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Los Angeles

Essays on Financial Crises and Sectoral Analysis

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Economics

by

KeyYong Park

2016

ABSTRACT OF THE DISSERTATION

Essays on Financial Crises and Sectoral Analysis

by

KeyYong Park

Doctor of Philosophy in Economics

University of California, Los Angeles, 2016

Professor Aaron Tornell, Co-chair

Professer Jinyong Hahn, Co-chair

This dissertation studies financial crises and sector-based analysis. Chapter 1 studies the balance of payments crisis in the euro area periphery countries preceded by significant private capital inflows from 1999 to 2007. With a detailed empirical investigation, I find that these capital inflows in the form of debt mainly financed the nontradable sector and the industries with weak forward linkages to the tradable sector. The model economy explains that domestic misallocation of the capital inflows in terms of inter-industry linkages can trigger the debt repayment problem which was experienced by PIIGS (Portugal, Italy, Ireland, Greece, and Spain). More precisely, it shows that the debt inflows under the protection of implicit bailout-guarantee cannot be repaid in the case when they primarily finance the nontradable sector with weak forward linkage to the tradable sector. Chapter 2, which is co-authored with Aaron Tornell and Hyo Sang Kim, looks at the size distribution of economic dis-

tress (ED) events over the recent period of globalization (1970 - 2014) and the long historical period (1830 - 2013). We find that there exists a remarkable relation between the magnitude of economic distress events and the frequency with which they occur. We document that there is a threshold below which the size of ED events follows an exponential distribution, while a Pareto distribution (a power-law) applies for ED events larger than the threshold. To explain the empirical results, we present a wildfire model in which the dynamics of an individual ED event is determined by the interaction of two opposing forces: (i) the natural stochastic growth of the ED, which is proportional to the size of the damage that has already occurred; and (ii) a policy that attempts to extinguish the economic distress. We then derive the steady-state cross-sectional distribution of the final size of the ED events. Chapter 3[1] studies a sector rotation strategy. I introduce a sector rotation model that generates forecasts of sector performance combining 4 factors which include price momentum, market sentiment, macroeconomic factors, and earnings expectations. The backtest results show that all 4 factors and the sector rotation model outperform its benchmark (Equal-Weight Basket). Moreover, macro factor as a single factor generates the highest risk-adjusted returns.

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[1]This chapter was written while I was a summer intern in the research division at Bank of America Merrill Lynch (BAML). The views expressed in this paper do not necessarily represent those of BAML.

The dissertation of KeyYong Park is approved.

Nico Voigtläender

Roger E. Farmer

Jinyong Hahn, Committee Co-chair

Aaron Tornell, Committee Co-chair

University of California, Los Angeles

2016

To my wife Somee,

To my beloved parents,

To my grandfather in heaven,

For their love, support, and encouragement

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1 The Impact of Financial Integration on Southern European Countries: An Input-Output Analysis

1.1 Introduction

Southern European countries, Portugal, Ireland, Italy, Greece, and Spain (hereafter PIIGS), experienced significant private capital inflows from 1999 to 2007, followed by European debt crisis in 2010 (Merler and Pisani-Ferry [2012]). After PIIGS joined the currency union in 1999 (Greece, in 2001), they received large capital inflows by decreasing credit risk and exchange rate risk. Many literature view this positive effect of the Euro currency union as the result of an implicit bailout guarantee by Eurozone or European Central Bank (ECB). This implicit bailout guarantee relaxed borrowing constraints for the peripheral countries because foreign investors to these countries believed that a bailout from European Central Bank (ECB) or the core countries would be forthcoming if a member state fell into any trouble. This belief is well evidenced by comparison between the government bond yields of Germany and PIIGS. Interestingly, the bond yields of PIIGS converged to that of Germany after the introduction of Euro.[2] This disappearance of risk in PIIGS was not possible without the implicit bailout guarantee.

One notable fact about the capital inflows to PIIGS is that most of them were in the form of debt (Lane [2013a] and Kalemli-Ozcan et al. [2014]). Then which industries (or sectors) are the main recipients of the large capital inflows? Did foreign borrowing finance productive investment projects to increase the economy's capacity to export and result in a current account surplus over debt service costs? The answer

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[2]Figure 4 in the appendix shows the government bond yields of PIIGS and Germany

to these questions is a key to explaining why PIIGS did not generate sufficient current account surpluses over the decade to repay their external debt leading up to the balance of payments crisis in 2010. For example, foreign borrowing to finance investment in the nontradable sectors such as land and housing is likely to generate a low foreign income stream to support debt repayment. In this context, an input-output analysis is a good tool explaining how a misallocation of capital flows can lead to a reduction in economy's capacity to produce the tradable goods.

In this paper, I offer a detailed empirical investigation showing how the capital inflows to PIIGS were allocated in terms of inter-industry linkages. Then I provide a model explaining the mechanism behind how domestic misallocation of the capital inflows could trigger the debt repayment problems faced by PIIGS. First, based on the input-output analysis, I investigate if the capital inflows in PIIGS financed investment in the industries with weak or strong forward linkages to the tradable sector (hereafter T-sector). Next, based on the sectoral approach, I investigate if the capital inflows in PIIGS financed investment in the nontradable sector (hereafter N-sector) or the T-sector. To measure industry's forward linkages to the T-sector, I construct 3 measures of tradability for each industry and use 2 approaches toward measuring inter-industry forward linkages with Leontief model (1936, 1986) and Ghosh model (1958) respectively. I find evidence, using difference in difference estimation, that the capital inflows mainly financed the N-sector and the industries with weak forward linkages to the T-sector only in PIIGS after the creation of Euro. Finally, I develop a two sector model economy based on Schneider and Tornell [2004], to show that the debt inflows taken on with the protection of an implicit bailout guarantee cannot be repaid if the capital inflows finance the N-sector (producing intermediate goods) with weak forward linkages to the T-sector. The bottom line of this paper is that a domestic misallocation of the capital inflows in terms of input-output linkages might

put a country in a bad position to repay the debt in the case that the country received large capital inflows with government's implicit bailout-guarantee.

This paper is structured as follows. Section 2 reviews the literature on the effect of financial integration and the input-output analysis. In section 3, I provide an empirical methodology and its results. Section 4 introduces a model economy to provide an interpretation of the empirical findings. Section 5 concludes.

1.2 Literature Review

This paper discusses the impact of financial integration using input-output analysis. Hence a brief survey on the effect of financial integration and the input-output analysis is given in this section. There is a vast literature on the effect of financial integration. According to them, benefits and adverse effects of financial integration coexist. Benefits include that financial integration may foster more efficient resource allocation, facilitate risk diversification, benefit the countries by lowering their cost of capital, leading to increased investment and economic growth (refer to King and Levine [1993], Rogoff [1999], Prasad et al., and Henry [2007]). According to these authors, many of the positive impacts of financial integration (or financial liberalization) are mainly stemmed from increased investment opportunities and capital market development. In other words, financial integration enables countries to have an access to a broader base of capital, which significantly reduces the cost of capital and leads to higher investment, which is a major engine for economic growth. Furthermore, Obstfeld [1995] and Levine [1997] show that financial integration can also provide great benefits for international risk-sharing.

Costs of financial integration is well summarized in Agenor [2003] and Kose et al. [2006]. According to the authors, the risk of volatility and abrupt reversals in capital

flows following capital account liberalization may cause a significant cost. Concerns associated with reversals in capital flows have been realized in a series of the past financial crises. They also point out that the large capital inflows induced by financial openness can cause macroeconomic instability such as rapid monetary expansion, inflationary pressures, real exchange rate appreciation and widening current account deficits.

Recent studies on the effect of financial integration, which this paper is the most relevant to are following. Guiso et al. [2004] observe that benefits from EU financial integration have large effects on countries and sectors growth. Using firm-level and industry-level data, they find that overall impact of financial integration depend on different country and sector effects reflecting heterogeneity of the EU in terms of sector composition and level of financial development. They show that gain from financial integration varies depending on the degree of financial backwardness (more backward countries gain more) and the sector specialization (countries that specialize in financially dependent sectors gain more). Ranciere and Tornell [2015] find that under financial repression, borrowing constraints in the input sector lead to underinvestment, which causes bottlenecks through the economy and low growth. Financial liberalization relaxes the financial constraints and improves allocative efficiency to enhance TFP and consumption possibilities. Sectors more dependent on external finance (usually the N-sector) grow faster and the rest of the economy (including the T-sector) benefits from the relaxation of the bottleneck via input-output linkage. Lane [2013b] documents that financial globalisation fuelled the asymmetries in credit growth and external positions across countries that have played a critical role in determining the cross-country incidence and propagation of the crisis.

There are not many papers explaining macroeconomic phenomena using input-output analysis. Two recent papers study the intersectoral input-output linkages

and its role in macroeconomic issues. Jones [2011] study how misallocation at the micro level reduces total factor productivity at the macro level through the input-output structure of the economy. Acemoglu et al. [2012] argue that in the presence of intersectoral input-output linkages, microeconomic idiosyncratic shocks may lead to aggregate fluctuations. They show that sizable aggregate volatility is derived from sectoral idiosyncratic shocks depending on the structure of the intersectoral network representing inputoutput linkages.

In this paper, I document that Southern European debt crisis was caused by a domestic misallocation of capital inflows. Agenor [2003] points out that a domestic misallocation of capital flows is one of the potential costs of financial integration. According to the author, the capital inflows associated with an open capital account may raise domestic investment but their impact on long-run growth may be limited if such inflows are used to finance speculative or low-quality domestic investments such as investments in the real estate sector. That is to say, unproductive investments in the nontradable sector may reduce the economy's capacity to export over time and lead to a growing external imbalance. In this context, input-output analysis can be used as a good tool explaining how unproductive investments in the nontradable sector lead to reduction in economy's capacity to produce the tradable goods and how it can result in the debt repayment problems. This paper contributes to the existing literature by demonstrating that Southern European debt crisis is the cost of financial integration in terms of domestic misallocation of the capital inflows. To my limited knowledge, there has been no attempt to explain the causes of European debt crisis using input-output analysis before.

1.3 Empirical Methodology

In this section, I investigate which industries, in terms of their forward linkages to the tradable industries, the capital inflows to PIIGS mainly financed. A tradable industry is defined as an industry producing the tradable goods. Some industries have weak and others have strong forward linkages to the tradable industries (industries with high tradability). For example, in Figure 1, industry i has a weak forward linkage to industry a and a strong forward linkage to industry b. Since industry a has high tradability and industry b has low tradability, industry i has a weak forward linkage to the tradable industry. Likewise, industry j has a strong forward linkage to the tradable industry. Instead of measuring industry's forward linkages to the classified specific tradable industries, I measure each industry's forward linkages to all the industries in the economy, weighting by their tradability. This will enable us to gauge how strongly an industry is linked to the tradable sector (a sector composed of the tradable industries) through its forward linkages. Following subsections introduce 2 approaches toward measuring inter-industry forward linkages and 3 methods of measuring tradability of an industry.

1.3.1 Measuring Inter-industry Linkages

Inter-industry linkages have been studied since the late 1950's with the purpose of identifying key industries that are central for economic development (Drejer [2002]). Input-output tables for the industries are used for linkage measures. There are two main approaches toward measuring inter-industry linkages: the Leontief model (Leontief [1936], Leontief [1986]) and the Ghosh model (Ghosh [1958]). The Leontief model assumes that all inputs are bought by producers in fixed proportions (demand-driven). On the other hand, the Ghosh model assumes that each commodity is sold to each
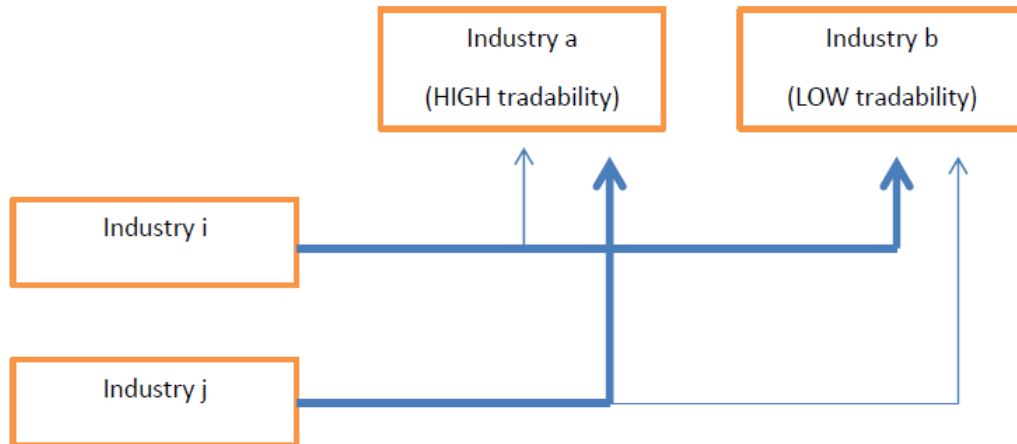
Figure 1: Forward Linkages to Tradable Industries

sector in fixed proportions (supply-driven).

Framework of an Input-Output Table, Industry by Industry

		Intermediate Demand	Final Demand	Total Output
		Sector j $(j=1,...,n)$		
Intermediate Input	Sector i $(i=1,...,n)$	x_{ij}	F_i	X_i
Primary Input		V_j		
Total Input		X_j		

Figure 2: Input-Output Table

The matrix $L = (I - A)^{-1}$ is known as the Leontief inverse matrix where I is an identity matrix and $A = \frac{x_{ij}}{X_j}$ is an input coefficient matrix (Figure 2 shows the structure of a typical input-output table). By the row identity of the IO table, we have $Ax + F = x$. This gives us $(I - A)^{-1}F = x$. x is interpreted as the level of total production necessary to satisfy final demand (F). Therefore the typical element l_{ij} of

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Leontief inverse matrix can be interpreted as that a 1% increase in productivity in sector j raises output in sector i by $l_{ij}\%$. Rasmussen [1956] presents an index called 'sensitivity of dispersion' to describe forward linkages. It measures the increase in the production of industry i, driven by a unit increase in the final demand for all industries in the system. This index is defined as the sum of row elements in Leontief inverse matrix: $\sum_{j=1}^{N} l_{ij}$, which captures the increase in production of industry i needed in order to cope with a unit increase in the final demand for the product of each N industry. An industry with a high value of Rasmussen's sensitivity of dispersion is interpreted as having high forward linkages to all the other industries in the economy.

Another way to establish industry's forward linkages is using the Ghosh model. The matrix $G = (I - B)^{-1}$ is known as the Ghosh inverse matrix where $B = \frac{x_{ij}}{X_i}$ is an output coefficient matrix. By the column identity of the IO table, we have $x'B + V' = x'$. This gives us $V'(I - B)^{-1} = x'$. x' is interpreted as the the level of output necessary to generate the desired level of value added. Hence the typical element g_{ij} of the Ghosh matrix can be interpreted as measuring the total value of production that comes about in sector j per unit of primary input in sector i (Miller and Blair [2009]). Like the Leontief model, the rows of the Ghosh inverse matrix are summated to measure forward linkages. $\sum_{j=1}^{N} g_{ij}$ measures the overall increase in the production of all the industries when there is a unit change of production in sector i.

Next, I construct tradability-weighted forward linkage index (TFLI) to capture a specific industry's forward linkages to the T-sector.[3] Multiplying the Leontief inverse matrix and the Ghosh inverse matrix by the vector of tradability (β) of each industry, respectively and summing up the rows of each matrix will yield:

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[3]Measure of tradability will be discussed in the following subsection.

$$TLFI_L = (I - A)^{-1}\beta = \sum_{j=1}^{N} \beta_j l_{ij}$$

$$TLFI_G = (I - B)^{-1}\beta = \sum_{j=1}^{N} \beta_j g_{ij}$$

$$\text{where} \quad \beta_j = \text{industry } j\text{'s tradability}$$

Both measures capture how industry i is connected to the tradable industries (or T-sector) through its forward linkages.

These two measures are constructed using input-output tables for 21 industries (Figure 5) and 11 Eurozone countries.[4] Therefore these measures are country- and industry- specific. Input-output tables are published every 5 years by OECD STAN (1995, 2000, 2005) and I use data of year 2000. TFLI's are highly stable over time representing industry's characteristics.[5] Also, stability of the forward linkage measures over time is well documented in other papers such as Drejer [2002].

1.3.2   Measuring Tradability

Most of literature regarding tradability of industries or sectors concern the size of international trade (import + export) relative to gross output to determine whether a particular industry or sector produces tradable goods or nontradable goods (Betts and Kehoe [2001]). In this section, I provide new methods of measuring tradability.

First, export intensity $\left(\frac{industry's\ export}{industry's\ output}\right)$ is used to measure industry's tradability (De Gregorio and Wolf [1994]). This shows how highly an industry is export-oriented.

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[4]11 Eurozone countries include Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The 6 countries other than PIIGS are used in the difference-in-differences estimation to be compared with PIIGS.

[5]TFLI's using data of other years (1995 and 2005) are available from the author upon request.

Second, export share ($\frac{industry's\ export}{total\ export}$) is used to proxy tradability of an industry. Relatively small (in terms of production) industries may produce limited amount of exports even though they are export-oriented. The size of export should be also considered to judge if an industry is producing tradable goods. In this context, the second measure captures the percentage of overall export accounted for by an industry.

Lastly, based on the stylized fact that the tradable goods have flexible prices while the nontradable goods have rigid prices, I construct tradability index for each industry by measuring volatility of industry-level real exchange rate. If an industry produces the tradable goods, variance of $(P_c^i - eP_w^i)$ over the given time span should be small. P_c^i and P_w^i are industry's value added deflator of country c and the world, respectively. e is nominal exchange rate between country c and the world. If it is small, that means industry i's price level in country c comoved highly with that in the world, reflecting that the goods produced in industry i are tradable. Since the world's price level for industry i is not available, Eurozone's average value added deflator of industry i will be used for P_w^i. Hence tradability index for each industry in a country is defined as:

$$TRAD_{i,c} \equiv [Var(P_c^i - eP_w^i)]^{-1}$$

for an industry i and country c

Following this definition, high $Trad_{i,c}$ can be interpreted as that industry i in country c has high level of tradability.

1.3.3 Difference in Difference (DID) Estimation

Back to the original question, what I want to investigate in this section is where the capital inflows to PIIGS were allocated. Because tracking how the capital inflows were used is not possible, investment and value added growth of the industries can be used as good proxies to see which industries were financed by those capital inflows. Jaumotte and Sodsriwiboon [2010] show that the creation of EMU and, especially, the introduction of EURO, contributed to the declines in current accounts by allowing countries to maintain their investment levels above what could be financed from domestic saving. In other words, financial integration in Europe benefited the member states in having improved access to the international pool of saving and hence the increase in investment is associated with the capital inflows. To investigate whether the capital inflows to PIIGS financed the industries with weak or strong forward linkages to the T-sector, I will study if investment growth rates (and value added growth rates) of the industries vary depending on their forward linkages to the T-sector. Since this should be compared in two dimensions (PIIGS vs. Non-PIIGS[6] and pre-EURO vs. post-EURO), the panel regression with the difference-in-differences estimator will be used.

Before introducing the empirical specifications, Figure 6 and 7 give an interesting motivation with a simple empirical practice. To briefly check the correlation between $TFLI$ and real investment growth at the industry-level, I plotted 5-year average growth rate of real investment for pre-Euro period (1994 - 1998) and post-EURO period (1999-2003) on y-axis and $TFLI$[7] of each industry on x-axis. Spain (Figure 6) representing PIIGS and Germany (Figure 7) representing Non-PIIGS show different

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[6]Non-PIIGS represent 6 Euro zone countries (Austria, Belgium, Finland, France, Germany, and Netherlands

[7]Leontief-based export intensity was used for $TFLI$ among 6 measures.

patterns before and after the EURO. These graphs show that in Spain, real investment was lowered in the industries with high $TFLI$ and was enhanced in the industries with low $TFLI$ after the introduction of Euro. Whereas there was no such change in the patterns of industrial investment in Germany after the introduction of EURO. This empirical practice suggests that the impact of financial integration might be different across the industries and the countries. In Spain, the real investment growth in the industries which have strong forward linkages to the T-sector had been reduced after the introduction of Euro while the real investment growth in the industries which have weak forward linkages to the T-sector had been augmented after the introduction of EURO. On the other hand, in Germany the EURO did not improve investment in the industries which have weak forward linkages to the T-sector.

This simple empirical practice can be extended to the panel regression with the difference-in-differences specification. In the previous sections, two measures of forward linkages and three measures of tradability index were introduced, which yield 6 combinations of TFLI. I investigate if real investment growth at the industry level differs across two groups (PIIGS and Non-PIIGS) and across time (before and after the introduction of EURO). The estimation equation is following:

$$I_{i,c,t} = \phi_i + \psi_c + \omega_t + \beta_1 Post_{c,t} + \beta_2 Post_{c,t} TFLI_{i,c} + \beta_3 Post_{c,t} TFLI_{i,c} PIIGS_c + \epsilon_{i,c,t} \quad (1)$$

where i, c, and t stand for industry, country, and year respectively. $I_{i,c,t}$ is real investment growth, ϕ_i, ψ_c, ω_t are industry, country, and time fixed effects respectively,[8] $Post_{c,t}$ is a dummy variable equal to one in years and countries in which the Euro is the official currency. $TFLI_{i,j}$ is a country- and industry- specific tradability-weighted

_____

[8]Interaction terms between fixed effects are not included to prevent a significant loss in the degree of freedom.

forward linkage index (6 measures as mentioned before), $PIIGS_j$ is a dummy variable equal to 1 for Portugal, Ireland, Italy, Greece, and Spain.

Interpretation of DID estimation equation is described as following:

1) β_1 shows the mean difference in real investment growth of a typical industry in the Eurozone countries before and after the introduction of Euro.

2) β_2 captures difference in real investment growth of a typical industry in non-PIIGS countries before and after the introduction of Euro.

3) $\beta_2 + \beta_3$ captures difference in real investment growth of a typical industry in PIIGS before and after the introduction of Euro.

4) β_3 is DID (Difference In Difference) coefficient which captures difference in real investment growth of a typical industry in PIIGS before and after Euro minus the difference in real investment growth of a typical industry in non-PIIGS before and after Euro.

The key coefficient is β_3 on the triple-interaction term, which shows the difference in real investment growth at the industry level comparing PIIGS and Non-PIIGS and comparing before and after EU-integration.

I repeated running the same panel regression, only changing the dependent variable to real value added growth of the industries.

$$Y_{i,c,t} = \phi_i + \psi_c + \omega_t + \beta_1 Post_{c,t} + \beta_2 Post_{c,t} TFLI_{i,c} + \beta_3 Post_{c,t} TFLI_{i,c} PIIGS_c + \epsilon_{i,c,t} \quad (2)$$

where $Y_{i,c,t}$ is real value-added growth.

Next, to figure out which sectors (tradable or nontradable) were financed by the capital inflows, I run the following panel regression.

$$I_{i,c,t} = \phi_i + \psi_c + \omega_t + \beta_1 Post_{c,t} + \beta_2 Post_{c,t} Trad_{i,c} + \beta_3 Post_{c,t} Trad_{i,c} PIIGS_c + \epsilon_{i,c,t} \quad (3)$$

where $Trad$ is one of the three measures of tradability constructed in section 3.2.

1.3.4 Data

Input-output matrices for OECD countries are published every 5 year by OECD STAN database. TFLI is constructed for 21 industries and 11 Euro zone countries using year 2000 data. Time period spans 10 years from 1994 through 2003, 5 years before and after the introduction of EURO. I used real gross fixed capital formation (STAN code: GFCF) and real gross value added (EUKLEMS: VA_QI) to calculate for real investment growth and real value added growth at the industry level, respectively. Because the industry-level data tend to be quite noisy, I dropped the extreme outliers. I removed 0.5 % of the highest and lowest values in real investment growth.[9] Industry-level value added deflator is provided by EU KLEMS. Data also includes some macroeconomic controls which will be used for robustness check in section 3.6. Real GDP per capita, real GDP growth, interest rates, and share price index are all provided by Oxford Economics.

Next, I used ISIC rev.3 classification for industry breakdown. Originally, OECD STAN has an industry-breakdown of 58 industrial sectors following ISIC rev.3. To make the size of the industries even, small industries were merged into a bigger industry[10] and I ended up with 21 industries. The table for these 21 industries is presented in figure 5 in the appendix.

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[9]I also removed Financial Intermediation industry (C65T67) due to its extreme volatility in real investment growth. For example, in Finland, real investment growth in this industry was 1100% during 1998.

[10]If a small industry has no upper category to be merged into, no change was made.

1.3.5 Empirical Results

All the panel regression results for (1), (2), and (3) are documented in the appendix tables. Table 6 and Table 7 are the results when I used the Leontief and Ghosh approach to measure forward linkages, respectively. Each column of the table represents which measure of tradability was used. For example, Leontief_EI corresponds to TFLI constructed using Leontief approach and export intensity (ES and TI stand for export share and tradability index, respectively). Table 6 and 7 show that both Leontief and Ghosh approaches produce similar results. Real investment growth in a typical industry is about 4.5% higher following the introduction of Euro. This result is consistent with Dvorak [2006]. The second coefficient which captures difference in real investment growth of a typical industry in non-PIIGS countries before and after the introduction of Euro is not significant. This means that there was no significant difference, before and after the EURO integration, in investment of the industries in non-PIIGS depending on the industries' forward linkages to the T-sector. Lastly, the coefficients on the triple interaction terms are all negative and statistically significant at more than 5% levels. This means that the introduction of Euro enhanced investment in the industries with weak forward linkages to the T-sector disproportionately only in PIIGS. In other words, it implies that the large capital inflows to Eurozone which started after the introduction of Euro mainly financed the industries that have weak forward linkages to T-sector only in PIIGS. For all 6 cases, the Wald test cannot reject the null hypothesis that $\beta_2 = 0$ (After the introduction of EURO, in Non-PIIGS, industries' investment growth rates are uniform regardless of their forward linkages to the T-sector) while the test rejects the null that $\beta_2 + \beta_3 = 0$ (After the introduction of EURO, in PIIGS, industries' investment growth rates are uniform regardless of their forward linkages to the T-sector). This again shows that

industry's post-EURO investment growth varies depending on their forward linkages to the T-sector only in PIIGS.

In Table 15, top 25% and bottom 25% average of all 6 $TFLI$'s are calculated for PIIGS. For example, 0.897 captures the average $TFLI$ of the industries in Spain which have the top 25% highest $TFLI$ measured by Leontief approach with export intensity. Plugging the average numbers into the panel regression equation (point estimation), post-EURO investment growth of the industries in the top 25% and the bottom 25% can be estimated. The results show that, on average in PIIGS, the industries which have strong forward linkages to T-sector (belong to the top 25%) had real investment growth of nearly 0% while the industries which have weak forward linkages to T-sector (belong to the bottom 25%) had real investment growth of approximately 4% after the introduction of Euro.

Table 8 and 9 show the results for the regression equation (2) when industry's real value added growth was used for the dependent variable. Real value-added growth in a typical industry is about 1.2% higher following the introduction of the Euro. The second coefficients are all not significant again. The coefficients of the triple interaction term are all negative and half of them (3 out of 6) are significant. This means that the industries that have weak forward linkages to the T-sector grew faster after the introduction of Euro only in PIIGS. This again reinforces the previous observations that the capital inflows to PIIGS primarily benefited the industries that have weak forward linkages to the T-sector after the introduction of Euro.

Finally, table 14 shows the result for the regression equation (3). The coefficient on the first term has the same interpretation as in equation (1) and the results are similar. The coefficient on the second term is not significant, which means that before and after the EURO there was no significant difference in industry's investment depending on its tradability in non-PIIGS. DID coefficients are all negative and significant, which

implies that after the EURO investment grew faster in the industries which have low tradability only in PIIGS. For all 3 measures of tradability, the Wald test cannot reject the null hypothesis that $\beta_2 = 0$ (After the introduction of Euro, in Non-PIIGS, industries' investment growth rates are uniform regardless of their tradability) while the test rejects the null that $\beta_2 + \beta_3 = 0$ (After the introduction of Euro, in PIIGS, industries' investment growth rates are uniform regardless of their tradability). This shows that the EURO enhanced investment in the N-sector disproportionately only in PIIGS.

In Table 16, top 25% and bottom 25% average of all 3 measures of tradability are calculated for PIIGS. Point estimation from panel regression yields the estimated value for post-EURO investment growth of the industries in the top 25% and the bottom 25%. The results show that, on average in PIIGS, the industries which have high tradability (belong to the T-sector) had real investment growth of -2% $\sim$ 1.4% while the industries which have low tradability (belong to the N-sector) had real investment growth of 3.3% $\sim$ 5.5% after the introduction of EURO.

In summary, there were large capital inflows to PIIGS in the form of debt after they joined the currency union and the empirical results show that these capital inflows mainly financed the industries with low tradability (N-sector) and the industries with weak forward linkages to the T-sector. And this asymmetric allocation of the capital inflows did not take place in non-PIIGS.

1.3.6 Robustness Check

To check robustness of the estimation results, I include a set of macroeconomic controls. I closely follow Bris et al. [2006] and Dvorak [2006]. First, I include lagged real GDP growth to capture accelerating effect of output on investment (Clark [1979]). Second, I include lagged log value of real GDP per capita as a measure of a country's

economic development. Third, I also include lagged real aggregate stock market returns as a proxy for Tobin's q and a financial accelerator. Finally I include lagged interest rates. As shown in table 10, and 11, 12, and 13, adding the macroeconomic controls did not change the results much. It obviously diluted the statistical significance of the first coefficients explaining real investment growth in a typical industry after the introduction of Euro. However, it did not alter the results on DID coefficients, which is the key result of the panel regressions.

1.3.7 Firm-level Evidence

This section provides the firm-level evidence reinforcing the industry-level empirical results that the capital inflows to PIIGS benefited the N-sector more than the T-sector. Using Italy's firm-level data, I test if the firms in the N-sector experienced the relaxation of financial constraints after the introduction of Euro. The Euler-equation framework and the GMM-difference estimator proposed by Arellano and Bond [1991] are used to check the relaxation of financial constraints. I closely follow Gilchrist and Himmelberg [1999] and Forbes [2007] to obtain the following Euler eqaution. Each firm maximizes the expected NPV of dividends such that capital accumulation constraint.

$$V_t(K_t, \xi_t) = \max_{I_{t+s}} D_t + E_t[\sum_{s=1}^{\infty} \beta_{t+s-1} D_{t+s}]$$

$$\text{subject to } D_t = \prod(K_t, \xi_t) - C(I_t, K_t) - I_t \tag{4}$$

$$K_{t+1} = (1 - \delta)K_t + I_t$$

$$D_t \geqslant 0$$

where ξ_t is a productivity shock, $\prod$ profit function, and C is the adjustment cost

function.

Solving the dynamic equations yields the Euler Equation.

$$1 + \frac{\partial C(I_t, K_t)}{\partial I_t} = \beta_t E_t [\frac{1 + \lambda_{t+1}}{1 + \lambda_t} \{ \frac{\partial \prod(K_{t+1}, \xi_{t+1})}{\partial K_{t+1}} + (1 - \delta)(1 + \frac{\partial C(I_{t+1}, K_{t+1})}{\partial I_{t+1}}) \}] \quad (5)$$

where λ_t is a multiplier for the constraint, $D_t \geqslant 0$.

Since λ_t is the Lagrangian multiplier for the financing constraint, $\Theta_t \equiv \frac{1 + \lambda_{t+1}}{1 + \lambda_t}$ is the key variable, which is the relative shadow cost of external financing in period $t + 1$ versus period t (i.e., the measure of financial constraints). Under perfect capital markets, $\lambda_t = \lambda_{t+1}$ and $\Theta_t = 1$. If the shadow cost of external funds is higher today (at t) than tomorrow (at $t + 1$), then $\frac{1 + \lambda_{t+1}}{1 + \lambda_t}$ and $\Theta_t < 1$, which means that the firm is financially constrained. Next, to estimate Eq. (5), assume that the term measuring financial constraints can be written as a function of firm-specific financing constraints and the firm's cash stock at the start of the period, then we can parametrize Θ_{it} as function of a firm's indicator of financial health (cash stock) and size.

$$\Theta_{it} = \frac{1 + \lambda_{t+1}}{1 + \lambda_t} = \psi_{0i} + (\psi_1 + \psi_2 Size_{it})(\frac{Cash}{K})_{it} \quad (6)$$

Also, define MPK_t as the marginal profit of capital, net of adjustment costs and financing costs (which is the term in {} in the Euler equation). If f production follows a CobbDouglas function, then MPK_t can be expressed as:

$$MPK_{it} = \vartheta_i + \vartheta_{1,t}(\frac{Sales}{K})_{it} \quad (7)$$

where ϑ_i is a firm-fixed effect, $\vartheta_{1,t}$ is the ratio of capital's share in production to the markup, and $Sales$ is total sales.

With the standard assumptions of linear homogeneity in capital and investment, capital adjustment cost is specified to obtain a closed-form solution. Then marginal adjustment cost turns out to be

$$\left(\frac{\partial C}{\partial I}\right)_t = \frac{1}{\alpha_1}\left[\left(\frac{I}{K}\right)_t - \alpha_2\left(\frac{I}{K}\right)_{t-1} - \alpha_i + \alpha_t\right] \tag{8}$$

where α_1 and α_2 are constants, α_i is a fixed effect for a firm i, and α_t is a period-specific effect.

Since $E\frac{1+\lambda_{t+1}}{1+\lambda_t} \cong 1$, first-order Taylor approximation around the means and inserting the equations (6), (7), and (8) back to the Euler equation yields the following estimating equation.

$$\left(\frac{I}{K}\right)_{it} = \theta_0 + \theta_1\left(\frac{I}{K}\right)_{i,t-1} + \theta_2\left(\frac{Sales}{K}\right)_{it} + \theta_3\left(\frac{Cash}{K}\right)_{it} + \theta_4\left(\frac{Cash}{K}*Size\right)_{it} + f_i + d_t + \epsilon_{it} \tag{9}$$

Adding the time dummy in the equation (9), I have the following equation to be estimated.

$$\left(\frac{I}{K}\right)_{it} = \theta_0 + \theta_1\left(\frac{I}{K}\right)_{i,t-1} + \theta_s\left(\frac{Sales}{K}\right)_{it} + \theta_{sm}\left(\frac{Cash}{K}*SM\right)_{it} +$$
$$\theta_l\left(\frac{Cash}{K}*Large\right)_{it} + \theta_{psm}*post*\left(\frac{Cash}{K}*SM\right)_{it} + \theta_{pl}*post*\left(\frac{Cash}{K}*Large\right)_{it} + f_i + d_t + \epsilon_{it}$$
$$\tag{10}$$

where *post* is a dummy variable equal to 1 when $t > 2000$.[11] *SM* and *large* are dummy variables that take the value of 1 for small, medium-sized enterprises

---

[11]Since the panel data is very unbalanced in the sense that the number of observations before 1999 is too small, I let the time dummy to be 1 when $t > 2000$ instead of $t > 1998$ (introduction of EURO). So, the period 1994-2000 and 2001-2005 are compared.

(henceforth SME) and large enterprises respectively. Following the classification of BvD Amadeus, large firms and SME are classified by the size of total assets (Large if total assets $\geq$ 20 million Euros, SME otherwise).

A test if the financial constraints exist for the SME before the introduction of Euro and decrease after the EURO is a test of the null hypothesis that $\theta_{sm} = 0$ and $\theta_{psm} = 0$ (against the alternative hypothesis that $\theta_s m > 0$ and $\theta_{psm} < 0$). Likewise, to investigate if the financial constraints exist for the large firms before the introduction of Euro and had been relaxed after the EURO, the null hypothesis that $\theta_l = 0$ and $\theta_{pl} = 0$ is tested against the alternative hypothesis that $\theta_l > 0$ and $\theta_{pl} < 0$). Since many of the variables are jointly endogenous and the lagged endogenous variable for investment will bias coefficient estimates, GMM-difference estimator developed by Arellano and Bond [1991] and Arellano and Bover [1995] is used. This estimator considers the equation in first-difference to remove fixed effect f_i, and then uses lagged levels of the variables as instruments.

The firm-level data is obtained from AMADEUS which is provided by Bureau van Dijk (BvD). It contains financial information on millions of publicly traded and private firms across the European countries. The variables used are summarized in table 2.

To classify the firms into the T-sector and the N-sector, I use table 5 in the appendix.[12] The criteria for this classification will be explained in section 4.7. The sample period spans from 1994 to 2005. Since BvD Amadeus through WRDS (Wharton Research Data Services) is not providing the data before 2000 for Portugal, Ireland, Greece, and Spain, the firm-level analysis for those countries could not be conducted.

I excluded outliers and unrealistic observations for the variables used to estimate

---

[12]Since BvD Amadeus is based on NACE Rev. 2 code (Figure 9) for its industry classification, I used correspondence tables between ISIC rev. 3 and NACE rev. 2.

Table 2: Variable Definitions

Variable	Code	Definition
Capital Stock	K	Tangible fixed assets, that is property, plant and equipment reported at the end of the period. Calculated at start-of-period.
Cash Stock	Cash	Cash and equivalents. Calculated at start-of-period.
Depreciation		Depreciation of tangible fixed assets
Investment	I	Capital expenditures used to acquire tangible fixed assets. Calculated as the difference between tangible fixed asset at the end-of-period and start-of-period, plus depreciation.
Sales	Sales	Gross sales, adjusted for inflation. Reported at the end of period.
Total Assets		Total assets, adjusted for inflation. Reported at the end of the period.

the equation (10). I followed the same criteria as in Forbes [2007] for removing outliers. Individual observations were excluded when:

- $K \leq 0$

- $\frac{I}{K} < 0$ or $\frac{I}{K} > 3$

- $\frac{Cash}{K} < 0$ or $\frac{Cash}{K} > 10$

- $\frac{Sales}{K} < 0$ or $\frac{Sales}{K} > 10$

The estimation results are in table 3. As shown in the table, there were no significant changes made in the financial constraints of the firms in the T-sector after the introduction of Euro. In the N-sector, however, both SME and large firms which were financially constrained before the EURO experienced significant relaxation of financial constraints after the introduction of Euro. For both sectors, the Sargan test statistics indicate that it is impossible to reject the null hypothesis that over-identifying restrictions are valid. This result reinforces the industry-level analysis in

Table 3: Estimation results of (5) using Italy's firm-level data

Firm-level Empirical Results (Italy)		
	N-sector	T-sector
$Investment_{t-1}$	0.102***	0.0776***
	(0.0112)	(0.00904)
$Sales$	0.0839***	0.0767***
	(0.0153)	(0.0177)
$Cash * SM(\theta_{sm})$	0.238***	0.0741
	(0.0648)	(0.0600)
$Cash * Large(\theta_l)$	0.369***	-0.124
	(0.0710)	(0.537)
$Post * Cash * SM(\theta_{psm})$	-0.119*	0.0353
	(0.0650)	(0.0530)
$Post * Cash * Large(\theta_{pl})$	-0.258***	0.157
	(0.0661)	(0.539)
# of Observations	24,704	28,303
# of Firms	21,641	23,650
Sargan Test	60.39	100.4

section in 3.5 that the capital inflows to PIIGS benefited the N-sector more than the T-sector.

In the next section, I introduce a simple model economy explaining why PIIGS could not repay their debt when the capital inflows in the form of debt mainly finance the N-sector and the industries with weak forward linkages to the T-sector.

1.4 Model Economy

I build a two-period (t and $t+1$) and two-sector (N-sector and T-sector) model based on Schneider and Tornell [2004]. There are two subsectors (industries), N_1 and N_2 in the N-sector. There are three goods in this economy. A final and tradable good (hereafter T-good) produced by the T-sector and two intermediate goods (N_1-good and N_2-good) which are used as inputs in the production of T-goods or consumed by consumers. Relative prices of N_1-good and N_2-good are defined as the ratios of

prices of N_1-good and N_2-good to price of T-good (price of T-good is a numeraire):

$$p_t^1 = \frac{p_t^{N_1}}{p_t^T} \; , \; p_t^2 = \frac{p_t^{N_2}}{p_t^T}$$

1.4.1 Agents

There are two agents in this model economy. First, there are competitive and risk neutral foreign investors with deep pockets whose cost of funds equals the world interest rate r. There is also a representative consumer endowed with labor at the beginning of each time period, $l_t = 1$ and $l_{t+1} = 1$. With labor income, she consumes T-goods, N_1-goods, and N_2-goods to maximize her utility,

$$u_t = (c_t^{N_1})^{\beta_1}(c_t^{N_2})^{\beta_2}(c_t^T)^{1-\beta_1-\beta_2} \tag{11}$$

where $c_t^{N_1}$, $c_t^{N_2}$ and c_t^T are consumption of N_1-goods, N_2-goods and T-goods respectively. And the consumer's preference over time is $u_t + \frac{u_{t+1}}{1+r}$.

1.4.2 Firms

In this model economy, I assume that there are infinite number of homogenous firms in the N_1-sector and N_2-sector. It leads to perfect competition and free entry/exit of the firms. A N_1-firm is endowed with internal fund, w_t^1 (denominated in T-good) at time period t. And due to the borrowing constraint it can borrow T-debt upto,

$$B_t^1 \leq (m-1)w_t^1 \tag{12}$$

from foreign investors.[13] m $(m > 1)$ stands for the borrowing limit due to imperfect contract enforceability (Tornell and Westermann [2005]) when N_1-firm's internal fund

---

[13]Firms in the nontradable sector are usually financially constrained and face enforceability problems which yield the borrowing constraint (Tornell and Westermann [2005]).

is w_t^1. Since the capital inflows (B_t^1)[14] to N_1-firm is denominated in T-good, it cannot be repaid with the production of N_1-firm, which is N_1-good, but should be repaid with T-goods produced by T-firm.

N_1-firm's production is linear in its investment:

$$q_{t+1}^{N_1} = \theta_1 I_t^1$$
$$\text{where } I_t^1 = w_t^1 + B_t^1 \tag{13}$$

Production of the N_1-firm is either consumed by the consumer $(c_t^{N_1})$ or used as an intermediate good for T-sector $(d_t^{N_1})$. So we have

$$q_t^{N_1} = c_t^{N_1} + d_t^{N_1} \tag{14}$$

N_2-firm has the same borrowing constraint (identical borrowing limit, m) and linear production function. So we have,

$$B_t^2 \le (m-1)w_t^2 \tag{15}$$

$$q_{t+1}^{N_2} = \theta_2 I_t^2$$
$$\text{where } I_t^2 = w_t^2 + B_t^2 \tag{16}$$

Production of the N_2-firm is also either consumed by the consumer $(c_t^{N_2})$ or used as an intermediate good for T-sector $(d_t^{N_2})$. So its market clear condition is

---

[14]Since B_t^1 captures debt inflows offered by foreign investors, it can be interpreted as the capital inflows to PIIGS.

$$q_t^{N_2} = c_t^{N_2} + d_t^{N_2} \tag{17}$$

T-firm produces T-good combining N_1-goods($d_t^{N_1}$), N_2-goods($d_t^{N_2}$) and labor ($l_t = 1$) using Cobb-Douglas technology.

$$y_t = A_t(d_t^{N_1})^{\alpha_1}(d_t^{N_2})^{\alpha_2}(l_t)^{1-\alpha_1-\alpha_2}, \alpha_1, \alpha_2 \in (0,1) \tag{18}$$

where A_t is productivity of T-firm. $A_t = A_L$ (bad state) with probability u and $A_t = A_H$ (good state) with probability $1 - u$. The key parameters in this equation are α_1 and α_2 which capture N_1- and N_2- sector's forward linkages to the T-sector, respectively.[15] Assume that N_1-firm has stronger forward linkages to T-sector than N_2-firm ($\alpha_1 > \alpha_2$). According to Figure 1, N_1-firm corresponds to industry j and N_2-firm corresponds to industry i.

The diagram below describes the flow of goods in this model economy.

1.4.3   Equilibrium

T-firm's profit maximization yields:

$$\text{Demand for } N_1\text{-good: } d_t^{N_1} = \frac{\alpha_1 y_t}{p_t^1}$$

$$\text{Demand for } N_2\text{-good: } d_t^{N_2} = \frac{\alpha_2 y_t}{p_t^2} \tag{19}$$

$$\text{Consumer's labor income: } v_t = (1 - \alpha_1 - \alpha_2)y_t$$

Consumer's utility maximization with the labor income yields demands for N-

---

[15]α_1 and α_2 correspond to TFLI of N_1- and N_2-sector.
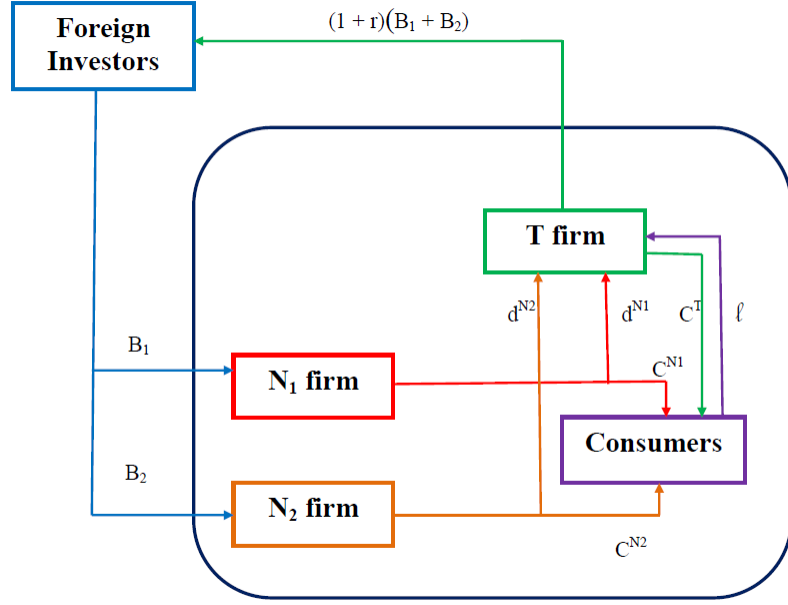
Figure 3: Model Diagram

goods and T-goods.

$$\text{Demand for } N_1\text{-good: } c_t^{N_1} = \frac{\beta_1(1 - \alpha_1 - \alpha_2)y_t}{p_t^1}$$

$$\text{Demand for } N_2\text{-good: } c_t^{N_2} = \frac{\beta_2(1 - \alpha_1 - \alpha_2)y_t}{p_t^2} \tag{20}$$

$$\text{Demand for T-good: } c_t^T = (1 - \beta_1 - \beta_2)(1 - \alpha_1 - \alpha_2)y_t$$

Combining equation (18) and (19),

$$y_t = A_t(\frac{\alpha_1 y_t}{p_t^1})^{\alpha_1}(\frac{\alpha_2 y_t}{p_t^2})^{\alpha_2}$$

$$y_t = [A_t(\frac{\alpha_1}{p_t^1})^{\alpha_1}(\frac{\alpha_2}{p_t^2})^{\alpha_2}]^{\frac{1}{1-\alpha_1-\alpha_2}} \tag{21}$$

Now, the market clear conditions for N_1-goods and N_2-goods pin down prices, p_t^1

and p_t^2. At period t+1,

$$q_{t+1}^{N_1} = c_{t+1}^{N_1}(p_{t+1}^1) + d_{t+1}^{N_1}(p_{t+1}^1)$$

$$q_{t+1}^{N_2} = c_{t+1}^{N_2}(p_{t+1}^2) + d_{t+1}^{N_2}(p_{t+1}^2)$$

(22)

Using equation (19) and (20),

$$\theta_1(w_t^1 + B_t^1) = \frac{\alpha_1 y_{t+1}}{p_{t+1}^1} + \frac{\beta_1(1 - \alpha_1 - \alpha_2)y_{t+1}}{p_{t+1}^1}$$

$$\theta_2(w_t^2 + B_t^2) = \frac{\alpha_2 y_{t+1}}{p_{t+1}^2} + \frac{\beta_2(1 - \alpha_1 - \alpha_2)y_{t+1}}{p_{t+1}^2}$$

(23)

Plugging (21) into (23) and solving for p_{t+1}^1 and p_{t+1}^2 yield

$$p_{t+1}^1 = \frac{[\frac{\theta_2(w_t^2 + B_t^2)}{\eta_2}]^{\alpha_2}}{[\frac{\theta_1(w_t^1 + B_t^1)}{\eta_1}]^{1-\alpha_1}} A_{t+1}(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2}$$

$$p_{t+1}^2 = \frac{[\frac{\theta_1(w_t^1 + B_t^1)}{\eta_1}]^{\alpha_1}}{[\frac{\theta_2(w_t^2 + B_t^2)}{\eta_2}]^{1-\alpha_2}} A_{t+1}(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2}$$

(24)

where $\eta_1 = \alpha_1 + \beta_1(1 - \alpha_1 - \alpha_2)$

and $\eta_2 = \alpha_2 + \beta_2(1 - \alpha_1 - \alpha_2)$

Now we have profit functions for each firm. T-firm's profit is zero, N_1 and N_2 firm's profits at period t+1 are given by

$$\pi_{t+1}^{N_1} = p_{t+1}^1 q_{t+1}^{N_1} - (1+r)B_t^1$$

$$\pi_{t+1}^{N_2} = p_{t+1}^2 q_{t+1}^{N_2} - (1+r)B_t^2$$

(25)

28

Plugging (24) into (25) yields

$$
\pi_{t+1}^{N_1} = [\frac{\theta_2(w_t^2 + B_t^2)}{\eta_2}]^{\alpha_2}[\theta_1(w_t^1 + B_t^1)]^{\alpha_1}(\eta_1)^{1-\alpha_1}A_{t+1}(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2} - (1+r)B_t^1
$$
$$
\pi_{t+1}^{N_2} = [\frac{\theta_1(w_t^1 + B_t^1)}{\eta_1}]^{\alpha_1}[\theta_2(w_t^2 + B_t^2)]^{\alpha_2}(\eta_2)^{1-\alpha_2}A_{t+1}(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2} - (1+r)B_t^2
$$
(26)

1.4.4 Debt Repayment Condition

As explained earlier, foreign investors lend T-goods to N_1- and N_2- firm. Since they cannot repay the debt with N_1-goods and N_2-goods, it should be repaid with T-goods produced by T-firm. Then we have the debt repayment constraint to be

$$
y_{t+1} - c_{t+1}^T \geq (1+r)(B_t^1 + B_t^2) \tag{27}
$$

Plugging (18) and (20) into (27), we have

$$
(1 - (1 - \beta_1 - \beta_2)(1 - \alpha_1 - \alpha_2))A_{t+1}(d_{t+1}^{N_1})^{\alpha_1}(d_{t+1}^{N_2})^{\alpha_2} \geq (1+r)(B_t^1 + B_t^2) \tag{28}
$$

T-goods produced by T-firm will be used for consumption and the rest will be used to repay the debt. In addition, it can be easily proved that $y_{t+1} - c_{t+1}^T$ is equal to the sum of the profits earned by N_1 and N_2-firm $(\pi_{t+1}^{N_1} + \pi_{t+1}^{N_2})$.

Proposition 1.1 *Debt repayment condition, $y_{t+1} - c_{t+1}^T \geq (1+r)(B_t^1 + B_t^2)$ is identical with that the sum of profits earned by N_1-firm and N_2-firm is positive,*
$\pi_{t+1}^{N_1} + \pi_{t+1}^{N_2} \geq 0.$

Proof. $\pi_{t+1}^{N_1} + \pi_{t+1}^{N_2} = p_{t+1}^1 q_{t+1}^{N_1} - (1+r)B_t^1 + p_{t+1}^2 q_{t+1}^{N_2} - (1+r)B_t^2$ by (18)
$= p_{t+1}^1 \theta_1(w_t^1 + B_t^1) + p_{t+1}^2 \theta_2(w_t^2 + B_t^2) - (1+r)(B_t^1 + B_t^2)$

$$= p_{t+1}^1 \left(\frac{\alpha_1 y_{t+1}}{p_{t+1}^1} + \frac{\beta_1(1-\alpha_1-\alpha_2)y_{t+1}}{p_{t+1}^1} \right) + p_{t+1}^2 \left(\frac{\alpha_2 y_{t+1}}{p_{t+1}^2} + \frac{\beta_2(1-\alpha_1-\alpha_2)y_{t+1}}{p_{t+1}^2} \right) - (1+r)(B_t^1 + B_t^2)$$

by (16)

$$= \alpha_1 y_{t+1} + \beta_1(1-\alpha_1-\alpha_2)y_{t+1} + \alpha_2 y_{t+1} + \beta_2(1-\alpha_1-\alpha_2)y_{t+1} - (1+r)(B_t^1 + B_t^2)$$

$$= (1 - (1-\beta_1-\beta_2)(1-\alpha_1-\alpha_2))y_{t+1} - (1+r)(B_t^1 + B_t^2)$$

$$= y_{t+1} - c_{t+1}^T - (1+r)(B_t^1 + B_t^2) \quad \blacksquare$$

1.4.5 Conditions Describing the Debt Problem of PIIGS

To make things simple, I assume that $B_t^2 = 0$ (N_2-firm received no debt from foreign investors and produced only using its initial internal fund) before the EURO and $B_t^2 = (m-1)w_t^2$ (N_2-firm borrowed from foreign investors until its borrowing constraint binds) after the EURO. In other words, N_1-firm had no access to the international financial markets before the EURO but the EURO integration enabled it to borrow from the international financial markets. On the other hand, $B_t^1 = (m-1)w_t^1$ before and after the EURO (no difference in N_1-firm's investment). This assumption is also consistent with the empirical findings that the industries which have strong forward linkages to T-sector had real investment growth of nearly 0% while the industries which have weak forward linkages to T-sector had real investment growth of approximately 4% after the introduction of Euro.

First, the expected N_2-firm's profit should be positive at $B_t^2 = (m-1)w_t^2$. Since there are infinite number of firms in N_2-sector with perfect competition, if the expected N_2-firm's profit is positive then firms will enter until its profit turns to be zero. Due to the borrowing constraint, if expected N_2-firm's profit is positive at $B_t^2 = (m-1)w_t^2$ then firms will enter with new borrowing until the total borrowing (B_t^2) is equal to $(m-1)w_t^2$. So the first inequality needed is

$$E[(\frac{\theta_1(mw_t^1)}{\eta_1})^{\alpha_1}[\theta_2(mw_t^2)]^{\alpha_2}(\eta_2)^{1-\alpha_2}A_{t+1}(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2} - (1+r)(m-1)w_t^2] \geq 0 \quad (29)$$

where $E[A_{t+1}] = uA_L + (1-u)A_H$.

Second, PIIGS can repay the debt if the capital inflows just finance N_1-firm ($B_t^1 = (m-1)w_t^1$) and not N_2-firm ($B_t^2 = 0$) even in the case when the economy hits the bad state. To explain this the following inequality is needed:

$$A_L(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2}\eta(\theta_1(mw_t^1))^{\alpha_1}(\theta_2 w_t^2)^{\alpha_2} \geq (1+r)(m-1)w_t^1 \quad (30)$$

where $\eta = \frac{\eta_1+\eta_2}{(\eta_1)^{\alpha_1}(\eta_2)^{\alpha_2}}$

Lastly, if the capital inflows finance both N_1-firm ($B_t^1 = (m-1)w_t^1$) and N_2-firm ($B_t^2 = (m-1)w_t^2$) then PIIGS are solvent when the economy is in the good state and insolvent when the economy is in the bad state. This can be explained by

$$A_H(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2}\eta(\theta_1(mw_t^1))^{\alpha_1}(\theta_2(mw_t^2))^{\alpha_2} \geq (1+r)(m-1)(w_t^1 + w_t^2) \quad (31)$$

$$(1+r)(m-1)(w_t^1 + w_t^2) \geq A_L(\alpha_1)^{\alpha_1}(\alpha_2)^{\alpha_2}\eta(\theta_1(mw_t^1))^{\alpha_1}(\theta_2(mw_t^2))^{\alpha_2} \quad (32)$$

1.4.6 Implications of the Model Economy

In summary, (29) through (32) characterize and explain why PIIGS had a difficulty in repaying their debt. Financial integration (EURO) enabled N_2-firm which were financially constrained before EURO to borrow from foreign investors. Since N_2-firm has weak forward linkages to T-sector, excessive debt flows invested into N_2-firm

would not lead to enough production of T-goods to repay the debt. Foreign investors are aware of possibility of default in debt repayment but due to the implicit bailout-guarantee by ECB they are willing to lend. Equation (29) shows why N_2-firm is willing to borrow until its borrowing constraint binds after financial integration. Equation (30) implies that if N_2-firm is not borrowing from foreign investors or no excessive debt built up for N_2-firm (describing the pre-EURO situation), then even though the economy falls into the bad state, the debt can be repaid. Equation (31) and (32) indicate that if N_2-firm borrows from foreign investors excessively, the economy might have difficulty in repaying the debt when the economy hits the bad state. In conclusion, misallocation of the capital inflows in terms of input-output linkages might put a country in a bad position to repay the debt in the case that the country received large capital inflows with government's implicit bailout-guarantee.

1.4.7 Calibration

In this section, I calibrate the parameters used in the model economy and check if the solution satisfying inequalities (29) through (32) exists. First, the industries should be classified into tradable and nontradable sectors. Adopting a 10% threshold for export intensity, as in De Gregorio and Wolf [1994] and Betts and Kehoe [2001], the industries can be classified into the T-sector and the N-sector. In Figure 9, the cells are highlighted when it is above the 10% threshold. And the last column counts the number of highlighted cells for 11 Eurozone countries. This shows that C01T05 through C36T37 (agriculture, mining, and manufacturing industries) and C65T67 (transport, storage and communications) belong to T-sector whereas C40T41, C45, C55, C65T67, C70, and C75T99 (construction and service industries) belong to N-sector. C50T52 and C71T74 (wholesale and retail trade and renting of machine and equipment) are in the middle range, which do not belong to either sector. This result

is almost similar to the classification of Schmillen [2011] and Lombardo and Ravenna [2012].

Next, I measure each industry (belongs to the N-sector)'s forward linkages to the T-sector by using Ghosh approach. The results are in table 4 in the appendix. It turns out to be that C40T41 (Electricity gas and, water supply) and C65T67 (Financial intermediation) have strong forward linkages to the T-sector whereas C45 (Construction) and C75T99 (Community, Social and Personal Services) have weak forward linkages to the T-sector. Mapping this into the model economy, the former industries correspond to N_1-firm and the latter to N_2-firm. So I set α_1 to be 0.4 and α_2 to be 0.1. Consumption share for nontradable goods is 0.75 according to Burstein et al. [2004]. Assuming that consumption share on N_1-goods and N_2-goods are the same, β_1 is 0.375 and β_2 is 0.375. The borrowing limit m is set to be 2.28 as in De Fiore and Uhlig [2012]. Risk-free interest rate (r) is calibrated to be 0.0374, which is the average U.S. T-bill rate during 1994-2003. N-sector's average productivity (θ) is calibrated to be 7.04[16] and assume that both N_1- and N_2-firm have the same productivity. $A_H = 1$ with probability 0.9 and $A_L = 0.8$ with probability $u = 0.1$. Initial internal funds at time t for N_1- and N_2-firm (w_t^1 and w_t^2) are free values to meet the other parametric conditions.

Plugging the calibrated values into the inequalities (29) through (32) and letting w_t^1 and w_t^2 be free give the curves in Figure 10. The overlapped part of the 4 ranges from 4 inequalities((29) - (32)) proves the existence of solutions in the model economy.

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[16]This is the average productivity of the nontradable sector in 11 Eurozone countries. Calculations are based on input-output tables of year 2000 data.

1.5 Conclusion

Southern European countries have gone through a severe debt crisis recently. In this paper, I show that one of the main reasons that triggered this debt crisis lies in domestic misallocation of the capital inflows in terms of inter-industry linkages after the introduction of Euro. Financial integration enabled PIIGS to receive the large capital inflows with implicit bailout guarantee. These capital inflows did finance the industries with weak forward linkages to the T-sector, which caused a reduction in capacity to produce T-goods to repay their debt over the medium term. In this sense input-output analysis is at the core of this paper. The misallocation is well evidenced at the aggregate level, too. Figure 12 shows that the sectoral linkage between the N-sector and the T-sector had been reduced after EURO in PIIGS in contrast to Non-PIIGS. Moreover, production of the T-sector in the share of total GDP plummeted after EURO in PIIGS.

Many literature[17] indicate that the capital inflows to PIIGS mostly financed the real estate boom.[18] Construction industry is classified to the N-sector and has weak forward linkages to the T-sector (see Table 4 and 5). Therefore the housing boom in PIIGS after the EURO integration directly supports the empirical results in this paper.

The policy implication of this paper is that if a country receives large debt inflows with implicit bailout guarantee, the domestic allocation of the capital inflows in terms of inter-industry linkages should be considered to avoid any debt repayment problems.

The question why the capital inflows to PIIGS financed the industries with weak forward linkages to the T-sector remains to be answered in the future research.

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[17]Capital inflows to PIIGS have mostly financed housing boom (investment in the N-sector) and consumption boom Lane [2013a].

[18]Figure 8 shows investment in construction for PIIGS and Germany.

1.6 Appendix

1.6.1 Tables and Figures

Table 4: N-sector's Forward Linkages to T-sector

Forward Linkages to T-sector of the Industries in N-sector												
	AUT	BEL	FIN	ESP	FRA	GER	ITA	GRC	IRL	NLD	PRT	Avg
C40T41 Electricity gas and, water supply	0.363769	0.530666	0.719904	0.67591	0.419677	0.53992	0.705233	0.389862	0.439636	0.420978	0.418502	**0.511278**
C45 Construction	0.078561	0.169475	0.075103	0.063561	0.0648	0.088947	0.170455	0.063713	0.04665	0.067949	0.081531	**0.088249**
C55 Hotels and restaurants	0.097688	0.21054	0.214023	0.060648	0.140676	0.067655	0.176684	0.02217	0.185715	0.176541	0.106356	**0.132609**
C65T67 Financial intermediation	0.375084	0.30883	0.585541	0.30109	0.388206	0.255822	0.482126	0.194526	0.23279	0.303341	0.343699	**0.342823**
C70 Real estate activities	0.119706	0.114515	0.10937	0.130206	0.096846	0.180815	0.167929	0.084264	0.034226	0.074312	0.095187	**0.109762**
C75T99 Community, Social and Personal Services	0.038174	0.045018	0.072552	0.060601	0.061468	0.078557	0.071322	0.00951	0.027352	0.063533	0.04454	**0.052057**

Table 5: Classification of the Industries into T-sector and N-sector

T-sector	N-sector
C01T05 Agriculture, Hunting, Forestry and Fishing	C40T41 Electricity Gas and, Water Supply
C10T14 Mining and Quarrying	C45 Construction
C15T16 Food Products, Beverages and Tobacco	C55 Hotels and Restaurants
C17T19 Textiles, Textile Products, Leather and Footwear	C65T67 Financial Intermediation
C20 Wood and Products of Wood and Cork	C70 Real Estate Activities
C21T22 Pulp, Paper, Paper Products, Printing and Publishing	C75T99 Community, Social and Personal Services
C23T25 Chemical, Rubber, Plastics and Fuel Products	
C26 Other Non-metallic Mineral Products	
C27T28 Basic Metals and Fabricated Metal Products	
C29T33 Machinery and Equipment	
C34T35 Transport Equipment	
C36T37 Manufacturing n.e.c. and Recycling	
C60T64 Transport, Storage, and Communications	

T-statistics calculated using robust and country clustered standard errors.

∗, ∗∗, ∗ ∗ ∗ indicate significance at the 10, 5, and 1 % levels.

Table 6: Does the impact of the EURO vary across industries and countries?
Real Investment Growth (Leontief Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.052** (0.018)	0.043** (0.018)	0.032 (0.018)
POST × Leonief_EI	-0.02 (0.017)		
POST × Leonief_EI × PIIGS	-0.046** (0.016)		
POST × Leonief_ES		0.006 (0.045)	
POST × Leonief_ES × PIIGS		-0.168** (0.069)	
POST × Leonief_TI			0.052 (0.040)
POST × Leonief_TI × PIIGS			-0.199** (0.086)
Number of Observations	2094	2094	2094
R-Squared	0.102	0.1	0.099

Table 7: Does the impact of the EURO vary across industries and countries?
Real Investment Growth (Ghosh Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.048** (0.019)	0.047** (0.020)	0.037* (0.018)
POST × Ghosh_EI	-0.005 (0.002)		
POST × Ghosh_EI × PIIGS	-0.041*** (0.013)		
POST × Ghosh_ES		-0.015 (0.010)	
POST × Ghosh_ES × PIIGS		-0.103** (0.044)	
POST × Ghosh_TI			0.001 (0.023)
POST × Ghosh_TI × PIIGS			-0.167** (0.078)
Number of Observations	2094	2094	2094
R-Squared	0.103	0.102	0.099

Table 8: Does the impact of the EURO vary across industries and countries?
Real Value Added Growth (Leontief Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.014*** (0.004)	0.010** (0.004)	0.011*** (0.003)
POST × Leonief_EI	-0.001 (0.007)		
POST × Leonief_EI × PIIGS	-0.014** (0.006)		
POST × Leonief_ES		0.026 (0.036)	
POST × Leonief_ES × PIIGS		-0.040 (0.034)	
POST × Leonief_TI			0.006 (0.010)
POST × Leonief_TI × PIIGS			-0.044** (0.019)
Number of Observations	2178	2178	2178
R-Squared	0.187	0.185	0.185

Table 9: Does the impact of the EURO vary across industries and countries?
Real Value Added Growth (Ghosh Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.014*** (0.003)	0.012*** (0.003)	0.012*** (0.003)
POST × Ghosh_EI	-0.000 (0.002)		
POST × Ghosh_EI × PIIGS	-0.011*** (0.003)		
POST × Ghosh_ES		0.002 (0.011)	
POST × Ghosh_ES × PIIGS		-0.021 (0.014)	
POST × Ghosh_TI			-0.004 (0.007)
POST × Ghosh_TI × PIIGS			-0.037 (0.021)
Number of Observations	2178	2178	2178
R-Squared	0.187	0.185	0.185

Table 10: Does the impact of the EURO vary across industries and countries? Real Investment Growth with Macro Controls (Leontief Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.039* (0.020)	0.034 (0.020)	0.024 (0.019)
POST × Leonief_EI	-0.17 (0.014)		
POST × Leonief_EI × PIIGS	-0.034* (0.017)		
POST × Leonief_ES		0.004 (0.035)	
POST × Leonief_ES × PIIGS		-0.165*** (0.041)	
POST × Leonief_TI			0.030 (0.028)
POST × Leonief_TI × PIIGS			-0.188*** (0.051)
Macro Controls	Yes	Yes	Yes
Number of Observations	1973	1973	1973
R-Squared	0.108	0.108	0.107

Table 11: Does the impact of the EURO vary across industries and countries? Real Investment Growth with Macro Controls (Ghosh Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.035 (0.022)	0.037 (0.022)	0.029 (0.020)
POST × Ghosh_EI	-0.004 (0.003)		
POST × Ghosh_EI × PIIGS	-0.034*** (0.011)		
POST × Ghosh_ES		-0.012 (0.014)	
POST × Ghosh_ES × PIIGS		-0.100** (0.034)	
POST × Ghosh_TI			-0.012 (0.020)
POST × Ghosh_TI × PIIGS			-0.155** (0.065)
Macro Controls	Yes	Yes	Yes
Number of Observations	1973	1973	1973
R-Squared	0.109	0.109	0.107

Table 12: Does the impact of the EURO vary across industries and countries? Real Value Added Growth with Macro Controls (Leontief Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.006 (0.005)	0.004 (0.005)	0.006* (0.003)
POST × Leonief_EI	0.007 (0.009)		
POST × Leonief_EI × PIIGS	-0.019 (0.012)		
POST × Leonief_ES		0.045 (0.043)	
POST × Leonief_ES × PIIGS		-0.064 (0.047)	
POST × Leonief_TI			0.010 (0.009)
POST × Leonief_TI × PIIGS			-0.082*** (0.020)
Macro Controls	Yes	Yes	Yes
Number of Observations	2038	2038	2038
R-Squared	0.203	0.203	0.202

Table 13: Does the impact of the EURO vary across industries and countries? Real Value Added Growth with Macro Controls (Ghosh Approach)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.008** (0.004)	0.008* (0.004)	0.008** (0.003)
POST × Leonief_EI	0.000 (0.003)		
POST × Leonief_EI × PIIGS	-0.012* (0.006)		
POST × Leonief_ES		0.003 (0.012)	
POST × Leonief_ES × PIIGS		-0.028 (0.018)	
POST × Leonief_TI			-0.005 (0.006)
POST × Leonief_TI × PIIGS			-0.054* (0.025)
Macro Controls	Yes	Yes	Yes
Number of Observations	2038	2038	2038
R-Squared	0.203	0.202	0.202

Table 14: Does the impact of the EURO vary across industries and countries? Real Investment Growth (Tradability)

Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)	Coefficient (Std. Err.)
POST	0.056*** (0.017)	0.040** (0.018)	0.034* (0.017)
POST × EI	-0.064 (0.046)		
POST × EI × PIIGS	-0.101** (0.041)		
POST × ES		0.059 (0.088)	
POST × ES × PIIGS		-0.341* (0.160)	
POST × TI			0.066 (0.048)
POST × TI × PIIGS			-0.383** (0.132)
Number of Observations	2094	2094	2094
R-Squared	0.104	0.100	0.099

Table 15: Post-EURO Real Investment Growth of the Industries in PIIGS (TFLI)

	Industry's TFLI (Leontief with Export Intensity)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.897239	0.714249	0.604288	1.847279	0.880298	-0.00722	0.00486	0.012117	-0.06992	-0.0061	-0.01325
Bottom 25% Average	0.103859	0.11123	0.067606	0.171808	0.124878	0.045145	0.044659	0.047538	0.040661	0.043758	0.044352

	Industry's TFLI (Leontief with Export Share)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.300922	0.279652	0.242078	0.35709	0.252209	-0.00575	-0.0023	0.003783	-0.01485	0.002142	-0.0034
Bottom 25% Average	0.027108	0.03307	0.01642	0.010133	0.031459	0.038609	0.037643	0.04034	0.041359	0.037904	0.039171

	Industry's TFLI (Leontief with Tradability Index)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.225283	0.052903	0.068209	0.072158	0.152404	-0.00112	0.024223	0.021973	0.021393	0.009597	0.015214
Bottom 25% Average	0.031958	0.016575	0.007208	0.006048	0.014322	0.027302	0.029563	0.03094	0.031111	0.029895	0.029762

	Industry's TFLI (Ghosh with Export Intensity)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	1.424287	0.97203	0.97712	2.173011	1.250864	-0.01752	0.003287	0.003052	-0.05196	-0.00954	-0.01454
Bottom 25% Average	0.06936	0.102652	0.043106	0.291829	0.083071	0.044809	0.043278	0.046017	0.034576	0.044179	0.042572

	Industry's TFLI (Ghosh with Export Share)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.520569	0.412641	0.47054	0.516384	0.363116	-0.01443	-0.00169	-0.00852	-0.01393	0.004152	-0.00688
Bottom 25% Average	0.029384	0.045811	0.023999	0.043491	0.032205	0.043533	0.041594	0.044168	0.041868	0.0432	0.042873

	Industry's TFLI (Ghosh with Tradability Index)					Post-EURO Investment growth					
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.3364	0.072287	0.102053	0.07507	0.230423	-0.01884	0.025	0.020059	0.024538	-0.00125	0.009901
Bottom 25% Average	0.025144	0.017097	0.010999	0.007464	0.010263	0.032826	0.034162	0.035174	0.035761	0.035296	0.034644

Table 16: Post-EURO Real Investment Growth of the Industries in PIIGS (Tradability)

| | Industry's Tradability (Export Intensity) | | | | | Post-EURO Investment growth | | | | | |
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.359679	0.363471	0.313432	0.853405	0.435901	-0.00335	-0.00397	0.004284	-0.08481	-0.01592	-0.02075
Bottom 25% Average	0.004091	0.005902	0.004348	0.011744	0.011116	0.055325	0.055026	0.055283	0.054062	0.054166	0.054772

| | Industry's Tradability (Export Share) | | | | | Post-EURO Investment growth | | | | | |
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.12372	0.132236	0.143218	0.169004	0.128435	0.005111	0.002709	-0.00039	-0.00766	0.003781	0.000711
Bottom 25% Average	0.001452	0.002	0.002185	0.000952	0.003568	0.039591	0.039436	0.039384	0.039731	0.038994	0.039427

| | Industry's Tradability (Tradability Index) | | | | | Post-EURO Investment growth | | | | | |
	ESP	ITA	GRC	IRL	PRT	ESP	ITA	GRC	IRL	PRT	Average
Top 25% Average	0.118747	0.0232	0.046357	0.038672	0.081554	-0.00364	0.026646	0.019305	0.021741	0.008147	0.014439
Bottom 25% Average	0.004917	0.005253	0.002774	0.001703	0.003448	0.032441	0.032335	0.033121	0.03346	0.032907	0.032853
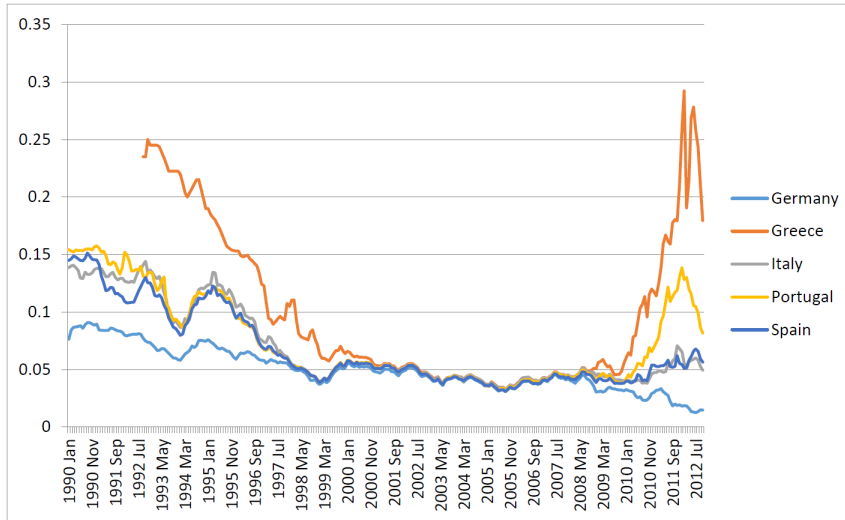
Figure 4: Government Bond Yield for PIIGS and Germany

C01T05 Agriculture, hunting, forestry and fishing	C26 Other non-metallic mineral products	C50T52 Wholesale and retail trade - repairs
C10T14 Mining and quarrying	C27T28 Basic metals and fabricated metal products	C55 Hotels and restaurants
C15T16 Food products, beverages and tobacco	C29T33 Machinery and equipment	C60T64 Transport, storage and communications
C17T19 Textiles, textile products, leather and footwear	C34T35 Transport equipment	C65T67 Financial intermediation
C20 Wood and products of wood and cork	C36T37 Manufacturing n.e.c. and recycling	C70 Real estate activities
C21T22 Pulp, paper, paper products, printing and publishing	C40T41 Electricity gas and, water supply	C71T74 Renting of mach. and equip. - other business activities
C23T25 Chemical, rubber, plastics and fuel products	C45 Construction	C75T99 Community, social and personal services

Figure 5: Industry classification following ISIC rev.3

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Figure 6: 5 Year Average Real Investment Growth for each industry Before and After EURO (Spain)

Figure 7: 5 Year Average Real Investment Growth for each industry Before and After EURO (Germany)

Figure 8: Investment in Construction

Figure 9: NACE Rev. 2 code

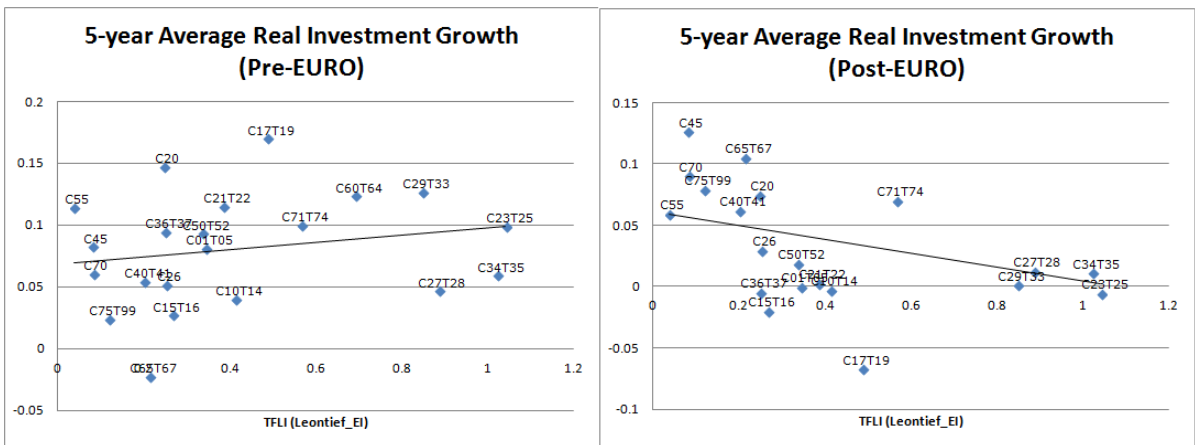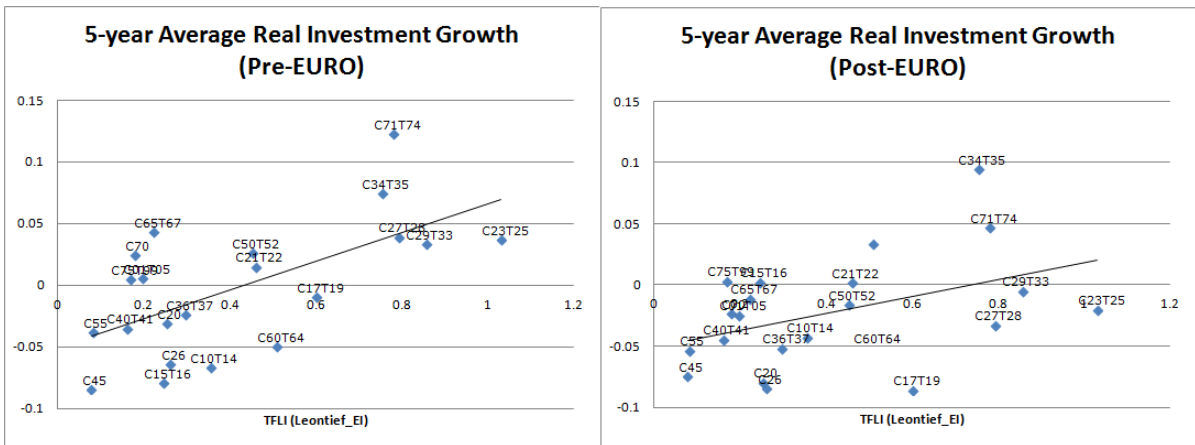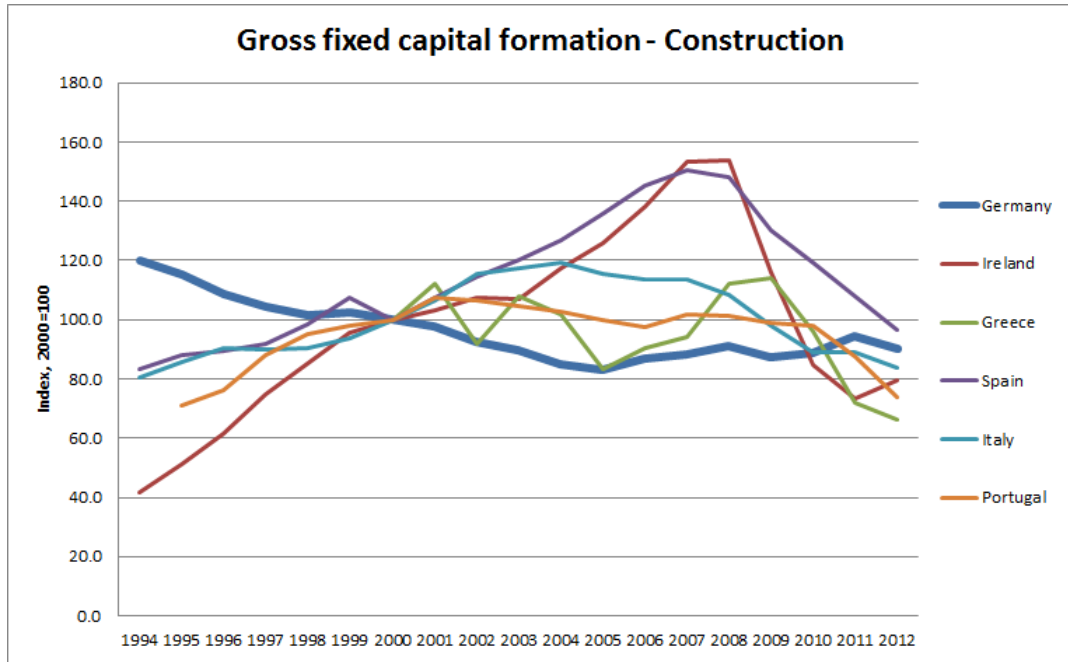| export intensity	AUT	BEL	FIN	ESP	FRA	GER	ITA	GRC	IRL	NLD	PRT		count
C01T05 AGRICULTURE, HUNTING, FORESTRY AND FISHING	0.09374	0.312887	0.06307	0.186154	0.128287	0.111549	0.081514	0.100228	0.117363	0.532086	0.042366		7
C10T14 MINING AND QUARRYING	0.127198	8.790831	0.146511	0.132359	0.120768	0.158618	0.071879	0.265759	0.220706	0.486414	0.17153		10
C15T16 Food products, beverages and tobacco	0.232332	0.530418	0.164787	0.138925	0.183286	0.184252	0.119188	0.107757	0.561765	0.613085	0.102614		11
C17T19 Textiles, textile products, leather and footwear	0.732343	0.929327	0.530955	0.277173	0.46835	0.682588	0.345201	0.365296	1.008217	1.521185	0.419626		11
C20 Wood and products of wood and cork	0.413661	0.556977	0.545	0.109093	0.157872	0.174365	0.094258	0.090534	0.22254	0.33413	0.355702		11
C21T22 Pulp, paper, paper products, printing and publishing	0.438153	0.440164	0.531685	0.150368	0.157841	0.265141	0.11259	0.054343	0.86647	0.297535	0.258048		10
C23T25 Chemical, rubber, plastics and fuel products	0.581579	0.900616	0.465747	0.296808	0.366104	0.460679	0.271198	0.256733	0.946663	0.917782	0.218215		11
C26 Other non-metallic mineral products	0.320604	0.467339	0.240918	0.18286	0.194512	0.200717	0.253467	0.119611	0.449984	0.302025	0.182436		11
C27T28 Basic metals and fabricated metal products	0.536008	0.688616	0.370477	0.202597	0.236628	0.355323	0.215531	0.285389	0.474832	0.644686	0.248348		11
C29T33 Machinery and equipment	0.785415	1.205846	0.600275	0.42908	0.545594	0.555697	0.439558	0.328305	1.092441	1.93973	0.543469		11
C34T35 Transport equipment	1.152732	1.081158	1.023412	0.592736	0.536347	0.578193	0.441382	0.330311	1.085751	0.892564	0.602662		11
C36T37 Manufacturing n.e.c. and recycling	0.424772	1.32376	0.365598	0.167439	0.292745	0.304401	0.350119	0.173539	0.39375	0.427973	0.151148		11
C40T41 ELECTRICITY GAS AND, WATER SUPPLY	0.054093	0.081851	0.003052	0.008884	0.058984	0.022861	0.005891	0.000111	0.00094	0.013042	0.006652		0
C45 CONSTRUCTION	0.035534	0.03305	0	0.002061	0.000203	0.008966	0.004966	0.012153	0.002298	0.013811	0.001722		0
C50T52 Wholesale and retail trade - repairs	0.132594	0.242059	0.001543	0.083919	0.118325	0.100785	0.088325	0.084788	0.045287	0.233289	0.151489		6
C55 Hotels and restaurants	0.005353	0.116693	0.003061	0.00035	0	0.056463	0.001169	0.000774	0.279668	0.001717	0.039543		2
C60T64 TRANSPORT, STORAGE AND COMMUNICATIONS	0.145855	0.318707	0.135144	0.134796	0.176097	0.114846	0.076552	0.472991	0.214393	0.374787	0.161373		10
C65T67 Financial intermediation	0.094784	0.091549	0.004203	0.068393	0.040625	0.048266	0.030643	0.029687	0.363608	0.038339	0.074989		1
C70 Real estate activities	0.003386	0.003215	0	0.000615	0	0.002266	0.013729	0	0	2.6E-05	0.001037		0
C71T74 Renting of mach. and equip. - other business activities	0.149751	0.202722	0.089904	0.126621	0.062299	0.060532	0.052468	0.056483	0.520638	0.155803	0.038935		4
C75T99 COMMUNITY, SOCIAL AND PERSONAL SERVICES	0.007332	0.013566	0.005428	0.008546	0.008511	0.002481	0.00377	0.010578	0.010195	0.02083	0.007234		0

Figure 10: Classification of Industries into the T-sector and the N-sector
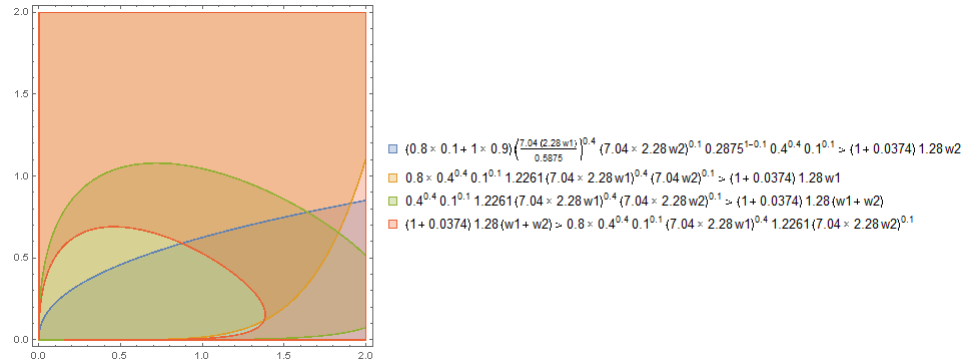
Figure 11: Existence of Solutions in the Model Economy
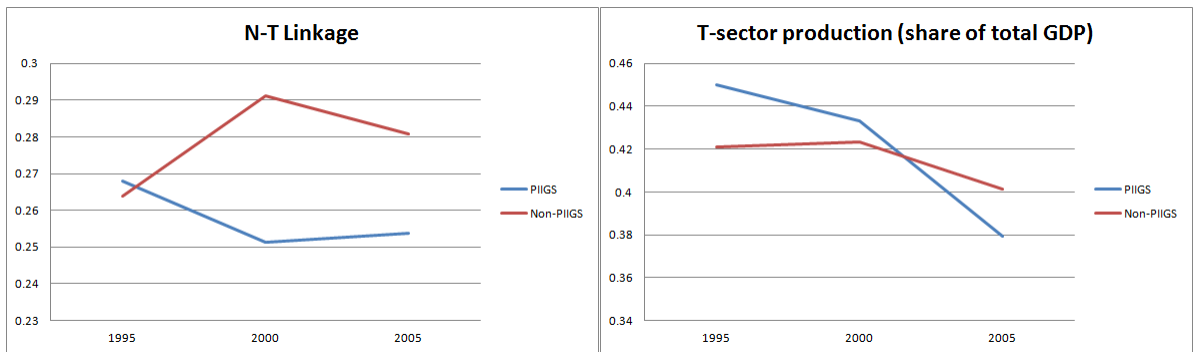
Figure 12: Sectoral linkages and the T-sector's production

2 Economic Recessions & Wildfires

2.1 Introduction

Economic crises, while rare and catastrophic, are not outliers. Our findings suggest that the size distribution of economic crises are a smooth extrapolation of smaller economic distress events, as it is often the case with extreme natural disasters.

We consider all economic distress (ED) events over the period 1970-2014. These ED events range from small deviations from trend-growth to large recessions, to well-known catastrophic crises, such as the 2008 crash, and they cover different economic systems and time periods.

Our contribution is to unearth a remarkable relation between the magnitude of economic distress events and the frequency with which they occur. Figure 14 plots the size of ED events in the abscissa against the (logarithm) of the complementary CDF, i.e., the probability that the distress is larger than a given size. As we can see, from a birds-eye's perspective, a linear regression fits quite well the ED magnitude-frequency data ranging from small economic disturbances to catastrophic crises ($R^2 = 0.995$).

Using the more rigorous statistical techniques of Clauset et al.[2009] , we find that the ED size distribution follows a power law with an exponential cutoff distribution. In other words, there is a threshold $\underline{x}$ below which the size of ED events follows an exponential distribution, while a Pareto distribution (a power-law) applies for ED events larger than $\underline{x}$, as shown in Figure 16. As we can see in the bottom panel, there is a linear relation between log(frequency) and log(magnitude) for ED events greater than $\underline{x}$. Meanwhile, in the top panel, we see a linear relation between log(frequency) and magnitude for ED events smaller than $\underline{x}$.

To understand the economic mechanism that may give rise to a power law with an exponential cutoff distribution of ED events, we model an ED event as a wildfire.

We present a model in which the dynamics of an individual ED event is determined by the interaction of two opposing forces: (i) the natural stochastic growth of the ED, which is proportional to the size of the damage that has already occurred; and (ii) a policy that attempts to extinguish the economic distress. We then derive the steady-state cross-sectional distribution of the final size of the ED events. We show that the size distribution is exponential for $x < \underline{x}$ and Pareto for $x \geq \underline{x}$ whenever the extinguishment policy is irresponsive to the spread of the fire up to a distress size $\underline{x}$, but for $x \geq \underline{x}$ it becomes increasingly responsive to the size of the fire.

Our findings are linked to the log(magnitude)-log(frequency) linear relation that characterizes many natural catastrophes: Earthquakes (Gutenberg-Richter relation); wildfires, landslides, hurricanes, epidemics, social upheavals, stock-market crashes, etc. Gabaix [2009, 2016] surveys the evidence for power law distributions in Economics and Finance. In the context of the equity-premium puzzle, Barro [2006] and Barro and Jin [2011] document the existence of such a power-law relation for economic catastrophes.

An implication of our findings is that policymakers' attempts to stop an ED-event may simply result in a larger future ED-event and eventually in a catastrophic crisis. This possibility stands in contrast to the centuries-old accepted wisdom that economic crises are the result of misguided macroeconomic and regulatory policies, and that they are avoidable with the appropriate policy menu.

2.2   Data and Methodology

We base our analysis on annual real GDP growth rates and level of GDP per capita. Two datasets are considered. The first dataset which comes from the World Bank Development Indicators (WDI, Code: NY.GDP.MKTP.KD.ZG) covers annual real

GDP growth rates over the period 1960-2014. The second data cover the level of GDP per capita over the period 1830-2014 and were obtained from Maddison Project Database (MPD).

2.2.1 Countries

We consider all countries with well-functioning financial systems, satisfying either of the following criteria.

1. High-income OECD members (with a GNI per capita of $12,736 or more)

2. Countries with a GNI per capita of more than $4,125 (high-income economies and upper-middle-income economies) that the World Bank classifies as financial creditworthy so as to be eligible to borrow from the International Bank for Reconstruction and Development (IBRD).

This generates us a set of 60 countries with data availability in both datasets. We classify an economy as "advanced" if they fall under the MSCI maket classification of developed markets. All others countries are classified as "emerging". The list of countries are summarized in Table 23 in the appendix.

2.2.2 Time Periods

We consider two time periods: the recent period of globalization (1970 - 2014) and the long historical period (1830 - 2013). For the recent period of globalization (1970 - 2014), both datasets (WDI and MPD) are available for all of the 60 countries on the list. In case of the long historical period (1830 - 2013), we only consider the advanced countries in MPD because most of the emerging market economies have short time series of data available. Table 23 in the appendix.

2.2.3 Identifying recessions

There exists an episode of "Economic Distress" (ED) if $g_{it} = y_{it} - \mu_{it} < 0$ holds where y_{it} is the growth rate of real GDP for country i in year t and μ_{it} is a filter that captures the potential GDP growth rate. Duration of "Economic Distress" (ED) is $t_1 - t_0$ where t_0 is the year when real output growth falls below the trend and t_1 is the first year after t_0 when it recovers the trend. This method is successful in identifying financial crises, which is validated by comparison with other crises database in Reinhart and Rogoff [2009], Laeven and Valencia [2013] and Ranciere and Tornell [2015].[19] Moreover, this method is successful in identifying the relatively small ED episodes. The ED episodes captured by this identifying method (when 10-yr MA is used for the filter) show significant overlap with the official recession dates announced by NBER. It is well visualized in Figure 19.

2.2.4 Measuring the Degree of Economic Distress

The degree of Economic Distress, X, is measured as the cumulative sum of standardized deviations from trend growth

$$r_{i,t} = \frac{y_{it} - \mu_{it}}{\sigma_{it}}$$

over "Economic Distress" years. It can be written as:

$$X_{i,t_1-t_0} = \sum_{t=t_0}^{t_1} r_{it} \cdot I(r_{it} < 0)$$

We consider two specific ED measures:

---

[19]This method has achieved 100 percent accuracy in identifying all types of financial crises indicated by the papers.

- Measure 1 (Standardized Growth Gap): We set μ_{it} to be 10-year moving average of y_{it} and σ_{it} to be 10-year moving standard deviation of y_{it}. This normalized growth gap in real GDP growth is similar to that used by Bordo et al.(2001) and Hoggarth et al.(2002).

- Measure 2 (Proportional Contraction): We set μ_{it} to be 0 and σ_{it} to be 1. This corresponds to the proportional contraction in the level of GDP per capita between t_0 and t_1 (Barro (2006) and Barro and Jin (2011)).

'Standardized growth gap' has a comparative advantage over 'proportional contraction' in capturing a economic stagnation such as "Japan's Lost Decade" because an event of sluggish economic growth is not identified as an ED episode by 'proportional contraction'.

In the following section we perform a power law test on various distributions:

1. Size distribution of ED episodes experienced by all 60 countries during the recent period of globalization (1970 - 2014). Standardized growth gap is used to measure the degree of ED. See Figure 14 in the Appendix.

2. Size distribution of ED episodes experienced by all 60 countries during the recent period of globalization (1970 - 2014). Proportional contraction is used to measure the degree of ED. See Figure15 in the Appendix.

3. Size distribution of ED episodes experienced by 23 advanced countries and 37 emerging market economies respectively during the recent period of globalization (1970 - 2014). Standardized growth gap is used to measure the degree of ED. See Figure17 in the Appendix.

4. Size distribution of ED episodes experienced by 23 advanced countries during

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the long historical period (1830 - 2013). Standardized growth gap is used to measure the degree of ED. See Figure18 in the Appendix.

2.3 Test for Power Law and Exponentiality

2.3.1 Test for Power Law

To test whether the empirical distribution of our data follows a power law in the upper tail, we use an empirical methodology introduced by Clauset et al. [2009]. A power-law distribution is described by a probability density $p(x)$ such that $p(x)dx = Pr(x \leq X < x + dx) = Cx^{-\alpha}dx$, where X is the observed value and C is a normalization constant. Clearly, this density diverges as $x \to 0$ so it cannot hold for all $x \geq 0$; there must be some lower bound to the power-law behavior. We will denote this bound by $\underline{x}$. Then a density of continuous power law distribution is given by:

$$p(x) = \frac{\alpha - 1}{\underline{x}} \left(\frac{x}{\underline{x}}\right)^{-\alpha} \tag{33}$$

The maximum likelihood estimator (MLE) of the power law exponent, α, is

$$\hat{\alpha} = 1 + n \left(\sum_{i=1}^{n} ln\frac{x_i}{\underline{x}}\right) \tag{34}$$

where x_i, $i = 1, 2, ... , n$ are independent observations such that $x_i > \underline{x}$. The lower bound on the power law distribution, $\underline{x}$, will be estimated using the following procedure. For each $x_i > \underline{x}$, we estimate α using the MLE and then compute the KolmogorovSmirnov (KS) statistic which is the maximum distance between the CDFs of the data and the fitted model. $\underline{x}$ is then selected as a value of x_i minimizing the KS statistic. That is to say, our estimate $\hat{\underline{x}}$ is the value of $\underline{x}$ that minimizes D which is

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$$D = \max_{x \geq \underline{x}} |S(x) - F(x)| \tag{35}$$

where $S(x)$ is the CDF of the data for the observations with value at least $\underline{x}$, and $F(x)$ is the CDF of the best fitted power law model in the region $x \geq \underline{x}$.

With the estimated $\hat{\underline{x}}$, the scaling parameter of the power law model (α) is estimated using maximum likelihood estimators (MLE) as in the equation (2). Next we test the goodness of fit of the power law model based on a semi-parametric bootstrap approach following Clauset et al. [2009]. We generate a large number of power-law distributed synthetic data sets with the estimated scaling parameters, $\hat{\underline{x}}$ and $\hat{\alpha}$. Then, power law models are fitted to each of the synthetic data sets individually using the same method as for the original data set and the KS statistics are calculated. P-value is defined to be the fraction of the synthetic distances that are larger than the empirical distance. According to Clauset et al. [2009], the rule-of-thumb P-value is 0.1 which means that if the resulting p-value is greater than 0.1 the power law is a plausible hypothesis for the data, otherwise it is rejected.

Table 17: Power Law Estimation when Measure 1 used (1970 - 2014)

Estimation of Power Law (MLE) & Goodness of fit test using KS statistic					
Measure 1	# of observations	$\underline{x}$	# of observations > $\underline{x}$	α	P-value
All Countries (60)	496	6.69	66	3.92	0.46
ADV (23)	184	5.42	43	3.76	0.74
EME (37)	312	6.69	41	3.97	0.29

Table 17 summarizes the result of the power law test when standardized growth gap is used to measure the degree of Economic Distress for the recent period of globalization (1970 - 2014). It shows that a power law behavior is observable for the whole sample (all 60 countries) and for the subsets of the sample (advanced countries and emerging market economies). The estimated scaling parameter (α) is

Table 18: Power Law Estimation when Measure 2 used (1970 - 2014)

Estimation of Power Law (MLE) & Goodness of fit test using KS statistic					
Measure 2	# of observations	$\underline{x}$	# of observations $> \underline{x}$	α	P-value
All Countries (60)	328	7.06	82	2.56	0.3
ADV (23)	114	3.79	33	3.17	0.34
EME (37)	214	7.64	67	2.52	0.17

Table 19: Power Law Estimation when Measure 1 used (1830 - 2013)

Estimation of Power Law (MLE) & Goodness of fit test using KS statistic					
Measure 1	# of observations	$\underline{x}$	# of observations $> \underline{x}$	α	P-value
ADV (23)	735	5.65	87	3.34	0.24

Table 20: Power Law Estimation when Measure 2 used (1830 - 2013)

Estimation of Power Law (MLE) & Goodness of fit test using KS statistic					
Measure 1	# of observations	$\underline{x}$	# of observations $> \underline{x}$	α	P-value
ADV (23)	543	5.51	158	2.44	0.27

found to be stable ranging from 3.76 to 3.97. The estimated lower bound of the power-law behavior $\underline{x}$ for the advanced countries is 5.42 which is lower than that for the emerging market economies (6.69). The upper tail of the datasets (in the region $x \geq \underline{x}$) include the large economic distress episodes such as the Mexican 1982 debt crisis (10.18), 1997 Asian financial crisis (Korea: 12.82, Indonesia: 18.32, Malaysia: 22.23), "Japan's Lost Decade" from 1991 to 1999 (11.71), the U.S. subprime mortgage crisis (8.02), Greece's debt crisis (14.5), etc. See table 22 in the Appendix. According to our estimates, about 13% of all available observations are above $\underline{x}$ in the case of datasets covering all countries. In the case of dataset covering the advanced countries and the emerging market economies, 23% and 13% of all available observations follow the power law behavior.

Table 18 summarizes the result of the power law test when proportional contrac-

tion is used to measure the degree of ED for the recent period of globalization (1970 - 2014). It shows that a power law pattern in the upper tail of the datasets is still valid for all the cases. The estimated scaling parameter (α) ranges from 2.52 to 3.17. The estimated lower bound of the power-law behavior $\underline{x}$ for the advanced countries is 3.79 which is much lower than that for the emerging market economies (7.64). 25%, 29%, and 31% of all available observations are above $\underline{x}$ in the case of datasets covering the all countries, the advanced countries, and the emerging market economies, respectively.

Table 19 and Table 20 summarize the result of the power law test when standardized growth gap and proportional contraction are used to measure the degree of Economic Distress, respectively for the long historical period (1830 - 2013). It shows that a power law pattern in the upper tail (12% and 29% of the observations) of the datasets is still observable (p-value is 0.24 and 0.27). Furthermore, it is worth noting that the estimated parameters (α and $\underline{x}$) are almost identical even though we now have much more observations in the long historical period than in the recent period of globalization (Table 19). Unlike the result of Table 19, the estimated $\underline{x}$ are quite different in Table 20. This is because proportional contraction, in comparison to standardized growth gap, is not a STD-adjusted measure and hence the estimated $\underline{x}$ is larger for the longer time period because we are adding more drastic events such as the great depression and the world wars.

2.3.2 Test for Exponentiality

Now, we test exponentiality of the empirical distributions using a nonparametric goodness-of-fit test, Kolmogorov-Smirnov test. Let $x_1,...,x_n$ be an ordered sample with $x_1 \leq ... \leq x_n$ and define $S_n(x)$ as follows:

$$S_n(x) = \begin{cases} 0 & x \leq x_1 \\ k/n & x_k \leq x \leq x_{k+1} \\ 1 & x_n \leq x \end{cases}$$

Now suppose that the sample comes from a population with CDF, $F(x)$ and define the KolmogorovSmirnov statistic, D_n as follows:

$$D_n = \max_x |F(x) - S_n(x)| \tag{36}$$

If F is continuous then under the null hypothesis $\sqrt{n}D_n$ converges to the Kolmogorov distribution for n sufficiently large. The goodness-of-fit test or the KolmogorovSmirnov test is constructed by using the critical values of the Kolmogorov distribution. The null hypothesis is rejected at level α if

$$\sqrt{n}D_n > K_a, \tag{37}$$

where K_a is found from

$$Pr(K \leq K_a) = 1 - \alpha \tag{38}$$

If $D_{n,a}$ is the critical value from the table, where n is the number of observations and a is the significance level. Then $P(D_n \leq D_{n,a}) = 1 - a$. D_n can be used to test the hypothesis that the data came from a population with a specific distribution function $F(x)$.

Table 21 summarizes the result of KS-test for exponentiality. For both measures, when we test the whole range, we reject the null hypothesis that the data is exponen-

Table 21: KS test

Kolmogorov-Smirnov Test for Exponentiality

	D_n	$D_{n,a}, a = 0.05$
Measure 1	0.088	0.061
Measure 1 (w/o tail)	0.045	0.066
Measure 2	0.130	0.075
Measure 2 (w/o tail)	0.059	0.085

tially distributed. It is straightforward in the sense that the upper tail of the data exhibits a power law behavior as seen in section 3.1 and this heavy upper tail generates some large deviations from the theoretical distribution which are picked up by the KS-test. If we truncate the sample to $x < \underline{x}$, however, then we do not reject the null at 5 % significance level. This implies that the data is exponentially distributed up to $\underline{x}$ and follows a power law pattern thereafter. This is called a exponential with a power law cutoff.

In summary, we used several empirical tests and found that the size-frequency distribution of ED episodes follows a mixture of a power law and an exponential distribution. In the following section, we introduce a stochastic model that explains the empirical distribution.

2.4 Model

We may think of an episode of economic distress (ED) as a wildfire. In a wildfire, the mass of trees burned determines the share of a forest that is destroyed. Intuitively, we may think of a ED episode as one where a mass of firms goes bankrupt, which reduces the rate of economic growth below its trend or may even lead to a recession. In both situations, the dynamics may be modelled as the interaction between two forces:

1. A recessionary stochastic process that spreads the distress over a larger share of firms in the economy and

2. An stochastic extinguishment policy that attempts to stop the economic distress.

In each ED episode, the interaction of these two forces determines the size of the economic loss (i.e., the area of the forest that is destroyed by the wildfire) as well as the duration of the episode. We have data on the cross-sectional distribution of final economic distress. Our objective is to establish a closed-form link between the dynamics of individual ED episodes and the cross-sectional distribution of final sizes. To such end we consider a specific recessionary process followed by a representative ED episode and an extinguishment policy.

Let t denote the time since the onset of distress: $t \in [0, T_i]$ and $X_i(t)$ be the cumulative share of output that has been lost since the onset of the ED event in economy i. Like in wildfire models, we can think of the rate at which distress progresses throughout the economy as a function of the share of the economy that has been distressed since the onset of the ED episode. In particular, we consider a monotone stochastic process that gives rise to a mean rate of destroyed output which is proportional to $X_i(t)$

$$E[dX_i|X_i(t)] = \mu(X_i(t))dt \geq 0 \quad \mu(X_i(t)) \equiv X_i(t). \tag{39}$$

To ensure that the sample paths of an individual fire are increasing, we consider the following "pure birth" continuous time setup with discrete states, labelled 1, 2, 3, . . .etc.[20] These states capture how wide has the fire spread.

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[20]See Berman and Frydman (1996) and Reed and McKelvey (2002).

The process is in state j at time t if the area $X_i(t)$ burned by time t exceeds marker size x_j, but not marker size x_{j+1}. That is,

$$x_j < X_i(t) < x_{j+1}, \quad \text{with} \quad x_{j+1} - x_j \equiv \Delta > 0 \text{ for all } j.$$

where the assumption that states are equaly spaced (i.e., $x_{j+1} - x_j \equiv \Delta$ for all j) is made for simplicity. If the process is in state j at time t, then the probability that it will be in state $j + 1$ at time $t + dt$, is

$$P(X_i(t+1) = x_{j+1}|x_j) = \lambda_j dt + o(dt), \quad \text{with } \lambda_j = \frac{\mu(x_j)}{\Delta}. \tag{40}$$

Similarly, the probability that it will remain in state j is

$$P(X_i(t+1) = x_j|x_j) = 1 - \lambda_j dt + o(dt).$$

It follows that the expected growth in the size of the area burned in the infinitesimal interval $(t, t + dt)$, given that $X_i(t) = x_j$, is

$$E(X_i(t+dt) - X_i(t)|X_i(t) = x_j) = \lambda_j \Delta dt + o(dt) = \mu(x_j)dt + o(dt) \tag{41}$$

Next, we model the extinguishment rate stochastically using a so-called killing rate function

$$k(t) = \lim_{dt \to 0} \frac{1}{dt} P(T_i < t + dt|T_i \geq t) \tag{42}$$

As we shall see below, the shape of the extinguishment policy is a key determinant of the cross-sectional distribution of final distress sizes. We assume that the extinguish-

ment policy is a state-dependent step function:

$$
k(t) = \nu(X_i(t)) = \begin{cases} C_0 & \text{if } X_i(t) < \underline{x} \\ C_1 X_i(t) & \text{otherwise} \end{cases}
\tag{43}
$$

This policy captures the notion that when an ED episode is mild (i.e., $X_i(t) < \underline{x}$) the government (or international organizations like the IMF or the EMS) do not face pressure to implement emergency interventions beyond the existing authomatic stabilizers, and so the ED episode is left to extinguish itself. However, if the ED episode morphes into a crisis (i.e., a threshold is crossed $(X_i(t) \geq \underline{x})$ then government policies to stop the crisis are implemented. The intensity of these policies grows proportionally to the size of the ED.

Let $\nu_j = \nu(x_j)$, $j = 1, 2, \dots$ so that the probability of the fire (ED episode) ending in the infinitesimal interval $(t, t+dt)$, given that it was in state j at time t is $\nu_j dt + o(dt)$.

We next derive the final size of the burned area (i.e., the final size of the ED) when extinguishment occurs. Let $\bar{X}$ denote the state when the ED process is killed. Then the discrete PDF is:

$$
f_j \equiv P(\bar{X} = j) = \frac{\nu_j}{\nu_j + \lambda_j} \prod_{n=1}^{j-1} \frac{\lambda_n}{\lambda_n + \nu_n}
\tag{44}
$$

$$
= \frac{\rho_j \Delta}{1 + \rho_j \Delta} \prod_{n=1}^{j-1} \frac{1}{1 + \rho_n \Delta}, \quad \text{where } \rho_n = \frac{\nu_n}{\lambda_n \Delta} = \frac{\nu_n}{\mu(x_n)}.
\tag{45}
$$

We can rewrite this expression in terms of the the discrete hazard function $\theta_n = \frac{\nu_n}{\nu_n + \lambda_n}$

$$
f_j = \theta_j \prod_{n=1}^{j-1} (1 - \theta_n), \quad \theta_n = \frac{\nu_n}{\nu_n + \lambda_n} = \frac{\rho_n \Delta}{1 + \rho_n \Delta}
\tag{46}
$$

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To derive this result consider the transition diagram of a birth-killing process in Figure 13. There are two types of transition: (i) a "birth" that moves the system from state n to state $n+1$, with a birth rateat λ_n; and (ii) a killing that moves system from state n to state 0, with a killing rate ν_n. As the transition diagram indicates, if the system moves to state 0, the process ends and the final size of economic distress is given by $\overline{x}_n$. To derive equation (44) notice that the likelihood that the ED episode ends after reaching state n is simply the likelihood that is not killed in any state lower than j $\left(\text{i.e., } S(j) = \prod_{n=1}^{j-1} \frac{\lambda_n}{\lambda_n+\nu_n}\right)$ times the likelihood that it is killed in state $j+1$ $\left(\text{i.e., } \theta_j = \frac{\nu_j}{\nu_j+\lambda_j}\right)$. In other words, with discrete states, the likelihood that the ED episode's final size equals x_n is given by the product of the discrete survival function $S(j)$ times the discrete hazard function θ_j.

To obtain the continuous limit we first obtain the continuous hazard function and then use it to derive the continuous survival function. The continuous hazard function $\rho(x)$ is defined as

$$\rho(x) = \lim_{dx \to 0} \frac{1}{dx} P(X < x + dx | X \geq x) = \frac{f(x)}{S(x)}. \tag{47}$$

To obtain the continuous hazard function $\rho(x)$ we divide the discrete hazard function $\theta_j = \frac{\rho_j \Delta}{1+\rho_j \Delta}$ by Δ and let $\Delta \to 0$. We get

$$\rho(x) = \lim_{\Delta \to 0} \frac{\rho_j}{1 + \rho_j \Delta} = \rho_j \equiv \frac{\nu(x_j)}{\mu(x_j)}. \tag{48}$$

Let the cumulative hazard rate function be

$$P(x) = \int_{x_0}^x \rho(u)du = \int_{x_0}^x \frac{f(u)}{S(u)}du = \int_{x_0}^x \frac{-\frac{dS(u)}{du}}{S(u)}du = -logS(x) \tag{49}$$

Thus, the continuous survival function $S_{\bar{X}}(x) \equiv P(\bar{X} > x)$ is

$$S_{\bar{X}}(x) = exp(-P(x)) = exp\left(-\int_{x_0}^{x} \rho(x')dx'\right), \quad \text{where } \rho(x) = \frac{\nu(x)}{\mu(x)}. \tag{50}$$

Taking the derivative of $S_{\bar{X}}(x)$, yields the following density for $\bar{X}$

$$f_{\bar{X}}(x) = \rho(x)\exp\left(-\int_{x_0}^{x} \rho(x')dx'\right) \tag{51}$$

From equation (50) and (51), it follows that

$$\rho(x) = -\frac{d}{dx}logS_{\bar{X}}(x) = -\frac{S'_{\bar{X}}(x)}{S_{\bar{X}}(x)} \tag{52}$$

Then it follows that $x\rho(x)$ is constant if and only if the cross-section of final sizes of ED events $\bar{X}$ follows a power-law distribution:

$$\log S_{\bar{X}}(x) = b - a\log x$$

Meanwhile, $\rho(x)$ is constant if and only if $\bar{X}$ follows an exponential distribution:

$$\log S_{\bar{X}}(x) = b - ax$$

We are now equiped to interpret our findings in the Empirical section since the empirical counterpart of $\log S_{\bar{X}}(x)$ is is the ordinate in Figure 14 through Figure 18. Since we have assumed that the growth rate of an individual ED episode $\mu(X)$ is X and the extinguishing policy $\nu(X)$ follows (43), we have that in the cross section $\rho(x) = \frac{\nu(X)}{\mu(X)}$

follows

$$\rho(x) = \frac{C_0}{X} \text{for } x \leq \underline{x} \text{ and}$$
$$\rho(x) = \frac{C_1 X}{X} = C_1 \text{ for } x > \underline{x}$$

This is consistent with the PL with an exponential cutoff we characterized in the empirical section.

2.5 Literature Review

This paper is linked to a vast literature both theoretical and empirical on economic downturns. Most of the studies concentrate on the catastrophic events such as financial crises and wars, so they focus only on the tail distribution of economic distress episodes. Barro [2006] and Barro and Jin [2011] document a power-law distribution of "rare disasters," which they define as a decline in per-capita GDP of more than 15 percent. While they only consider rare disasters whose probability is quite slim (1.5-2 percent per year), our study covers all economic downturns from small economic disturbances to catastrophic crises. Laeven and Valencia [2013] identify the starting date of systemic financial crises by policy indices. Bordo et al. [2001], Hoggarth et al. [2002] and Reinhart and Rogoff [2009] focus on frequency and severity of several different types of financial crises based on internal propagation mechanism of several kinds of economic crises.

While there is huge literature on economic disturbances and financial crises, a distributional analysis of the economic distress has rarely been performed. A distributional approach to other economic issues is growing and is comprehensively surveyed

in Gabaix [1999, 2009, 2016]. He documents that there is much empirical evidence for the existence of power-laws in Economics.

However, Clauset et al. [2009] show that in most cases, the hypothesized power law distribution is not tested rigorously against the data, and hence the power law appears to be not convincing. They argue that the standard practice of identifying and quantifying power-law distributions by the approximately straight-line behavior of a histogram on a doubly logarithmic plot should not be trusted. Clauset et al. [2009] present a statistically principled set of techniques that test a power law along with the likelihood ratio tests for model selection based on Vuong [1989]. Pisarenko and Sornette [2006] provide a statistical tool to compare the behavior of tail distributions with power-law and exponential distributions.

In the context of measuring the size of economic distress, Ormerod and Mounfield [2001] analyze the duration of the recession of 17 capitalist economies and reports that the duration follows a power-law distribution. Similarly, Redelico et al. [2008] collect data from 19 additional Latin America countries and reinforce the results of Ormerod and Mounfield [2001]. Duration of recessions is closely related to economic distress, however, the dispersion in the size of economic distress for the same length of duration is very huge. See Figure 20. Moreover, it is hard to analyze the duration of recession statistically as it is categorical data. Wright [2005] concludes that the duration of recessions follows an exponential distribution using the same dataset of Ormerod and Mounfield [2001].

2.6 Conclusion

Power laws appear widely in both the natural and social sciences. In this paper, we use the analytical tools in Clauset et al. [2009] and the nonparametric goodness-

of-fit test to characterize the frequency and size distribution of the past economic distress episodes in history. Our empirical results demonstrate that power law distributions provide a clear explanation to the upper tail of the frequency and size distributions. It has been also found that the power law pattern is valid for different measurements of economic distress, different set of countries, and for different time periods. Furthermore, We document that there is a threshold below which the size of ED events follows an exponential distribution. After characterizing the empirical distribution, we provide a stochastic wildfire model explaining how the distribution could be generated.

2.7 Appendix

2.7.1 Birth and Killing Process

The transition diagram of a birth/killing process looks like the following:

Figure 13: Transition Diagram
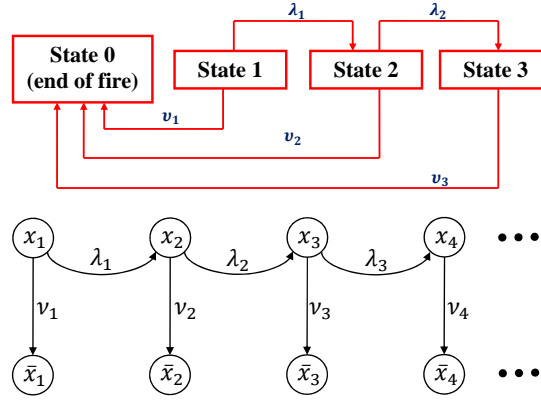
There are two transition types: λ_n (birth rate) moves system from n to $n + 1$. ν_n (killing rate) moves system from n to 0 (extinguishment stage). As the transition diagram indicates, if the system is moved to "stage 0", the process is terminated and the final size of economic distress is determined. With discrete states, $\theta_n = \frac{\nu_n}{\nu_n + \lambda_n} = \frac{\rho_n \Delta}{1 + \rho_n \Delta}$ is the discrete hazard function. This gives that the discrete survival function is $S(j) = \prod_{n=1}^{j-1} \frac{\lambda_n}{\lambda_n + \nu_n}$.

In a continuous setting, dividing $\frac{\rho_n \Delta}{1 + \rho_n \Delta}$ by Δ and then letting $\Delta \to 0$, yields the continuous hazard function, $\rho(x)$.

$$\rho(x) = \lim_{dx \to 0} \frac{1}{dx} P(X < x + dx | X \geq x) = \frac{f(x)}{S(x)} \tag{53}$$

Let the cumulative hazard rate function be

$$P(x) = \int_{x_0}^{x} \rho(u)du = \int_{x_0}^{x} \frac{f(u)}{S(u)}du = \int_{x_0}^{x} \frac{-\frac{dS(u)}{du}}{S(u)}du = -logS(x) \tag{54}$$

Thus

$$S(x) = exp(-P(x)) = exp\left(-\int_{x_0}^{x} \rho(x')dx'\right) \tag{55}$$

2.7.2 Figures and Tables

Figure 14: Size-frequency Distribution of Economic Distress Events (Measure 1)
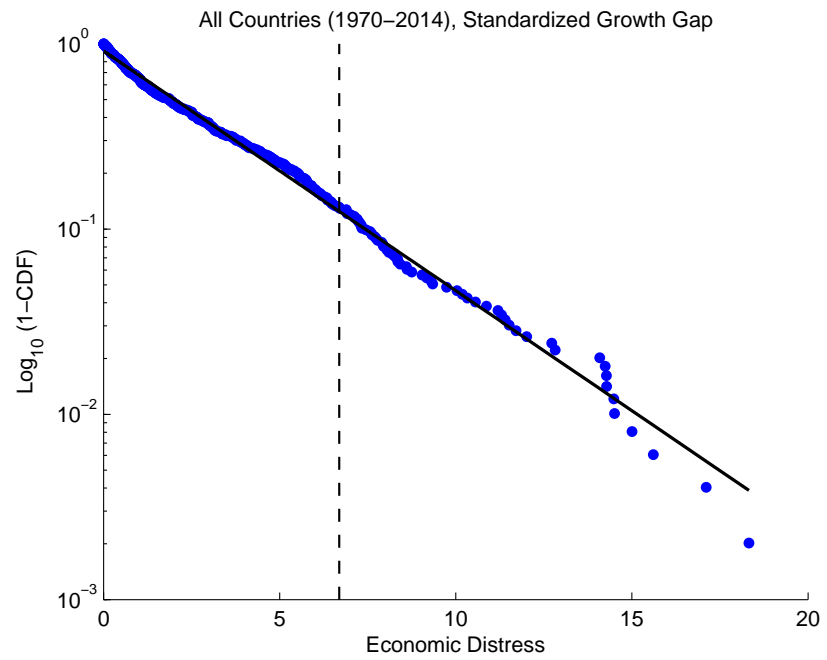
Figure 15: Size-frequency Distribution of Economic Distress Events (Measure 2)

All Countries (1970–2014), Proportional Contraction
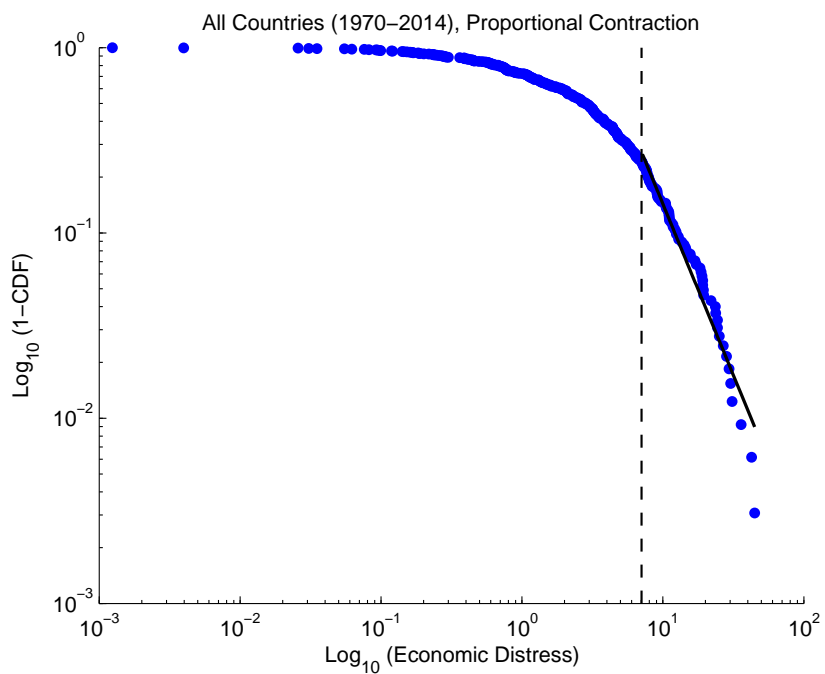
Figure 16: Exponential with a Power Law Cutoff

All Countries (1970–2014), Standardized Growth Gap

All Countries (1970–2014), Standardized Growth Gap
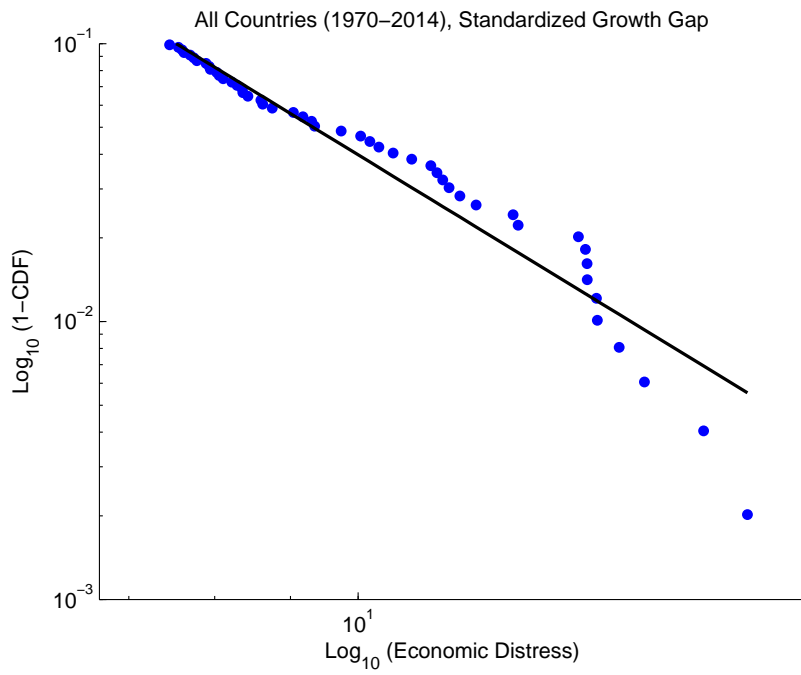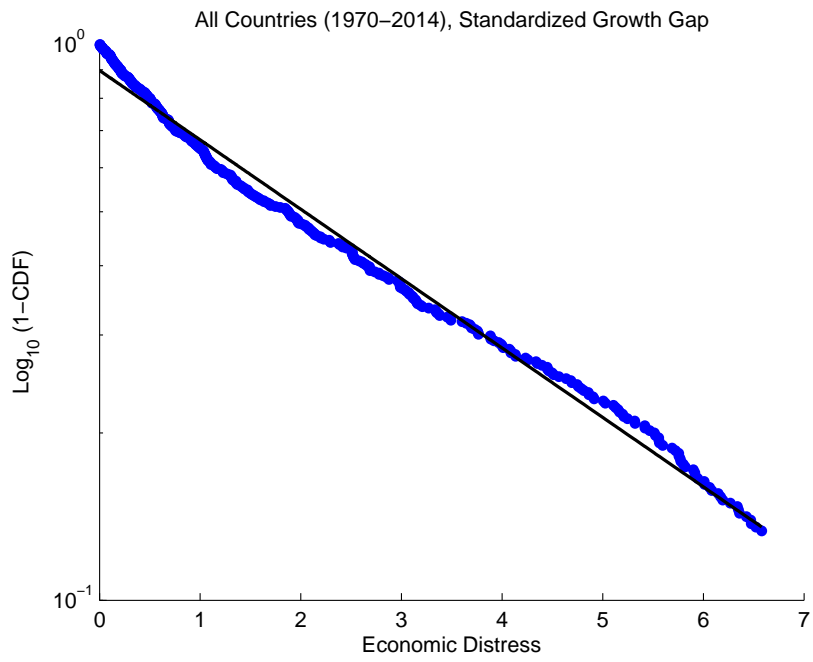
Figure 17: Size-frequency Distribution of Economic Distress Events (Advanced Economies vs. Emerging Market Economies)

All Countries (1970–2014), Standardized Growth Gap
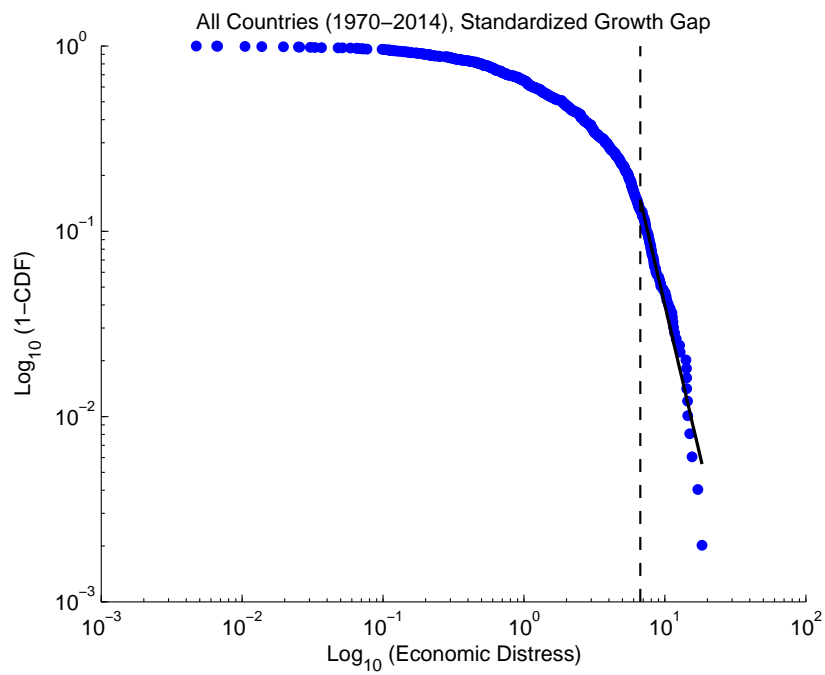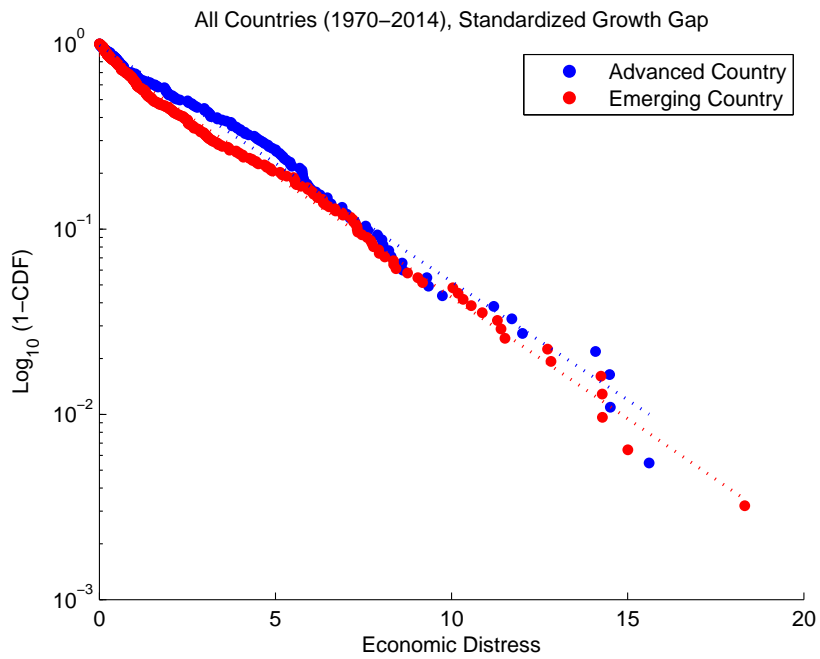
Figure 18: Size-frequency Distribution of Economic Distress Events (1830 - 2014)

Long Period (1830–2014), Standardized Growth Gap

Long Period (1830–2014), Standardized Growth Gap
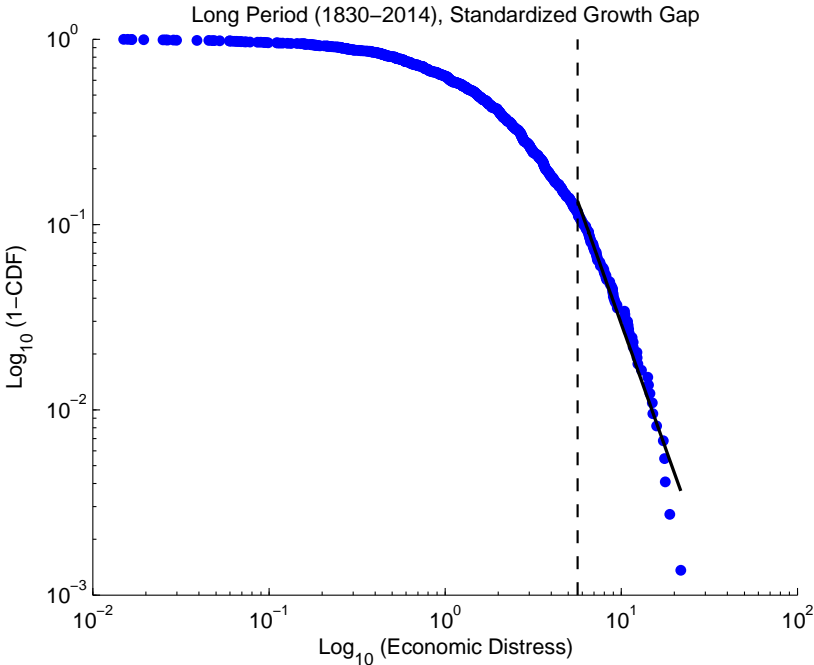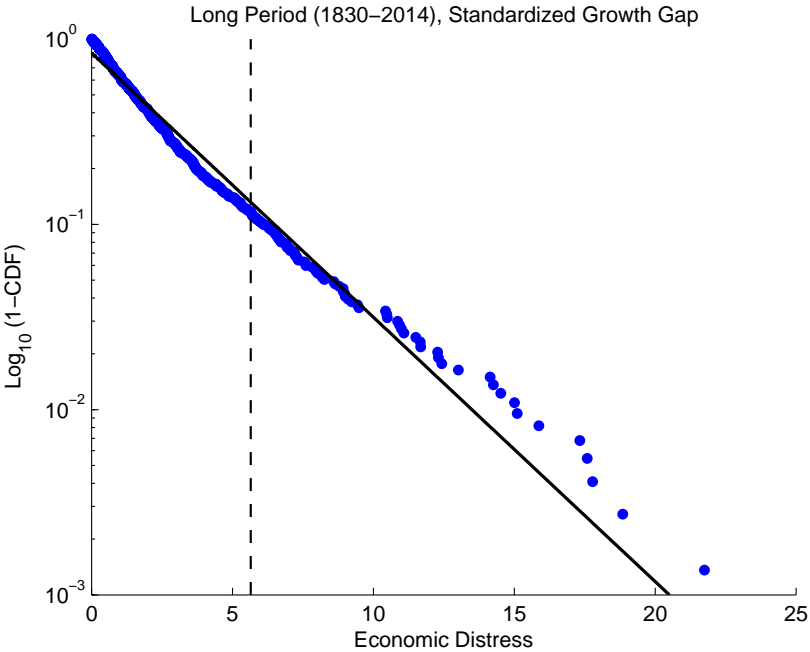
Figure 19: Official recession dates announced by NBER

Recession (Moving Average)

NBER Recession

Normalized Growth Rate of Real GDP per Capita
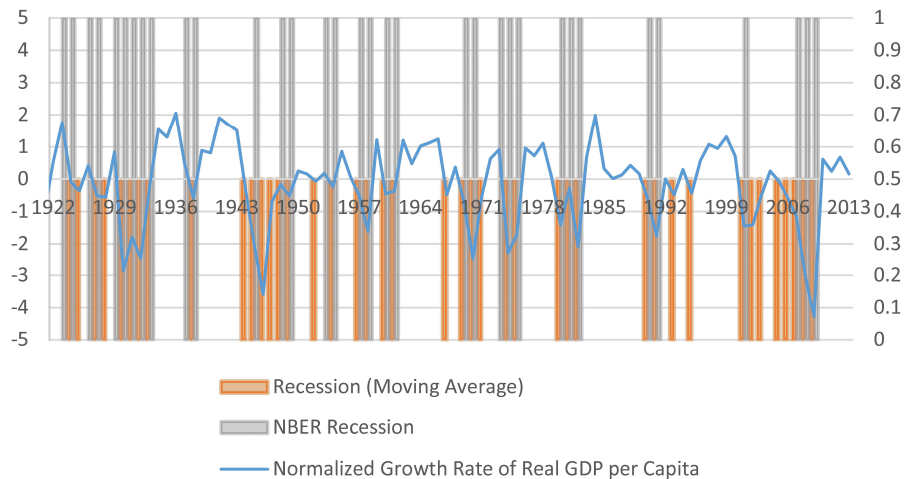
Figure 20: Duration vs. Size of Economic Distress
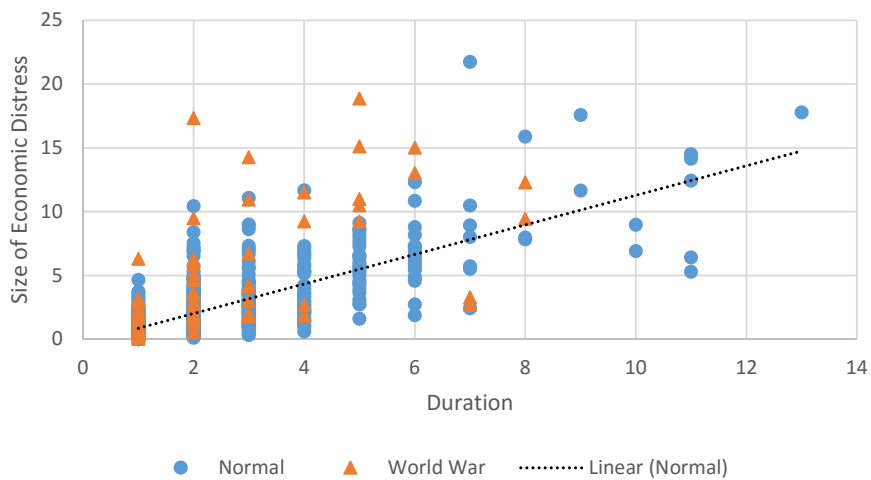
Table 22: Major Financial Crises

Major Financial Crises in recent decades

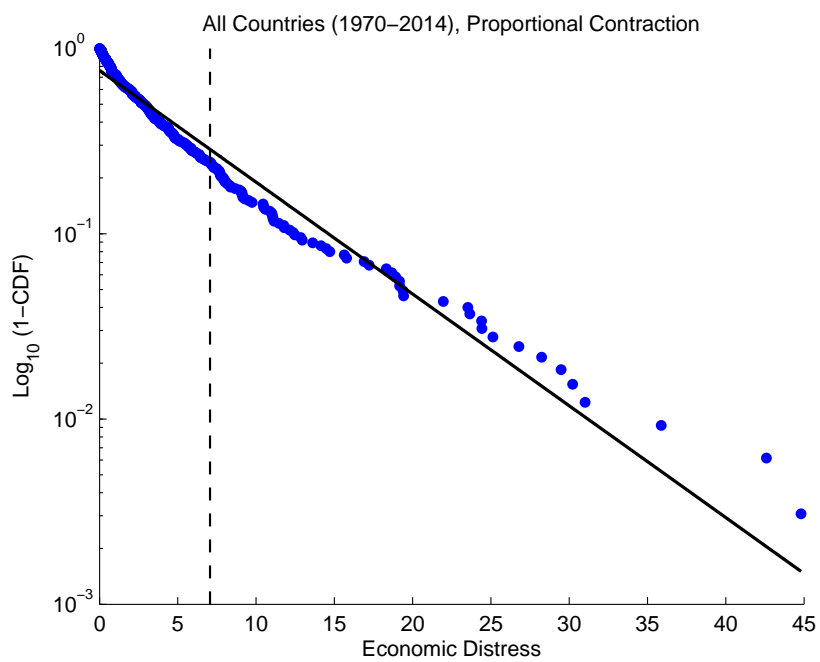|	Name of Crisis	Size of Economic Distress (Measure 1 used)	Duration	Ending Year of ED
Mexico	Latin American debt crisis	10.18	7 years	1988
Finland	Scandinavian banking crisis	11.19	4 years	1993
Sweden	Scandinavian banking crisis	8.62	4 years	1993
Argentina	Argentine economic crisis (1999-2002)	6.19	4 years	2002
Malaysia	1997 Asian Financial Crisis	22.23	3 years	1999
Indonesia	1997 Asian Financial Crisis	18.32	3 years	1999
Greece	European sovereign debt crisis	14.5	7 years	2013
Spain	European sovereign debt crisis	15.61	7 years	2013
Japan	Collapse of Japanese asset price bubble	11.71	9 years	1999
United States	Global financial crisis	8.02	5 years	2009

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Table 23: Classifications of countries based on their level of development

Emerging Economies	Data Availability (WDI)	Data Availability (MPD)	Advanced Economies	Data Availability (WDI)	Data Availability (MPD)
Algeria (DZA)	1961 - 2014	1956-2014	Austrailia (AUS)	1961 - 2014	1831-2014
Argentina (ARG)	1961 - 2014	1886-2014	Austria (AUT)	1961 - 2014	1881-2014
Belize (BLZ)	1961 - 2014	1962-2014	Belgium (BEL)	1961 - 2014	1856-2014
Botswana (BWA)	1961 - 2014	1956-2014	Canada (CAN)	1961 - 2014	1881-2014
Brazil (BRA)	1961 - 2014	1861-2014	Denmark (DNK)	1961 - 2014	1831-2014
Chile (CHL)	1961 - 2014	1831-2014	Finland (FIN)	1961 - 2014	1871-2014
China (CHN)	1961 - 2014	1851-2014	France (FRA)	1961 - 2014	1831-2014
Colombia (COL)	1961 - 2014	1916-2014	Germany (DEU)	1961 - 2014	1861-2014
Costa Rica (CRI)	1961 - 2014	1931-2014	Greece (GRC)	1971 - 2014	1931-2014
Dominican Rep. (DOM)	1961 - 2014	1961-2014	Ireland (IRL)	1961 - 2014	1931-2014
Ecuador (ECU)	1961 - 2014	1951-2014	Israel (ISR)	1961 - 2014	1931-2014
Egypt (EGY)	1966 - 2014	1916-2014	Italy (ITA)	1971 - 2014	1861-2014
El Salvador (SLV)	1966 - 2014	1931-2014	Japan (JPN)	1961 - 2014	1881-2014
Gabon (GAB)	1961 - 2014	1956-2014	Luxembourg (LUX)	1961 - 2014	1960-2014
Georgia (GEO)	1966 - 2014	1901-2014	Netherlands (NLD)	1961 - 2014	1831-2014
Guatemala (GTM)	1961 - 2014	1931-2014	New Zealand (NZL)	1978 - 2014	1881-2014
Honduras (HND)	1961 - 2014	1931-2014	Norway (NOR)	1961 - 2014	1841-2014
Iceland (ISL)	1961 - 2014	1881-2014	Portugal (PRT)	1961 - 2014	1876-2014
India (IND)	1961 - 2014	1895-2014	Spain (ESP)	1961 - 2014	1861-2014
Indonesia (IDN)	1961 - 2014	1881-2014	Sweden (SWE)	1961 - 2014	1831-2014
Iran, Islamic Rep. (IRN)	1961 - 2014	1956-2014	Swiss (CHE)	1981 - 2014	1861-2014
Iraq (IRQ)	1969 - 2014	1961-2014	United Kingdom (GBR)	1961 - 2014	1831-2014
Jamaica (JAM)	1967 - 2014	1951-2014	United States (USA)	1961 - 2014	1831-2014
Korea (KOR)	1961 - 2014	1926-2014			
Malaysia (MYS)	1961 - 2014	1926-2014			
Mexico (MEX)	1961 - 2014	1911-2014			
Morocco (MAR)	1961 - 2014	1961-2014			
Panama (PAN)	1961 - 2014	1956-2016			
Paraguay (PRY)	1961 - 2014	1951-2014			
Peru (PER)	1961 - 2014	1926-2014			
Phillippines (PHL)	1961 - 2014	1926-2014			
South Africa (ZAF)	1961 - 2014	1831-2014			
Thailand (THA)	1961 - 2014	1961-2014			
Trinidad and Tobago (TTO)	1961 - 2014	1961-2014			
Turkey (TUR)	1961 - 2014	1936-2014			
Uruguay (URY)	1961 - 2014	1882-2014			
Venezuela (VEN)	1961 - 2014	1896-2014			

3 Sector Rotation Model for the U.S. Market: Predicting performance across 9 U.S. sector ETFs

3.1 Introduction

Interest in smart-beta strategies continues to surge as they outperform cap-weighted indexes by using alternative weighting systems. Smart beta, a jargon from the fund-management industry is "an approach that tries to enhance the return from tracking an asset class by deviating from the traditional cap-weighted approach, in which investors simply buy shares or bonds in proportion to their market value" (The Economist, 2013). Reflecting this trend, sector investing has received large attention from the financial industry.

Sector investing is one of the building blocks of many investors' portfolios and is essential for successful investing. This is because sector investing is an optimal solution to the investors who seek a compromise between the passive indexing strategies and active stock picking. More than 300 ETFs in the U.S. are designed to enable investors to target their exposure to specific sectors. This allows investors to easily access sectors for their sector investing. The average difference in monthly returns between best-performing and worst-performing sector over the past 11 years is 9.4%. This high sector return dispersion creates more scope for achieving excess returns from tactically rotating between sectors. Unlike market indexes that have exposure to all of the sectors, a key goal of sector rotation strategies is to provide systematic entry and exit timing for sector allocation. Therefore the main aim of sector rotation strategies is to limit exposure to underperforming sectors and to participate in the top-performing sectors.

SPDR (Standard & Poor's Depositary Receipts) Funds are a family of exchange-traded funds (ETFs) traded in the United States, Europe, and Asia-Pacific and managed by State Street Global Advisors. The advantages of ETFs are well described by Drake and Fabozzi (2009) and these advantages make sector rotation strategies more implementable and easier to accomplish. Select Sector SPDRs are unique ETFs that divide the S&P 500 into nine sectors.[21] Hence, this enables us to customize investment by picking and weighting these sectors. Throughout the paper, Select Sector SPDRs are used for sector rotation strategies.

In this paper I introduce a sector rotation model that generates forecasts of sector performance combining price momentum, market sentiment, and macroeconomic factors. c The empirical results show that my sector rotation model exhibits successful backtest results and delivers strong performance. It beats a benchmark strategy significantly in terms of performance measurements; Info ratio and Calmar ratio (metrics for risk-adjusted return). The remaining paper will be constructed as follows. Section 2 reviews the literature related to sector rotation strategies. Section 3 introduces how the sector rotation model is constructed and what are the factors feeding this model. Section 4 introduces the phase-adjusted model. The conclusions follow in Section 5.

3.2   Literature Review

A crucial stage in top-down approach is in identifying the most promising sectors in a given market. Therefore the sector or industry dimension has played an important role for investment management. In this context, several studies suggest the sector or industry factor for stock returns is significantly strong. While earlier studies, such as Heston and Rouwenhorst (1994), find that the country factor completely dominates

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[21]Nine sectors include XLY (Consumer Discretionary), XLF (Financials), XLE(Energy), XLP(Consumer Staples), XLV(Health Care), XLI(Industrials), XLB(Materials), XLK(Technology), and XLU(Utilities).

the industry/sector factor, more recent research, such as Baca, Garbe, and Weiss (2000), Cavaglia and Moroz (2002) found that country effects no longer dominate sector effects and that the industry/sector factor for stock returns is as strong or stronger than the country factor. In a related paper, Cavaglia, Brightman, and Aked (2000) present evidence that industry factors have been growing in relative importance and may even dominate country factors. Past studies on sector rotation strategies can be categorized into two groups depending on whether they use a timeseries or a cross-sectional approach. A time-series approach uses a different set of macroeconomic variables to forecast sector returns, whereas a cross-sectional approach uses sector characteristics that capture the cross sectional variation in different sectors.

Using term spread, default spread, commercial paper minus T-Bill spread, aggregate dividend yield, real interest rates, and expected inflation, Beller, Kling & Levinson (1998) create an industry trading strategy that earned statistically significant monthly returns of about 1.7% from 1981 to 1995. Johnson & Sakoulis (2003) find that macroeconomic factors such as S&P 500 dividend yield, term spread, and oil price default spread are useful in forecasting returns directly. They show statistically significant results for each of the factors examined.

Sorensen & Burke (1986) use relative strength analysis for 43 industries in the U.S. and document that a rotation strategy based on price momentum produces significant abnormal return over 1972-1982 period. ONeal (2000) also constructs momentum-based portfolios which have higher returns than S&P 500 but also higher risk. Cavaglia & Moroz (2002) use multi-factors such as price momentum, dividend yield, two-year EPS forecast, analyst revisions, and expected long-term earnings growth to show that long-short portfolio based on those factors generates average annualized returns between 3% and 4.5% from 1990 to 2001.

Besides the main papers listed above, some papers focus on other factors and

consider different phases faced by the economy. Conover et al. (2008) selects cyclical stocks during period of FED easing, and selects defensive stocks during periods FED tightening. This strategy generates an annual excess return of 3.5%. Chordia and Shivakumar (2002) show that momentum trading delivers reliably positive profits only during expansionary periods but statistically insignificant profits during recessions. Cooper, Gutierrez, and Hameed (2004) also find that momentum profits depend on the state of the market in a procyclical way. Doeswijk (2008) documents that a seasonal effect can be observed in the way that the sector allocation strategy prefers cyclical stocks in the winter period and defensive stocks in the summer period.

3.3 Sector Rotation Model

The sector rotation model generates signals combining 4 components to provide forecasts of sector performance. See Figure 21. These 4 factors which include price momentum, positioning (fund manager survey), macro (composite macro indicator), and earnings revision ratio cover market sentiment, momentum, and macro view. The philosophy behind the sector rotation model is utilizing all the sources of information to identify short-term patterns in the sectors.

The sector rotation model assigns higher ranks to the sectors exhibiting strong price momentum. Hence the sectors exhibiting high momentum are preferred. To capture market sentiment, Fund Manager Survey which is a flagship product of BAML is used. Over-owned sectors are preferred. CMI (Composite Macro Indicator) is used for classification of economic phases (tactical cycle). Higher beta sectors are preferred in a 'risk-on' environment and lower beta sectors in a 'risk-off' environment. The sector rotation model also assigns higher ranks to the sectors with a higher and improving ERR. The details of each factor will be covered in the following subsections.
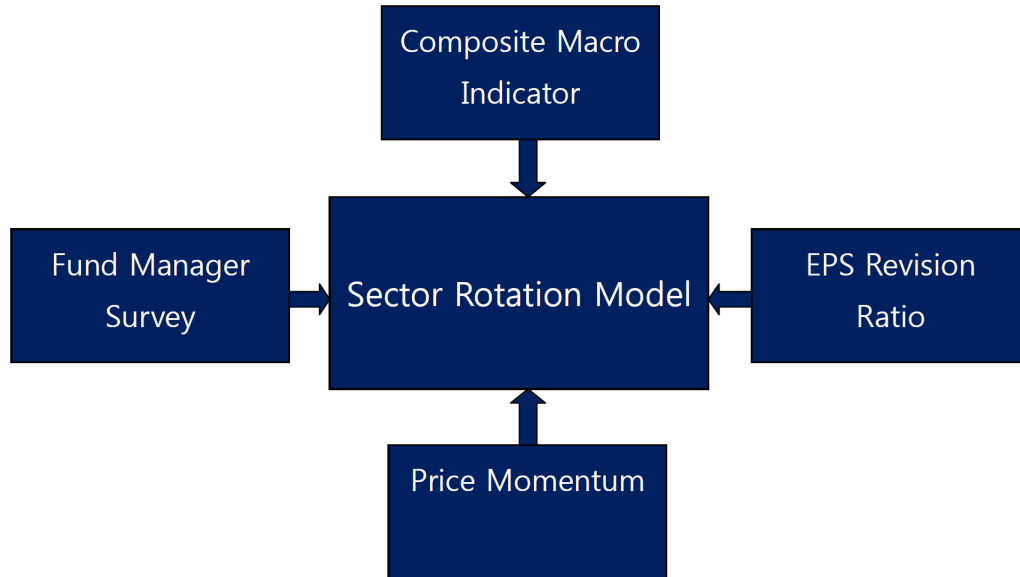
Figure 21: Sector Rotation Model

3.3.1 Benchmark Strategy

Equal-weighted basket serves as a benchmark strategy. Equal-weighted (EW) basket is a strategy of holding the 9 sector ETFs in equal weight. Market Cap weighting (SPY) results in a skewed allocation and hence a small number of companies dominate the performance of the ETF as a whole. According to Greenblatt, Market Cap weighed indexes suffer from a systematic flaw because they increase the amount they own of a particular company as that company's stock price increases. This causes a systematic over-investment in stocks when they are overpriced. In this sense, EW basket is a more balanced portfolio and outperforms SPY by a substantial amount (1.1% excessive annualized return). This is also validated by Plyakha et al. (2014) which demonstrates that the equal-weighted portfolio with monthly rebalancing outperforms the value and price-weighted portfolios.

3.3.2 Price Momentum

Moskowitz and Grinblatt (1999) demonstrated that price momentum works at the industry level and that industry-level momentum can explain a significant portion of stock-level momentum. They rank 20 U.S. industries on 1-, 6-, and 12-month price momentum and used the top three and bottom three industries to form a winner and a loser portfolio. In finance literature there is a general agreement that price returns exhibit a short-term (1 month) reversal, a medium-term (12 months) continuation, and a long-term (more than 12 months) reversal. Accordingly, in this paper, price momentum is measured by total return over the eleven months prior to last month. This is called a 2-12 month momentum and is widely used by practitioners and academics. It is validated by Doeswijk and Vilet (2010), Novy-Marx (2012), and Xiong and Ibbotson (2014). Sectors with higher momentum are favored and thus are assigned higher ranks. Figure 22 shows the cumulative back-tested performance when I long top 3 sectors based on the signals from price momentum at the beginning of every month. Throughout the paper, net total return index is used to track the sector returns. Total return index assumes that any cash distributions such as dividends are reinvested back into the index. Net total return index reinvests dividends after the deduction of withholding taxes.

3.3.3 Market Sentiment

To gauge market sentiment, Fund Manager Survey (FMS) is used. FMS is a flagship product of BAML and reports net % of overweight investors for each sector which can be used as a reference point for positioning. More than 200 panelists with US$600 billion of assets under management participated in the survey every month. If current
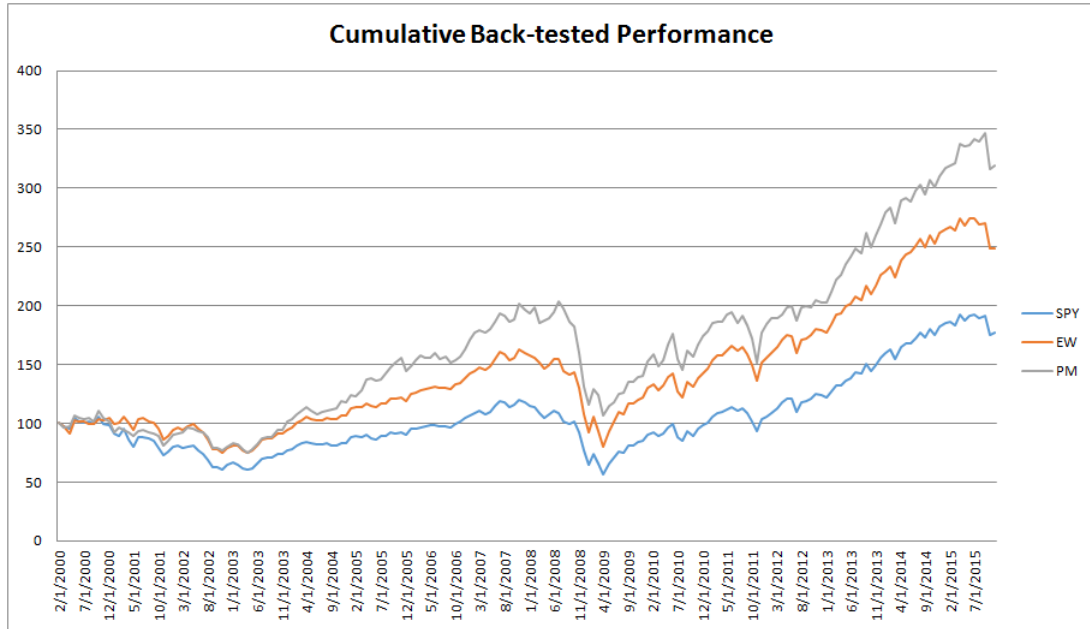
Figure 22: A single factor (PM)

positioning is above the historical average and the sectorial average[22], the sector is considered to be over-owned. It is thus assigned a higher rank. Some papers find that this positioning can be used as a non-consensual factor and a contrarian strategy can realize excess returns. According to my analysis, a contrarian strategy avoiding crowded positions and finding opportunities in uncrowded places does not hold when FMS is used. Figure 23 shows the cumulative back-tested performance when I long top 3 sectors based on the signals from FMS at the beginning of every month.

3.3.4 Macro View

Chen, Ross and Roll (1986) studied an asset pricing model using macro economic factors such as industrial production, unexpected inflation, change of expected inflation, yield spread, and credit spread. They found that each macro factor is significant in predicting stock returns. In this paper Composite Macro Indicator (CMI) is used for

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[22]I assign equal weights to the deviations from last 12-month moving average and sectorial average.
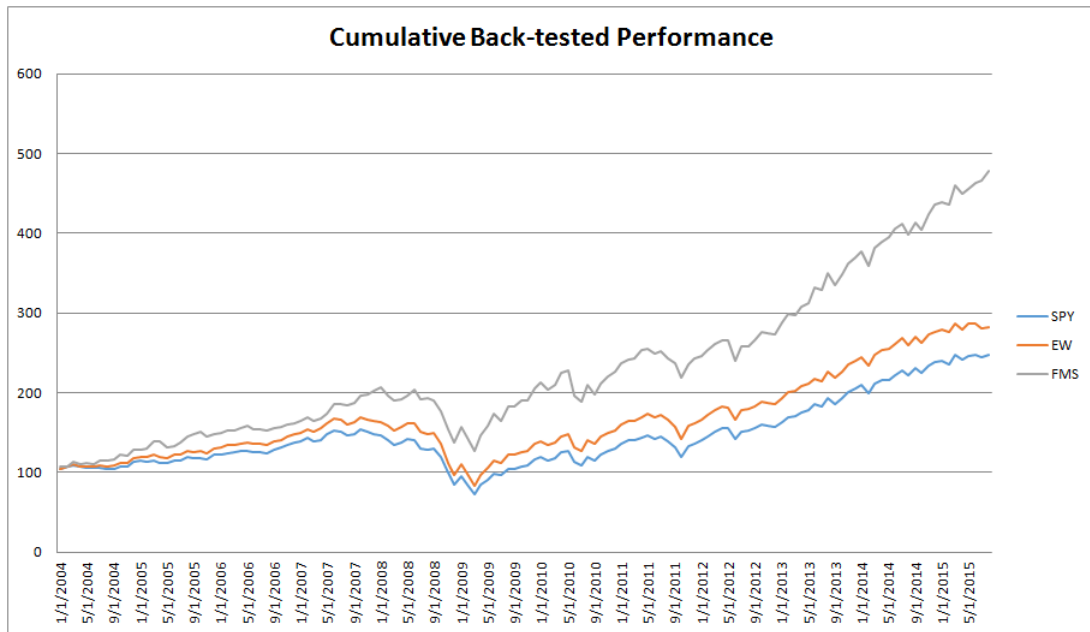
Figure 23: A single factor (FMS)

classification of economic phases. CMI is constructed based on 5 macro variables, incorporating industrial production, expected 1-yr inflation rate, credit spread (yield spread between AAA- and BAA- rated corporate bonds), yield spread (10-2 Year Treasury Yield Spread), and the Conference Board Leading Economic Index. Historically, changes in these key indicators have provided a reliable guide to recognizing the different phases of an economic cycle. Because these inputs are published on a monthly basis, CMI is changing every month and is designed to capture the macro outlook over small time frames. All the components in CMI are normalized by z-scores before feeding them into the aggregates. The tactical cycle is divided into 4 phases: Boom, Slowdown, Recovery, and Recession. See Figure 24.

Depending on the economic phase, it is determined whether to prefer higher beta sectors or lower beta sectors. In the Boom and Recovery phases, higher beta sectors such as XLY (Consumer Discretionary), XLF (Financials), and XLK (Technology) are assigned higher ranks. In Recession and Slowdown phases, lower beta sectors such
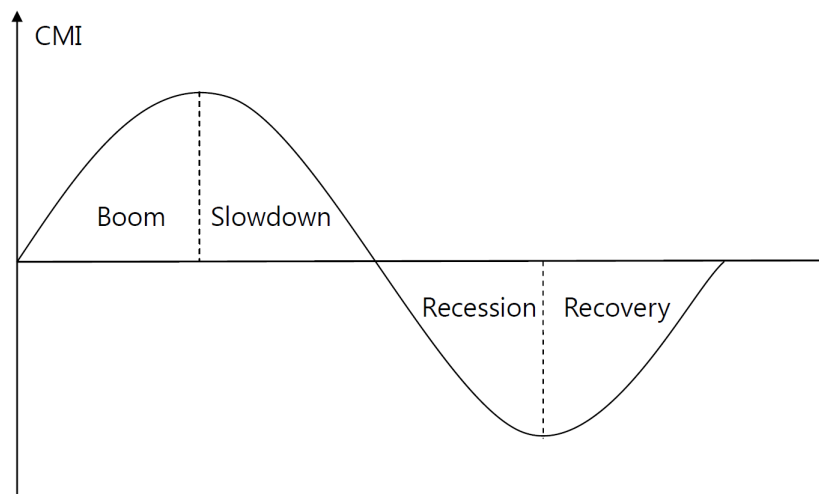
Figure 24: CMI and Economic Phases

as XLP (Consumer Staples), XLU (Utilities), XLE (Energy, and XLV (Health Care) are preferred.[23]

Figure 25 shows the cumulative back-tested performance when I long top 3 sectors based on the signals from CMI at the beginning of every month.

3.3.5 Earnings Revision Ratio

Earnings revision ratio (ERR) is a measure of the direction of consensus earnings expectations. It is a flagship product of BAML. Every month, they count the number of stocks for which consensus earnings estimates have risen and divide it by the number for which it has fallen. I assign higher ranks to the sectors with a higher and improving revision ratio.[24] Barber, Lehavy, McNichols, and Trueman (2001) document that a trading strategy based on the stocks with the most (least) favorable consensus analyst recommendations provides a annual 4% abnormal return on the

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[23]Beta for each sector is updated every month. Top 3 high beta sectors have not been changing since 2000: XLY, XLF, and XLK. Bottom 3 low beta sectors used to be XLP, XLU, and XLE before 2009 and XLE has been replaced by XLV after 2009.

[24]I assign equal weights to the deviations from last 12-month moving average and sectorial average.
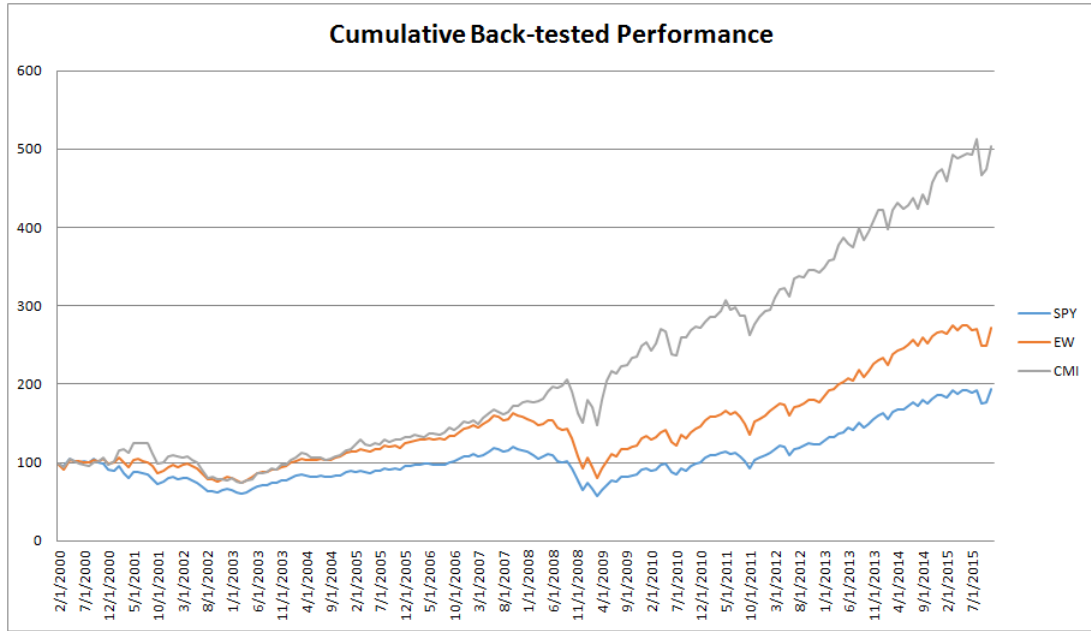
Figure 25: A single factor (CMI)

portfolio. This paper shows that changes in analyst stock recommendations and earnings estimates are able to forecast stock returns and hence gives a theoretical background that ERR can be used as a factor to generate profits as a piece of the sector rotation model.

Figure 26 shows the cumulative back-tested performance when I long top 3 sectors based on the signals from ERR at the beginning of every month.

3.3.6   Sector Rotation Model

Using 4 inputs described above, I rank 9 sectors on a balanced scorecard of 4 equally-weighted factors and calculate aggregate rank on a simple average.[25]   Then I long top 3 sectors to compose a portfolio. I rebalance sectors based on the signals at the beginning of every month and top 3 sectors are equally weighted at each rebalancing.

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[25]If the ranks are the same for any of the sectors, the sector rotation model prefers the sector with higher price momentum.
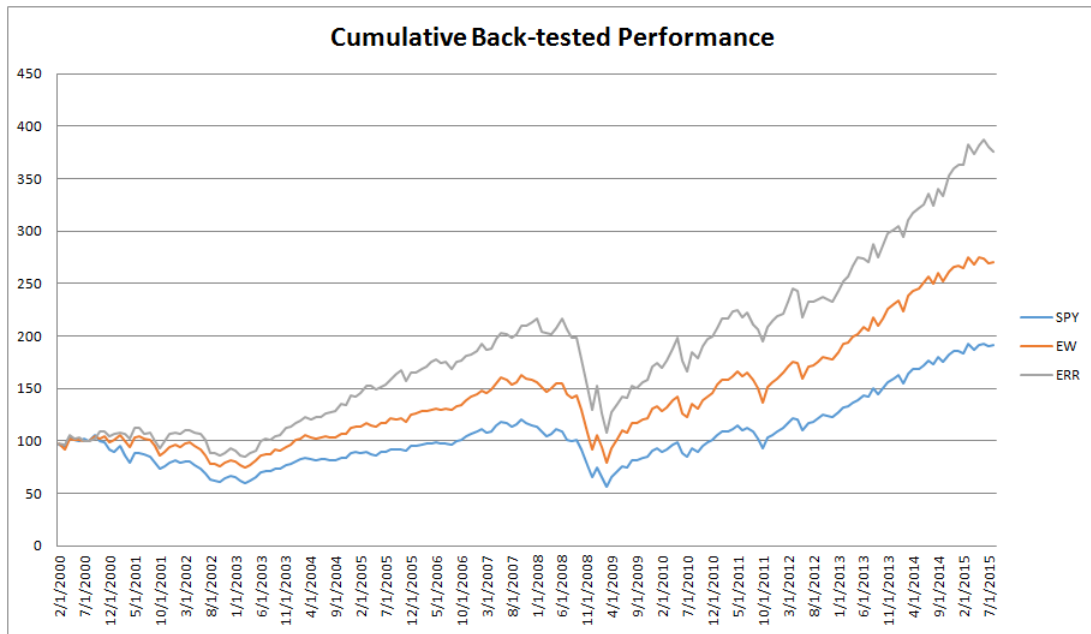
Figure 26: A single factor (ERR)

In sum, sectors with better exposure to macro forecasts, better earnings revisions and price momentum, more bullish positioning and sentiment are ranked at the top. Figure 27 shows the cumulative back-tested performance when I long top 3 sectors based on the signals from the Sector Rotation Model (SRM) at the beginning of every month.

All the graphs indicate that cumulative backtested performance of the single factors and the sector rotation model has shown reasonable consistency in delivering stronger hypothetical returns relative to its benchmark (EW) and market cap weighed index (SPY). [26] And it confirms that the tactical sector allocation had a significant portfolio return during volatile periods. Figure 28 shows the that standard deviation of monthly returns across 9 sectors are bigger in crisis or recession periods than in normal times. This indicates that picking sectors is critical in these time periods

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[26]By nature backtested performance is hypothetical and is not intended to be indicative of future performance.

for a successful sector rotation strategy. For example, during mid 2008 to mid 2009, average monthly return of a typical sector was merely -2 %. However, XLY and XLF experienced 22 % of price return in December 2008, XLF and XLB 29 % and 26 %, respectively in March 2009. Those sectors for the corresponding months were all selected by the SRM.
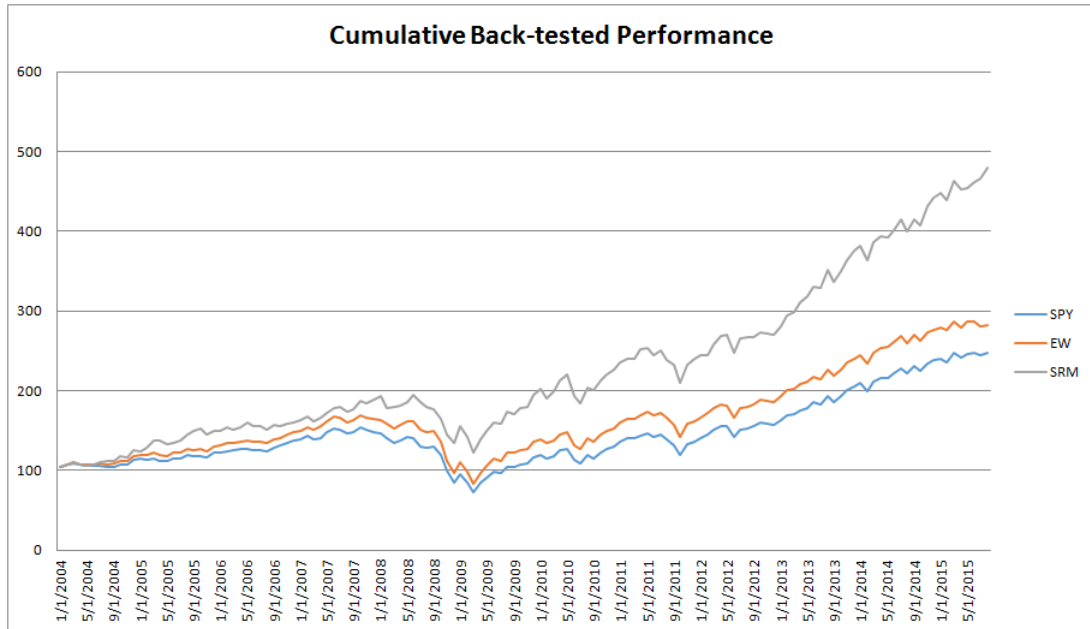
Figure 27: A single factor (SRM)

3.3.7 Empirical Results

In this section, historical back-testing statistics and the result of t-tests on different strategies are provided.

Table 24 shows the annualized return, annualized risk (standard deviation of returns), maximum drawdown (maximum loss from a peak to a trough of a portfolio), winning ratio, Info ratio (annualized return divided by annualized risk), and Calmar
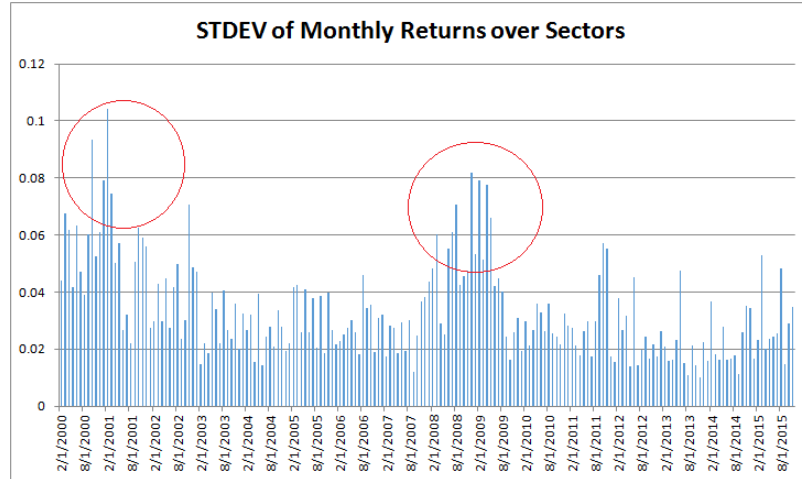
Figure 28: STD of Monthly Returns over Sectors

Table 24: Back-tested Performance

	SPY	EW	PM	CMI	FMS	ERR	SRM
Ann. Return	9.5%	10.8%	12.5%	16.7%	15.9%	12.5%	15.9%
Ann. Risk	16.4%	16.4%	16.7%	16.0%	16.3%	17.3%	16.1%
MDD	-52.9%	-50.9%	-47.6%	-28.7%	-37.8%	-50.3%	-37.3%
Win Ratio			52.1%	57.1%	57.9%	54.3%	57.1%
Info Ratio	0.58	0.66	0.75	1.04	0.97	0.72	0.98
Calmar Ratio	0.18	0.21	0.26	0.58	0.42	0.25	0.43

ratio (annualized return divided by MDD) of the benchmark strategy, single factors, and the sector rotation model. All 4 factors and the SRM beat its benchmark (EW) in terms of risk-adjusted returns. However, CMI as a stand-alone factor generates a higher Info and Calmar ratio than the combination of signals used in the SRM. This result supports that globalization has increased the impact of macroeconomics on indutry/sector-level risk factors and caused the performance of sectors to be more closely tied to the economic cycle.
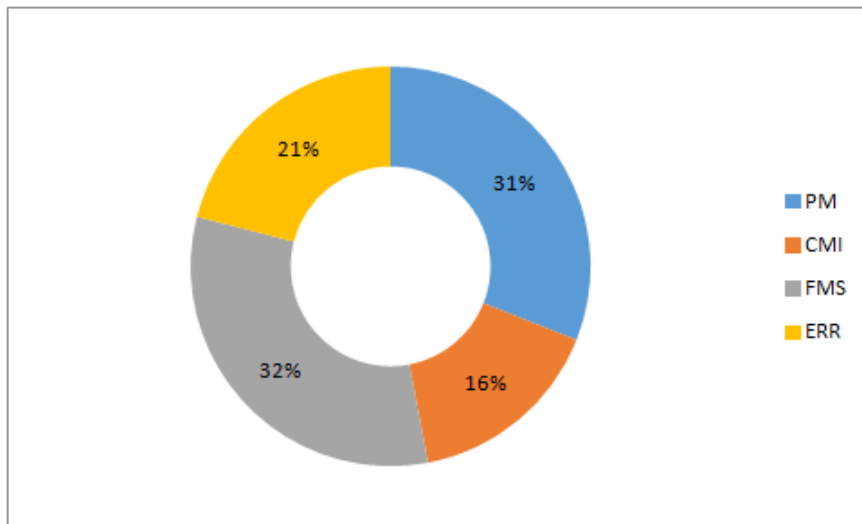
Figure 29: Contribution of Each Factor to SRM

The weaker performance of the sector rotation model than CMI can be explained when the contribution of each factor to the SRM is scrutinized. I regress monthly returns of the SRM versus the other four time series (based solely on the individual factors). Contribution of each factor to the SRM is the following: 31% (PM), 16% (CMI), 32% (FMS), and 21% (ERR). This confirms that the contribution of weak factors such as PM and ERR washes away performance of the SRM.

Next, using two-sample t-test, I examines whether the performance of an investment strategy is different from that of the benchmark strategy. Therefore the null hypothesis states that the annualized return of an investment strategy, i is equal to

the annualized return of EW.

- $H_0 : r_{EW} = r_i$ where $i =$ PM, CMI, FMS, ERR, and SRM

- $H_a : r_{EW} < r_i$ where $i =$ PM, CMI, FMS, ERR, and SRM

Table 25: t-test results

	PM	CMI	FMS	ERR	SRM
p-value	0.24	0.01	0.07	0.19	0.03

The result of t-test is summarized in Table 25. As shown in table 1, the result of t-test reaffirms that the performance of CMI, SRM, and FMS against the benchmark strategy is statistically significant.

3.4   Phase-Adjusted Model

The sector rotation model dominates its benchmark but CMI as a stand-alone factor generates a higher risk-adjusted return than the SRM. So, how can the sector rotation model be improved? The reason behind outperformance of CMI is that the performance of sectors is closely tied to economic phases. This implies that phase-adjusted strategy might improve the performance of sector allocation. Table 26 shows that signals do not have equal qualification for different phases. This table calculates the average performance of a factor in a particular phase of the tactical cycle. Historical analysis of the individual factor's performance in different economic phases shows the relative performance of the factors has tended to be very phase-dependent. In boom phases, price momentum has shown outstanding relative performance and in recession phases, CMI has excelled. In transition phases, all the factors yield similar performance.

Table 26: Average Monthly Return (%) for Different Phases

	PM	FMS	CMI	ERR
Boom	**0.9**%	0.7%	0.2%	0.6%
Recession	-0.3%	-0.6%	**-0.1**%	-1.7%
Recovery	2.7%	3.6%	4.5%	3.8%
Slowdown	1.2%	1.2%	1.6%	1.5%

Based on this stylized fact, I introduce a new model called Phase-Adjusted Model. In this model, the current economic phase is needed to be identified. Once the economic phase is identified, I investigate which single factor performed the best in the corresponding economic phase. Then I pick out top 3 sectors based on the signals from that single factor. I use an expanding window, which uses all the data available up to the point in time when the model is tested. Table 27 summarizes the back-tested result. The Phase-Adjusted Model dominates the benchmark and the Sector Rotation Model. Moreover, it outperforms CMI.

Table 27: Back-tested Performance

Historical Back-testing Statistics (Since April, 2004)				
	EW	CMI	SRM	PAM
Holding Period (Months)	136.00	136.00	136.00	136.00
Holding Period Return (%)	155.54	305.21	246.96	308.00
Annualized Return (%)	9.70	13.75	12.41	13.80
Annualized Risk (%)	16.59	16.58	16.83	16.20
Max Drawdown (%)	50.90	37.90	34.42	34.99
# of Winning Months		75	72	74
# of Losing Months		61	64	62
Info Ratio	0.58	0.83	0.74	0.85
Calmar Ratio	0.19	0.36	0.36	0.39

The Phase-Adjusted Model has the highest risk-adjusted returns in the recent years. It has performed particularly well over the past year and past 3 years. It is well summarized in Table 28 and Table 29.

Table 28: Recent 3-year Performance

Historical Back-testing Statistics (Recent 3 Year)							
	EW	PM	FMS	CMI	ERR	SRM	PAM
Annualized Return (%)	17.4	18.8	14.3	18.2	20.4	16.3	19.9
Annualized Risk (%)	9.6	9.6	9.8	10.6	10.5	10.5	10.0
Info Ratio	1.8	1.9	1.5	1.7	1.9	1.6	2.0

Table 29: Recent 1-year Performance

Historical Back-testing Statistics (Recent 1 Year)							
	EW	PM	FMS	CMI	ERR	SRM	PAM
Annualized Return (%)	7.0	4.1	11.1	13.5	8.4	10.1	12.8
Annualized Risk (%)	9.0	10.4	9.8	10.5	9.7	10.2	8.6
Info Ratio	0.8	0.4	1.2	1.3	0.9	1.0	1.5

Now, the annual total returns are calculated on a calendar-year basis. See Table 30. The number is in bold if it outperforms EW in the given year. Over the past 10 years, the PAM outperformed its benchmark except 2 years. Compared to a mild suffering in 2010, the suffering in 2006 was severe. There can be two possible explanations. First, the PAM depends on the past performance when it makes forecasts. In 2006 it only has 2-year data and it might lead to a less robust forecast due to lack of sufficient observations for economic phases. Secondly, the PAM heavily depended on the signals from price momentum (6 times out of 12 in 2006) which performed the worst among the 4 single factors. Even worse, it was the worst year for PM historically.

3.5   Conclusion

A smart-beta strategy is a investment strategy that chooses stocks based on some criteria other than market capitalization. Because cap-weighted equity index automatically increase (decrease) their exposure to stocks whose prices appreciate (depreciate).

Table 30: Annual Return Analysis

	EW	PM	FMS	CMI	ERR	SRM	PAM
2005	11.0	**22.8**	**11.2**	**14.3**	**15.8**	7.8	**24.0**
2006	14.0	3.8	**18.0**	11.0	6.6	9.7	0.8
2007	8.4	**14.4**	3.0	4.2	4.3	**14.8**	18.4
2008	-32.4	**-26.5**	**-31.9**	**-19.2**	**-26.4**	**-17.1**	**-22.7**
2009	26.5	20.2	25.5	**54.0**	31.1	41.5	49.6
2010	15.3	**16.5**	**22.4**	16.0	**15.6**	**16.6**	12.8
2011	3.6	**5.3**	**11.5**	**9.9**	2.7	**6.6**	**5.2**
2012	16.0	10.7	**21.8**	**22.1**	7.2	12.6	**22.9**
2013	26.5	**33.6**	18.2	**27.5**	24.5	24.7	**28.1**
2014	14.4	12.9	**21.4**	**18.5**	**25.6**	18.3	**19.2**

This built-in pattern tend to overweight overvalued securities and underweight undervalued securities. The equal-weight basket is the most simple smart-beta strategy that overcomes the drawbacks of market cap-weighted equity indexes.

This paper introduces the sector rotation model that can beat the equal-weight basket. Furthermore, the phase-adjusted model is introduced to overcome some drawbacks of the sector rotation model.

For future research, more factors can be added to the model. In literature some papers prove that the seasonal effect such as 'Sell in May' and traditional valuation metrics (mean reversion, dividend yield, and PE ratio) add some value in sector rotation strategy. Moreover, bearish signals can be extracted from the model so it can select bottom 3 sectors. With long top3 / short bottom3 strategy, a more market-neutral position can be achieved.

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