure 4.3.1. Here we can see variables in rows and 1000 of the estimated models by columns. A cell is colored if the Posterior Inclusion Probability or PIP is siginificant while the color indicates the sign (red for negative and blue for positive). Variables with a PIP smaller than 15% have been excluded from Figure 4.3.1. As we can see, more than half of the variables we selected have a very high Posterior Inclusion Probability (PIP), and more than half the variables (33 out of 54) have a probability of inclusion greater than 50%, and 87% of these most likely to be included in the CDS spread linear model are actually included in the index, providing solid evidence that the selected variables are indeed relevant in order to build a measure of risk and vulnerability.

The variables with smaller PIP in this analysis are for the most part containing information similar to other series that are identified as relevant by the BMA. For example, the debt & soe sentiment is excluded from the model, but *state owned enterprises* is included as well as the intersection with several other variables. A similar situation arises with asset management or some of the housing market related variables. Then it is possible to see that a certain degree of collinearity may induce the exclusion of these variables, and as such, these excluded variables might not be irrelevant when building the index. Furthermore, as we try to provide a measure for vulnerability, it is important to keep in mind that this risk is unobserved. For this robustness check, vulnerability is proxied through the CDS spread, then the result that a certain variable has a low PIP might not indicate that it does not add relevant information when building a risk indicator. Thus, the results of this analysis provide evidence that the selection of variables used to build the index is in general terms adequate.

Figure 4.3.1. BMA Results.



Source: BBVA Research

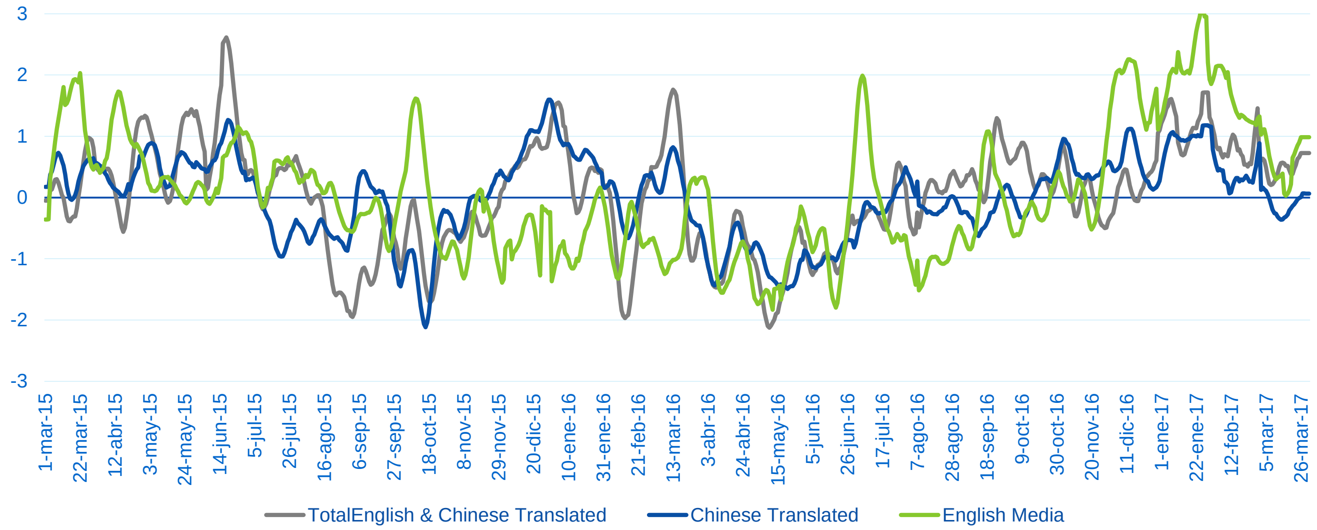
4.4. Disentagling the language effects in narratives (the local media bias)

In this section we check whether there is a systematic language bias in the vulnerability sentiment about China. The GDELT database includes several languages around the world including the Chinese one. We build up two new indexes according to the languages in which the news are written. In our case we choose English (as representative media of worldwide financial centers) and Chinese written media.

Figure 4.4.1 shows some interesting patterns. First, there is no systematic bias in sentiment in any of the languages. Sentiment in English media was more negative at the end of 2015 and the beginning of 2016, but it has become more positive thereafter. Second, the Chinese index looks more stable and its standard deviation is in fact lower (0.66 the Chinese and 0.99 the English one), thus global narratives could amplify vulnerability sentiment.Third, according to the correlogram, the Chinese language sentiment looks to have leading indicator properties over the English one. This is not surprisingly at all if we assume more complete information by the Chinese media.

However, a striking result is that the English media looks to have a higher correlation with market risk measures like the Chinese CDS than the local one. A reason of it is that this instrument will be priced in more liquid markets and therefore more influenced by the language of big financial centres. In fact, some previous works show that global factors have increased the role in explaining the Chinese CDS (Eyssell, Fung and Zhang, 2013). Moreover, the fact that tere seems to be no inherent bias in English versus Chinese media also confirms theories by other authors. Pan, King and Roberts (2017) argue that the Chinese government fabricates 448 million social media comments a year with the objective of distracting public opinion with themes that are favorable for China. This is in contrast to previously held assumptions that online censors intervene to oppose dissenting views or change narratives.

Figure 4.4.1 Indices for different languages.



Source: BBVA Research

4. Conclusions

We develop an index to track vulnerability sentiment in China in real time using Big Data techinques which has shown to be robust and coherent to reflect the developments on the ground in China. The included variables in the analysis were carefully selected in order to capture the main vulnerabilities in China. The Bayesian Model Average analysis confirms that the posterior inclusion probability of most of the sentiment variables in explaining the market price of risk. Thus, our empirical analysis confirms that "sentiment" and narratives matter and can also explain vulnerabilities.

The results show that most of the analyzed components were deteriorating since mid 2015 and bottoming out at the first quarter of 2016. Since then, the combination of tigten monetary policy a looser fiscal policy were able to improve the vulnerability sentiments in both SoE, Housing and Shadow Banking dimensions. The speculative pressure has performed more divergent as the global component is also the result of global forces.

The analysis shows that there's no any systematic language bias in the vulnerability sentiment about China and, as expected, the local Chinese language sentiment seems to be a leading indicator over the English one. However, the latter has a higher correlation with market risk measures like the Chinese CDS. This is a key result as it confirms the existence of information asymmetries in emerging markets that could arise in low liquid markets. In this sense, communications policies could be enhanced if they are directed to these centers.

Further research will focus on analyzing the effects of CSVI using VAR analysis including policy variables. This would help us to design optimal policies to cope with global vulnerability in the four different dimensions of vulnerability. The effects of the language narratives have been tested with market measures of risk (CDS), but the analysis could be extended to a more analytical risk premium measures.

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