Identifying External Vulnerability
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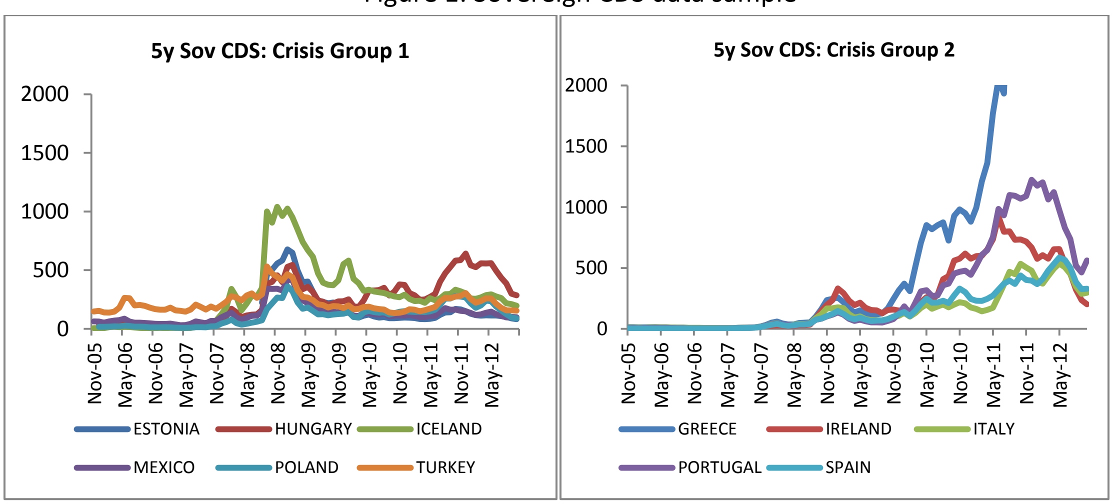
1. Introduction

In economics, external vulnerability refers to susceptibility of an economy to outside shocks, like capital outflow. An economy that is externally vulnerable is prone to currency crisis or debt crisis. Because of the grave consequences of the crisis, Early Warning Systems (EWS) have been built by central banks and research institution to predict the external vulnerability.

In this project, we do not follow the common practice of building the system with VAR. Instead, we explore the possibility of using machine learning techniques to forecast the crisis from macro-economic variables. Due to data availability, we focus only on the Euro Area sovereign debt crisis, studying OECD countries. Our study shows that: although the market lacked awareness to the crisis before its outbreak, signals can be generated to give strong warning to countries that later suffered heavily in the crisis.

From technical view, this problem is also highly interesting, because (1) unlike most other machine learning applications, macro feature data is very scarce. Missing data point is common, and frequency is low. (2) unlike engineering application where labels are clear, macro trend may stay latent for many years before breakout. Euro Crisis is especially interesting: even when first round of crisis broke out in peripherals, people still thought that Eurozone was safe, until more than one year later. Therefore, we are especially interested at Oct-2009, the month before Greece crisis outbreak.

Figure 1: Sovereign CDS data sample



2. Data and software package

We use 5 year sovereign credit default swap (SovCDS) as a quantitative indicator of the degree of crisis for each country, downloaded from Bloomberg, sampled monthly. Higher the CDS rate, higher the risk of country default. Totally there are about twenty variables, available monthly or annually, downloaded from EIU, OECD Stat, and World Bank database. Explanatory data set differ slightly for each method due to data availability on different frequency. We use Matlab stats toolbox and OSU-SVM 3.0 for some functions.

3. Looking backward descriptive regression

Before trying to predict the crisis, we start from a simple case. Given our current knowledge of the crisis, we want to see how much we can explain from 2008 (pre-crisis) data. The intuitive way of doing this is to regress CDS data on macro variables. However, we found this process frustrating because of nonlinear relationships. To avoid this, we put labels on the six countries that suffered most in the crisis, and run logistic regression.

Because of severe missing data, multi-variable regression can only work in very small samples. Therefore, we used single variable logit regression for each variable and combine the results. Table 1 shows the result of calculating average fitted value from leave one out test. It shows that looking backward, we can identify most of the crisis countries (with high false alarm rate) except Italy. This serves as a baseline for our prediction attempts below.

Table 1.Identifying crisis country using logit regression and ex post knowledge

	ICELAND	**GREECE**	AUSTRALIA	**IRELAND**	UNITED KINGDOM	**SPAIN**	JAPAN	ESTONIA	**PORTUGAL**	UNITED STATES	NEW ZEALAND	FRANCE	SLOVENIA	HUNGARY	BELGIUM	SLOVAKIA	AUSTRIA
Mean	**0.5**	**0.35**	0.34	**0.33**	0.31	**0.23**	0.22	0.21	**0.2**	0.19	0.16	0.16	0.15	0.14	0.13	0.12	0.12
	NETHERLANDS	TURKEY	KOREA, REP. OF	FINLAND	CANADA	GERMANY	POLAND	SWEDEN	NORWAY	CZECH REPUBLIC	DENMARK	**ITALY**	SWITZERLAND	ISRAEL	LUXEMBOURG	MEXICO	CHILE
Mean	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.1	0.1	**0.1**	0.1	0.1	0.08	0.07	0.06

4. Leave one out SVM fitting

Starting from this section, we will run backtesting and use only information up to the date of concern (e.g., in 2008, we do not know Greece will enter crisis). Every month, we use k-means clustering to separate CDS into two groups, and label the upper group as ‘risky’. Because in the previous test, we found SVM to be more robust than the logit regression, and since we are working on data separation, we use leave one out SVM to train and test the data. If a country labeled ‘safe’ was found to be risky by SVM, we will count it as a warning (normally called false alarm). We found that counting number of warning is an effective way of identifying risky countries:

Table 2. Cumulative warning signals by Oct-2009, LOO-SVM

	Warning	Fitting (Safe)	Missing Warning	Fitting (Crisis)	Sum
MEXICO	4	21	5	5	35
GREECE	**3**	32	0	0	35
IRELAND	**3**	18	0	1	22
HUNGARY	2	17	13	3	35
ITALY	**2**	33	0	0	35
POLAND	2	33	0	0	35
PORTUGAL	**2**	33	0	0	35
KOREA	1	29	1	4	35
NETHERLANDS	1	13	0	0	14
SPAIN	**1**	34	0	0	35
AUSTRALIA	0	14	0	0	14
…	0	…	0	0	…

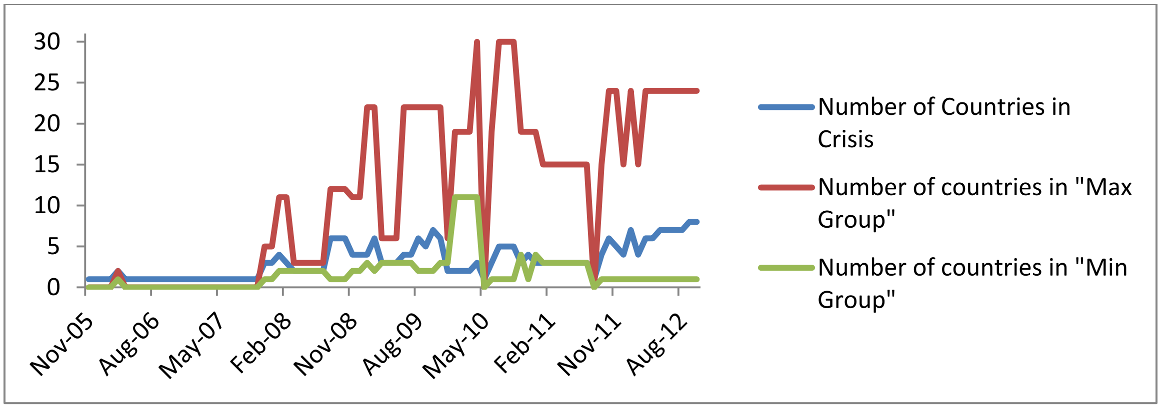
Table 2 shows the cumulative number of warnings by Oct-2009, outbreak of Greece crisis. If we ignore the countries that have already suffered crisis (like Mexico, characterized by missing warnings and fitted crisis), the five Eurozone crisis countries almost occupied the top block.

This method seems encouraging, but there is an issue with it. The signal is so scarce that people will doubt that it is temporary noise. The reason is that labels are misleading. According to CDS data, before Oct-2009, these five countries are considered relatively safe. Such information is trained into the model, so that the model tends to indicate the countries to be safe.

5. Long term early prediction using clustering

The first reaction to the above mentioned problem is to use only data from risky countries (and some countries hand-picked to be safe) and run the LOO-SVM. This failed because the training set is too small. The second answer is to use unsupervised learning. However, crisis countries do not form a well separated cluster. However, combining these two threads, we developed a method that provides reasonable score for the countries' risk.

We ran k-means clustering, overlaying it with the current crisis information. We first find the largest number of clusters so that ALL crisis countries fall in the same cluster. The cluster containing all risk countries is dubbed as "Max group". If a "safe" country fall into "Max group", it has a good match for the risky cluster. We then find the smallest number of clusters so that EVERY crisis country falls into different cluster. The clusters containing risky countries are dubbed as "Min group". If a "safe" country falls in to "Min group", it has high similarity to a certain crisis countries. If a "safe" country falls into both groups, then we count it as a risky signal. We count the cumulative number of signals for each country as the indicator of the risk.



	FRANCE	POLAND	SLOVAKIA	ITALY	ISRAEL	PORTUGAL	SPAIN	AUSTRALIA	IRELAND	NEWZEALAND	SLOVENIA	CZECH	DENMARK	BELGIUM	UK	US	AUSTRIA	NETHERLANDS	GREECE
Cumulative Indicator By Oct-09	24	24	24	**18**	17	**17**	**17**	16	**16**	16	16	15	15	14	13	13	11	11	**8**
Historical Average CDS	15.6	78.7	46.8	**44.7**	77.4	**33.9**	**35.0**	74.7	**127.7**	61.5	68.3	59.8	64.7	25.2	76.0	23.8	46.3	55.2	**62.5**

This method proved to be effective, except for Greece. Other countries on top of the list may not be false alarm. Poland and Israel already have CDS above peers, and Slovakia later experienced CDS hike. Up to today, there are discussions on whether France will be hit next in the Euro Crisis.

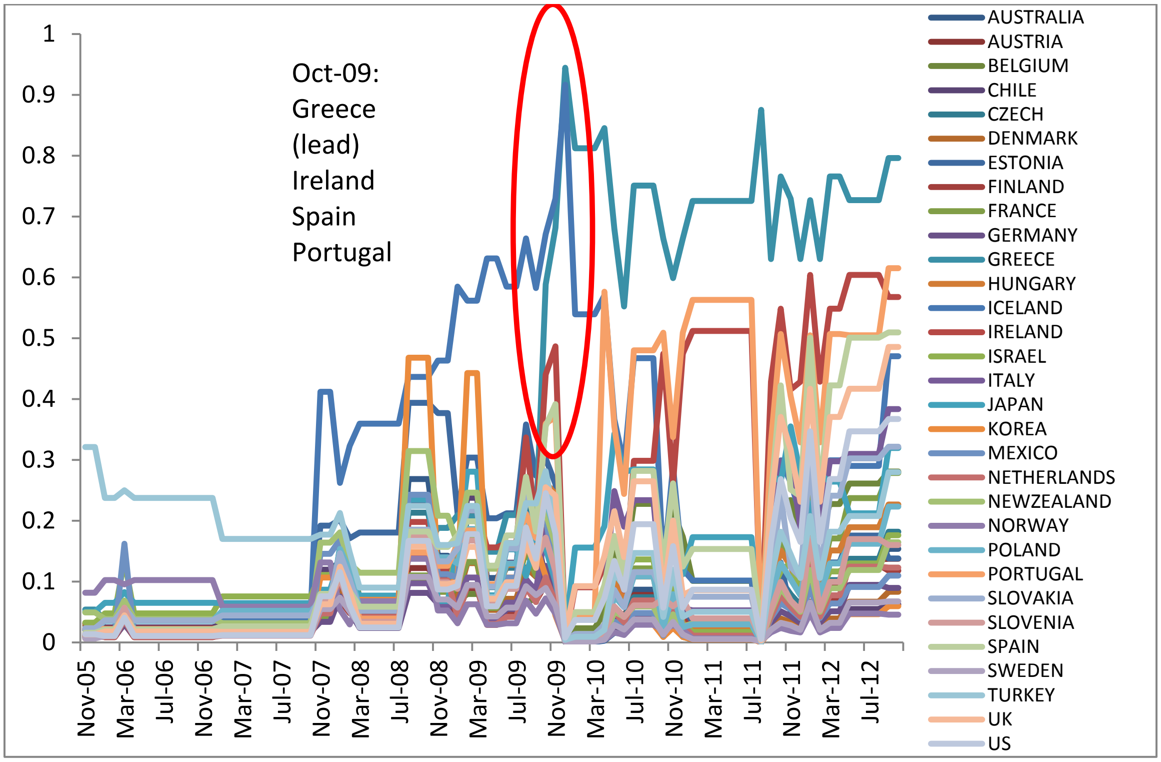
The drawback of this method is that there is no clear cut between risky and safe. Risk Indicator goes down smoothly in the table. The next method will provide a clearer signal in the near term.

6. Quickly responsive prediction using dynamic model selection and aggregation

Once market sentiment change (for example, worries about debt level), we want to capture it, and identify all countries that may be considered risky with such sentiment. This family of method does not provide long term identification of external vulnerability; instead, it works right after the crisis outbreak, helping you to identify who will be hit next. Therefore, it can be separated into two parts: identifying the sentiment, and rate the country.

Multi-variable regression suffers from multi-colinearity, which makes coefficients notoriously unreliable. Single regression, however, suffers severe bias. As a tradeoff, we use models with two explanatory variables. Since we don't know which model to choose, we maintain a large pool of models (10 explanatory variables yields 45 models), and select them dynamically using p-value (perfect separation is considered p-value of 0). We select the better half of the models at each time, use significance to generate weights, and aggregate their predictions according to the weights.

The result is encouraging. In Oct-2009, besides of the expected spike of Greece and Iceland, we found they are followed by Ireland, Spain, and Portugal. Comparing this to Figure 1, the warning signal is given 6 months or 1 year earlier than the crisis in these countries.



7. Summary and future work

Our work proved the potential of using machine learning to study macro features in order to deliver early warning signals for future crisis. Comparing to the mainstream VAR based economic forecasting models, our method requires least human input for model selection. Outdated model selection by hands for economic prediction may cause under-reaction to new changes. Fully automatic learning system would be useful in overcoming this problem.

For future work, dynamic model selection has the potential of improvement by introducing memories to the model. A model with memory has higher resistance to noise, and also possibly more responsive to certain structure changes. We implement some designs of model memory without observing significant improvement, but it is an interesting topic to work on. Also, if implemented with more historical data, our system has the potential of expanding into a fullsize early warning system for both Emerging markets and OECD, covering different kinds of crisis.

8. Reference

Debt- and Reserve-Related Indicators of External Vulnerability, International Monetary Fund, http://www.imf.org/external/np/pdr/debtres/index.htm