Do words hurt more than actions?
The impact of trade tensions on financial markets

Massimo Minesso Ferrari[1] Frederik Kurcz[2] Maria Sole Pagliari[3]

[1]European Central Bank [2]Deutsche Bundesbank [3]Banque de France

Nontraditional Data & Statistical Learning with Applications to Macroeconomics

12 November 2020

Introduction

- Trade tensions have been on the rise since 2017. ▸ Chart

- Existing macro-models based on trade elasticities imply very limited effects of tariffs on real activity. ▸ Chart

- However, the literature has not isolated "pure trade tension" shocks.

What this paper does

- Construction of an indicator for high-frequency “pure trade tension shocks”

What this paper does

- Construction of an indicator for high-frequency "pure trade tension shocks"
- Performance assessment of the indicator vis-à-vis well-known events in the US-China trade negotiations and check of potential endogeneity issues w.r.t. US and global financial variables

What this paper does

- Construction of an indicator for high-frequency “pure trade tension shocks”
- Performance assessment of the indicator vis-à-vis well-known events in the US-China trade negotiations and check of potential endogeneity issues w.r.t. US and global financial variables
- Quantification of impact of rising trade tensions between the US and China on international financial variables

Literature review.

The 3T Index

Our "Tweet trade tension"(3T) index is constructed as follows:

- We collect all tweets from President Trump's Twitter account from the beginning of the 2016 US electoral campaign and we select those in the Bloomberg's "trade war" events list.

The 3T Index

Our "Tweet trade tension"(3T) index is constructed as follows:

- We collect all tweets from President Trump's Twitter account from the beginning of the 2016 US electoral campaign and we select those in the Bloomberg's "trade war" events list.

- We construct a sentiment indicator that captures the degree of protectionism of each tweet via a supervised learning algorithm:

The 3T Index

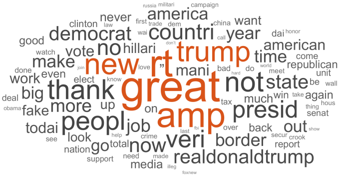
Our "Tweet trade tension"(3T) index is constructed as follows:

- We collect all tweets from President Trump's Twitter account from the beginning of the 2016 US electoral campaign and we select those in the Bloomberg's "trade war" events list.
- We construct a sentiment indicator that captures the degree of protectionism of each tweet via a supervised learning algorithm:
  1. We set up a training sample (2016-2018) of tweets with given scores
  2. We estimate an econometric model on the training sample
  3. Protectionism scores are then automatically assigned to the remaining tweets using the results of the training sample.

Preliminary evidence

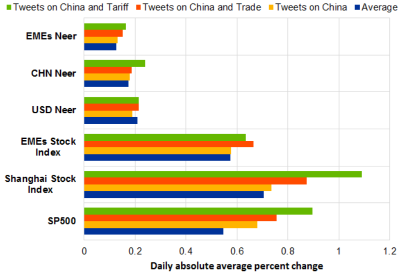
Figure: Word clouds

All tweets (2016-2019)



Tweets in Bloomberg's timeline

Figure: Daily reactions on financial markets



Notes: Average absolute daily changes in days with tweets related to (1) China and tariffs; (2) China and trade; (3) China; (4) all other days. **Source**: Haver Analytics and authors' calculations.

Event study.

Econometric framework

We set up an elastic net model:

$$\min_{\beta_0,\beta,\lambda} \left[\frac{1}{2N} \sum_{i=1}^{N} \left(S_i - \beta_0 - x_i^T \beta \right)^2 + \lambda P_\alpha(\beta) \right] \tag{1}$$

$$\text{with } P_\alpha(\beta) = \frac{1-\alpha}{2} ||\beta||^2 + \alpha ||\beta||$$

Econometric framework

We set up an elastic net model:

$$\min_{\beta_0,\beta,\lambda} \left[\frac{1}{2N} \sum_{i=1}^{N} \left(S_i - \beta_0 - x_i^T \beta \right)^2 + \lambda P_\alpha(\beta) \right]$$
$$\text{with } P_\alpha(\beta) = \frac{1-\alpha}{2} ||\beta||^2 + \alpha ||\beta|| \tag{1}$$

- $S_i \in [-1, 1]$ is the score for tweet i in the training sample

Econometric framework

We set up an elastic net model:

$$\min_{\beta_0,\beta,\lambda}\left[\frac{1}{2N}\sum_{i=1}^{N}\left(S_i-\beta_0-x_i^T\beta\right)^2+\lambda P_\alpha(\beta)\right] \tag{1}$$

$$\text{with } P_\alpha(\beta)=\frac{1-\alpha}{2}||\beta||^2+\alpha||\beta||$$

- $S_i \in [-1,1]$ is the score for tweet i in the training sample
- x_i^T is a vector of dummies for words;

Econometric framework

We set up an elastic net model:

$$\min_{\beta_0,\beta,\lambda} \left[\frac{1}{2N} \sum_{i=1}^{N} \left(S_i - \beta_0 - x_i^T \beta \right)^2 + \lambda P_\alpha(\beta) \right] \tag{1}$$

$$\text{with } P_\alpha(\beta) = \frac{1-\alpha}{2} ||\beta||^2 + \alpha ||\beta||$$

- $S_i \in [-1, 1]$ is the score for tweet i in the training sample
- x_i^T is a vector of dummies for words;
- λ is the weight of the penalty term ($\lambda = 0 \rightarrow$ OLS);

Econometric framework

We set up an elastic net model:

$$\min_{\beta_0,\beta,\lambda} \left[\frac{1}{2N} \sum_{i=1}^{N} \left(S_i - \beta_0 - x_i^T \beta \right)^2 + \lambda P_\alpha(\beta) \right] \tag{1}$$
$$\text{with } P_\alpha(\beta) = \frac{1-\alpha}{2} ||\beta||^2 + \alpha ||\beta||$$

- $S_i \in [-1, 1]$ is the score for tweet i in the training sample
- x_i^T is a vector of dummies for words;
- λ is the weight of the penalty term ($\lambda = 0 \rightarrow$ OLS);
- α scales the penalty score between lasso ($||\beta||$) and ridge ($||\beta||^2$).

Econometric framework

We set up an elastic net model:

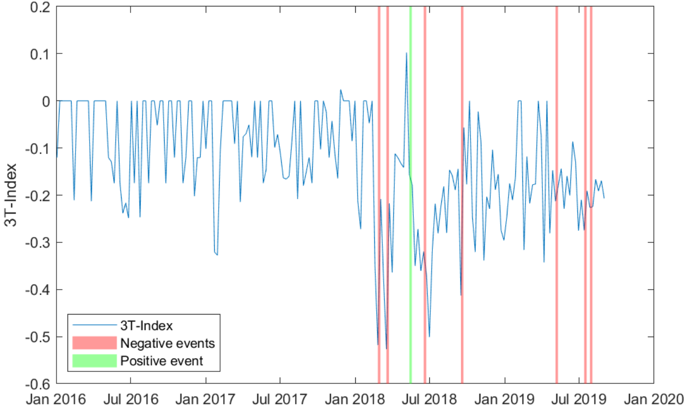
$$\min_{\beta_0,\beta,\lambda}\left[\frac{1}{2N}\sum_{i=1}^{N}\left(S_i-\beta_0-x_i^T\beta\right)^2+\lambda P_\alpha(\beta)\right]$$
$$\text{with } P_\alpha(\beta)=\frac{1-\alpha}{2}||\beta||^2+\alpha||\beta|| \tag{1}$$

- $S_i \in [-1,1]$ is the score for tweet i in the training sample
- x_i^T is a vector of dummies for words;
- λ is the weight of the penalty term ($\lambda = 0 \rightarrow$ OLS);
- α scales the penalty score between lasso ($||\beta||$) and ridge ($||\beta||^2$).

$\rightarrow$ **β_0; λ; α are cross validated**

The Tweet Trade Tension Index (3TI)

Figure: Weekly Index against Bloomberg's trade war events



Notes: the indicator is aggregated at weekly frequency because many important tweets take place over weekends or outside trading hours.

Model output. Relevant tweets. Daily aggregation.

Exogeneity w.r.t. financial markets developments

We regress the 3TI on a set of weekly financial variables

Results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$\Delta SP500_t$	-0.096			-0.090	-0.203		-0.165
	(0.588)			(0.620)	(0.583)		(0.609)
$\Delta SP500_{t-1}$	0.147			0.296	0.128		0.231
	(0.984)			(0.999)	(1.027)		(1.031)
$\Delta SP500_{t-2}$	0.706			0.414	0.691		0.478
	(0.839)			(0.849)	(0.819)		(0.832)
$\Delta NEER_t^{USD}$		0.129		0.035		0.493	0.373
		(1.574)		(1.653)		(1.629)	(1.680)
$\Delta NEER_{t-1}^{USD}$		1.581		1.709		1.334	1.318
		(1.900)		(2.030)		(2.056)	(2.138)
$\Delta NEER_{t-2}^{USD}$		-3.018*		-2.694		-2.587	-2.368
		(1.591)		(1.658)		(1.711)	(1.756)
$\Delta Stock_t^{CHN}$			0.382		0.474	0.445	0.482
			(0.483)		(0.493)	(0.505)	(0.514)
$\Delta Stock_{t-1}^{CHN}$			-0.555		-0.707	-0.544	-0.672
			(0.477)		(0.514)	(0.495)	(0.532)
$\Delta Stock_{t-2}^{CHN}$			0.816		0.645	0.679	0.562
			(0.549)		(0.521)	(0.580)	(0.548)
Constant	-0.002	-0.001	-0.001	-0.002	-0.002	-0.000	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	190	190	190	190	190	190	190
F test	0.757	1.208	1.017	0.879	0.684	1.374	0.999
F prob	0.519	0.308	0.386	0.511	0.663	0.227	0.442
R^2	1.20	1.21	1.22	1.22	1.23	1.24	1.24

Notes: explanatory variables are in log-differences; the China stock index is the Shanghai stock market index. T-stats reported in parenthesis below coefficients and computed based on HAC standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

▸ Daily regression.

Effect on financial variables

We estimate the *weekly* response of financial variables via linear local projections à la Jordà (2005):

$$y_{t+k} = \alpha + \beta^k \bar{S}_t + \delta y_{t-1} + \Gamma' X_t + \varepsilon_{t+k} \tag{2}$$

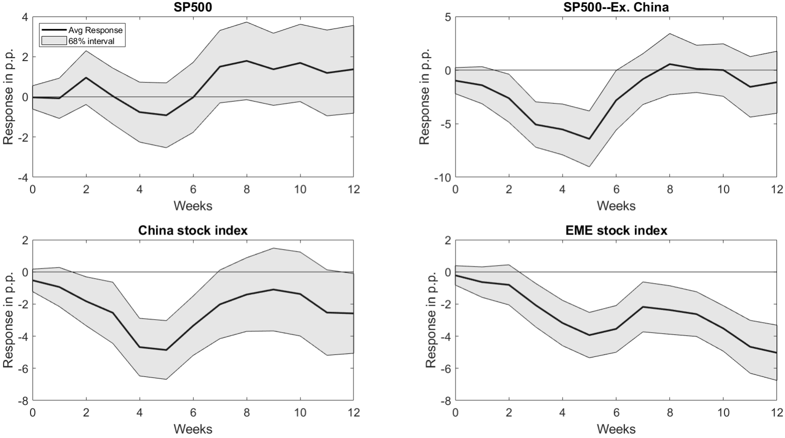
- $\bar{S}_t$: weekly 3TI
- X_t: lagged controls (VIX, US 2-year yield, Citi Macroeconomic surprise index)
- β^k: response at time $t+k$ to trade tension shocks

Robustness checks:

- time trend and lags of 3TI in X_t ▸ Time trend ▸ Lag of the index
- different lag length of control variables ▸ Lag of controls
- $\bar{S}_t$ replaced with residuals of AR(1) regression of 3TI, i.e. $\bar{S}_t = a + \varrho \bar{S}_{t-1} + \eta_t$ ▸ AR(1) residuals

Stock indices

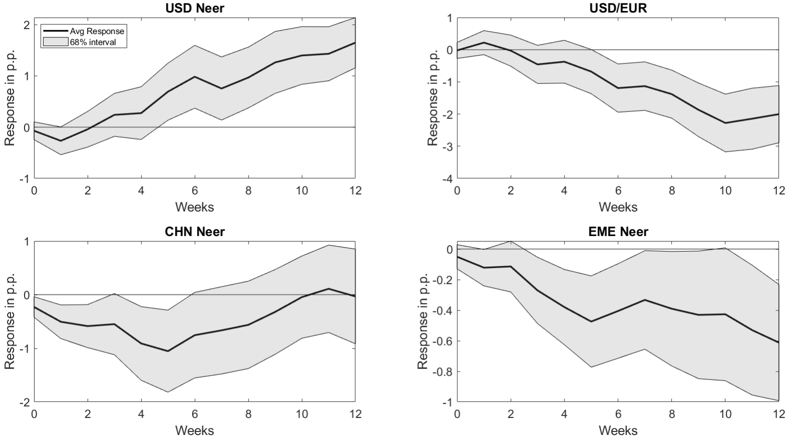
Figure: Response of stock market indices to the 2018 steel and aluminium tariffs announcement



Notes: We use the Shanghai stock market index as proxy for the stock index of China. The subindex of S&P500 exposed to China is computed including in the S&P500 only those firms that generate at least 10% of revenues from China.

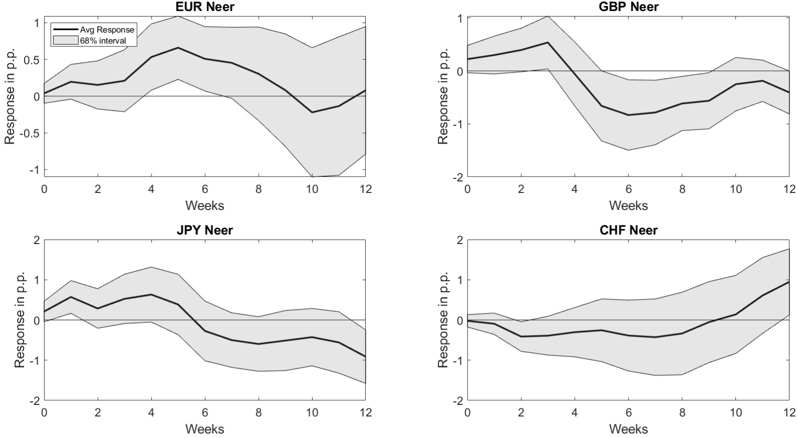
Exchange rates

Figure: Response of selected exchange rates to the 2018 steel and aluminium tariffs announcement.



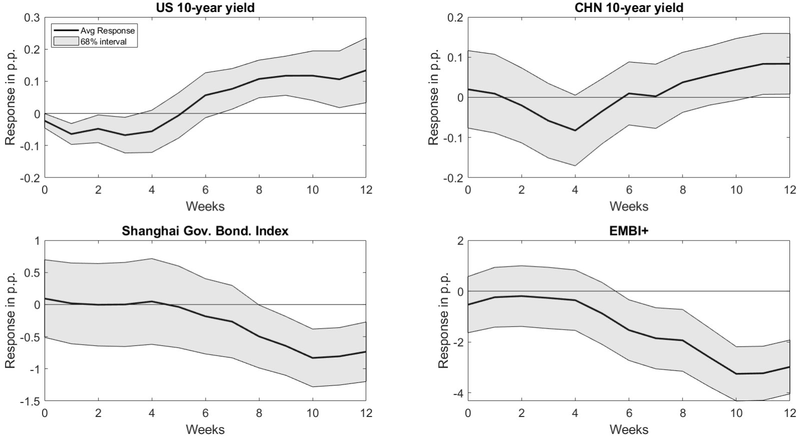
Safe haven currencies

Figure: Response of safe haven currencies to the 2018 steel and aluminium tariffs announcement.



Bond markets

Figure: Response of bond indices and yields to the 2018 steel and aluminium tariffs announcement.



Contribution to financial market volatility

We assess the impact of rising trade tensions on the volatility of financial variables by computing the forecast error variance decomposition as in Gorodnichenko and Lee (2020):

Figure: Financial market indices.

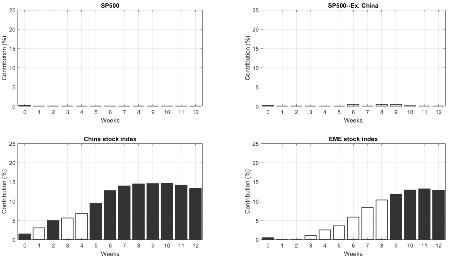
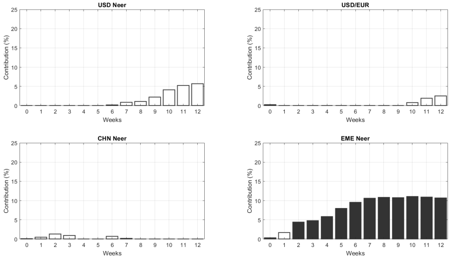


Figure: Exchange rates



Notes: White bars indicate contributions that are not statistically different from 0 at the 68% confidence level.

▸ Other variables.

Conclusion

- The 3TI captures trade tensions between the US and China, matches well-known events and is exogenous to financial variables.

Conclusion

- The 3TI captures trade tensions between the US and China, matches well-known events and is exogenous to financial variables.
- The reaction to trade shocks differs across markets:

Conclusion

- The 3TI captures trade tensions between the US and China, matches well-known events and is exogenous to financial variables.
- The reaction to trade shocks differs across markets:

  Stock markets

  → US and EA stock indices do not move (except for firms highly exposed to China).

  → Chinese and EMEs stock markets contract (-5% to steel and aluminium tariffs).

Conclusion

- The 3TI captures trade tensions between the US and China, matches well-known events and is exogenous to financial variables.
- The reaction to trade shocks differs across markets:

Stock markets

→ US and EA stock indices do not move (except for firms highly exposed to China).

→ Chinese and EMEs stock markets contract (-5% to steel and aluminium tariffs).

Exchange rates

→ USD appreciates.

→ EMEs exchange rates depreciate. Safe haven currencies do not move.

Portfolio rebalancing

→ Within EMEs investors move from equity to bonds.

Conclusion

- The 3TI captures trade tensions between the US and China, matches well-known events and is exogenous to financial variables.
- The reaction to trade shocks differs across markets:

  Stock markets
  → US and EA stock indices do not move (except for firms highly exposed to China).
  → Chinese and EMEs stock markets contract (-5% to steel and aluminium tariffs).

  Exchange rates
  → USD appreciates.
  → EMEs exchange rates depreciate. Safe haven currencies do not move.

  Portfolio rebalancing
  → Within EMEs investors move from equity to bonds.

- **Interpretation**: markets *have read trade shocks as a negative demand shock for China*, not as global risk.

Thank you!

Questions?

Background slides

Trade tensions on the rise

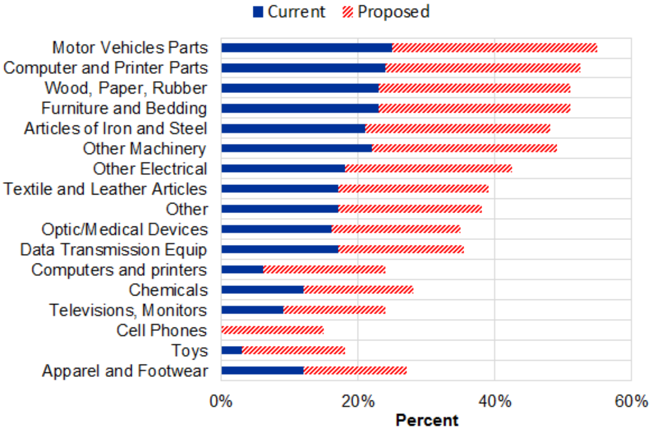
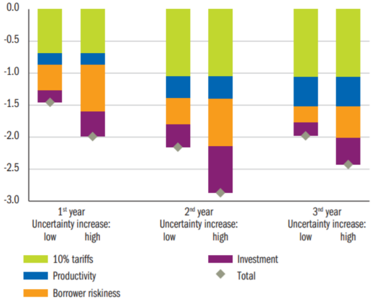


Figure: Current and proposed US tariffs against China by product category.
Source: US Congressional Research Service (2019).

Go back.

Effects of tariffs based on trade elasticities

Figure: Effects on global GDP of 10% tariff increase by all countries.



Source: Berthou et al. (2018).

Go back.

Issues

- Tariffs' income effects are very limited.
- Elasticities might be downward-biased. Furceri et al. (2018) show that tariffs have asymmetric impact on the economy.
- The adjustment through the exchange rate might have changed (Eichengreen (2017)).

Related literature

The impact of trade tensions: Caldara et al. (2019); Berthou et al. (2018); Gloe Dizioli and van Roye (2018); Furceri et al. (2018); Feenstra et al. (2019); Autor et al. (2016); Feenstra and Sasahara (2018) Acemoglu et al. (2016); Barattieri et al. (2018). [*We look at the response of financial markets to shocks.*]

Measures of uncertainty: Caldara et al. (2019); Caldara and Iacoviello (2018); Bakeret al. (2016); Bloom (2009). [*We don't count words but use a ML algorithm.*]

Textual analysis and ML in economics: Gholampour and van Wincoop (2019) [FX & info from Twitter]; Bianchi et al. (2019) [threats to central bank independence & Trump tweets]; Ke et al. (2019) [stock returns and text data]; Werner and Murray (2004); Bollen et al. (2011); Da et al. (2011); Leung and Ton (2015); Loughran and McDonald (2011)

▸ Go back.

Event study

$$\Delta y_{t,t+k} = \alpha_k + \beta_k Event_t + \varepsilon_{t+k}$$

	S&P 500 index				Shanghai stock narket index		
k	0	1	2		0	1	2
β_k	0.104*	0.181**	0.228**	β_k	0.106*	0.335***	0.326***
	(0.062)	(0.084)	(0.111)		(0.059)	(0.078)	(0.118)
α_k	0.070	0.169*	0.234**	α_k	0.037	-0.040	-0.040
	(0.064)	(0.098)	(0.104)		(0.065)	(0.103)	(0.118)
Obs.	212	161	155	Obs.	212	161	155
R^2	0.011	0.020	0.024	R^2	0.012	0.057	0.035
	USD NEER				CHN/USD		
β_k	-0.027	-0.083***	-0.086**	β_k	-0.040	-0.134***	-0.151***
	(0.019)	(0.020)	(0.038)		(0.026)	(0.028)	(0.046)
α_k	-0.005	-0.008	0.006	α_k	-0.006	-0.025	0.008
	(0.020)	(0.030)	(0.035)		(0.016)	(0.025)	(0.031)
Obs.	212	161	155	Obs	212	161	155
R^2	0.008	0.047	0.031	R^2	0.022	0.140	0.109

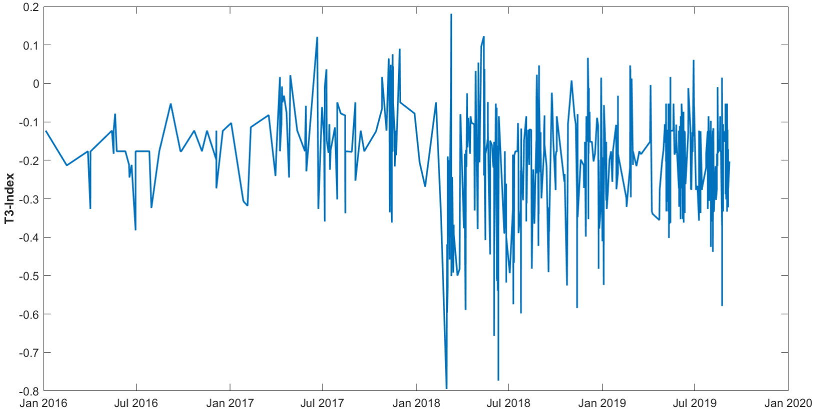
Notes: estimates of Equation (2.1) on daily data for the S&P500 index, the Shanghai stock market index, the USD nominal effective exchange rate and the CHN/USD exchange rate. The dependent variable is expressed in log changes $\times 100$ and $Event_t$ is a dummy of value 1 (-1) for positive (negative) tweets as identified by the Bloomberg "trade war" timeline. We consider the contemporaneous daily change ($k = 0$) and the change 1 and 2 days after the event. Robust standard errors are reported in parentheses with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ confidence intervals.

▸ Go back.

13/05/2018 15:01	President Xi of China and I are working together to give massive Chinese phone company ZTE a way to get back into business fast. Too many jobs in China lost. Commerce Department has been instructed to get it done!
13/05/2018 19:22	China and the United States are working well together on trade but past negotiations have been so one sided in favor of China for so many years that it is hard for them to make a deal that benefits both countries. But be cool it will all work out!
14/05/2018 20:06	ZTE the large Chinese phone company buys a big per- centage of individual parts from U.S. companies. This is also re ective of the larger trade deal we are negotiating with China and my personal relationship with President Xi.
15/05/2018 12:35	Trade negotiations are continuing with China. They have been making hundreds of billions of dollars a year from the U.S. for many years. Stay tuned!

Go back.

Daily index



Go back.

Exogeneity test with daily data

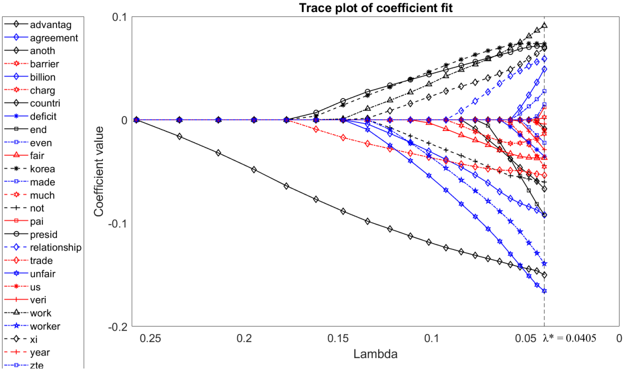
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$\Delta SP500_t$	1.164			-0.080	3.250		1.856
	(4.944)			(5.477)	(4.671)		(5.096)
$\Delta SP500_{t-1}$	0.821			-0.447	1.432		0.292
	(4.010)			(3.882)	(4.482)		(4.671)
$\Delta SP500_{t-2}$	3.729			3.420	2.266		2.338
	(3.535)			(3.718)	(3.164)		(3.275)
$\Delta SP500_{t-3}$	1.176			2.181	1.333		2.258
	(6.761)			(7.656)	(8.136)		(8.560)
$\Delta NEER^{USD}_t$		1.460		0.501		-7.380	-6.627
		(13.543)		(14.194)		(9.642)	(10.375)
$\Delta NEER^{USD}_{t-1}$		-9.874		-10.421		-9.079	-8.193
		(14.237)		(14.987)		(11.496)	(12.482)
$\Delta NEER^{USD}_{t-2}$		-9.648		-6.532		-6.998	-4.436
		(11.374)		(13.061)		(12.593)	(14.156)
$\Delta NEER^{USD}_{t-3}$		6.568		9.603		4.550	6.332
		(9.214)		(8.027)		(13.186)	(10.237)
$\Delta Stock^{CHN}_t$			-11.013		-11.816	-11.598	-12.101
			(8.607)		(9.880)	(8.704)	(9.971)
$\Delta Stock^{CHN}_{t-1}$			-1.079		-1.606	-1.718	-1.997
			(4.126)		(4.221)	(4.016)	(4.027)
$\Delta Stock^{CHN}_{t-2}$			5.715		4.845	4.636	3.901
			(4.092)		(3.686)	(4.114)	(3.437)
$\Delta Stock^{CHN}_{t-3}$			2.007		1.476	2.111	1.606
			(2.820)		(3.330)	(3.011)	(3.544)
Constant	-0.041	-0.037	-0.027	-0.041	-0.029	-0.027	-0.029
	(0.043)	(0.041)	(0.042)	(0.040)	(0.037)	(0.039)	(0.035)
Observations	158	158	158	158	158	158	158
F test	0.463	0.458	0.974	0.442	0.989	0.921	0.741
F prob	0.708	0.712	0.407	0.849	0.434	0.482	0.671
R^2	0.00	0.00	3.32	0.00	1.24	1.26	0.00

Notes: explanatory variables are in log-differences; the China stock index is the Shanghai stock market index. T-stats reported in parenthesis below coefficients and computed based on HAC standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Go back.

Model output

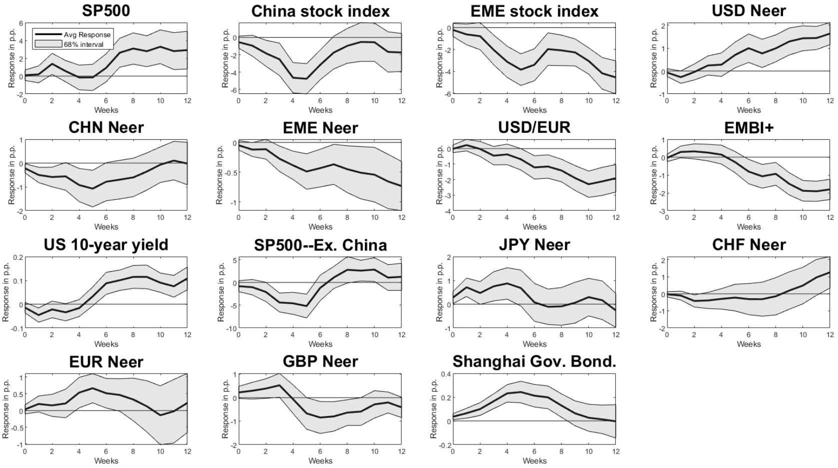
Figure: Trace plot of elastic net coefficients estimates



Notes: The trace is the plot of the optimal value of the coefficient β_i associated to the selected word i for all values of λ until λ converges to its optimal level λ^*.

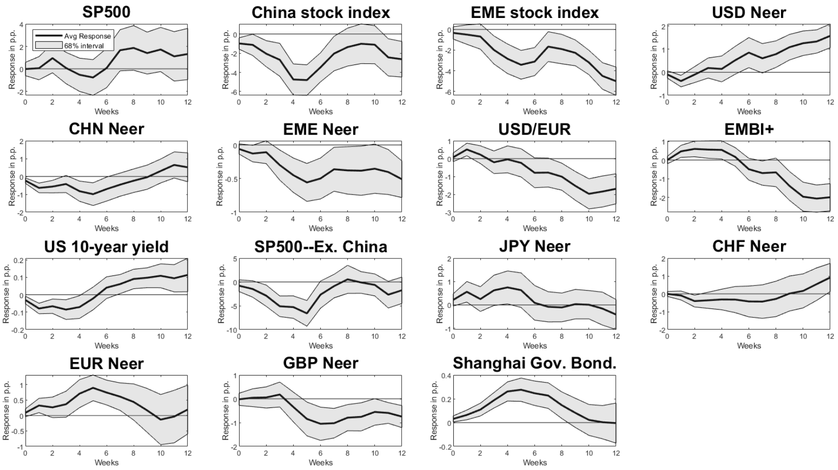
Go back.

Time trend as control



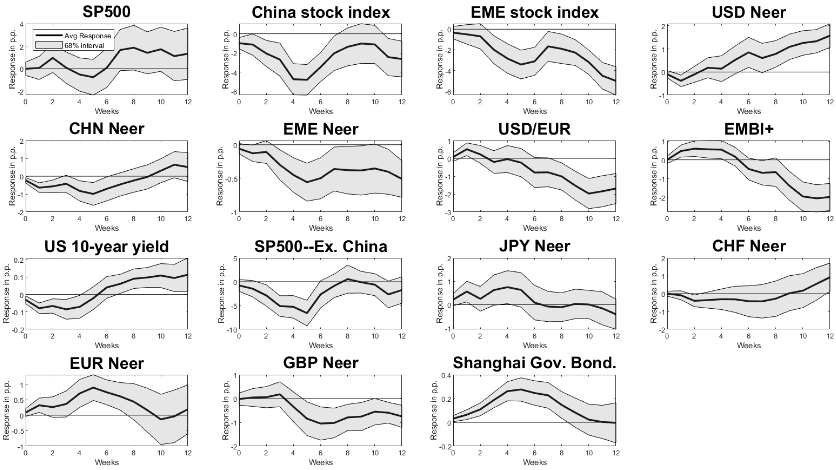
Go back.

Two lags of controls



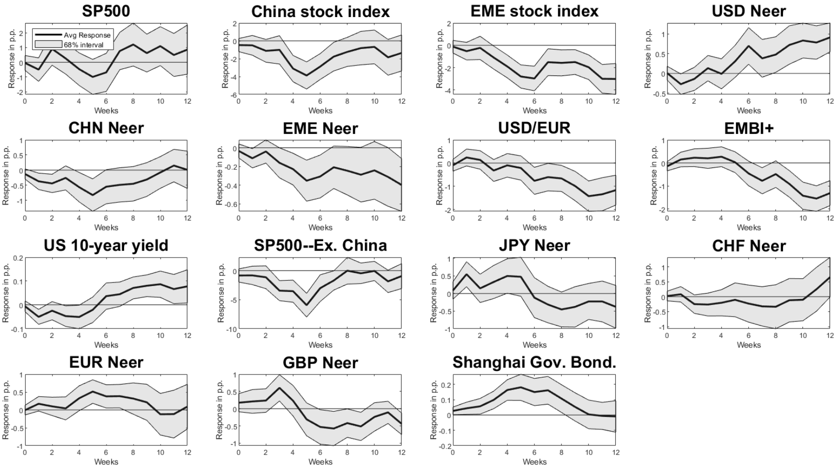
▸ Go back.

Lag of the index



Go back.

AR(1) residuals



Go back.

Contribution to financial market volatility

Figure: Safe haven currencies.

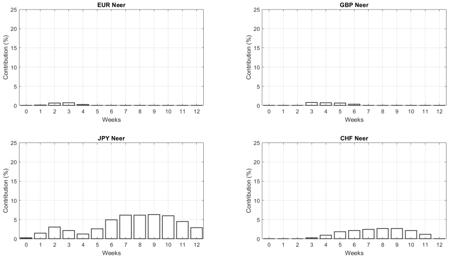
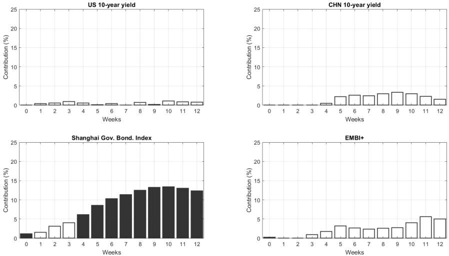


Figure: Bond markets



Notes: White bars indicate contributions that are not statistically different from 0 at the 68% confidence level.

Go back.