SOVEREIGN DEBT RESTRUCTURING: AN ASSESSMENT OF INVESTOR PRICING BEHAVIOR

By

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ABSTRACT

This research paper focuses on the analysis of investor behavior in sovereign bonds, with the aim of assessing their ability to detect impending default risk. Using a dataset of external sovereign bonds spanning from 1820 to 1980, the paper performs a dynamic difference in difference regression. The paper finds that sovereign bond investors begin to react to early signs of default, with defaulting bonds beginning to be priced down 40 months before default. The prices reduce steadily relative to non-defaulting bonds until around 10 months before the default date. At around 10 months the drop in prices accelerates until the default date. Post-default, the prices continue to decrease, but at a decreasing rate, reflecting the uncertainty in the haircut.

Table of Contents

INTRODUCTION

Sovereign defaults have a pervading presence in financial history to such a degree that it could be viewed as an inherent feature in a country's economic development. Carmen M. Reinhart and Kenneth S. Rogoff found that virtually all countries defaulted when they were still in the developmental stage, with several having spent more than 40 years since 1800 in default or rescheduling, and having had multiple defaults over this time period (Reinhart and Rogoff 2009, p.99).

Furthermore, external credit is a key source of financing for many economies especially developing markets. From a forward-looking perspective, the less favourable global economic environment could trigger a wave of defaults over the next decade. The IMF (International Monetary Fund) found that, as of 2019, 40% of low-income countries were facing debt distress or high-risk debt levels. Since then, the covid crisis, inflation and geopolitical tensions have exacerbated sovereign distress. Recent restructurings in Zambia, Argentina and Lebanon are reflective of the increasing difficulty of developing countries to manage their obligations. As such, both investors and borrowers will need to be prepared to operate in an environment with greater sovereign distress.

Sovereign debt is typically considered a relatively safe asset class when compared to corporate debt, largely stemming from the ability to tax future income. Conversely, the lender often does not possess the same ability to enforce debt contracts as they would have for corporate issuances under the legal jurisdiction of their own country. In the case of a default, foreign courts rarely have the ability to force the defaulter to hand over its assets, which are normally contained within the borrower's borders.

With the likelihood of asset seizure far lower for sovereign bonds than for corporate debt, the imbedded option to default is far more valuable to sovereign borrowers. As can be expected from this, sovereign defaults often occur at much lower debt levels, before they have reached an inability to pay (Reinhart et al 2009, p.51). Moreover, countries also have political and social considerations, rather than purely financial ones. As a result, anticipating when a country will choose to default is an additional complication to investors as they cannot entirely focus on projections of when the country runs out of resources and physically cannot cover its obligations. Investors must assess the probability of default differently than corporate debt, as well as the expected recovery. This research seeks to analyse investor behaviour across sovereign bonds and assess their ability to detect greater impending risk of default.

This paper will attempt to analyse when the prices of bonds react to an impending default. The main beneficiaries will be investors in sovereign bonds and sovereign borrowers. Understanding when prices react can help both investors and issuers determine the triggers of these responses. It also can help gauge how far in advance investors begin to recognise signs of distress.

Sovereign debt is a comparatively opaque asset class, with less complete information on pricing and genuine cost of default that makes the determinants of haircuts unclear. However, sovereign debt has demonstrated strong performance (Meyer, Reinhart 2019). Meyer and Reinhart found that the returns on external sovereign bonds have been sufficiently high to compensate for risk, underpinned by large average coupons. They found that these returns were hard to reconcile with theoretical models and the credit risk in the market. Thus, understanding the mechanics surrounding left tail scenarios (i.e., a credit event) is important and this thesis seeks to build upon other research in this area.

LITERATURE REVIEW

Sovereign debt issues have been used as a financing tool for centuries, and defaults have likewise accompanied them. Importantly, serial default is not a unique characteristic of the current emerging markets. Carmen M. Reinhart and Kenneth S. Rogoff noted defaults on external debt in Europe in every century since the 1300s. Defaults occurred amongst countries such as England, France, and Germany - rich nations with advanced economies in today's world (Reinhart et al 2009, p.86, 87)**.**

External debt is defined as the total liabilities of a country with foreign creditors, both official (public) and private (Reinhart et al 2009, p.9)**.** A country's external debt results from its ability to participate in global capital markets. Access to foreign capital is key for the growth and development of a country. As a result, one of the key considerations a country must make when deciding whether or not to default is how defaulting on external debt may inhibit its ability to access global capital markets. Extensive research has been conducted focusing on the cost of default, taking the perspective of the borrower and their future access to global capital markets This paper instead focuses on how investors respond to news in the build-up to a default, and does not look at the decision to default.

In their paper *Sovereign Defaults: The Price of Haircuts* Juan J. Cruces and Christoph Trebesch construct a database of restructurings with foreign banks and bondholders from 1970 until 2010, to assess the relationship between haircuts and subsequent yield spreads. They show that the size of haircuts experienced by investors results in substantially higher spreads on future debt raised. Their paper focuses on the post-default behaviour of investors, observed from the lender's perspective. This contrasts with the findings of other papers, that investors' subsequent reactions can be characterized more by "debt that is forgiven is forgotten," meaning that defaulting countries are typically not punished to a notable degree after defaulting on debt. However, in their work, Cruces and Trebesch were able to quantify the haircuts for the debt, whereas previous research used binary data dependent on any missed payment. Cruces and Trebesch's haircut dataset showed considerable variation in haircuts (American Economic Journal: Macroeconomics 2013, p.86), with one half of haircuts either below 23% or above 53%. Such variation in restructuring outcomes is an important consideration that the use of binary data fails to capture. The paper finds that the size of haircuts has substantial prediction power on the spreads for up to seven years after restructuring. With contrasting conclusions regarding investor responses to restructuring outcomes, this paper can provide a different perspective to investor responses by assessing the pre-default responses.

Carmen M Reinhart, Kenneth S. Rogoff, and Miguel A. Savastano establish a link between a country's default history and its debt intolerance. Debt intolerance is defined as the extreme duress many emerging markets experience at external debt levels that would seem quite manageable by the standards of advanced economies (Reinhart et al 2009, p.21)**.** They find that nations can be categorized in various clubs of debt intolerance, which are heavily influenced by their inflation and credit history. These clubs in turn have varying access to international capital markets, with the worst club being completely shut off.

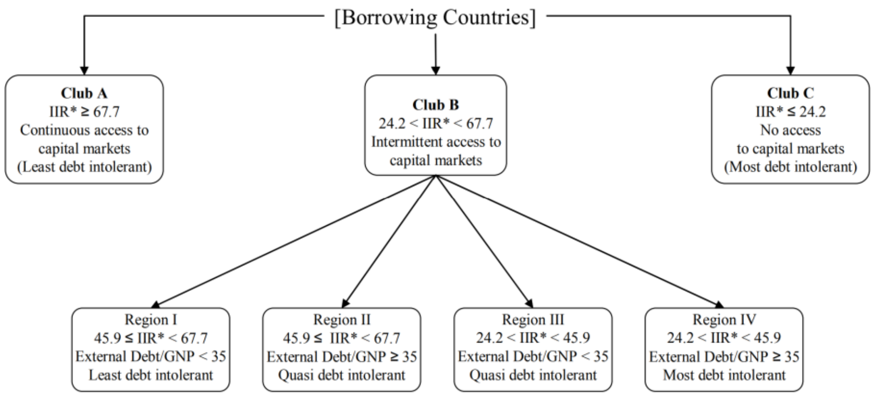

Figure 1: Debt intolerance club classification (Reinhart, Rogoff, Savastano, 2009)

The club categorization is a function of Institutional Investors' Ratings and their external debt to GNP (Gross National Product) ratios. As shown in Figure 1, Club C has no access to capital markets, an extremely costly situation that would entail sustained long term economic stagnation.

Other research into the cost of sovereign defaults found that Sovereign debt restructurings are associated with declines in GDP, investment, bank credit and capital flows (Asonuma, Chamon, Erce, Sasahara 2019, p1). Asonuma, Chamon, Erce and Sasahara found that the adverse effects of a restructuring were amplified if the restructuring was post-default, whereas countries that engaged in pre-emptive restructurings fared better.

Meyer, Reinhart and Trebesch take the perspective of the investor in their paper *Sovereign Bonds since Waterloo*. In this paper, they provide an exhaustive overview of sovereign bond returns from 1815 to 2016. They compiled the dataset that this paper will use, using around 250,000 monthly pricing entries for foreign currency bonds. The pricing dataset spans bonds traded in London and New York since 1815. In the paper, they seek to answer why, given frequent defaults and limited enforcement, investors are attracted to this asset class. Their findings correspond with Cruces and Trebesch's work - haircuts are relatively low (median is below 50%) and full repudiation is rare.

Broadly speaking, there is less literature focused on analysing investor responses. Gulati, Panizza, Weidemaier and Willigham look at how the market responds to a government's promise to prioritize public debt. They find that such promises have no impact on yields, unless the borrower is a sub-sovereign such as Puerto Rico. They focused their analysis on Spain and Puerto Rico. In 2011, there was an amendment to the Spanish constitution, that gave super-priority to holders of their public debt. To assess, they looked at the preceding yields and compared them to the post default period. Legislation applying to one group of bonds but not another allowed them to apply an equivalent analysis for Puerto Rico. This paper similarly looks at the evolution of prices over an event (default). But the dataset spans a much larger time frame and uses a broader set of sovereigns. It also uses monthly, rather than daily prices.

Donaldson, Kremens and Piacentino investigate whether sovereign bondholders benefit from committing to not restructure. They find that the commitment for one class of bonds benefits not only that class, but other classes as well. This shows an interesting behavioural phenomenon that is not based on fundamentals. Flexibility in the restructuring of one class of bonds would decrease the debt burden, which should, in turn, make the borrower more capable of fulfilling its other obligations without a restructuring. However, if this were the case then such a commitment to not restructure would not lead to other classes of bonds benefiting. Such an observation highlights the need for a greater understanding of investor behaviour. This paper can help contribute to this understanding by comparing the market pricing for defaulting and non-defaulting bonds.

Indarte also finds that sharing an underwriter can lead to significant contagion across bonds – a default in one series can (negatively) affect the prices of other non-defaulting bonds issued under the same underwriter (Indarte 2021). This phenomenon can be further unpacked by seeing if prices react earlier if the underwriter has defaulted in the past. Thus, this paper, which studies the pricing impact over time, can provide a new angle to assessing the reputation effect on bond prices.

There has been a growing amount of literature looking into the errors of expectations. Reinhart and Rogoff discuss this as a key aspect of the causes behind financial crises. During periods of optimism and financial stability, creditors begin to neglect the probability of default. This upward bias in the expected returns results in a lending boom, planting the seeds of the impending bust. D'Agostino and Ehrmann estimate the determinants of G7 bond spreads. Across these developed markets, they found evidence of under and over pricing of risk. The degree that risk factors are priced was reduced in the years preceding a financial crisis, and higher during the European debt crisis, providing evidence of errors of expectations playing a role in sovereign bond pricing. Ferrucci sought to build an empirical model for sovereign bond spreads in emerging markets, based on fundamentals**.** This paper can allow a broader test for this model to see if price changes can be matched to changes in the fundamentals captured in the pricing model. In particular, this paper could provide a way to observe the error of expectations by comparing how far in advance investors recognise and price in the risk of an impending default during boom periods versus their behaviour during bust periods. One can expect that in the presence of errors of expectations, investors would be caught off guard if the default came during or shortly after a boom period as compared to defaults occurring in periods of lesser sentiment.

DATA & METHODS

The dataset being used comes from the Sovereign Bonds since Waterloo paper by Meyer, Reinhart and Trebesch. The original dataset has 255,000 monthly pricing entries, but, for proprietary reasons, data from 1995-2016 had to be excluded since it was taken from JP Morgan's EMBIG dataset. As a result, the dataset has monthly prices of 911 bonds, the first price entry from 1822. Within this dataset, there is also a binary indicator column, equal to one if the bond is in default, and zero otherwise. Other information relevant to the research is an indicator column equal to one if the country is a serial defaulter, and zero otherwise.

The dataset is a compilation of foreign-currency bonds traded on the London and New York stock exchanges. The focus is on bonds issued by central governments in foreign (USD and GBP) currency and excludes bonds with a maturity of less than one year or any bonds with a floating coupon rate. Furthermore, price quotations are end-of-month.

Meyer et al pooled the data from several resources depending on the type of information and the time period. For pre-1870, they used Money Market Review, The Economist, Circular to Bankers, Course of the Exchange, and Banker's Magazine for price data. For the 1870 to 1930 period, the pricing data from the British Investor Monthly Manual was used. Meyer et al added bond-level information on default characteristics, including the timing and details regarding missed or partial coupon and principal payments, and the terms of the restructuring. They added monthly prices for external sovereign bonds trading in the London Stock Exchange from 1930-1980, getting this information from The Economist and the Financial Times, as well as including data on prices for sovereign bonds on the New York Stock Exchange, from the Bank and Quotation Section of the Commercial Financial Chronicle and the Bank and Quotation Record.

The below table from the Sovereign Bonds since Waterloo paper summarizes the data characteristics. Note that post 1980 data is not covered in this paper.

	Total sample	**By era** 1815-1869	1870-1913	1914-1945	1946-1980	1989-2016
Number of countries covered	91	30	45	52	43	67
Share of countries covered	70.5%	73.2%	88.2%	85.2%	35.8%	51.9%
Pricing observations	266,134	12,070	74,884	78,257	44,679	56,244
Number of active bonds	1,552	140	437	507	313	641
… issued in British pounds	635	140	430	335	108	0
….issued in US dollars	917	0	7	172	204	641
Avg. maturity of bonds	27	33	41	40	33	16
Average coupon (nominal)	5.8	5.1	4.7	4.9	5.2	7.0
Average amount issued (nominal, in m USD)	739	29	35	35	37	1,738

Figure 2: Summary of the bond pricing database (Meyer, Reinhart, Trebesch, 2019)

Out of the 911 bonds in the core dataset, 299 are defaulting bonds. Of the 299 defaults, 283 were issued by a country labelled as a serial defaulter. Defaults are very concentrated among developing countries and regions. In particular, South America accounted for more than 100 defaults. Most of the bonds were issued by serial defaulters (571 out of 911 in the core dataset).

Defaults occurred mainly in clusters across time and are most concentrated around systemic shocks such as the Great Depression and World War II. Notably, all the defaults by non-serial countries occur in early 1940, during World War II. Defaults appear to be more dispersed pre-1870, after which visible clusters appear in 1870s, around 1900, around 1918 and the 1930s.

Figure 3: Timing of defaults across years, and the price on the default date of the full sample.

Said clusters occurred around financial crises and during periods of global conflict. 1880- Baring crisis; 1907 – Banker's Panic; 1918 – World War I; 1930s – Great Depression; and 1940s - World War II.

Gauging how investors price the risk of default for sovereign bonds, the analysis uses a staggered difference-in-differences regression.

$$y_{it} = \beta_1 \times 1[Default_i]it + \sum_{k=-T}^{T} \beta_{2k} 1[t = t^* + k] + \sum_{k=-T}^{T} \beta_{3k} 1[t = t^* + k][Default_i] + \gamma X_{it} + e_{it}$$

In the above specification, y_{it} is the price of bond *i* at time *t*; $1[Default_i]$ is an indicator variable that equals one if the bond defaults and zero otherwise; t^* is the month that the default occurs; X_{it} is a set of controls.

β_{3k} describes the average difference between the treated and untreated groups and is the coefficient of interest. The regression will cover T months before default (negative k) and T months afterwards (positive k). The paper will look at bond pricing for up to four years before and after default (thus T = 48).

This required the data to be transformed into a stack format. Each defaulting bond was assigned an event number (resulting into 299 events). Then non-defaulting bonds occurring 48 months before, and 48 months after the default date of the event were assigned that event number. The resulting dataset has 865 individual bonds, and 299 events.

Each bond has its monthly price recorded, but not all month's prices were captured for every bond (some bonds had missing prices). To get a better sense of the completeness of the data, the number of monthly prices that each bond had for each event was calculated. The below plot shows the distribution of price count for the bonds per event. A price count of 97 is the maximum, given that the transformed data only includes prices 48 months before and 48 months after the event default.

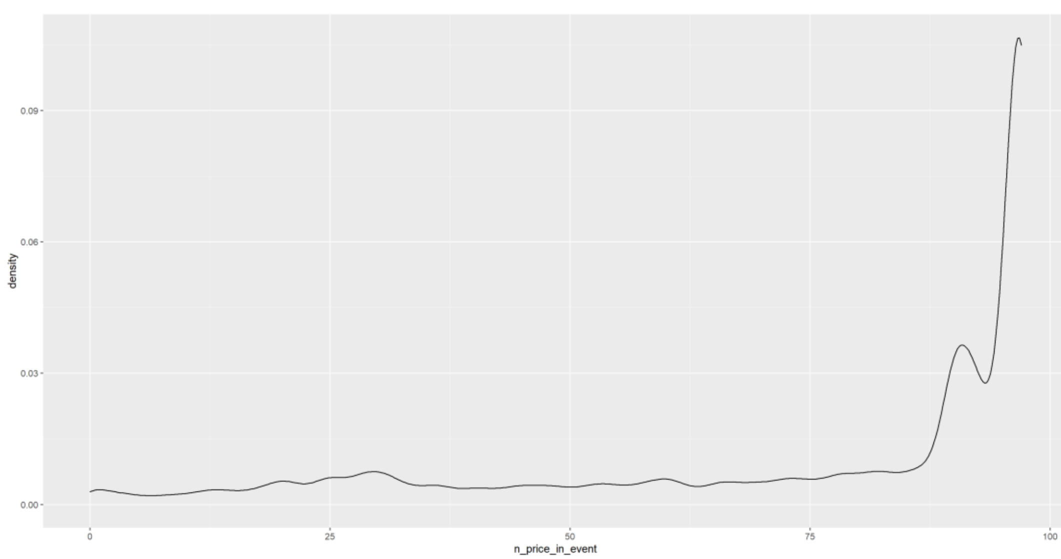

Figure 4: Distribution of price entries per bond of the transformed dataset.

As seen, most of the data is complete or close to complete with less than 20% of missing prices across each default event. However, some bonds are missing a very large portion of the prices.

As a result, the data was cleaned to remove bonds with too few prices. This posed a trade-off between sample size and completeness of the data. With this in mind, the paper performs the regression several times, with different price-count thresholds for each one.

Setting the price-count to 100% (no missing prices) reduced the size of the dataset to 345 unique bonds, with 274 untreated and 71 treated bonds. Setting such a high threshold result in a much smaller sample. Another important consideration is the bias that it may introduce in the dataset. For example, the completeness of data will vary across time and potentially across country, so cutting bonds without any missing prices may yield results that are not applicable to the broader dataset. This is why several thresholds were assessed.

Price-count threshold (>=)	Total unique bond count	Defaulting bonds (treated)	Untreated
100%	345	71	274
95%	459	121	338
90%	515	151	364
85%	543	164	379
80%	564	176	388

Figure 5: Sample size with different price-count thresholds. Note that a threshold of 100% implies zero missing values, 95% implies up to 5% missing values (for each bond) etc.

For the main result, the 90% cut-off was used, but broad comparisons are made between the results using the other thresholds, and the figures are included in the Appendix.

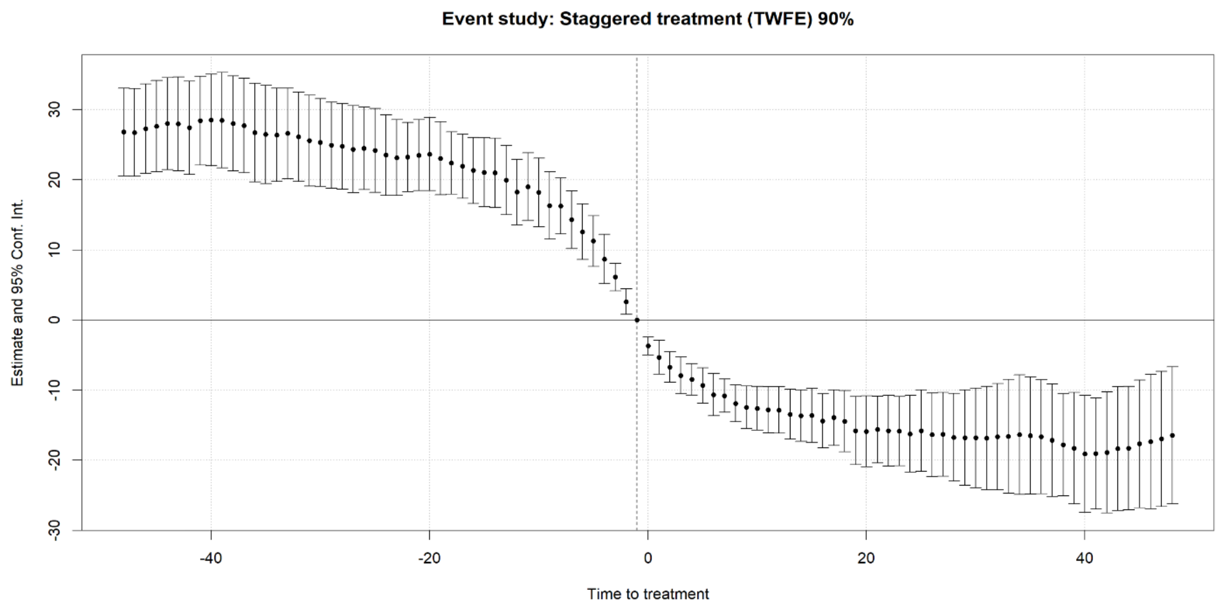

Figure 6: Staggered Difference in Difference on data with 90% price-count threshold

The panel data employed fixed effects to control for time, country, event ID and whether the issuer was a serial defaulter or not. Furthermore, two-way clustering was used across country of the issuer and time. The findings indicate that investors begin to price bonds that eventually end up defaulting differently from non-defaulting bonds around 40 months before default. The downward pressure on price continues steadily until about 10 months before default. At this point, awareness of default risk seems to increase as the defaulting bonds get priced down increasingly faster. Interestingly, the bond prices continue to drop long after default has occurred.

The expected credit loss on a bond investment can be disaggregated into the perceived probability of default, and the expected loss given default. Cruces and Trebesch found that there is significant variation in haircuts of sovereign bonds. Their study covers all sovereign debt restructurings with foreign banks and bondholders between 1970 and 2010. The haircut estimates span 180 sovereign debt restructurings. Critically, they find that half of the haircuts are either greater than 53% or less than 23%. This large variation means that predicting the haircut on a defaulting sovereign bond is challenging. As such, even after a default is known with certainty (i.e., after a default has taken place), there is still pronounced uncertainty surrounding how much investors end up losing (loss given default). Based on the behaviour of investors post-default, the expectation of haircut size appears to increase with time. In other words, investors anticipate steadily higher haircuts as the time after default increases. Beyond 40 months after default, prices flatten and even appear to increase relative to non-defaulting bonds. This may suggest that by this time, a resolution is reached (in the aggregate) and investors receive a fraction of face value.

Below is the plot for the same specification but on the data with 100% price-count threshold. A key difference is the steepness at which the bond prices drop.

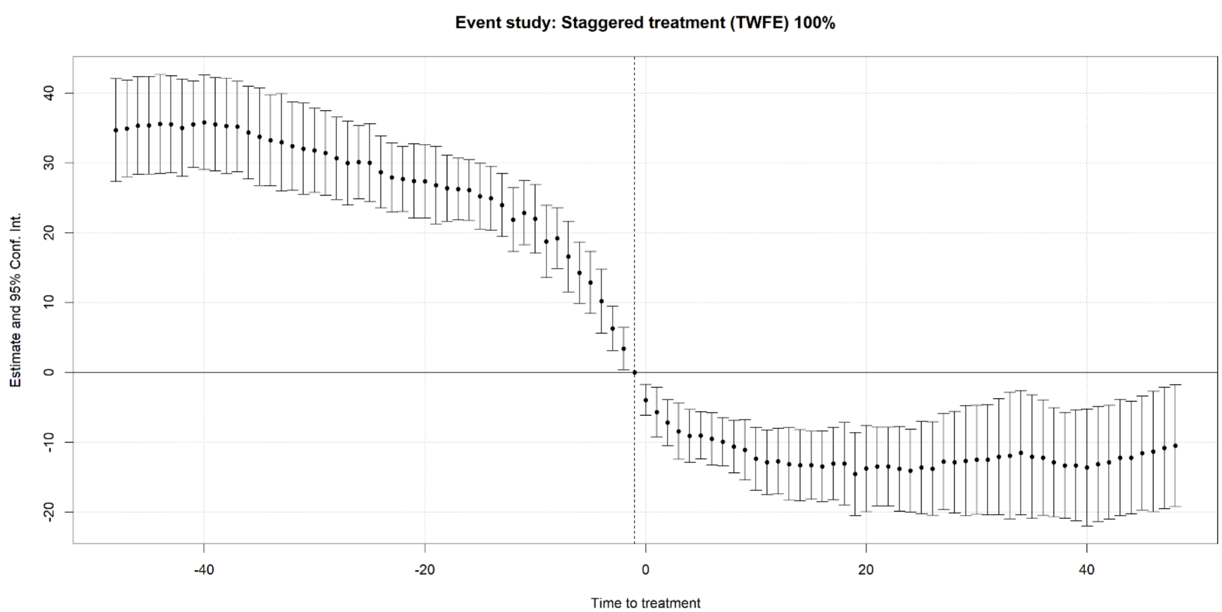

Figure 7: Staggered Difference in Difference on data with no missing prices.

The prices appear to drop faster preceding default. They also plateau earlier in the post-default phase. In general, the lower the price-count threshold the steeper the drop in the 10 months preceding default. This may be driven by the differing samples (both size and composition of bonds in them) or by differing "completeness" of the data - while the 80% price-count threshold regression removed over 38,000 observations because of NA values, the 100% price-count threshold regression had no NA values since any bond with missing data had been completely removed. Missing values mean that the number of prices that the treated (defaulting) bond is being compared to varies across months, which is problematic if the number of prices recorded each month varies a lot. Plots of the regressions using the other price-count thresholds is presented in the appendix.

The critical components of pricing the bonds are the expected cash flows, and the risk of the cash flows. In the absence of an extreme shock that irrecoverably inhibits the country's ability to fulfil its obligations more than two years out, the price changes are more of a reflection of the changing risk profile of a bond (indicative of higher risk of default) than an expectation that the bond will not be repaid. Adverse information such as slowing GDP growth can push a bond into a different risk category (from the investor's perspective). While it may not be that a default is expected by sellers, but rather that the riskiness of the expected cash flows is no longer appropriate for the risk tolerance/specifications of the seller's portfolio. As a result, they offload the security to another investor with a differing risk appetite, and so goes a sort of clientele effect that drives the changes in the bond prices far out (in terms of time) from default. This is underpinned by the fact that an investor can lose money from credit risk even without default, if the bond's risk profile changes (i.e., if the discount rate on the cash flows increases).

Closer to the default date, information about the expected cash flows becomes much stronger, as there is less that a country can do to "turn the ship around." This can explain the increased rate at which the defaulting bond is priced down 10 months before treatment. The price change driver shifts from the clientele effect described earlier to explicit bets on repayment.

SUMMARY OF RESULTS

The results indicate that investors do detect increased default risk around 40 months before it happens, at which point the prices begin to decline. 10 months before, the prices drop quickens, and post default, continues to decline at a slowing rate. Before interpreting these results, this paper will discuss limitations.

Firstly, the sample is unbalanced. Gathering data on monthly bond prices across time is an involved process, pooling information from multiple sources. As a result, the sample size and countries covered varies across time due to changing data (un)availability and political factors (World Wars, capital controls). Another issue that has already been discussed but remains relevant is the missing data issue for bonds in the data set. As described, while the overall conclusions do not change, the results under different price-count thresholds are materially different. This is no doubt partly attributable to the imbedded bias in which bonds had the most complete data. Below (Figure 8) is a scatter plot of the defaults across time for the transformed dataset with no missing price (i.e., the 100% price-count threshold). Comparing to Figure 3, the pre-1875 sample has lost a substantial number of bonds (effectively all), and the defaults are more clustered.

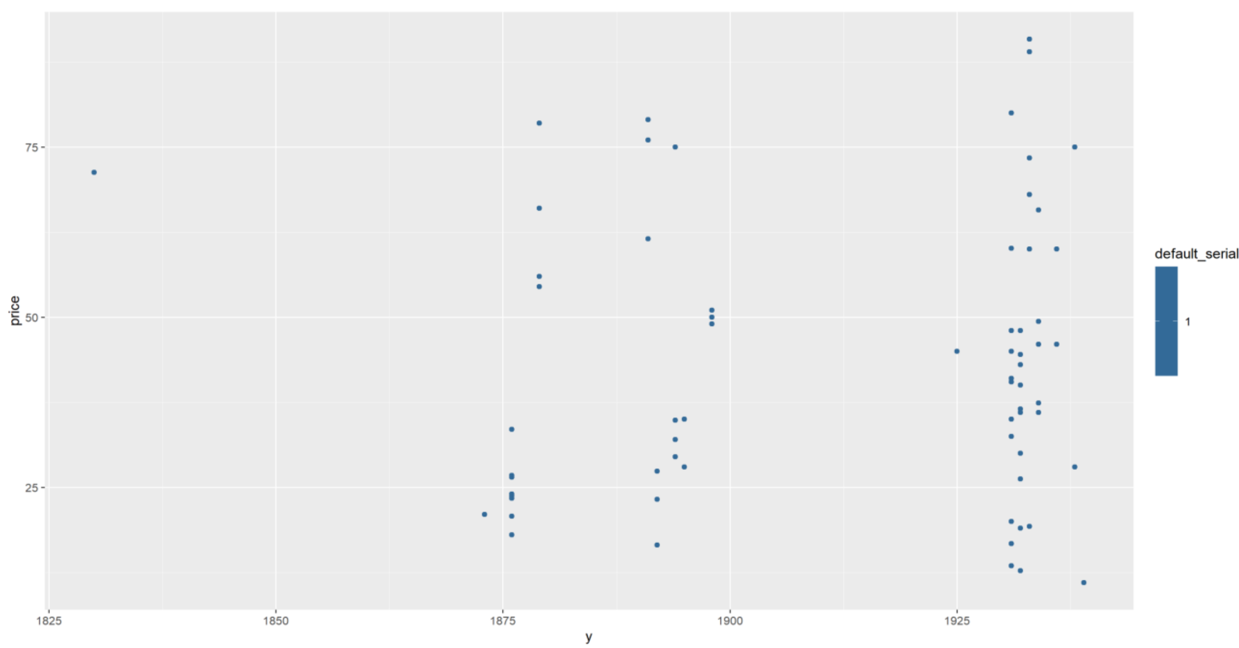

Figure 8: Timing of defaults across years, and the price on the default date of the sample with no missing data.

Regardless, the results indicate strongly that investors are not completely taken off-guard in the aggregate but do detect early warning signs and react accordingly to these signs. This result is shared across the different regressions run.

CONCLUSION & NEXT STEPS

Investors begin to price in the increasing risk of default 40 months prior to default, given the steady decrease in prices until approximately 10 months before. This may be indicative of the bond's evolving risk profile rather than taking an explicit stance on default. 10 months before, the decline in the bond price suggests that investors gain access to much stronger information about the expected cash flows of default. Post default, the price continues to decline but at a decreasing rate, reflecting the uncertainty in the haircut.

Future papers could use more recent data (post-1980) and compare results. Newer data will have fewer missing entries that constrained this study. Moreover, more complete data will allow more sub-sample comparisons to be made. By tracking the portfolios of public funds, the clientele effect briefly touched on may be more explicitly observable. The expectation would be that a bond will be sold once it has a higher perceived risk that makes it unsuitable for the portfolios designated risk tolerance. If one can track the bond as it changes hands, it may reveal this clientele effect (if the bond shifts to funds with a different risk profile mandate). This is likely to be most clearly observable when the perceived increase in risk results in a downgrade.

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APPENDIX

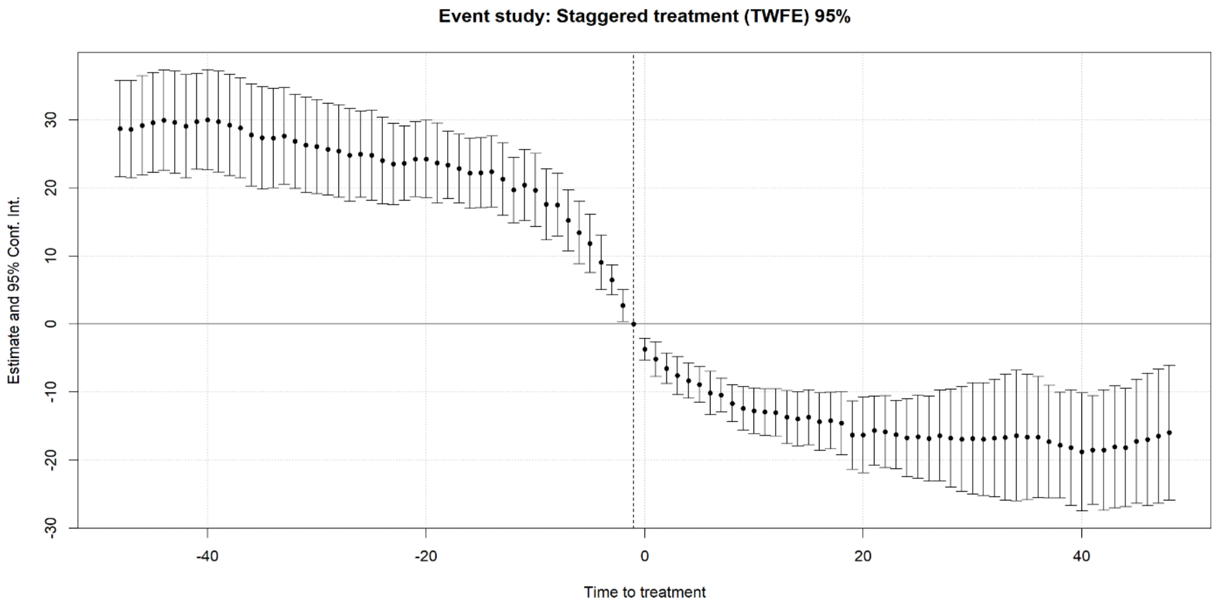

Figure 9: Staggered Difference in Difference on data with 95% price-count threshold.

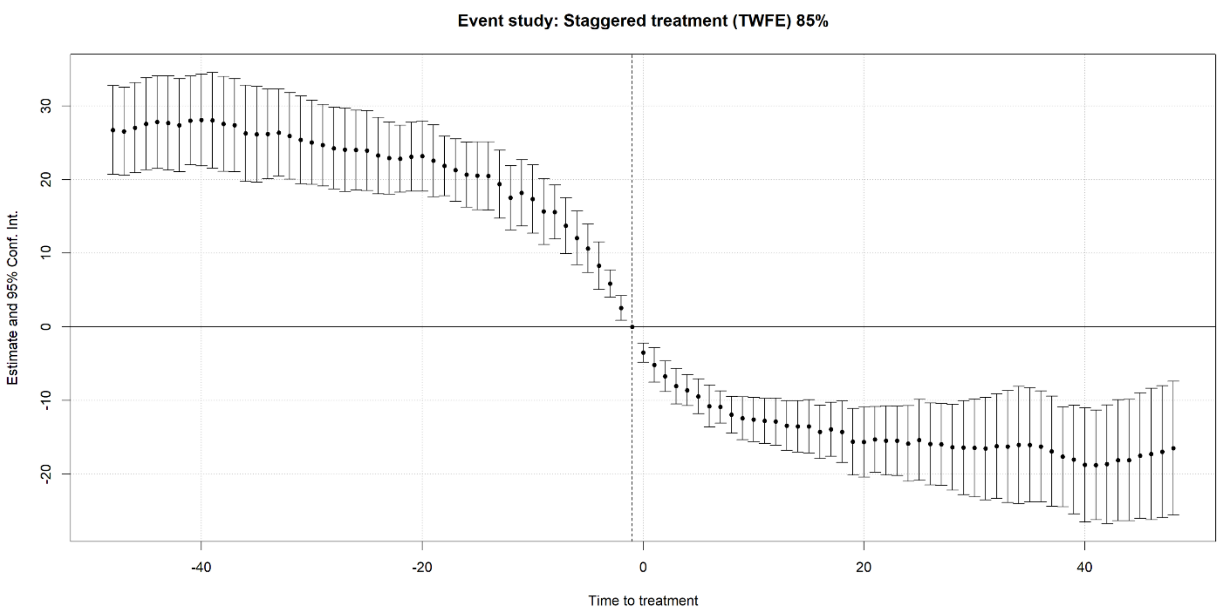

Figure 10: Staggered Difference in Difference on data with 85% price-count threshold

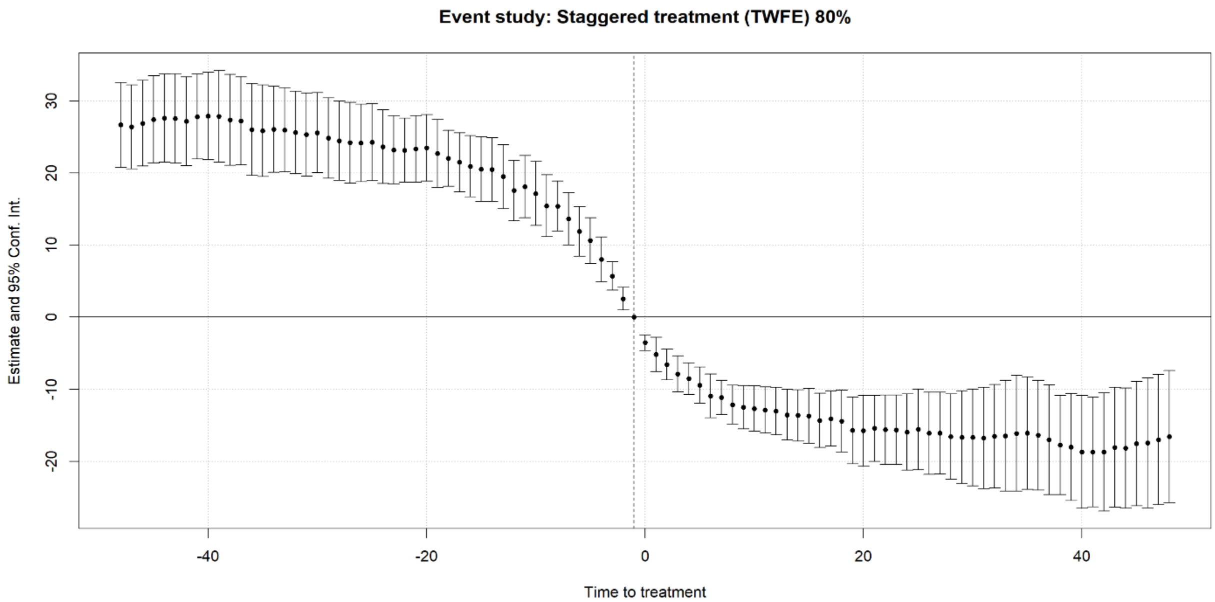

Figure 11: Staggered Difference in Difference on data with 80% price-count threshold