Can uncertainty signals from the policy-maker infer stock market crises in Latin America?

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ABSTRACT

Uncertainty around economic policy keeps economic agents on their toes, this study shows that this uncertainty can help predict crises periods in the Latin American stock markets, measured by the index from Brazil, Colombia, Chile, Mexico and also US as a comparison. For each country a set of market and sentiment variables are transformed with PCA testing the first two components with OLS, Probit and Logit. Also, a fixed effects logit model was tested considering the months of the year as fixed. The results shows that the crisis index with higher sensitivity are correlated with idiosyncratic EPU but only Mexico's index shows robust correlationship with Global EPU.

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JEL classification: G40, G14, G10.

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Every time crises hit the financial market, the analysts and politicians start the blame game. Alesina and Tabellini (1989) suggests that irrational political behaviour of accumulating large debts is linked with the current politicians establishment maximizing the welfare of its own social group without any regard to the whole, and the polarization and uncertainty about the political scenery inspires a cycle of lending to anticipate welfare so the current group can benefit themselves.This conforms as a cycle of bad decisions and uncertainty around the future of a country's institutions.

Looking only at Central Banks' (*CB*) actions, Khan et al. (2013) studies how the independence of the CB affects the stability of the banking sector, which although has the main goal of maintaining price stability, as need arises it acts to keep financial stability. The results suggests that not only independence is available, but if the country has a stronger law-and-order tradition it indicates less chance of opportunistically and erratic behaviour of CBs.

After major economic and political shocks, like the Sub-Prime shock, 9/11 and OPEC I oil-price shock, there seems to be a dramatically increase in uncertainty. Bloom (2009) shows that stock-market (implied) volatility on average doubles after shocks, but uncertainty after a second moment negative shock makes firms temporarily very insensitive to price changes, indicating that the economy might be unresponsive suggesting that there is a trade-off between "correctness" and "decisiveness" for policy makers, and it seems it is better to act decisively, with the risk of overdoing/under-doing, than to take long rounds of discussion to make the better choice, which leads to uncertainty and some kind of inertia on the economy.

Pástor et al. (2013) studies the relationship between the risk premia on the stock market and political uncertainty and states that this have a negative effect because, as a non-diversifiable risk, it depresses asset prices by raising discount rates, even though those are not related to economic shocks. Schwarz and Dalmácio (2021) Also shows that in general, firms individually tend to reduce their financial leverage when policy uncertainty is high.

Recently, due to *COVID-19*, every financial market felt the changes in the economic perspective, the supply and demand for some goods changed drastically and most countries rushed to create a plan to deal with it. Although Brazil just got out of a lengthily recession from 2014 to 2016, the current president, Jair Bolsonaro, had a different strategy from the governors, even filing a request against them on the Supreme Court. This political fight extended to economic policies, with a 110 USD aid approved by both houses, started at a third of that as a government policy (Reverdosa et al., 2021).

Based on Patel and Sarkar (1998), Baker and Wurgler (2006) develops a model to test investor sentiment proxies to stock returns, and finds that the suggested sentiment proxies for optimism have a significant relationship with the data. Further studies by Zouaoui et al. (2011) shows that investor sentiment is related to the occurrence of crises in the stock-market within a year, suggesting that waves on investor sentiment has relationship with prices. Zhang et al. (2019) develops a early-warning model for stock market crises in China, which uses a set of macro and sentiment variables, showing that sentiment variables add to the predictive capability of the signal-based binary system.

I use Zhang et al. (2019) methodology and besides the general behavioural sentiment variables, linked to herd-like propositions and optimism towards the economy, and also add an Economic Policy Uncertainty (henceforth EPU) dimension working with the hypothesis that the uncertainty level is in fact a predictor of market crises, showing that the opportunistic struggle within a government can be one of the things to blame for financial crises. The results on this study shows that in Brazil, the indecisiveness and lack of proper state-wide strategy is one of crises culprits.

I Literature Review

A Political uncertainty and the stock market

Alesina and Tabellini (1989) is one of the earliest works on how the struggle between a binary,right and left wings, election choice can lead to poor usage of a country's financial abilities when some imminent loss of power is expected on next election cycles. This clearly means that the current party on power might disregard future investment constraints due to poor debt handling to secure their "entitled" benefits although the people in general might be in a worse condition.

Political uncertainty could be thought as an idiosyncratic risk, not affecting the market as a whole but Pástor et al. (2013) finds out that the risk premia required by the market in uncertain times, due to noise from politicians, is not only non-idiosyncratic but orthogonal to the discount factor related to the current economic state, indicating that it works as a modifier of economic risk discount rate.

In spite of the stated relationship between the matter at hand and the stock market, the difficulty lies in defining specifically what measures compose this uncertainty, thus Baker et al. (2016) instead of finding a proxy for the space generated by it, it defines a subset called *economic policy uncertainty* which is easier to specify and hence creates an index, EPU[1], and then shows how it is related to bear markets in United States and how much of volatility and negative returns it explains. The same index is afterwards created on similar fashion for Brazil.

Kelly et al. (2016) and Brogaard et al. (2020) more recently study the affects of political uncertainty on the option market and the global influence on asset prices, where both using different proxies confirm previous findings over its negative relationship with prices in stock market.

B Sentiment and prices

About 50 years ago, Zweig (1973) discussed the puzzle of closed-end fund premiums, asking if the goodwill paid on top of the book value of closed funds could be an indicator of the expectations, in general, of the market agents. The findings suggested that the bigger the deltas between price and book over those assets without any growth expectation signalizes if the market is currently giving a better chance of positive scenario.

[1] Economic Policy Uncertainty index

Baker and Wurgler (2006) creates a sentiment proxy and test it against a cross-section of stock returns, suggesting that when there is a more positive sentiment related to some stock, then it generally suggest better return rates over the more negative group of stocks. Bloom (2009) studies the second moment of uncertainty shocks over the market stating that more important then the choice of action of the government is the time it takes to act, which reduces the uncertainty for the market.

After some advancements in the behavioural area, Cochrane (2011) directly shows that all in all, those models are in reality discount based models, over which the stochastic discount factor is changed not only because of macroeconomic variables, but the market sentiment.

Zouaoui et al. (2011) does a further analysis on how investor sentiment is related to crises points over stock markets, stating a direct relationship between the general expectations that investors shows through proxies to downward movement of stock prices. Based on that work, Zhang et al. (2019) develops an early-warning system to predict market crises through similar sentiment proxies, indicating that those provides better crises prediction power on truncated models such as tobit an logit, which this paper uses.

II Data

A Crisis Index

The first step on testing if uncertainty around policy-makers actions over economy explains crises is to define crises points, which will be tested in a monthly time frame such as proposed by Zhang et al. (2019). On that regard, Patel and Sarkar (1998) developed an indicator for crises ($CMAX_{T,\Delta}$) which simply compares the current price over the *max* value over the previous T periods, 24 months being the suggestion, but since Zouaoui et al. (2011) shows only a one-year relationship, both are considered initially. The Δ is the threshold where the ratio is considered as a "crisis period",with Patel and Sarkar (1998) suggesting the 25% and 35% numbers according to each type of country (developed and emerging) and Zhang et al. (2019) suggesting 20% and 50% for China, thus in this study $(0.20, 0.25, 0.35, 0.50)$ are evaluated. The formula for $CMAX$ at some period t is,

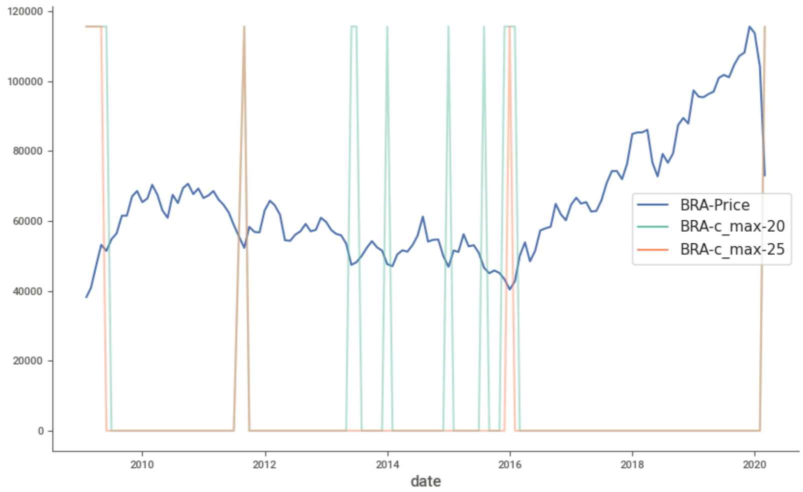
$$CMAX_t = \frac{P_y}{max(P_{t-T}, \cdots, P_t)}, \tag{1}$$

and the signal $CMAX$, is therefore modelled from $CMAX_t$ after the equation 1 as,

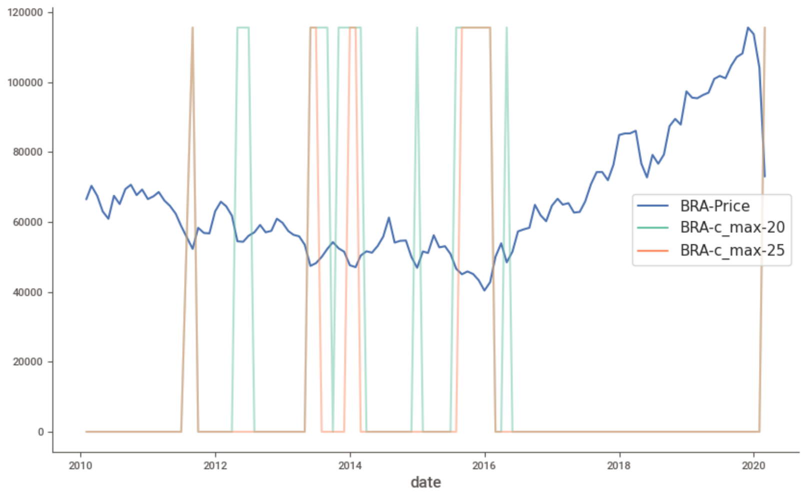
$$CMAX_{T,\Delta} = \begin{cases} 1 & , \ if \ CMAX_t < (1 - threshold); \\ 0 & , \ otherwise. \end{cases}, \tag{2}$$

where $threshold = \Delta$.

Analysing figure 1 it can be noted that the 24 month period for the brazilian stock market is a more sensitive, it gives out more signals (in and out crises in few months, instead of a single one) for the period after 2012 it captures a crisis era which the 12 month does not. In 2014 for an example, the wider baseline for $CMAX$ yields better signals for each crises period and "out of crises" periods.



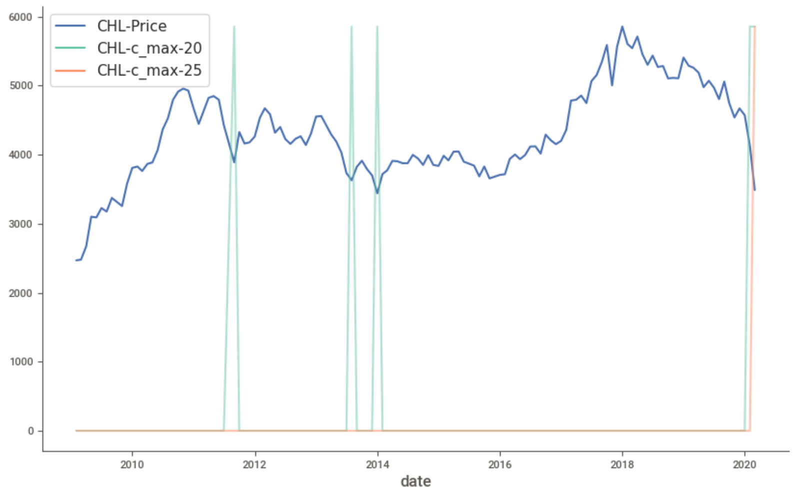
(a) $CMAX_{12,(20\%,25\%)}$



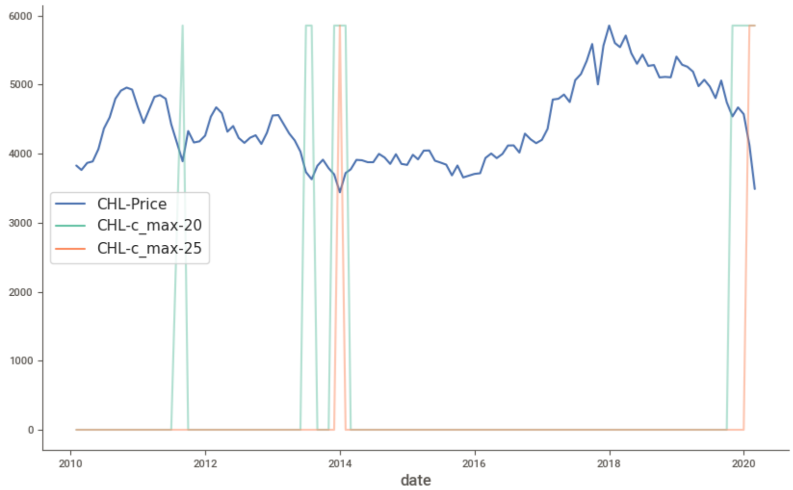
(b) $CMAX_{24,(20\%,25\%)}$

Figure 1: CMAX for brazilian stock market at $T = 12, 24$.

The same conclusion can be stated for the other countries in this study, such as Chile (2), Colombia (3), Mexico (4) and the United States of America (5) wich serves as baseline.

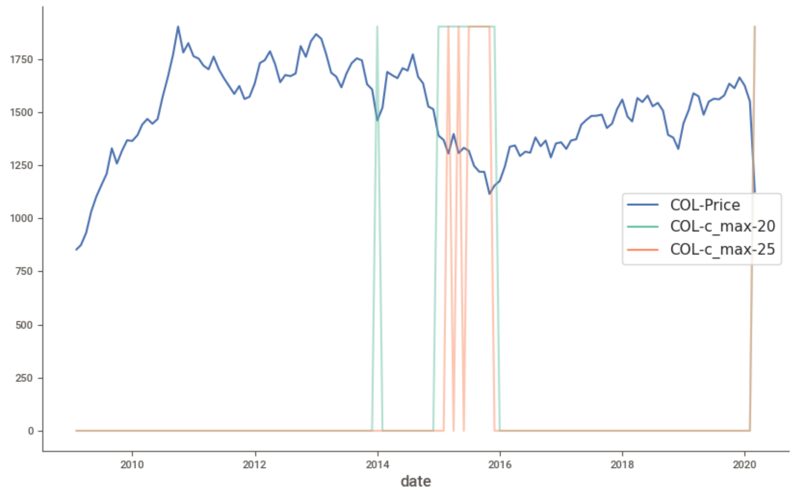


(a) $CMAX_{12,(20\%,25\%)}$

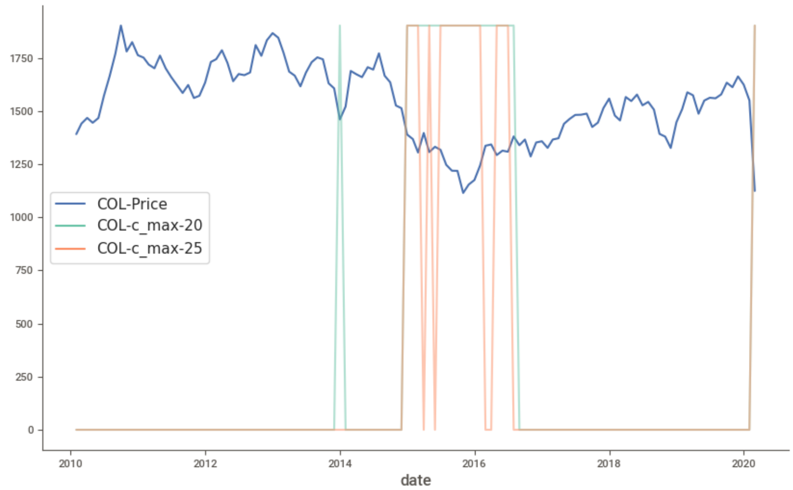


(b) $CMAX_{24,(20\%,25\%)}$

Figure 2: CMAX for chilean stock market at $T = 12, 24$.

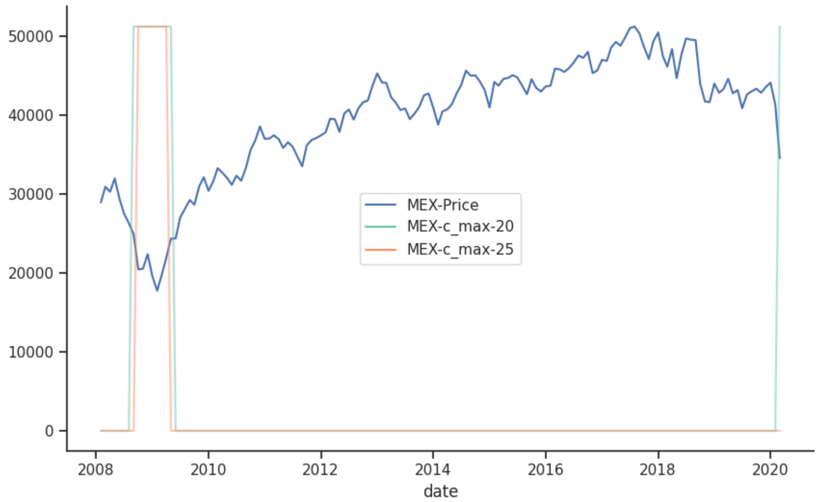


(a) $CMAX_{12,(20\%,25\%)}$



(b) $CMAX_{24,(20\%,25\%)}$

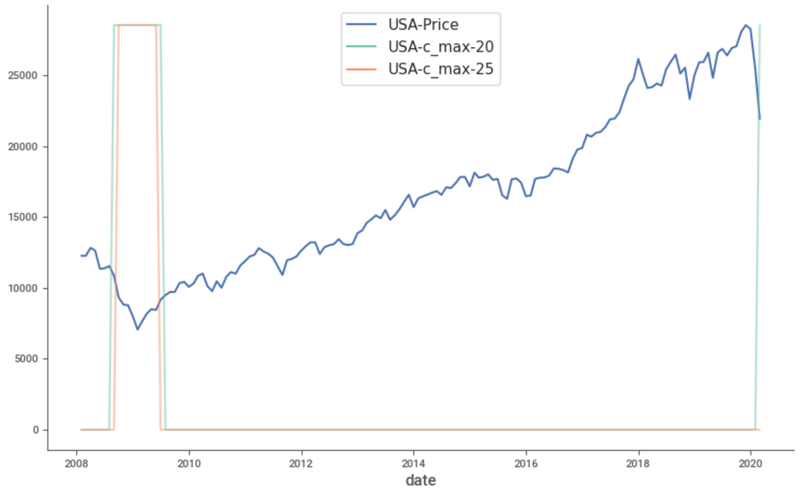
Figure 3: CMAX for colombian stock market at $T = 12, 24$.



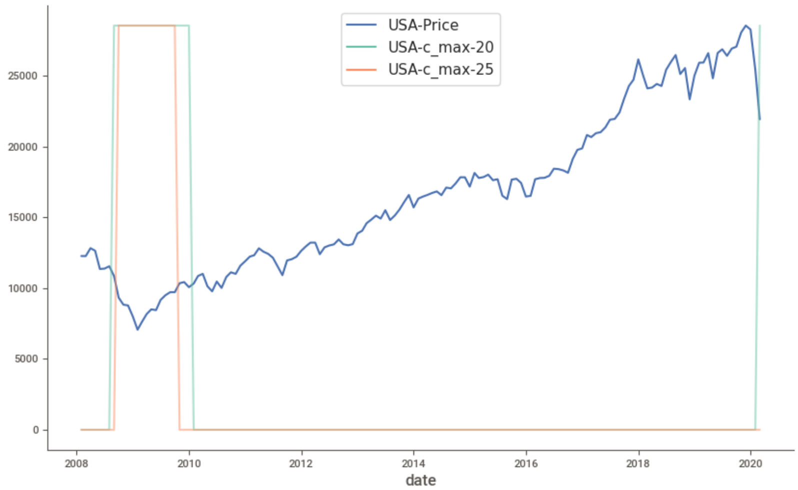
(a) $CMAX_{12,(20\%,25\%)}$

(b) $CMAX_{24,(20\%,25\%)}$

Figure 4: CMAX for mexican stock market at $T = 12, 24$.



(a) $CMAX_{12,(20\%,25\%)}$

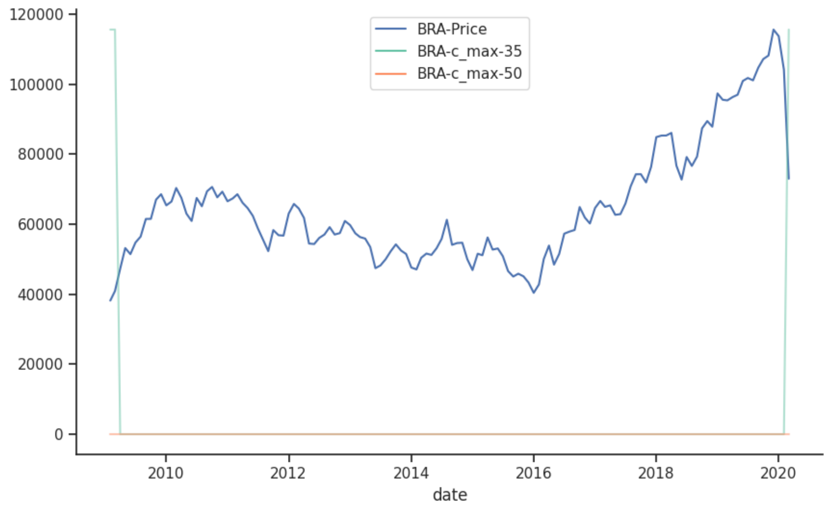


(b) $CMAX_{24,(20\%,25\%)}$

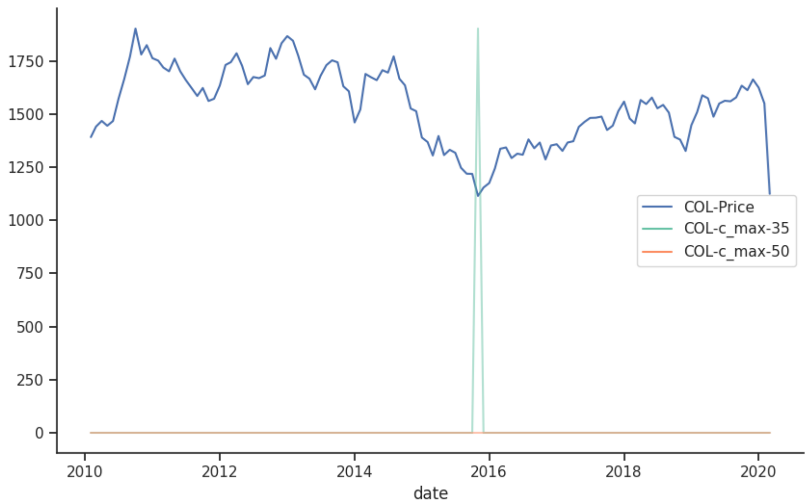
Figure 5: CMAX for american stock market at $T = 12, 24$.

The pattern on figure sets above shows clearly that the 24 month lag suggested by Patel and Sarkar (1998) and used by Zhang et al. (2019) signals more crisis periods, even when considering previous sentiment relationship testing (Baker and Wurgler, 2006; Bloom, 2009; Zouaoui et al., 2011; Nguyen et al., 2020) is done mainly with twelve-month periods aggregations, the $T = 24$ will be used in the model.

Even considering some data is lost over different $CMAX$ rolling mean (12 months and 24 months), from figures 6 and 7 it can be noted that the 20% and 25% tresholds (Δ) fits better the whole crisis period than the 35% and 50% ones. In Brazil, 2015 for an example, the lower threshold gives a brief crisis indication, and takes more time to consider an "out of crises" scenario. On the other hand, the larger thresholds (35% and 50%) only give a single period signal or no signal at all, respectively,

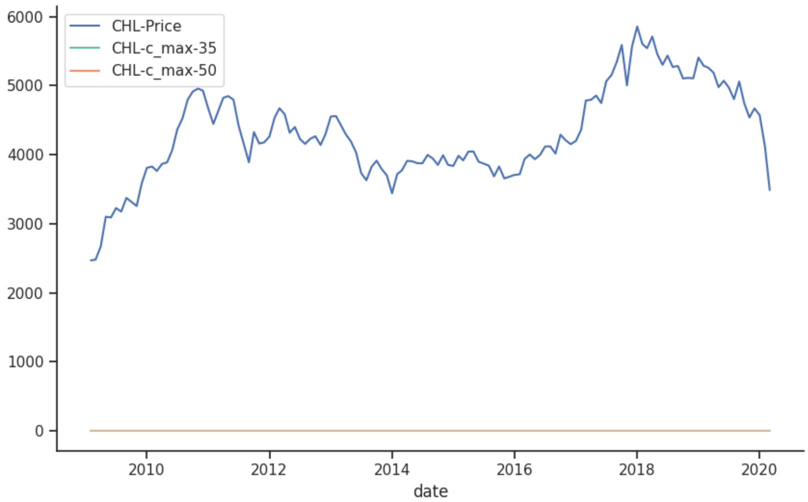


(a) $CMAX_{12,(35\%,50\%)}$



(b) $CMAX_{24,(35\%,50\%)}$

Figure 6: CMAX for Brazil and Colombia at $T = 12, 24; \Delta = 35, 50$.



(a) $CMAX_{12,(35\%,50\%)}$

(b) $CMAX_{24,(35\%,50\%)}$

Figure 7: CMAX for Chile and Mexico at $T = 12, 24; \Delta = 35, 50$.

Considering the figures above for the many variations on $CMAX$'s Δ, all the tresholds were tested on the methodology proposed, but as expected the 50% one almost never signals a crisis period and no model got any statistically significant result.

B *Economic Policy Uncertainty*

The economic policy uncertainty comes from Baker et al. (2016) study, which develops a measurement, the Economic Policy Uncertainty Index (henceforth EPU). This index is elaborated on top of newspaper text analysis for USA, and then replicated by with the same methods using text archives from each country's newspapers and provided by *PolicyUncertainty.com*, but its availability is not similar to others.

The EPU is shown to correlate to stock markets such as in Brazil, tested by Schwarz and Dalmácio (2021) and Brogaard and Detzel (2015) builds a stock portfolio showing that EPU can predict log excess returns in United States of America. Liu and Zhang (2015) findings suggests that a high EPU is also connected to the market volatility and Beckmann and Czudaj (2017) shows the correlation between EPU and exchange rates expectations.

Davis (2016) also developed a Global Economic Policy Uncertainty index (GEPU), which indicates uncertainty that affects the world as a whole, such as the 2008 financial crisis, the Brexit referendum in June 2016, the Iraq invasion and more. The version that is calculated using PPP weights is used as a global benchmark and control.

C Control Data

The macro data to model the relationship and also to serve as control to macroeconomic factors are based on Zhang et al. (2019) work, but limited by availability of the data on a public level the *M2* growth rate, climate index and fixed asset index were not available. The macro data used was acquired from the Joint External Debt Database (*JEDD*) and Global Economic Monitor (*GEM*) which are available at the World Bank Database.

Table I: Variable list

	description	**source**	**type**
Price	Country's stock market index	Yahoo Finance	Regressand
EPU	Economic Policy Uncertainty	PolicyUncertainty[2]	Sentiment
CO_spread-ipo	First day Close-Open spread on IPOs	Yahoo Finance	Sentiment
HL_spread-ipo	First day High-Low spread on IPOs	Yahoo Finance	Sentiment
Volume-ipo	First day trading volume on IPOs	Yahoo Finance	Sentiment
Reserves	International reserves (excluding gold)	*JEDD*	Macro
Debt	International Debt	*JEDD*	Macro
CPI	Consumer Price Index, seas. adj.	*GEM*	Macro
GDP	Gross Domestic Product, seas. adj.	*GEM*	Macro
IP	Industrial Production	*GEM*	Macro
EMBI	J.P. Morgan Emerging Mkt. Bond spread	*GEM*	Macro
REER	Real Effective Exchange Rate	*GEM*	Macro

All variables, besides the EPU, are suggested in the model from Zhang et al. (2019). The market close prices are used as the P in eq. 1, which then gives the $CMAX$ values as shown on figures 1,3, 2, 4 and 5 to define the binary variable indicating 0 for normal periods and 1 for crises.

D Descriptive Statistics

Since the range of available data from the World Bank database and EPU varies between each country a different number of observations is available, the descriptive statistics is presented considering a panel for all countries for the period that all have data, which is from 2010-02 to 2020-03 of monthly data, or 121 observations each. EMBI is not available to USA, hence a lower count. $CMAX$ with $\delta = .50$ also is zero for all observations.

Table II: Summary statistics 1

	CPI	GDP	IP	EMBI	REER
count	605	605	605	484	605
mean	119.994	1022020.289	71567022069	209.389	92.018
std	17.120	1566115.868	101063015099	71.406	12.777
min	99.913	49614.584	6070499647	110.476	58.331
25%	106.959	76981.627	7919704948	159.221	81.965
50%	115.735	294390.294	31013238757	191.545	94.519
75%	127.722	556974.492	43085125406	244.125	100.865
max	172.687	4589278.686	291638497619	557.550	119.115

Table III: Summary statistics 2

	debt	reserves	epu	Volume-ipo	CO_spread-ipo
count	605	605	605	605	605
mean	396557780165	144216429696	2.090	35258331.796	0.007
std	619414195730	117550371281	58.720	678816792.385	0.061
min	13858000000	24896330995	-223.584	0.000	-0.154
25%	46938000000	41083736988	-25.242	0.000	0.000
50%	95752000000	115331272237	-2.823	0.000	0.000
75%	239410000000	177176653572	22.480	2958749.722	0.000
max	1802096000000	385035630518	406.256	16680333160.000	1.239

Table IV: Summary statistics 3

	HL_spread-ipo	GEPU_ppp	c_max-20	c_max-25	c_max-35
count	605.000	605.000	605.000	605.000	605.000
mean	0.041	163.082	0.098	0.053	0.005
std	0.124	57.954	0.297	0.224	0.070
min	0.000	84.945	0.000	0.000	0.000
25%	0.000	119.175	0.000	0.000	0.000
50%	0.000	147.884	0.000	0.000	0.000
75%	0.049	188.128	0.000	0.000	0.000
max	2.231	355.365	1.000	1.000	1.000

From the statistics it is clear that many months there are no IPOs and the related variables are mostly zero. Those values are still inflated because the panel also considers USA numbers, a much more developed country. The $CMAX$ indicators ($c\_max - \Delta$ variables), shows that the 35% tresholds already have very little information since most of it is 0.

III The Model

The early-warning model from Zhang et al. (2019) describes a simple relation. Consider $\boldsymbol{S}$ the matrix of the *sentiment* regressors and $\boldsymbol{M}$ the macro independent variables matrix with a constant α.

As the only interest in this study is to define the relationship with crises periods, the binary variable C can be modelled naturally with three methods, which Zhang et al. (2019) and Baker and Wurgler (2006) use, starting of from,

$$C = f(\alpha + \boldsymbol{S} + \boldsymbol{M}), \tag{3}$$

where the function $f(\cdot)$ can collapse to a simple linear equation (OLS), assume a logistic *c.d.f.* function (*logit*) and representing the *c.d.f.* of a normal (*probit*).

The regressions are done for each country using the variables from the table I, and using the signal $CMAX$ for 20% and 25% thresholds since the 50% one yields no information and the 35% have near to 0 information. Also, since the 12-month period considering its failure to signal some representative dips in the stock return, opposing the 24-month one, and the fact that the original proposition by Patel and Sarkar (1998) and recently Baker and Wurgler (2006) and Zhang et al. (2019) also uses the 24-month period to calculate $CMAX$, the relationship expressed on equation 3 will be tested for the three mentioned techniques with $CMAX_{24,(20\%,25\%)}$.

A Principal Components

Principal Components Analysis (PCA) was suggested on multivariate regressions by Hotelling (1957) among others, as a way to deal with multicolinearity, as the PCA yields orthogonal exgoenous variables making inverse matrix calculations more computationally stable, an issue that still affects nowadays.

PCA simply decomposes an matrix into eigenvectors from the covariance matrix and arranges them from lowest to highest variance explanation ratio using their associated eigenvalues, which can be easily calculated with an SVD decomposition, as

$$\boldsymbol{X} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{W}^T, \tag{4}$$

where $\boldsymbol{U}$ is an $n_x n$ matrix of left singular vectors, $\boldsymbol{\Sigma}$ the matrix with singular values and $\boldsymbol{W}^T$, the right singular vectors, the PCA of a zero-mean and unit variance balanced regressors $\boldsymbol{X}$ can be calculated with

$$\boldsymbol{PCA} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{W}^T\boldsymbol{W} = \boldsymbol{U}\boldsymbol{\Sigma} = \boldsymbol{W}\boldsymbol{X}. \tag{5}$$

Due to the nature of numerical solvers to maximum likelihood estimators, such as used on Logit and Probit regressions, the PCA provides dimentionality reduction and assuring sometimes the existance of a solution depending on the function choice in the model (3), Aguilera et al. (2006) discusses the benefits and feasability of PCA usage on logistic regressions.

Gilmore et al. (2008) uses this technique to study the equity market comovement in Central Europe and Kritzman et al. (2011) uses this to measure systemic risk in the stock market. Baker and Wurgler (2006) and Zhang et al. (2019) uses the PCA to derive a single vector to all the sentiment variables, testing if these create significant information over crisis in the stock market.

Since the hypothesis to test is that the policy uncertainty in a country can predict a stock market crisis, all the regressors except EPU and Global EPU are decomposed with PCA, assuring that at least 94% of variance can be explained with the first and second principal components.

B Conditional Logit

Although the $CMAX$ is a binary variable with just sparse signals, it is calculated based on stock returns, which certainly has at least an AR(1) component considering perfect information on financial markets. To assure robustness over seasonalities and "month-to-month" relationships, a panel logit model is proposed with

$$Pr(y_{it} = 1|\beta_{it}, \varepsilon_{it}) = F(x_{it}\beta + \varepsilon_{it}). \tag{6}$$

The methodology proposed is the Fixed-Effects Logit, but the Conditional variance of its MLE optimization as discussed by Abrevaya (1997), as it has better consistance than the unconditional optimization. The fixed effects considered for this method is the month for the panel with all the countries, thus controling for seasonal and idiosyncratic effects of each month.

IV Results

The model from 3 is set up starting with monthly data for most of the variables, except *Res* and *Debt* because *JDDM* have only quarterly data, which means each data point is repeated throughout all the months in the respective quarter. The time-frame for this study is set according to the availability of data for each country and the panel regression is from 2003 to 2020. The following tables shows the results of the OLS regression, Logit and Probit for each country and set of $CMAX$ indicators.

A Country level regression

A.1 Brazil

For Brazil, the two first principal components have an 94.8% and 4.7% variance explaining ratio, respectively. Only the second component seems to be statistically significant, which Jolliffe (1982) pointed out that not necessarily the first component would have all, or the required information, to project a variable.

The tables for the regressions with $CMAX_{20\%}$ (V) and $CMAX_{25\%}$ (VI) shows that indeed, the policy uncertainty can infer crisis, since it is highly correlated and its' mechanisms are clear due to increase in risk. Global EPU on the other hand, is not significative, indicating that Brazilian market might be more sensitive to its own uncertainty than the world generated risk.

Table V: Brazil's regression results with 20% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	0.0869	0.151	-2.4558	1.401*	-1.5128	0.678**
Pca_1	-0.0157	0.023	-0.0474	0.222	-0.0389	0.116
Pca_2	0.1315	0.045	0.9565	0.356***	0.5792	0.188***
EPU	0.0007	0.000**	0.0055	0.002***	0.0033	0.001***
GEPU	0.0010	0.001	0.0040	0.009	0.0026	0.004
F/LogLikelihood		4.654		-50.46		-49.934
Probability		0.001		0.002		0.001
N		121		121		121
R^2/Pseudo-R^2		0.131		0.142		0.151

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

Table VI: Brazil's regression results with 25% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.0002	0.150	-3.4447	2.090*	-1.9984	0.848**
Pca_1	0.0119	0.021	0.2263	0.261	0.1188	0.116
Pca_2	0.0531	0.035	0.7314	0.458	0.4029	0.213*
EPU	0.0007	0.000**	0.007	0.002***	0.004	0.001***
GEPU	0.0006	0.001	0.0052	0.013	0.0031	0.005
F/LogLikelihood		2.18		-35.001		-34.661
Probability		0.075		0.083		0.063
N		121		121		121
R^2/Pseudo-R^2		0.067		0.105		0.113

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

B Chile

For Chile, the two first principal components have an 96.1% 3.84% variance explaining ratio, respectively and none is statistically significant at any regression.

The tables for the regression with $CMAX_{20\%}$ (VII) shows that the policy uncertainty can also infer crisis in the market but $CMAX_{25\%}$ (VIII) yields no significant result or model, indicating that this measure is not informative in this sample.

Table VII: Chile's regression results with 20% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.1777	0.136	-5.4117	1.258***	-3.0263	0.644***
Pca_1	-0.0227	0.026	0.9851	1.880	0.2911	0.735
Pca_2	-0.0172	0.026	-1.9649	2.225	-0.8434	0.862
EPU	0.0016	0.001**	0.0135	0.005**	0.0075	0.003***
GEPU	0.0016	0.001*	0.0117	0.010	0.0073	0.005
F/LogLikelihood		2.852		-30.385		-30.615
Probability		0.0269		0.01151		0.01405
N		121		121		121
R^2/Pseudo-R^2		0.099		0.175		0.169

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

Table VIII: Chile's regression results with 25% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.0952	0.11	-6.9663	2.744	-3.2416	1.06^{***}
Pca_1	-0.0010	0.013	0.3974	0.763	0.162	0.255
Pca_2	0.0100	0.016	0.2774	1.239	-0.0643	0.396
EPU	0.0006	0.000	0.0143	0.009	0.0058	0.004
GEPU	0.0007	0.001	0.0148	0.011	0.0061	0.005
F/LogLikelihood		0.6979		-11.211		-11.633
Probability		0.595		0.223		0.303
N		121		121		121
R^2/Pseudo-R^2		0.066		0.202		0.172

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

C Colombia

For Colombia, the two first principal components have an 95.5% 3.05% variance explaining ratio, respectively and both are statistically significant at all non-linear regressions.

The tables for the regression with $CMAX_{20\%}$ (IX) and $CMAX_{25\%}$ (X) displays significant evidence that policy uncertainty is correlated with the crisis indicator, but not the global component.

Table IX: Colombia's regression results with 20% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	0.1913	0.159	-2.5031	1.451*	-1.3337	0.708*
Pca_1	-0.0870	0.034**	-1.8239	0.596***	-0.9739	0.322***
Pca_2	0.0366	0.027	-1.8239	0.350**	0.4288	0.202**
EPU	0.0051	0.001***	0.0415	0.016***	0.0219	0.007***
GEPU	-0.0001	0.001	-0.0026	0.008	-0.0016	0.004
F/LogLikelihood		9.956		-37.334		-37.590
Probability		583e-07		4.17e-08		5.33e-08
N		121		121		121
R^2/Pseudo-R^2		0.284		0.3493		0.3448

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

Table X: Colombia's regression results with 25% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	0.0672	0.152	-3.4051	1.583**	-1.8087	0.761**
Pca_1	-0.0532	0.031*	-1.6829	0.652***	-0.8594	0.333***
Pca_2	0.0284	0.021	0.8006	0.345**	0.3905	0.197**
EPU	0.0040	0.001***	0.0365	0.014**	0.019	0.007***
GEPU	0.0004	0.001	0.001	0.009	0.0004	0.004
F/LogLikelihood		5.752		-33.773		-33.996
Probability		2.94e-04		2.00e-05		2.46e-05
N		121		121		121
R^2/Pseudo-R^2		0.198		0.285		0.280

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

D Mexico

For Mexico, the two first principal components have an 95.3% 4.59% variance explaining ratio, respectively and both are statistically significant for all regressions when $\Delta = .20$. The Logit and Probit models fail to converge with the second component, even though there are more observations (2 years) comparing to previous countries in Latin America, hence being dropped to achieve the results for $\Delta = .25$.

The tables for the regression with $CMAX_{20\%}$ (XI) and $CMAX_{25\%}$ (XII) differently shows that the mexican policy uncertainty has no correlation considering the non-linear models but the global EPU has. Also, the Logit and Probit regressions shows a high Pseudo R^2, much differently from other countries.

Table XI: Mexico's regression results with 20% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.122	0.084	-26.9738	11.905**	-13.5014	3.607***
Pca_1	0.0971	0.030***	5.8305	2.942**	2.8422	0.924***
Pca_2	-0.0462	0.025*	-6.1433	2.186***	-3.2909	0.851***
EPU	0.0023	0.001*	0.025	0.025	0.0094	0.011
GEPU	0.0013	0.001**	0.0887	0.041**	0.044	0.013***
F/LogLikelihood		5.831		-10.250		-10.892
Probability		2.27e-04		9.613e-13		1.79e-12
N		145		145		145
R^2/Pseudo-R^2		0.280		0.752		0.736

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

Table XII: Mexico's regression results with 25% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.1155	0.077	-21.0442	6.741***	-11.2388	2.949***
Pca_1	0.0494	0.022**	5.094	1.726***	2.798	0.865***
Pca_2	-0.0064	0.018	-	-	-	-
EPU	0.0035	0.001***	0.0567	0.023**	0.0296	0.010***
GEPU	0.0011	0.001**	0.0785	0.028***	0.0418	0.013***
F/LogLikelihood		3.952		-9.1249		-9.0609
Probability		0.00453		1.785e-09		1.676e-09
N		145		145		145
R^2/Pseudo-R^2		0.289		0.705		0.707

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

E United States of America

For Mexico, the two first principal components have an 97.1% 2.15% variance explaining ratio, respectively and only the second is statistically significant for all non-linear regressions.

The tables for $CMAX_{20\%}$ (XIII) and $CMAX_{25\%}$ (XIV) shows that the country that works like a base line has similar results with Brazil, Chile and Colombia.

Table XIII: USA's regression results with 20% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	-0.0165	0.102	-2.9061	1.407**	-1.5218	0.686**
Pca_1	0.0129	0.017	-0.4458	0.298	-0.2424	0.157
Pca_2	0.2004	0.031***	1.2892	0.237***	0.7487	0.127***
EPU	0.0015	0.001	0.0356	0.009***	0.019	0.005***
GEPU	0.0009	0.001	-0.0032	0.008	-0.0024	0.004
F/LogLikelihood		18.65		-30.172		-29.72
Probability		2.63e-12		7.674e-10		4.97e-10
N		145		145		145
R^2/Pseudo-R^2		0.412		0.445		0.453

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

Table XIV: USA's regression results with 25% threshold

	OLS		Logit		Probit	
	coef	std. Error.	coef	std. Error.	coef	std. Error.
constant	0.0152	0.072	-2.6176	1.897	-1.2593	0.903
Pca_1	0.0372	0.013	0.5262	0.472	0.1932	0.183
Pca_2	0.1901	0.035	1.4859	0.310(***)	0.8226	0.146(***)
EPU	-0.0002	0.000	0.0055	0.013	0.0026	0.006
GEPU	0.0005	0.000	-0.0075	0.011	-0.005	0.006
F/LogLikelihood		8.685		-23.415		-23.073
Probability		2.72e-06		3.138e-08		2.265e-08
N		145		145		145
R^2/Pseudo-R^2		0.407		0.464		0.472

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

F Conditional Logit

The table for $CMAX_{20\%}$ and $CMAX_{25\%}$ (XV) reports the regression of fixed-effects conditional logit with each month of the year being the fixed effect. Since this is a FE type panel regression there is no constant, a due to the nature of conditional logit estimation, although less biased, group coefficients are not available as discussed by Abrevaya (1997). For $\Delta = .25$ 50 observations were dropped for having no within-group variance.

Table XV: Conditional logistic results

	$CMAX_{20\%}$		$CMAX_{25\%}$	
	coef	std. Error.	coef	std. Error.
	coef	std. Error.	coef	std. Error.
Pca_1	-0.2842	0.173	-0.269	0.231
Pca_2	0.4855	0.164***	0.5424	0.220**
EPU	0.0114	0.002***	0.0128	0.003***
GEPU	0.0039	0.003	0.0050	0.004
F/LogLikelihood		-150.73		-90.519
N		605		555

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author

First, it is important to note that the respective reported Likelihood ration and F statistics for all regressions above indicates that those regressions are relevant, except over Chile's $\Delta = 0.25$. The two components selected from the PCA also explain at least 98% variability from the original data for control, but mainly the second vector is the one with highets statistically significant cases.

The Economic Policy Uncertainty index is significant on all non-linear models but not the global index, except for Mexico's case, which is the other way around. This uncertainty seems not only related but relevant to express the crises on the market, but Latin American markets have a behavior much like United States of America, more independent in their crisis except for the country that borders USA, and has many trade deals with it.

The conditional logit results adds robustness to the claims, even with Mexico in the panel, which exhibits a flipped behavior. Doing a seasonal control with month year over year fixed-effects control shows that a big EPU spike can trigger a crisis.

V Conclusion

It is not new the idea that politics influences the financial market. Cochrane (2011) stated that deep down, behaviour models are price/discount models and Bloom (2009) suggested that uncertainty has a deep impact over the market. Pástor et al. (2013) stated that political uncertainty, although orthogonal to economic factors, clearly affects prices in a broad way, suggesting its non-idiosyncratic impact.

With Baker et al. (2016) Economic Policy Uncertainty measurement and results, following the results from Schwarz and Dalmácio (2021) showing that under this policy uncertainty firms reduce their leverage levels, it is straight-forward to think that this uncertainty can be one-of-a-many triggers for crises in Latin American' financial market.

In fact, using behavioural modelling proposed by Baker and Wurgler (2006) and expanded by Zhang et al. (2019) to show how the general optimistic sentiment can predict some market crashes but adapting it to test the uncertainty about the actions around policy-makers regarding the economy brings clear results that this uncertainty requires a risk premium at which some point can be an ingredient to crises.

The intricacies of the mechanism, or the channel, over how this uncertainty affects prices and stock-markets are left to be studied further down the road.

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A Appendix

Here are the tables with probit and logit estimation, not marginal effects. The coefficients are presented in the same order as in the paper.

Table XVI: Estimation results with macro data for 25%

	(1) OLS		(2) LOGIT		(3) PROBIT	
jeb_24	-2.27e-12***	(-3.05)	-3.89e-11**	(-2.46)	-2.12e-11***	(-2.67)
jeb_17	-1.25e-11***	(-3.64)	-2.12e-10***	(-2.91)	-1.10e-10***	(-3.20)
gem_5	-0.00467**	(-1.98)	-0.211***	(-2.83)	-0.112***	(-2.94)
gem_16	0.0000113***	(5.38)	0.000243***	(3.98)	0.000129***	(4.21)
gem_25	-5.00e-11***	(-3.30)	-1.14e-09***	(-3.65)	-6.04e-10***	(-3.79)
gem_28	0.000795***	(8.89)	0.00715***	(3.29)	0.00386***	(3.80)
gem_32	0.00681***	(2.63)	0.0651	(1.56)	0.0333	(1.64)
_cons	-2.248***	(-4.34)	-36.52***	(-3.29)	-19.61***	(-3.59)
N	201		201		201	
R^2	0.519					
pseudo R^2			0.619		0.624	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XVII: Estimation results with macro data for 30%

	(1) OLS		(2) LOGIT		(3) PROBIT	
jeb_24	-2.07e-12***	(-2.68)	-3.29e-11**	(-2.15)	-1.81e-11**	(-2.40)
jeb_17	-1.15e-11***	(-3.09)	-2.39e-10***	(-3.29)	-1.29e-10***	(-3.55)
gem_5	-0.00501*	(-1.89)	-0.159**	(-2.19)	-0.0902**	(-2.25)
gem_16	0.0000105***	(4.69)	0.000206***	(3.65)	0.000115***	(3.75)
gem_25	-5.62e-11***	(-3.38)	-1.10e-09***	(-3.52)	-6.03e-10***	(-3.76)
gem_28	0.000429**	(2.51)	0.00442***	(2.62)	0.00241***	(3.05)
gem_32	0.00564*	(1.72)	0.0743	(1.21)	0.0380	(1.45)
_cons	-1.504**	(-2.24)	-25.60**	(-2.43)	-14.22***	(-2.77)
N	201		201		201	
R^2	0.364					
pseudo R^2			0.562		0.575	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XVIII: Estimation results with macro data for 35%

	(1) OLS		(2) LOGIT		(3) PROBIT	
jeb_24	-1.62e-12**	(-2.41)	-5.73e-11**	(-2.44)	-3.34e-11***	(-2.67)
jeb_17	-7.09e-12*	(-1.88)	-8.17e-11	(-1.04)	-4.80e-11	(-1.20)
gem_5	-0.00330	(-1.16)	-0.626**	(-2.42)	-0.329**	(-2.31)
gem_16	0.00000739***	(3.04)	0.000357***	(4.37)	0.000200***	(4.20)
gem_25	-4.01e-11**	(-2.53)	-9.65e-10**	(-2.36)	-6.01e-10***	(-2.98)
gem_28	0.000361**	(2.31)	0.00368***	(2.64)	0.00204***	(2.80)
gem_32	0.00569*	(1.69)	0.0383	(0.71)	0.0220	(0.78)
_cons	-1.258**	(-2.06)	-64.87***	(-2.58)	-35.32***	(-2.94)
N	201		201		201	
R^2	0.307					
pseudo R^2			0.629		0.641	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XIX: Estimation results with macro and sentiment data for 25%

	(1) OLS		(2) LOGIT		(3) PROBIT	
Epu	0.000627**	(2.30)	0.0208***	(3.09)	0.0110***	(2.97)
vol	5.07e-13	(1.07)	1.72e-11	(1.45)	9.44e-12	(1.52)
delta_ipo	-0.000188*	(-1.91)	-0.0479	(-0.75)	-0.0161	(-0.60)
jeb_24	-2.32e-12***	(-3.25)	-4.25e-11**	(-2.02)	-2.65e-11**	(-2.51)
jeb_17	-1.06e-11***	(-3.24)	-1.91e-10	(-1.64)	-9.01e-11*	(-1.73)
gem_5	-0.00584**	(-2.26)	-0.367***	(-2.96)	-0.194***	(-2.92)
gem_16	0.0000105***	(5.68)	0.000276***	(2.98)	0.000150***	(3.25)
gem_25	-4.10e-11***	(-3.04)	-1.11e-09**	(-2.38)	-5.88e-10***	(-2.69)
gem_28	0.000776***	(8.75)	0.00623***	(3.20)	0.00340***	(3.73)
gem_32	0.00683***	(2.69)	0.0448	(1.00)	0.0261	(1.27)
_cons	-2.337***	(-4.62)	-42.42***	(-3.10)	-24.62***	(-3.58)
N	201		201		201	
R^2	0.535					
pseudo R^2			0.677		0.679	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XX: Estimation results with macro and sentiment data for 30%

	(1) OLS		(2) LOGIT		(3) PROBIT	
epu	0.000623**	(2.22)	0.0247***	(3.40)	0.0135***	(3.10)
vol	4.20e-13	(0.88)	1.50e-11	(1.34)	8.12e-12	(1.35)
delta_ipo	-0.000196*	(-1.90)	-0.0323	(-0.34)	-0.0203	(-0.31)
jeb_24	-2.12e-12***	(-2.83)	-3.18e-11*	(-1.95)	-1.91e-11**	(-2.26)
jeb_17	-9.80e-12***	(-2.75)	-2.35e-10*	(-1.93)	-1.28e-10**	(-2.21)
gem_5	-0.00606**	(-2.18)	-0.277***	(-2.74)	-0.153***	(-2.71)
gem_16	0.00000975***	(4.83)	0.000212***	(3.37)	0.000121***	(3.56)
gem_25	-4.79e-11***	(-3.10)	-9.66e-10***	(-2.76)	-5.46e-10***	(-3.10)
gem_28	0.000410**	(2.39)	0.00349**	(2.28)	0.00198**	(2.57)
gem_32	0.00571*	(1.77)	0.0507	(0.98)	0.0305	(1.24)
_cons	-1.599**	(-2.41)	-25.98**	(-2.23)	-15.41***	(-2.62)
N	201		201		201	
R^2	0.387					
pseudo R^2			0.641		0.651	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XXI: Estimation results with macro and sentiment data for 35%

	(1) OLS		(2) LOGIT		(3) PROBIT	
epu	0.000391*	(1.71)	0.0564**	(2.27)	0.0325**	(2.46)
vol	-2.46e-13	(-0.79)	-6.35e-11	(-1.14)	-3.69e-11	(-1.12)
delta_ipo	-0.000129	(-1.47)	-0.373	(-1.61)	-0.209*	(-1.73)
jeb_24	-1.68e-12**	(-2.53)	-1.08e-11	(-0.20)	-7.11e-12	(-0.25)
jeb_17	-6.89e-12*	(-1.90)	-2.42e-11	(-0.16)	-1.51e-11	(-0.19)
gem_5	-0.00326	(-1.21)	-0.902**	(-2.08)	-0.516**	(-2.24)
gem_16	0.00000735***	(3.28)	0.000439***	(2.73)	0.000254***	(2.89)
gem_25	-3.89e-11**	(-2.59)	-1.82e-09**	(-2.25)	-1.04e-09**	(-2.34)
gem_28	0.000344**	(2.22)	0.00342*	(1.75)	0.00198**	(2.05)
gem_32	0.00598*	(1.79)	-0.0248	(-0.25)	-0.0109	(-0.22)
_cons	-1.346**	(-2.20)	-59.63**	(-2.14)	-34.99**	(-2.53)
N	201		201		201	
R^2	0.326					
pseudo R^2			0.726		0.734	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$