

Estimating the Effects of
Information Quality of Macro Aggregates on Sovereign Risk

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ABSTRACT

This is the first essay to my dissertation which explores the link between information quality of macro aggregates and sovereign risk. I establish that data quality of macro aggregates increases the repayment ratio after default but has a positive, yet insignificant, effect on the default probability. My estimation accounts for selection bias by using a cross-country panel data of 69 developing countries for 1989-2002. Results are robust to controlling for various governance factors and income levels. I conclude that good information of macro aggregates reduces sovereign risk by enhancing the repayment ratio conditional on default.

JEL Classification: F34

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CHAPTER 1

INTRODUCTION

This essay tackles the statistical question of how information quality of macro aggregates affects sovereign risk. To my knowledge, this paper is not only the first to address the issue of information quality and sovereign default behavior, it is also the first to attempt a detailed empirical analysis of the repayment ratio after a country defaults.

The background to this inquiry rests on two strands of literature related to sovereign default issues. The first is related to the cost of default, which includes the research on debt renegotiations. To explain the high frequency of sovereign default occurrences, Eaton and Gersovitz (1981) pioneered the literature by illustrating sovereign default as a strategic decision given the costs (or benefits) of default – they emphasized sovereign borrowing and lending is characterized by lack of collateral and a supranational entity to enforce contracts. As Eaton and Fernandez (1995) point out, “the challenge, especially early in this literature, was not so much to produce a model consistent with some set of “stylized facts”, but rather to explain the phenomenon of sovereign lending in the first place.” Likewise, research focused on the penalties – exclusion from future credit markets or intertemporal autarky, distortions to trade, or a loss of output. Put simply, the smaller the penalty relative to the benefits, the less likely a country was to default. Past theoretical investigations have led to recent empirical research to identify variables that were linked to these penalties, such as for the role of trade in Rose (2002), and Rose and Spiegel (2004), and for the role of volatility in output in Catão and Kapur (2004).

The prevalence of partial defaults added to the puzzle of sovereign risk issues, as seldom did we see countries refusing to repay *everything* they owed. It was Bulow and Rogoff (1989) that first introduced a model that incorporated debt renegotiation into the sovereign risk debate with bargaining power related to the trade-disruption capabilities of the creditors, while Fernandez & Rosenthal (1990) added to the discussion by allowing the debtor and creditor to take actions that strategically determine the strength of the two parties. However, empirical implications were often scarce as bargaining models were quite sensitive to the exact specification of the game, as they were worked out only to explain the prevalence of partial repayments. Though studies related to bond spreads have become more prevalent, such as Mauro, Sussman, and Yafeh (2002) where it is revealed that spreads commove more now than a century ago, these studies give an unsatisfactory answer to the puzzle that concerns which countries repay more of what they owed after defaulting. Indeed, analyzing estimates of the repayment ratios after a country defaults provides a logical piece to the puzzle concerning not only the prevalence of partial defaults, but also the frequency of sovereign defaults.

The second strand of literature this dissertation tries to advance is the research on information asymmetry and sovereign risk. Most of the current and past research concerning information and sovereign risk focuses on information asymmetry and moral hazard. Gertler and Rogoff (1990) described a world where moral hazard leads to a less-than-efficient amount of investment; whereas, Atkeson (1991) adopted contingent claims to show that we see capital outflow in times of crises, as creditors do not observe it is a crisis due to bad luck or bad use of borrowed funds and identifies inefficient resource

allocations for the purposes of consumption smoothing. Recently, at a more empirical level, Gelos and Wei (2002) look at how opacity, or lack of transparency measured by various indicators, leads to less capital flows in emerging market funds. For general capital flows, Alfaro, Kalemli-Ozcan, and Volosovych (2002) conclude that institutional factors substantially affect capital flows, adding that asymmetric information measured by weighted distances between countries' capitals also plays a role in a form of credit rationing. Consequently, the IMF has actively worked to enhance the timeliness and frequency of data dissemination for emerging markets to alleviate some of these obstacles for capital flows, while the World Bank has pursued transparency in a broader context by incorporating governance-enhancing policies in their various programs to help developing countries.¹

However, a more fundamental problem has been overlooked when it comes to information in international capital markets – the role of information *quality*. Sovereignty adds many extra dimensions to the typical credit risk that creditors must account for, especially when lending in international capital markets without an international bankruptcy court. One of the dimensions is the availability or accuracy of the data concerning a debtor economy, as the majority of emerging markets do not have the capacity, such as manpower and resources, nor the motivation to gather and process

¹ The IMF's Special Data Dissemination Standard (SDDS) and General Data Dissemination System (GDDS) were set up to guide members that have, or that might seek, access to international capital markets in the provision of their economic and financial data to the public. Both are expected to enhance the availability of timely and comprehensive statistics and therefore contribute to the pursuit of sound macroeconomic policies and are also expected to contribute to the improved functioning of financial markets. The World Bank has also worked to enhance transparency through documenting governance measures with various policy implications.

information for macro aggregates. Taking into account data quality is possibly as important in understanding sovereign risk as considering whether a government is hiding or deliberately falsifying information. In addition to institutions, human capital, and moral hazard, information quality may provide a good explanation of why a great deal of capital does not flow from rich to poor countries. In tandem with this observation, in 2003 the IMF recently established the Data Quality Assessment Framework (DQAF) to be used for comprehensively assessing countries' data quality. Members receive feedback that covers institutional environments, statistical processes, and characteristics of the statistical products. However, the justification for such a policy, which actively attempts to improve data quality, is not yet fully understood.

The goal of this essay is to reveal the statistical relationship between data quality of macro aggregates and sovereign risk so as to find a possible explanation for a causal relationship. In terms of the method of looking at how various factors affect both the default probability and the repayment ratio conditional on default, the essay contributes to providing a solid empirical framework for analyzing sovereign risk. More specifically, by looking at the relationship between information quality and sovereign risk, the dissertation also contributes to the literature by concluding that bad data quality of macro aggregates increases sovereign risk by lowering the repayment ratio conditional on default. This conclusion gives a more tractable justification for the IMF's policies such as the DQAF and provides a plethora of further policy implications.

The general outline of this essay is the following. Chapters 2 and 3 establish the statistical relationship between information quality of macro aggregates, the default

probability, and the repayment ratio conditional on default. More specifically, Chapter 2 introduces the two main variables of interest – the repayment ratio after a country defaults and information quality of macro aggregates. I am careful to go through the estimation of the repayment ratio as the main dependent variable and to establish a data quality index as my main independent variable. In Chapter 3, I estimate the relationship between data quality and sovereign risk by using Maximum Likelihood Estimation (MLE) based on the Heckman Selection Model. This is necessary to account for sample selection bias, as the expected repayment ratios may be related to how likely a country is to default. For robustness and to address the possible estimation error in calculating the repayment ratio, I account for different cut-off repayment ratios (from 80-100%), below which I may consider a country-year observation to be a default-distress episode. The main findings from the empirical investigation confirm that better data quality (more accurate and more available information of macro aggregates), proxied by an index from 0 to 5 (with the best data quality given 5) used in the Penn World Tables 6.1, increases the expected repayment ratio after default while having a positive but statistically insignificant effect on the default probability. In other words, if the effect on the default probability is negligible, bad data quality increases sovereign risk. Chapter 4 concludes the paper with policy implications related to the better functioning of the markets in international borrowing and lending.

CHAPTER 2

THE VARIABLES

This Chapter explains the main variables under consideration. First, I describe the method in which the repayment ratio and default occurrences are measured using a dataset from the World Bank - the Global Development Finance (GDF) database. Second, I describe in detail the main independent variable in question – data quality, the data for which exists in the Penn World Tables version 6.1 (PWT6.1), and how this index can be interpreted as an exogenous institutional variable. Third, I provide a basic plot that reveals a positive correlation between data quality of macro aggregates and the repayment ratio conditional on default. Finally, other independent variables related to sovereign risk are listed with a brief discussion of how they may relate to sovereign risk.

2.1 The Repayment Ratio Conditional on Default

In order to find a systematic estimate of the repayment ratio, I define the repayment ratio (X) as total debt service (TDS) over total payments due (TPD), where

$$X = \frac{TDS}{TPD} = \frac{TDS}{TDS + \text{rescheduled} + \text{forgiven} + \text{debt stock reduction} + \text{repudiation}}. \quad (2.1)$$

This measures the repayment ratio of debt servicing at the beginning of a period. If by the end of a year, a debtor country repaid only 50% of what it owed during that year, the

repayment ratio would be 50%. The repayment ratio may not be one (full-payment) in that year if creditors agree to reschedule or forgive payments that were due, if creditors agree to debt stock reduction schemes such as debt-buybacks that affect promised repayments, or if debtors decide to repudiate some debt that was due that year. Though this is a simplification of default and sovereign risk issues in international capital markets, it will reveal important implications concerning sovereign debt.

The GDF includes variables for total debt service, principal/interest rescheduled (*RSC*), and principal/interest forgiven (*FGN*). However, a problem arises when the GDF does not differentiate between whether anyone of these variables, including *TDS*, is for principal/interest *due* or for principal/interest in *arrears* as I am concerned with the repayment ratio in relation to debt service payments *due*. However for the purposes of estimating total payments due for a given year, information on cumulative principal/interest in *arrears* is all that I need. Cumulative arrears enable me to calculate repudiation, which is just the change in arrears minus the change in arrears due to debt repaid, rescheduled, or forgiven etc. In other words, all the positive entries that incorporate arrears in *TDS*, *RSC*, *FGN*, and debt stock reduction (*DSR*), are offset by the negative change in total arrears due to these factors, leaving the amount of repudiation in a given year. Thus, adding everything leaves me with total payments *due* in a given year.

A caveat exists when it comes to debt stock reduction (*DSR*) (like debt buybacks, etc.). There, the GDF does not have separate data for debt stock reduction for payments due, in arrears, or in the debt payments to be paid in the future. I assume that debt stock

reduction for payments in arrears and due is proportional to the ratio of arrears (ARR) to the total external debt (EDT) for the previous year.¹ I also take into account cross-country valuation (CCV), which is just the increase in debt due and in arrears to exchange rate fluctuations (as everything is in dollar terms in the GDF).² I assume that changes in arrears from cross-country valuation are also proportional to ARR/EDT . Then what I can calculate from the data will be

$$X = \frac{TDS'}{TPD} = \frac{TDS + \alpha}{TDS + RSC + FGN + DSR \left(\frac{ARR}{EDT} \right) + \Delta ARR - CVV \left(\frac{ARR}{EDT} \right)}, \quad (2.2)$$

where total payments due (TPD) during the current period will be

$$TPD = TDS + RSC + FGN + (DSR - CVV) \left(\frac{ARR}{EDT} \right) + \Delta ARR. \quad (2.3)$$

It could be the case that the X variable can be bigger than one. Apart from the estimation error mentioned above, this may occur because α may exist as some countries might repay part of their *arrears*, which is a part of TDS in the GDF data. I will first assume that if X is greater than one, there is full repayment for a given year. The following is the final equation for my estimation of the repayment ratio.

¹I note that this is likely to be an overstatement of payments made in arrears as most buybacks are likely to incorporate substantial amounts of debt *not* in arrears. This may lead to a bias leaning towards more default episodes. I account for this by looking at different cut-off repayment ratios.

²This consideration may also lead to estimation error.

$$X = \frac{TDS \times EDT}{(TDS + RSC + FGN + \Delta ARR) EDT + (DSR - CCV) ARR} \quad (2.4)$$

According to the estimated repayment ratios, all the occurrences below one will be defined as default distress periods. I will also look at different cutoff points for fear of measurement error that was discussed above. I note that it is impossible to differentiate between specific characteristics of loans to the private sector and to other bilateral or multilateral institutions or countries such as debt forgiven, etc. Therefore, the measure of the repayment ratio encompasses external debt of all kinds, which includes non-publicly guaranteed debt and debt to bilateral institutions. As seen in the Asian Financial Crisis, non-publicly guaranteed debt always has the potential to be part of a government's prospective deficit.³ As for debt obligations to bilateral institutions, Rose (2002) has looked at Paris Club restructuring for his investigation on the costs of default, noting the simultaneity of debt distress for both bilateral and private debt. However, I do eliminate country-year observations for which there is no debt owed to private lenders so that countries with solely official financing are not considered in our sample. To give an idea of how our measure compares with other empirical studies of sovereign risk, I describe the work that has been done, mainly by the IMF, on the issue of debt and default crisis or distress in Table 2.1.

³See Burnside, Eichenbaum, and Rebelo (2001)

There are many different definitions associated with debt crisis and distress. Standard & Poor's (2004) documents all periods in which a debtor did not repay its private creditors the full value of the original contract, which includes instances of exchange offers of new debt that contain less favorable terms than the original issue and rescheduling of bank loans, etc. The IMF Working Paper by Manasse, Roubini, and Schimmelpfening (2003) characterize debt crises as events that either led to initial debt repayment difficulties according to S&P or if countries had access to nonconcessional IMF financing in excess of 100% of their quotas. Their view is that even if a country did not default on its loans, if the default was avoided only through extraneous factors, then it is *de-facto* default. They run a logit regression on debt crises (and distress as defined in S&P) to see what factors are associated with both crisis and distress. Pescatori and Sy (2003) argue that the reason we don't see more defaults post 1994 is because bond markets have evolved to assess this through the movement in spreads. A critical value of 1,000 basis points above the U.S. treasuries is also defined as a 'crisis' along with the S&P measure. Detragiache, and Spilimbergo (2001) define a debt crisis if either there are arrears of principal or interest on external obligations towards commercial creditors of more than 5% of total commercial debt outstanding or if there is a rescheduling or debt restructuring agreement with commercial creditors as listed in the GDF. As they include crises beginning within four years since the end of the previous episode, they manage to identify only 54 crisis episodes out of 950 country-year observations.

Table 2.1 Various measures of debt crisis and distress

<i>Paper Source</i>	<i>Definition of “Crisis” or “Distress”</i>	<i>Observations (countries)</i>	<i>Crises or (Distress)</i>	<i>Years</i>	<i>Data source</i>
Detragiache, & Spilimbergo (2001)	Arrears, commercial rescheduling with commercial creditors	950 (69)	54	1971-1998	GDF
S&P (2004)	Not paid when due, exchange offer, rescheduling	(all)	Numerous (255 of 794)	1824-2003 1989-2002	S&P
Manasse, Roubini & Schimmelpfening (2003)	S&P + Large IMF loan	594 (37)	31	1970-2002	S&P IMF
Pescatori & Sy (2003)	S&P + Large bond spreads	886 (31)	(238)	1975-2002	S&P
Lee (2006)	When there are payments rescheduled, forgiven, restructured or repudiated (when repayment ratio is less than x %)	794 (69)	100% (521) 90% (352) 80% (294) 70% (249) 60% (196) 50% (151)	1989-2002	GDF

Though the literature tries to form an early-warning model of debt crisis, it is difficult to measure the degree of the crisis without a continuous variable. By calculating the repayment ratio, I succeed in adding to the discussion at hand. Likewise, I can arbitrarily define a debt crisis if the repayment ratio is below x %. In our sample from 1989 to 2002, we can observe 521 observations of debt distress where the repayment ratio was less than 100%. Table 2.1 gives the number of observations for other cutoff points. The S&P data shows 255 distress periods in our sample. The cutoff points with the highest correlation with the often-used S&P data is the cut-off level of 91% and 83%, with 0.5585 and 0.5596 respectively.

The main reason it makes sense to look at different cutoff points is that measurement error may exist. There are three ways in which our measure may not be accurate besides the typical error concerned with the original data. One is that *TDS* does not include short-term principal payments, yet it includes debt service payments in arrears. A second problem occurs when calculating how much debt buybacks should count toward total debt payments due. Thirdly, since all the units are in dollars, there might be a measurement problem connected with accounting for debt reduction due to exchange rate fluctuations. Though I can mitigate the problem by controlling for the short-term debt to long-term debt ratio, the other problems require a more general control for bias by looking at various cutoff points for the repayment ratio in order to determine default.⁴ Likewise, I will concentrate on the cutoff spectrum between 80% and 100%. The observations below these cutoff levels, I will define as “debt distress” country-year episodes.

Another reason for looking at different cutoff levels is that minor non-repayments from the private sector to creditors may distort the analysis related to sovereign risk. These episodes should be ignored as it captures firm and industry risk as most of the borrowing from creditors from abroad for developing countries is through the government or government guaranteed loans.

⁴The reason that it is less feasible to take account for the bias considerations for debt-buybacks is because of certain endogeneity problems associated with debt-buybacks and default. For short-term loans the problem is less critical, since we control for the general level of debt and not short term finance.

2.2 Information Quality of Macro Aggregates

PWT 6.1 provides information on the variance of price level estimates that are used to compare real output etc, which I use as a proxy for information quality of macro aggregates. There are three ways of coming up with purchasing power parity levels of output for each country – they can be calculated through benchmark studies, extrapolation, or ‘short-cut’ estimates -

1. If a country goes through the International Comparison Program (ICP) benchmark study in pricing conducted by the UN, price data for hundreds of different commodities are available. Based on these estimates, one can compute an aggregate purchasing power parity (PPP) exchange rate.
2. If a country did not conduct the ICP study, one can use various price comparison indices, usually calculated from various post-allowance indices such as from the ICSC (The International Civil Service Commission) of the UN, or from Barry Rodin from ECA (Employment Conditions Abroad), which includes clients such as multinational firms, governments and non-profit international agencies, and finally from the US State Department. First, they run a regression for the benchmark countries accounting for regional differences with the price levels calculated by the benchmark studies on the left hand side, and price levels from various indices in the right hand side. With the estimated coefficients, one will be able to calculate an

estimate of the actual price level for PPP comparisons – this is referred to as the ‘short-cut method.’

3. If a country did not undertake the ICP study, it can rely on a past study (say conducted 5 years ago), or on a past ‘short-cut’ estimate with a PPP exchange rate and use that to extrapolate what the real level of output is for a given year based on the change in output in constant local currency.

PWT6.1 takes these estimates and calculates the variance. If the variance is high, the country is considered to have less accurate data as estimates for real output, consumption etc. are that much more debatable. To calculate the overall data quality of the PWT6.1 data set, they weigh in how many times a country participated in benchmark studies throughout the years and the income level, assuming that richer countries can afford more resources to better quality data. Indeed, they weigh the variance measure we will use two times more than the other considerations. Our sample from 1989 to 2002 is in line with just the variance measure (which measures the variance of price level estimates for the year 1996) as I wish to control for income levels. This seems to be the most comprehensive data set related to data quality – how accurate a country’s data is in estimating real output. I consider this measure a key proxy for information quality for other macro aggregates as well.

It is important to note why the official ICP measure of PPP’s may have different qualitative implications for different countries. In fact the various price data that is used to

calculate PPP is critically dependent on the National Statistic Organizations (NSOs) without which the survey would be impossible to conduct. In a report of the consultant on the evaluation of the ICP program to the Economic and Social Council of the UN, the author notes that “To an extent unequalled by any other statistic in the international domain, PPPs depend on the intimate cooperation between NSOs and the statistical arms of international agencies. However, the mechanisms that support what should be both an easy and an intimate partnership are mostly embryonic. In some cases, they are simply not there.”⁵ According to another evaluation, the Castles Report, conducted by the OECD, complaints among the actual producers of the data had the following grievances with “disturbing frequency:”⁶

- “...country x, which we happen to know well, must have interpreted the reporting guidelines incorrectly because all its prices are much lower than we know to be the case...”;
- “...countries x, y, and z produced unexplained numbers for rent and the coordinators did not feel they could intervene. The result is that for an important segment of expenditures we have distortion right at the level of basic data...”;

⁵Evaluation of the International Comparison Programme, Statistical Commission 13th session, 1-5 March 1999, p. 8.

⁶See OECD (1997).

- “...the prices submitted by our neighbors cannot be right because they look as if they only apply to the capital city, which we know not to be representative and in any case cannot be compared with our prices etc...”

The reasons for the inaccuracy of price level data, all the reports note, hinges on the lack of resources and motivation for these statistical projects. As these factors are difficult to manage or control as data quality of macro aggregates depend on quality of personnel and institutions from the micro level, I propose that information quality of macro aggregates can be considered as an exogenous institutional variable in my analysis.

The second justification for considering information quality as an exogenous institutional factor comes from comparing the data quality index used in a previous survey of the Penn World Tables (version 5). A simple comparison of the data quality index between PWT6.1 (based on the 1996 ICP survey) and PWT5 (based on the 1985 ICP survey) reveals that this variable does not change over time for the majority of the countries. Since the variance measure is not available for PWT5, I compare the data quality index from “A” to “D”, which incorporates both the variance measure, the number of times a country has gone through the ICP survey *and* the income level (with “A” denoting the highest data quality possible). The majority of countries – 79%, had changes of less than half a letter grade, for instance from “C-“ to “C”. Only 2 countries had changes in excess of a full letter grade out of 131 – Hong Kong from “B-“ to “A” and Uruguay from “C-“ to “B”. The rest, or only 18% of the sample countries, had a full letter

grade change. The fact that these comparisons are stable despite the fact that the data quality assessment was based on ICP surveys 11 years apart reinforces my justification for considering information quality of macro aggregates as an exogenous institutional variable.

For further comparison, however, other related transparency or opacity measures that are possibly related to information *asymmetry* for a smaller set of countries are found in Gelos and Wei (2002). They use several factors of transparency and opacity to look at the relationship between opacity and international portfolio investment with the conclusion that investment funds invest less to countries that are “opaque” which amounts to a form of credit rationing. Among the different measures they use are the O-factor in 2001 from an accountancy and consulting company, PricewaterhouseCoopers, that creates an index that incorporates corruption, the legal system, government macro policies, accounting standards and practices, and regulatory regime. The correlation between the measure I use and theirs turns out to be close to zero. However, other measures such as macro data opacity (from the IMF), which measures timeliness and frequency of data, and corporate opacity (based on a financial survey by the Global Competitiveness Report), have correlations around -0.23 and -0.24. Next, Gelos and Wei (2002) use data from Oxford Analytica for Wilshire Associates that provides a measure of macro policy opacity, which measures how countries conform to the prescribed standards and codes of the IMF. Finally, Allum and Agça (2001) provide timeliness and frequency measures for data collection by the Institute for International Finance (IIF) that includes some Middle-

Eastern countries that have low measures of timeliness and frequency of data from 1997.

Their measure highly correlates with the measure I use – the correlation is 0.43.

Table 2.2 Correlations with different data-related measures
(number of countries in parentheses)

Measures related to “Data”	O-Factor (30)	Macro Data Opacity (39)	Macro Policy Opacity (27)	Corporate Opacity (32)	IIF timeliness and frequency (27)
What it measures	Composite index of corruption., legal system, Government macroeconomic policies, accounting standards and practices, regulatory regime	Frequency and timeliness	Transparency of fiscal and monetary policy	Survey on the level of financial disclosure	Frequency and timeliness
Correlation with Variance Measure in PWT 6.1	-0.006	-0.229	-0.110	-0.241	0.432
Source	Gelos & Wei (Pricewaterhouse Coopers)	G&W (A&A-IMF)	G&W (Oxford Analytica for Wilshire Associates)	G&W (Global Competitiveness Report)	Allum & Agca

Table 2.2 describes the comparisons and it is confirmed that all the ‘opacity’ measures have negative correlations with the PWT6.1 measure of data quality and positive correlations with the ‘transparency’ ones. It is important to note that all these measures deal with a mixture of information asymmetry and timeliness and frequency of the data as opposed to data quality. Though they are likely to be correlated, Allum and Agça (2001) note that one does not necessarily imply the other.

Figure 2.1 Repayment Ratios Conditional on Default According to Data Quality (0-5)

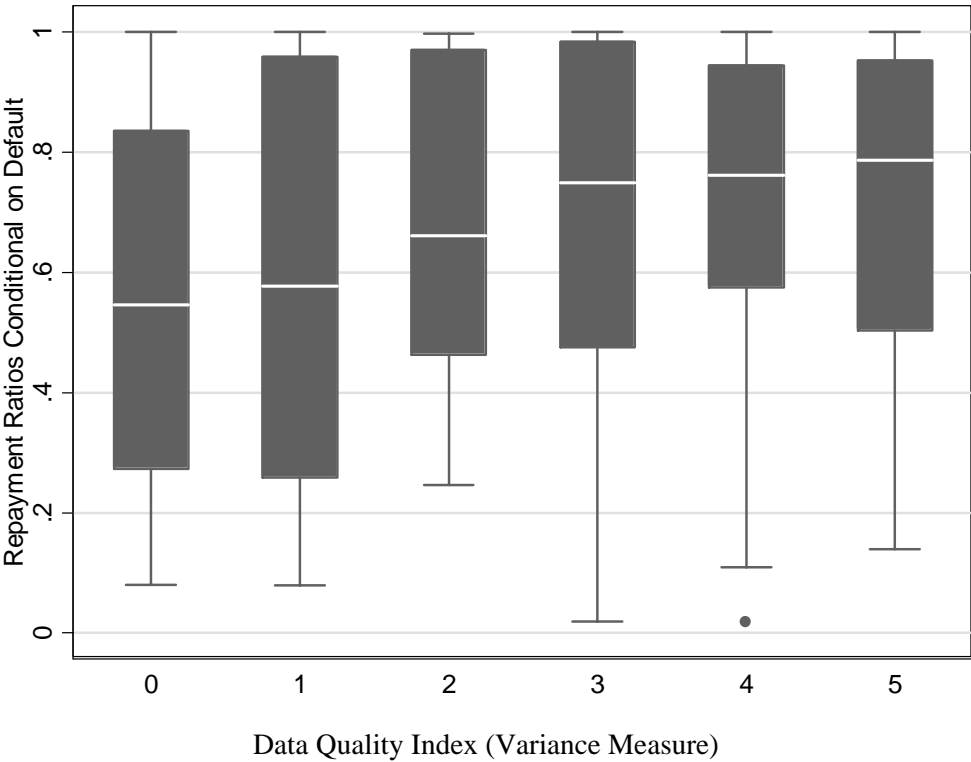
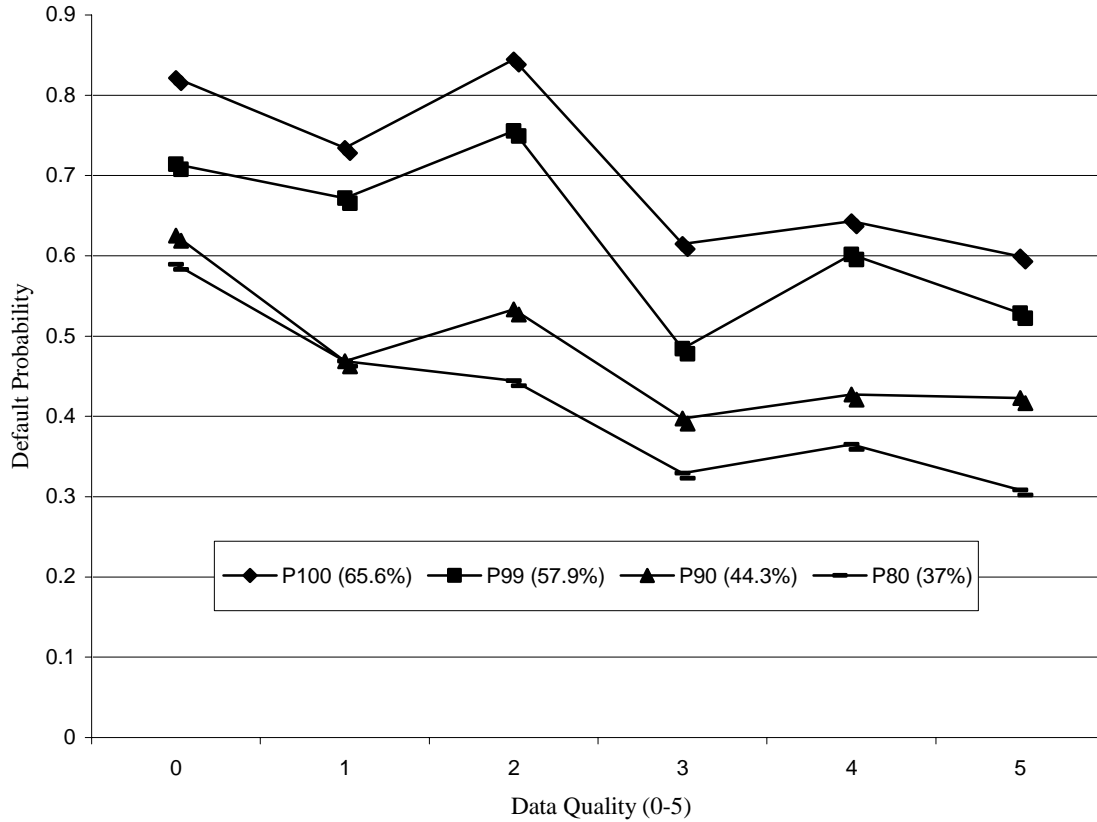


Figure 2.2 Default Occurrences According to Data Quality by Cut-offs



Notes: Percentage of default occurrences in parentheses are for the whole sample of 794 observations. P100 stands for cutoff at the 100% level, P99 at the 99% level, etc.

For my initial findings, the box-plot in Figure 2.1 shows how good data is positively associated with a higher repayment ratio for a country conditional on default for

my panel data of 69 countries from years 1989 – 2002. The boxes represent the middle 50% of all the observations and the line inside corresponds to the median. In other words, creditors that lend to a country with better data recoup more of the promised payments due when the country defaults. Many of the observations have really high repayment ratios. Yet eliminating values above a certain cutoff point and considering these as non-default episodes do not affect the graph (see Tables A.1 – A.4 in Appendix). Figure 2.2, on the other hand, illustrates the lack of any monotone relationship between data quality and the occurrence frequency of default, though there does seem to be a negative trend.

2.3 Other Independent Variables

To accurately assess the effect of data quality on sovereign risk, I control for various other factors related to sovereign risk as well. Suter (1992) provides a benchmark as to which variables to include - mainly variables that measure default history, the debt burden, reserves capacity, economic growth, interest burden, and net transfers (new debt inflows minus debt-service payments). Most of the variables in Suter (1992) were scaled by GNP, imports, or exports. Since Suter's logit regression results hold for periods 1932-1933 and 1978-1985, I can use this as a structural benchmark for our sample of 1989-2002. It turns out that most of the variables that related to default have similar effects to default probability for my sample as well, though differences exist in the significance. In addition, Manasse, Roubini & Schimmelpfenning (2003) also provide independent variables that

have significance in their logit regressions, and I add as many variables from their list as well. However, I do use my own estimates for interest rates - the one-year treasury rate at the beginning of the year minus the expected inflation rate according to the Survey of Professional Forecasters administered by the Philadelphia Federal Reserve to calculate the expected real interest rate.

Next, I am also careful to add the necessary variables that will account for the possible estimation errors associated with the repayment ratios. Since, the sample deals with both lending from official and private sources, I also include private to total debt owed as one of my explanatory variables. Second, since short term principle payments are not included in my repayment ratios, I include short term debt to long term debt as well. Finally, since the positive relationship between data quality and the repayment ratio may be actually revealing something else that is highly correlated with data quality, I find other institutional and political variables to control for. All of these institutional variables are from Kaufman, Kraay, and Mastruzzi (2004).⁷

⁷They use 25 separate data sources constructed by 18 different organizations to aggregate various institutional measures related to governance. The six different governance measures are the following – 1. Voice and Accountability – measures the extent to which citizens of a country are able to participate in the selection of governments (includes independence of the media). 2. Political Stability and Absence of Violence – measures perceptions of the likelihood that the government in power will be destabilized or overthrown by possibly unconstitutional and/or violent means, including domestic violence and terrorism. 3. Government Effectiveness – measures the quality of public service provision, the quality of the bureaucracy, the competence of civil servants, the independence of the civil service from political pressures, and the credibility of the government’s commitment to policies. 4. Regulatory Quality – measures the incidence of market-unfriendly policies such as price controls or inadequate bank supervision, as well as perceptions of the burdens imposed by excessive regulation in areas such as foreign trade and business development. 5. Rule of Law – measures the extent to which agents have confidence in and abide by the rules of society. This includes perceptions of the incidence of crime, the effectiveness and predictability of the judiciary, and the enforceability of contracts. 6. Control of Corruption – measures perceptions of corruption, conventionally defined as the exercise of public power for private gain.

Table 2.3 summarizes the various independent variables used in the regressions. Variables of interest that are *not* in the list of independent variables include currency overvaluation due to data limitations. However, variables such as the ones related to the exchange rate regime should be able to capture some implications concerning these factors. In addition, I account for various political factors that are deemed relevant to sovereign debt and default from the Cross-National Time-Series Archive by Databanks International such as warfare, revolutions, etc.

Table 2.3 Independent Variables Used in the Regressions

<i>Independent Variables</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>	<i>Source</i>
1. Debt held in bonds as % of PPG debt ^a	10.10	18.26	0	80	GDF
2. Debt owed to private creditors as % of PPG debt	28.98	26.06	0.05	100	GDF
3. Default history (past 5 years) ^b	1.95	2.21	0	5	S&P
4. Average growth % (past 3 years)	1.44	3.12	-10.31	12.12	WDI
5. Average inflation % (past 3 years)	61.67	305.16	-26.85	3849.12	WDI
6. Trade to GDP Ratio % (Imports + Exports)/GDP	64.08	32.59	13.24	229.28	WDI
7. Financial openness % (gross flows/GDP)	15.89	46.67	0.00	632.89	F&W
8. Reserves to imports (months)	3.77	3.33	0.03	25.87	GDF
9. Interest payments to exports %	8.43	5.46	0.10	34.29	GDF
10. Concessional debt as % of PPG debt	35.70	27.29	0	98.45	GDF
11. Net transfers as a % of GNI ^c	-0.45	4.85	-39.82	26.46	GDF
12. Trade balance as a % of GDP	-4.39	9.90	-57.36	27.73	WDI
13. Expected real interest in the US	2.07	1.26	-0.18	3.85	Fed
14. Log of PPP GDP per capita	7.85	0.84	6.10	9.40	WDI
15. External Debt as a % of GDP	77.85	60.98	7.62	674.16	WDI
16. Short term debt as a % of GDP	9.18	10.26	0.12	125.95	WDI
17. Short term debt as a % of long term debt [']	12.70	8.94	0.30	50.63	WDI
18. Data quality ^d	0.95	1.51	-2.5	2.5	PWT6.1

^aPPG stands for public or publicly guaranteed debt.

^bDefault history is the number of years a country is in default for the previous 5 years for private loans according to S&P.

^cDisbursements minus total debt service payments.

^dData Quality was scaled from 0 - 5 to -2.5 – 2.5 so that it could have the same numerical structure as the other institutional variables.

Table 2.3 Independent Variables Used in the Regressions (continued)

<i>Independent Variables</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>	<i>Source</i>
19. Political stability	-0.20	0.68	-2.61	1.19	KK&M
20. Political shock ^e	1.65	3.04	0	39	CNTS
21. Revolutions	0.26	0.55	0	3	CNTS
22. Warfare	0.20	0.52	0	3	CNTS
23. Control of corruption	-0.32	0.53	-1.54	1.19	KK&M
24. Voice and accountability	-0.22	0.60	-1.57	1.3	KK&M
25. Regulatory quality	-0.02	0.52	-1.51	1.28	KK&M
26. Rule of law	-0.25	0.58	-1.50	1.19	KK&M
27. Government effectiveness	-0.20	0.58	-1.61	1.50	KK&M
28. Fixed exchange rate regime (dummy) ^f	0.37	0.48	0	1	F&W
29. Intermediate exchange rate regime (dummy)	0.34	0.47	0	1	F&W
30. Standard deviation of the growth rate in %	2.22	2.08	0.04	12.87	WDI
31. Standard deviation of the inflation rate in %	40.67	246.96	0.04	3415.78	WDI
32. Export diversification (dummy) ^g	0.39	0.49	0	1	WDR
33. Population (in millions)	63.78	191.78	0.84	1280.84	CNTS
34. Year			1988	2001	

^eNumber of strikes, demonstrations and political crises defined in the Cross-National Time-Series Data Archive by Arther Banks (CNTS), Databanks International.

^fFixed exchange rate regimes include currency boards, dollarization, and common currencies. Intermediate regime is when there exists an official band on the currency. Data is from Frankel & Wei (2004).

^gExport diversification is one when a country does not export more than 50% of goods in one sector (manufactures, nonfuel primary products, fuels, services) according to the World Development Report 1995.

CHAPTER 3

ESTIMATION

In this Chapter, I first provide justification for using the Heckman Selection set-up rather than the censored Tobit model to analyze the repayment ratios and default occurrences. I then describe my exclusion restriction and the basic set-up of the empirical estimations. Finally, I go on to provide results from a Maximum Likelihood Estimation (MLE) that combines the selection equation with the repayment ratio equation concerning sovereign risk. The main findings are that better information of macro aggregates increases the repayment ratio conditional on default, but has a statistically insignificant effect on the probability of default. Finally, I introduce basic hypotheses to explain the results with a few words on risk sharing.

3.1 Why Not Tobit?

I base my regressions on the Heckman set-up. The reason I do not use a Tobit censored regression model is that low default probabilities do not seem to be greatly related with high repayment ratios. The Tobit model is a special case of the Heckman equation in that the error terms between the selection equation for defaulting and the regression equation for the repayment ratio are perfectly negatively correlated. In this case, censoring would arise (i.e. there would be no default) when the factors positively affecting the repayment

ratios were strong enough. However, a closer look at the data shows how the default occurrences and repayment ratios may *not* be negatively correlated.

Apart from the crude panel description of how good information of macro aggregates in Figure 2.1 and Figure 2.2 may be related to high repayment ratios but not necessarily to lower default occurrences, the non-negative relationship appears across countries as well. Figure 3.1 illustrates the distribution of countries via box-plots of repayment ratios according to the number of default occurrences that each country has experienced in the 14 year sample. For the 100% cutoff level, countries that had 12 default occurrences between 1989 and 2002 actually had higher repayment ratios conditional on default than the countries with only 6. This pattern is accentuated when I use lower cutoff levels as is shown in Figure 3.2 for the 99% cutoff level where we almost see a *positive* relationship between repayment ratios and default occurrences. Later, I will justify the Heckman set-up by reporting estimations for the correlations of the error terms in Section 3.3. I find evidence for consistently *positive* correlation estimates between the error terms from the selection equation and the repayment regression equation.¹

¹Yet, another possible justification for *not* using the Tobit is that when I do run a Tobit, the coefficients for data quality on the repayment ratios are not significant. By specifying the Heckman, I can always uncover the Tobit if the data preferred it.

Figure 3.1 Repayment Ratios and Default Occurrences (1989-2002)

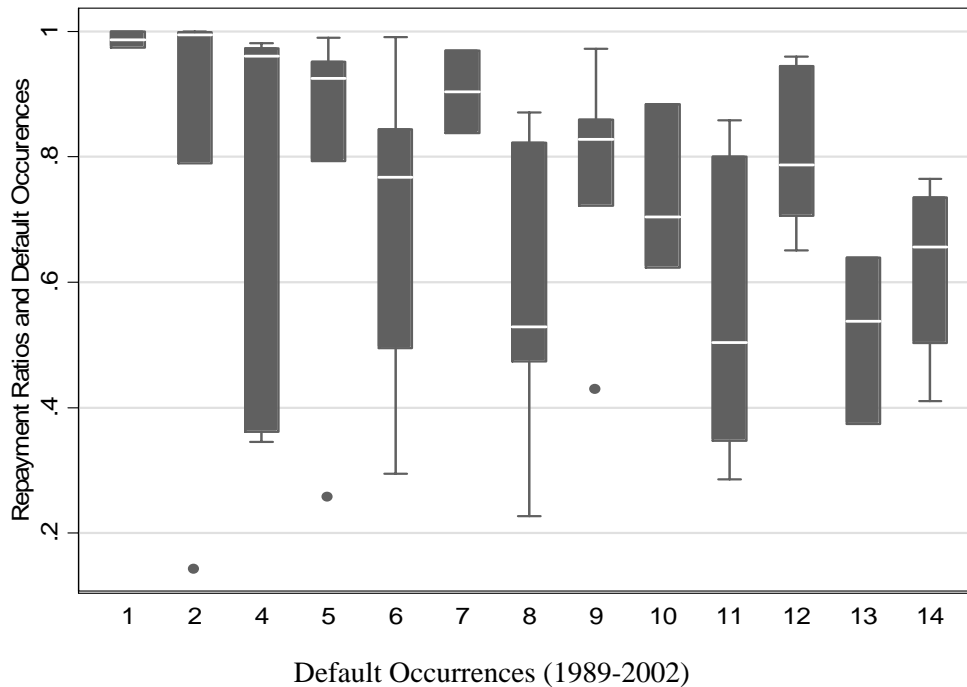
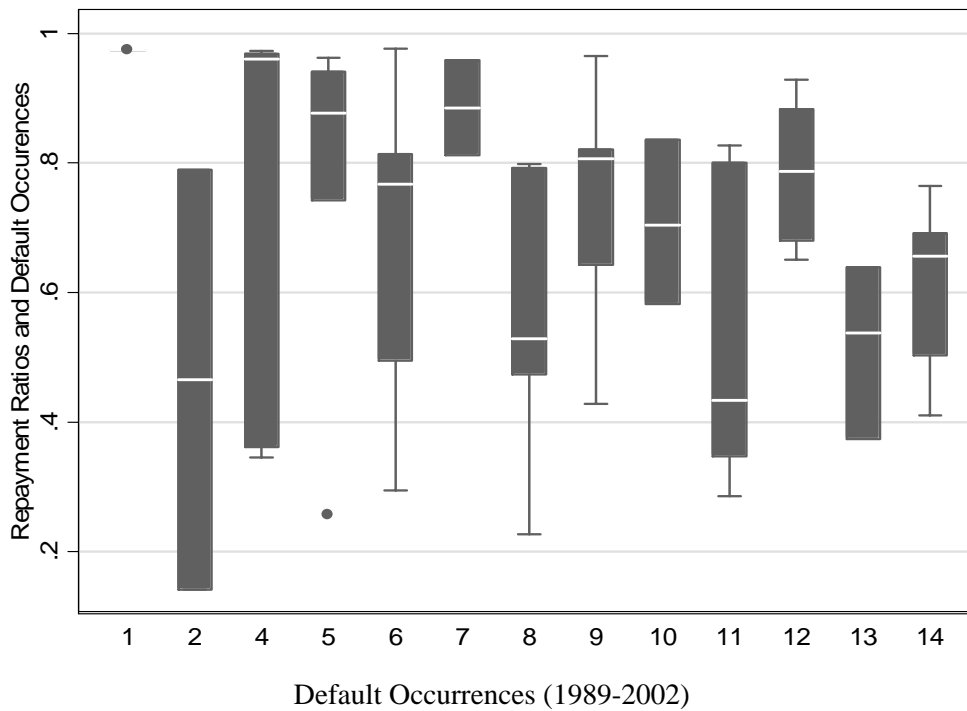


Figure 3.2 Repayment Ratios and Default Occurrences (99% cutoff)



3.2 The Heckman Selection Model Set-up

I use the following equations to account for possible selection bias in the truncated sample

-

$$\begin{aligned} XX &= W_1\beta + u, \quad E(u|W_1) = 0 \\ Z &= 1[W_2\gamma + v \geq 0], \quad E(u|W_2) = \tau v \end{aligned} \tag{3.1}$$

where XX is a scaled form of the repayment ratio ($XX = \ln\left(\frac{X}{X+1}\right)$), while Z is a binary variable to distinguish between defaulting ($Z = 1$) or not ($Z = 0$). The rescaling of the repayment ratio is necessary lest it be bounded.

W_1 and W_2 are vectors of the independent variables for the regression and selection equations. Since the Maximum Likelihood Estimation is notorious for its tendency not to converge, a critical part of the analysis deals with the exclusion restriction that I invoke. Among the 34 explanatory variables that I have selected related to sovereign risk in Table 2.3, I try to minimize potential omitted variable bias in the regression equation by trying to choose a candidate variable that is related to the probability of default, but not necessarily to the repayment ratio conditional on default. Such a variable will appear in W_2 , but not in W_1 . A good choice will make the MLE tractable for different cutoff points, as I need robustness tests of my estimations for fear of estimation error described in Section 2.1.

The logic behind my exclusion restriction is the following – keeping variables that are important in the literature regarding sovereign default (such as default history, growth

trend, and the interest rate), I am left with volatility measures of output, inflation, and export diversification, along with new variables related to the loan structure. Since the loan structure has been important recently in evaluating both the probability of default and debt renegotiations, which is likely to affect the repayment ratio, I am left with the various volatility measures as possible candidates to exclude from the repayment regression equation. Among the remaining three volatility measures (inflation, output, and export diversification), I conclude that both output and inflation volatility will have a tendency to lead to lower repayment ratios, if these variables measure a second order stochastic dominant distribution of growth.

This reasoning leaves export diversification as the only candidate to exclude from W_1 . The effect of export diversification on the default probability seems clear in that export diversification will minimize adverse export earnings shocks that lead to default. However, the effect on the repayment ratio has two countering forces – First, with more export diversification, we should see a better conditional distribution for export earnings given default, which will lead to a greater repayment ratio. Second, with more export diversification, we should see a deterioration of bargaining power for creditors in debt renegotiations as undiversified exports in a particular sector are easier to sanction. For my exclusion restriction, I assume that these two forces counter each other and the total effect on the repayment ratio is negligible.²

²Estimation of the MLE is possible without the exclusion restriction. However, I am not able to account for estimation error by looking at different cutoff levels. For the MLE estimation including export diversification in the regression equation for only the 100% cutoff level, I find that the coefficient to export diversification in the regression equation is positive, but insignificant – this potentially provides further justification for using export diversification as an excluded variable in the regression equation.

I also restrict the explanatory variable that measures short term debt to long term debt ratio to W_1 to account for estimation error mentioned in Section 2.1. I suspect that the coefficient here will be negative as the repayment ratio does not include short-term principal payments, which gives a downward bias to the repayment ratios. More short term debt relative to long term debt will aggravate this bias, so the sign on the estimated coefficient should be negative. However, since the fact that countries did not repay part of their promised payments did not change, it should remain in W_2 . Table 3.1 summarizes *a priori* the expected signs to the coefficients of all the 34 independent variables.

Finally, residuals u and v have a bivariate normal distribution with zero means, standard deviations σ_1 and $\sigma_2 = 1$, and covariance σ_{12} . If $\tau = 0$, there would not be a selection bias problem and we could run the first equation by OLS without worrying about selection bias. The MLE I do run is based on the repayment ratio conditional on default, which is the following regression equation

$$E(X_j | W_1, Z = 1) = W_1\beta + \tau\psi(W_2\gamma) \quad (3.2)$$

where $\psi(W_2\gamma)$ is the inverse Mills ratio and $\tau = \sigma_{12}\sigma_1$. I also take into account the probit function for the selection equation³

³The exact form of the log likelihood function is the following.

$$l_j(\beta, \gamma) = (1 - Z_j) \log [1 - \Phi(W_2\gamma)] + Z_j (\log \Phi \{ [W_2\gamma + \sigma_{12}\sigma_1^{-2} (X_j - W_1\beta)] \} + \log \phi \{ (X_j - W_1\beta) / \sigma_1 \} - \log(\sigma_1))$$

$$P(Z = 1 | W_2) = \Phi(W_2\gamma) \quad (3.3)$$

Finally, I account for a second sample selection bias, as I confirmed in Section 2.2 that information quality is related to information availability of macro aggregates as well. I take into account this second selection bias, by weighting the countries with poor data quality more, as they are underrepresented in my sample.⁴

The partial likelihood (due to selection) is obtained by summing $l_j(\beta, \gamma)$ across all observations. See Wooldridge (2002) for a detailed description.

⁴I consider the correct sample to be the one in PWT6.1, which has over 130 countries represented. The weights are 4.05 for DQ = 0, 1.89 if DQ = 1, 2.24 if DQ = 2, 1.44 if DQ = 3, 1.73 if DQ = 4, 1.71 if DQ = 5.

Table 3.1 Expected Signs of Coefficients

<i>Variables</i>		<i>Expected Sign</i>	<i>Explanation</i>
1. Debt held in bonds	X	[-]	Hard to restructure.
	Z	[+]	Less costly to default.
2. Debt owed to private creditors	X	?	Control for estimation error.
	Z	?	Control for estimation error.
3. Default history	X	?	Too important in the default literature.
	Z	[+]	Literature and evidence on reputation.
4. Average growth	X	[+]	Better distribution of output.
	Z	[-]	Literature and evidence on distribution.
5. Average inflation	X	[+]	Better distribution of output.
	Z	[-]	Literature and evidence on distribution.
6. Trade to GDP ratio	X	[+]	More sanctionable exports.
	Z	[-]	Literature - more costly to default.
7. Financial openness	X	[+]	More sanctionable assets.
	Z	[-]	Literature – more costly to default.
8. Reserves to imports	X	[+]	More sanctionable assets.
	Z	[-]	Evidence on averting liquidity crises.
9. Interest payments to exports	X	[-]	Greater interest payments owed relative to earnings.
	Z	[+]	Evidence is solid.
10. Debt on concessional terms	X	[-]?	Creditors do not ask for much. Estimation error.
	Z	[+]?	Cost of default is low. Estimation error.
11. Net transfers to GNI	X	?	Important in literature.
	Z	[+]	Evidence that disbursements avert defaults defaults.
12. Trade balance to GDP	X	[+]	More export earnings on net.
	Z	[-]	Accumulation of foreign assets.
13. Expected real interest in the US	X	[-]	Higher interest payments due.
	Z	[+]	Higher interest payments.
14. Log of PPP GDP per capita	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
15. External debt to GDP	X	?	Too important in the default literature.
	Z	[+]	Literature and evidence.
16. Short term debt to GDP	X	?	Too important in the default literature.
	Z	[+]	Literature and evidence.
17. Short to long term debt	X	[-]	Estimation error.

Table 3.1 Expected Signs of Coefficients (continued)

<i>Variables</i>		<i>Expected Sign</i>	<i>Explanation</i>
18. Data quality	X	[+]	Want to see if this relationship holds.
	Z	?	Possible negative relationship?
19. Political stability	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
20. Political shock	X	?	Political considerations.
	Z	?	Political considerations.
21. Revolutions	X	?	Political considerations.
	Z	?	Political considerations.
22. Warfare	X	?	Political considerations.
	Z	?	Political considerations.
23. Control of corruption	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
24. Voice and accountability	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
25. Regulatory quality	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
26. Rule of law	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
27. Government effectiveness	X	?	Correlated with data quality.
	Z	?	Correlated with data quality.
28. Fixed exchange rate regime	X	?	Too important to ignore.
	Z	[+]	Evidence on overvaluation and default.
29. Intermediate exchange rate regime	X	?	Too important to ignore.
	Z	[+]	Evidence on overvaluation and default.
30. Growth volatility	X	[-]	Conditional distribution shifts left.
	Z	[-][+]	Reputation. More adverse shocks.
31. Inflation volatility	X	[-]	Conditional distribution shifts left.
	Z	[-][+]	Reputation. More adverse shocks.
32. Export diversification	Z	[-]	More adverse shocks.
33. Population	X	?	Scale.
	Z	?	Scale.
34. Year	X	?	Trend.
	Z	?	Trend.

3.3 Maximum Likelihood Estimation Results

Table 3.2 illustrates the estimated coefficients for a selection of variables in the MLE regression for the scaled repayment ratios conditional on default, and the probit parameters for default. Results are listed for different cutoff levels of the repayment ratios. I also show the marginal effects of the selected variables in Table 3.3, which takes into account selection bias.⁵

Table 3.4 gives the signs for the marginal effects (in comparison with our expected signs in the “Exp” column) for all variables for the scaled repayment ratio conditional on default and the probability of default. The marginal effects, $\frac{\partial E[XX | W_1, Z = 1]}{\partial w_i}$ and

$\frac{\partial P(Z = 1 | W_2)}{\partial w_i}$, are different for every observation i , as the derivatives also depend on the regressors and other independent variables. The documented marginal effects are listed by setting all the exogenous variables at their mean values. Notice that for some variables the signs for the coefficient and the marginal effects on XX are opposite. This is because the variables from the selection equation can also influence the regression equation through the inverse Mill’s ratio function in equation (3.2). Therefore, the marginal effect on the dependent variable may turn out to be different from the one implied just from the regression equation. The default history variable is a good example. The negative

⁵Marginal Effects for dummy variables such as exchange rate regime and diversification of exports denotes the effect of that treatment.

marginal effect on XX exists because the effect from the selection equation outweighs that from the regression equation.

Table 3.2 MLE Results for the Heckman Selection Equation (for Certain Variables)

<i>Cutoff (defaults)</i>	<i>Data quality</i>		<i>Default History</i>		<i>Correlation btwn u & v</i>	$\hat{\tau}$	<i>WaldTest (p-value)</i>
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$			
100 (521)	0.034 (0.020)	-0.046 (0.053)	-0.007 (0.013)	0.138 (0.045)	0.477 (0.151)	0.159 (0.056)	7.09 (0.01)
99 (460)	0.043 (0.021)	0.021 (0.060)	0.000 (0.014)	0.182 (0.046)	0.410 (0.154)	0.141 (0.057)	5.53 (0.02)
98 (436)	0.052 (0.021)	0.066 (0.060)	0.007 (0.015)	0.204 (0.044)	0.386 (0.159)	0.133 (0.059)	4.78 (0.03)
97 (417)	0.048 (0.021)	0.035 (0.062)	0.013 (0.016)	0.226 (0.045)	0.375 (0.171)	0.130 (0.064)	3.93 (0.05)
96 (404)	0.044 (0.022)	0.054 (0.056)	0.009 (0.015)	0.192 (0.045)	0.301 (0.198)	0.104 (0.071)	2.04 (0.16)
95 (392)	0.048 (0.023)	0.076 (0.055)	0.012 (0.016)	0.189 (0.043)	0.297 (0.201)	0.103 (0.072)	1.93 (0.17)
94 (381)	0.049 (0.023)	0.071 (0.058)	0.010 (0.015)	0.172 (0.043)	0.278 (0.202)	0.097 (0.073)	1.70 (0.19)
93 (376)	0.048 (0.023)	0.053 (0.060)	0.010 (0.016)	0.167 (0.042)	0.287 (0.202)	0.101 (0.073)	1.80 (0.18)
92 (369)	0.049 (0.023)	0.055 (0.058)	0.008 (0.016)	0.145 (0.041)	0.264 (0.224)	0.093 (0.081)	1.26 (0.26)
89 (343)	0.053 (0.023)	0.048 (0.065)	0.004 (0.016)	0.139 (0.040)	0.224 (0.217)	0.080 (0.079)	0.99 (0.32)
82 (300)	0.040 (0.023)	-0.026 (0.063)	0.009 (0.018)	0.136 (0.041)	0.256 (0.213)	0.091 (0.077)	1.33 (0.25)
81 (296)	0.038 (0.023)	-0.035 (0.062)	0.011 (0.018)	0.141 (0.041)	0.243 (0.216)	0.086 (0.078)	1.16 (0.28)
80 (294)	0.036 (0.024)	-0.037 (0.063)	0.013 (0.019)	0.139 (0.041)	0.246 (0.215)	0.087 (0.077)	1.21 (0.27)

Notes: Parentheses for estimates are robust standard errors. The MLE was clustered by country. Figures in bold are significant at the 10% level.

Table 3.3 Marginal Effects (from the mean) for XX Conditional on Default, and for the Probability of Default (for Chosen Variables)

<i>Cutoff (De- faults)</i>	<i>Data Quality</i>		<i>Growth</i>	<i>Default History</i>	<i>Extn'l Debt</i>		<i>Divers- Export</i>	<i>Wars</i>	<i>Corrup- tion</i>
	<i>XX</i>	<i>Z</i>	<i>XX</i>	<i>Z</i>	<i>XX</i>	<i>Z</i>	<i>Z</i>	<i>XX</i>	<i>Z</i>
100 (521)	0.037 (0.020)	-0.014 (0.016)	0.020 (0.007)	0.042 (0.014)	-0.005 (0.001)	0.004 (0.001)	-0.220 (0.049)	-0.144 (0.059)	-0.174 (0.071)
99 (460)	0.042 (0.021)	0.007 (0.022)	0.023 (0.007)	0.066 (0.017)	-0.006 (0.001)	0.005 (0.001)	-0.256 (0.067)	-0.148 (0.066)	-0.241 (0.093)
98 (436)	0.047 (0.021)	0.025 (0.023)	0.025 (0.007)	0.077 (0.016)	-0.006 (0.001)	0.005 (0.002)	-0.252 (0.067)	-0.159 (0.064)	-0.226 (0.087)
97 (417)	0.046 (0.021)	0.014 (0.024)	0.025 (0.007)	0.087 (0.017)	-0.006 (0.001)	0.006 (0.002)	-0.244 (0.071)	-0.156 (0.064)	-0.246 (0.089)
96 (404)	0.041 (0.022)	0.021 (0.022)	0.023 (0.007)	0.076 (0.017)	-0.005 (0.001)	0.005 (0.002)	-0.235 (0.068)	-0.154 (0.065)	-0.231 (0.082)
95 (392)	0.043 (0.023)	0.030 (0.022)	0.024 (0.008)	0.075 (0.017)	-0.005 (0.001)	0.006 (0.002)	-0.237 (0.071)	-0.149 (0.065)	-0.206 (0.086)
94 (381)	0.044 (0.023)	0.028 (0.023)	0.024 (0.008)	0.069 (0.017)	-0.005 (0.001)	0.006 (0.002)	-0.224 (0.071)	-0.168 (0.064)	-0.221 (0.086)
93 (376)	0.045 (0.023)	0.021 (0.024)	0.024 (0.008)	0.067 (0.017)	-0.005 (0.001)	0.005 (0.002)	-0.239 (0.071)	-0.169 (0.064)	-0.223 (0.087)
92 (369)	0.045 (0.024)	0.022 (0.023)	0.024 (0.008)	0.058 (0.016)	-0.005 (0.001)	0.005 (0.002)	-0.243 (0.069)	-0.167 (0.064)	-0.245 (0.088)
89 (343)	0.051 (0.024)	0.019 (0.025)	0.025 (0.008)	0.054 (0.016)	-0.005 (0.001)	0.005 (0.002)	-0.198 (0.066)	-0.150 (0.071)	-0.206 (0.081)
82 (300)	0.042 (0.023)	-0.009 (0.022)	0.020 (0.009)	0.048 (0.014)	-0.005 (0.001)	0.005 (0.001)	-0.174 (0.062)	-0.184 (0.075)	-0.196 (0.071)
81 (296)	0.040 (0.023)	-0.012 (0.022)	0.020 (0.009)	0.049 (0.014)	-0.005 (0.001)	0.005 (0.001)	-0.171 (0.060)	-0.190 (0.076)	-0.205 (0.069)
80 (294)	0.038 (0.024)	-0.013 (0.022)	0.021 (0.009)	0.048 (0.014)	-0.005 (0.001)	0.005 (0.001)	-0.165 (0.060)	-0.209 (0.074)	-0.205 (0.067)

Table 3.4 Marginal Effects from MLE Results for Different Cutoff Levels

Variables		Exp	100	99	98	97	96	95	94	93	92	89	82	81	80
1. Debt held in bonds	X	[-]	-	-	-	-	-	-	-	-	-	-	[-]	[-]	[-]
	Z	[+]	-	-	-	-	-	-	-	-	-	-	[-]	[-]	[-]
2. Debt owed to private creditors	X	?	+	+	+	+	+	+	+	+	+	+	+	+	+
	Z	?	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	-	-	-
3. Default history	X	?	-	-	-	-	-	+	-	-	-	-	-	+	+
	Z	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
4. Average growth	X	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
	Z	[-]	+	+	+	+	-	-	-	-	-	-	[-]	[-]	[-]
5. Average inflation	X	[+]	+	+	+	+	+	+	+	+	+	+	[+]	[+]	[+]
	Z	[-]	[+]	+	+	+	+	+	+	+	+	+	-	-	-
6. Trade to GDP ratio	X	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	+
	Z	[-]	-	+	-	+	+	-	-	-	-	-	[-]	[-]	[-]
7. Financial openness	X	[+]	-	-	-	-	+	-	-	-	-	-	-	-	-
	Z	[-]	[+]	[+]	+	+	+	+	+	+	+	+	+	+	+
8. Reserves to imports	X	[+]	-	-	-	-	-	-	-	-	-	+	+	+	+
	Z	[-]	[-]	[-]	-	-	-	-	-	-	-	-	-	-	-
9. Interest payments to exports	X	[-]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
	Z	[+]	+	+	-	-	+	+	-	-	-	-	+	-	-
10. Debt on concessional terms	X	[-]?	-	-	-	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
	Z	[+]?	-	-	-	-	-	-	-	-	-	[-]	[-]	[-]	[-]
11. Net transfers to GNI	X	?	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
	Z	[+]	-	[-]	[-]	-	[-]	[-]	[-]	[-]	[-]	[-]	-	-	-
12. Trade balance to GDP	X	[+]	-	-	-	-	-	-	-	-	-	-	-	-	-
	Z	[-]	[+]	+	+	+	+	+	+	+	+	+	-	-	-
13. Expected real interest in the US	X	[-]	+	+	+	+	+	+	+	+	+	+	+	+	+
	Z	[+]	-	-	-	-	-	-	-	-	-	-	[-]	[-]	[-]
14. Log of PPP GDP per capita	X	?	+	-	-	-	-	-	-	-	-	-	-	-	-
	Z	?	-	-	-	-	-	-	-	-	-	[-]	-	-	-
15. External debt to GDP	X	?	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
	Z	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
16. Short term debt to GDP	X	?	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
	Z	[+]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	-	-	[-]	[-]	-
17. Short to long debt	X	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]

Notes: The numbers for the independent variables match those from Table 2.3. Bold variables are only in one of the equations. Bold brackets mean significant at the 10% level.

Table 3.4 Marginal Effects from MLE Results (Continued)

<i>Variables</i>		Exp	100	99	98	97	96	95	94	93	92	89	82	81	80
18. Data quality	X	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	+
	Z	?	-	+	+	+	+	+	+	+	+	+	-	-	-
19. Political stability	X	?	+	+	+	+	+	+	+	+	+	[+]	+	+	+
	Z	?	[-]	-	-	-	-	-	-	-	-	+	+	+	+
20. Political shock	X	?	-	-	-	-	-	-	-	-	-	-	-	-	+
	Z	?	+	+	+	+	+	+	+	[+]	[+]	[+]	[+]	[+]	[+]
21. Revolutions	X	?	+	+	+	+	+	+	+	+	+	+	+	+	+
	Z	?	-	-	-	-	+	+	+	+	+	+	+	+	-
22. Warfare	X	?	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
	Z	?	+	-	-	-	-	-	-	-	-	+	+	+	-
23. Control of corruption	X	?	+	+	+	+	+	+	+	+	+	-	+	-	+
	Z	?	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
24. Voice and accountability	X	?	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
	Z	?	[+]	[+]	+	+	[+]	[+]	+	+	+	+	+	+	+
25. Regulatory quality	X	?	+	+	+	+	+	+	+	+	+	-	+	+	+
	Z	?	+	-	+	+	-	-	-	-	-	-	-	-	-
26. Rule of law	X	?	+	+	+	+	+	+	+	+	+	+	+	+	+
	Z	?	+	+	-	-	-	-	-	-	-	-	-	-	-
27. Government effectiveness	X	?	+	+	+	+	+	+	+	+	+	+	+	+	+
	Z	?	-	+	+	+	+	+	+	+	+	+	+	+	[+]
28. Fixed exchange rate regime	X	?	-	-	-	-	-	-	-	-	-	-	+	+	+
	Z	[+]	[+]	[+]	[+]	[+]	+	[+]	+	[+]	[+]	[+]	[+]	[+]	[+]
29. Intermediate exchange rate regime	X	?	-	-	[-]	-	-	-	-	-	-	-	[-]	[-]	[-]
	Z	[+]	+	+	+	+	+	+	+	+	+	+	+	+	+
30. Growth volatility	X	[-]	[-]	-	-	-	[-]	[-]	[-]	[-]	-	-	[-]	[-]	[-]
	Z	?	-	-	-	-	-	-	-	-	-	-	-	-	-
31. Inflation volatility	X	[-]	+	-	-	-	-	-	-	-	-	-	-	-	-
	Z	?	[-]	-	+	+	+	+	+	+	+	+	-	[+]	[+]
32. Export diversification	X	?	[+]	[+]	[+]	[+]	+	+	+	+	+	+	+	+	+
	Z	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
33. Population	X	?	+	-	-	-	-	-	-	-	-	-	-	-	-
	Z	?	[-]	[-]	[-]	-	-	-	-	-	-	-	-	-	-
34. Year	X	?	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]	[+]
	Z	?	-	[-]	[-]	-	-	-	-	-	-	[-]	-	-	-

Based on the marginal effects and the cutoff levels between the converging MLE estimates between 80% and 100%, the main empirical findings are the following –

1. The covariance between the regression equation (for the repayment ratio) and the selection equation (for default) is consistently positive, which gives justification for our Heckman MLE estimation and not for the Tobit framework.
2. Good data quality seems to increase the conditional repayment ratio, while having an insignificant, yet positive, effect on the probability of default. More specifically, a one step increase in the data quality index led to, on average, a 3.6% increase in the repayment ratio for an average country, and led to a statistically insignificant slight increase in the default probability (less than 1.1% on average).⁶ Table 3.5 gives the marginal effects for the actual repayment ratio, X , in percentage terms and default probability of a one step increase in the data quality index for an average country.
3. Default history, on the other hand, consistently posited a strong positive effect on default as was expected from the literature, and a negligible or slightly positive effect on the repayment ratio (due to the selection equation).⁷

⁶Though not identical significance-wise, this matches the signs for the coefficients for bonds as a percentage of total debt – more bonds outstanding leads to a lower probability of default and a negligible or slightly lower repayment ratio. Bolton and Jeanne (2002) argue that bonds are harder to restructure than other loans, such as syndicated bank loans, since it is harder for numerous investors with bonds to coordinate than a small number of banks in debt renegotiations. This suggests that bargaining power may have something to do with the effect that data quality has on the repayment ratio.

⁷Reinhart, Rogoff, and Savastano (2003) emphasized the role of default history on credit ratings, while Suter (1992) found a significant default-history effect on default in his regressions for the early and mid 20th century.

4. External Debt as a percentage of GDP consistently increases sovereign risk, both by reducing the conditional repayment ratio and by increasing the probability of default as seen in the literature.
5. Along with default history, a fixed exchange rate, corruption, and less diversification of exports increase a country's chances of default for all cutoff values between 80% and 100%. Diversification of exports reduces your probability of default by 20%, for example.
6. High real growth rates, a large trade to GDP ratio, and no warfare contributed to increasing a country's repayment ratio for most or all cut-off values, as did the interest payments to exports ratio.
7. In sum, most of the coefficients were consistent with what the literature and other empirical evidence has described so far.⁸

Table 3.5 Marginal Effects for an Average Country
(with a one step increase in the Data Quality Index)

	100	99	98	97	96	95	94	93	92	89	82	81	80
X (Repayment Ratio)	3.7	3.9	4.4	4.1	3.6	3.8	3.8	3.8	3.9	4.1	2.8	2.6	2.4
Z (Prob. of Default)	-1.4	0.7	2.5	1.4	2.1	3.0	2.8	2.1	2.2	1.9	-0.9	-1.2	-1.3

Notes: Bold means the statistic is significant at the 10% significance level.

⁸ More net transfers as a percentage of GNI, more short term debt as a percentage of GDP, and less voice and accountability actually led to less sovereign risk where it affected the conditional repayment ratio negatively and the probability of default positively (though most of the time only one effect was significant). The first two quantities may be related with liquidity issues, while the voice and accountability may enhance a populist government's chances of obtaining power. These were the findings that were unusual.

3.5 Further Robustness Testing

As we have seen, the main finding that better information quality of macro aggregates are related to higher repayment ratios and has a statistically insignificant effect on the default probability are robust to the different cutoff levels for defining a default. The empirical results are also robust to using regional dummies instead of institutional variables, using the aggregated data quality index⁹ in PWT6.1, and running MLE without any institutional variables. Table 3.6 summarizes the results. As the variations to the letter grade in PWT6.1 of information quality of macro aggregates are limited (from 1 to 3), the coefficients become larger. However, the effect of data quality is consistently positive with respect to the repayment ratio; whereas, the effect on the default probability is consistently negative, yet insignificant. Adding regional dummies instead of my institutional variables or discarding the institutional variables altogether reinforce my finding that better information quality is related to greater repayment ratios conditional on default, but has a negligible effect on the default probability.

Finally, I run a probit on the more standard S&P data as the dependent variable, and the find that data quality has a negligible effect on the probability of default – a one step increase in the data quality index increases the default probability by 1.2% and the

⁹The sample only has variation between a “D” and “B” letter grade. In my regressions, I gave number 3 to “B”, the highest grade and 1 to “D”, the lowest. In PWT version 5, they have more categorized break-ups – A, B+, B, B-, etc.

statistic is insignificant (p-value is 58%). I emphasize that the evidence that better data quality leads to any effect on the default probability is absent in any of my regressions.

Table 3.6 Robustness Testing

<i>Cutoff (defaults)</i>	<i>Base</i>		<i>With Letter Grade PWT6.1</i>		<i>With Regional Dummies</i>		<i>Without Institutions</i>	
	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\beta}$	$\hat{\gamma}$
100 (521)	0.034 (0.020)	-0.046 (0.053)	0.188 (0.087)	-0.546 (0.330)	0.046 (0.021)	-0.012 (0.055)	0.045 (0.019)	-0.037 (0.055)
99 (460)	0.043 (0.021)	0.021 (0.060)	0.199 (0.092)	-0.326 (0.355)	0.053 (0.021)	0.034 (0.058)	0.053 (0.020)	0.004 (0.061)
98 (436)	0.052 (0.021)	0.066 (0.060)	0.201 (0.092)	-0.344 (0.352)	0.057 (0.021)	0.068 (0.054)	0.059 (0.021)	0.036 (0.059)
97 (417)	0.048 (0.021)	0.035 (0.062)	0.167 (0.091)	-0.585 (0.374)	0.055 (0.021)	0.045 (0.054)	0.057 (0.019)	0.010 (0.059)
96 (404)	0.044 (0.022)	0.054 (0.056)	0.159 (0.088)	-0.253 (0.336)	0.054 (0.020)	0.052 (0.049)	0.056 (0.019)	0.020 (0.054)
95 (392)	0.048 (0.023)	0.076 (0.055)	0.168 (0.089)	-0.097 (0.300)	0.057 (0.020)	0.066 (0.050)	0.060 (0.019)	0.034 (0.053)
94 (381)	0.049 (0.023)	0.071 (0.058)	0.169 (0.090)	-0.102 (0.306)	0.056 (0.020)	0.047 (0.050)	0.058 (0.019)	0.016 (0.054)
93 (376)	0.048 (0.023)	0.053 (0.060)	0.165 (0.090)	-0.138 (0.307)	0.055 (0.020)	0.034 (0.050)	0.058 (0.019)	0.006 (0.054)
92 (369)	0.049 (0.023)	0.055 (0.058)	0.166 (0.090)	-0.083 (0.305)	0.054 (0.019)	0.026 (0.049)	0.058 (0.018)	0.001 (0.054)
89 (343)	0.053 (0.023)	0.048 (0.065)	0.178 (0.091)	-0.142 (0.305)	0.053 (0.019)	0.028 (0.049)	0.060 (0.018)	0.017 (0.053)
82 (300)	0.040 (0.023)	-0.026 (0.063)	0.112 (0.083)	-0.351 (0.320)	0.042 (0.018)	-0.051 (0.047)	0.052 (0.016)	-0.050 (0.054)
81 (296)	0.038 (0.023)	-0.035 (0.062)	0.111 (0.084)	-0.348 (0.319)	0.040 (0.018)	-0.060 (0.047)	0.050 (0.016)	-0.059 (0.054)
80 (294)	0.036 (0.024)	-0.037 (0.063)	0.111 (0.086)	-0.353 (0.315)	0.039 (0.019)	-0.059 (0.048)	0.050 (0.016)	-0.056 (0.055)

Notes: Bold means that the statistic is significant at the 10% significance level.

3.6 Possible Explanations of the Estimates and a Word on Risk Sharing

The statistical relationship I find that better information of macro aggregates leads to higher repayment ratios, offers clues to the mechanisms behind the relationship between data quality of macro aggregates and sovereign risk. Since it is natural to think of the repayment ratio conditional on default increasing with bargaining power for creditors, it is logical to conclude that better data quality leads to greater bargaining power for creditors. Hence, the bargaining-power explanation is set forth as the first hypothesis. A second possible explanation behind the link may have to do with additional costs that creditors may require before lending to an emerging market, such as search costs. If creditors believe that data quality of macro aggregates are poor, they might need to spend more resources on searching for information before investing. Moreover, if it is impossible for creditors to observe certain properties of the economy that they normally take for granted when investing in advanced economies, they might ask for a premium to account for the uncertainty involved with less or worse information of macro aggregates. I define either the search costs or the premium discriminatory costs associated with a reputation for having bad data quality as ‘reputational’ costs.¹⁰ The search-cost or ‘reputational’ cost explanation is set forth as the second hypothesis.

¹⁰I also note a more direct possible link between data quality of PPP estimates and sovereign risk. By manipulating the PPP, debtor countries may use their lower-than-actual wealth measures to influence *concessional lending* by official and bilateral creditors. To criticisms about the ICP survey, a previous Deputy Vice President of the World Bank is quoted as saying, “they (many developing countries) have found the work financially burdensome and have seen little policy use for the resulting estimates. Second, some

It is important to note the issue that constantly lurks behind the issue of information quality. Given institutional factors that may determine information quality, the role that information *asymmetry* may play should be looked at once again. Just looking at the typical moral hazard problem where the lender cannot identify if a borrowing country is using its loans for investment or consumption purposes, it is easy to understand how the theory may not support my empirical findings.

Both Gertler and Rogoff (1990) and Atkeson (1991) start out with the premise that “investment” is what cannot be observed. This is a critical factor in the economies they study as investment is directly linked to the distribution of output in the following period. Greater investment leads to a greater probability of a “good” state tomorrow, which, *ceteris paribus*, leads to a lower chance of not being able to repay loans incurred by the sovereign. If lenders could accurately observe this sort of investment behavior, they would be able to contract out, through contingent claims, a more optimal level of investment. As they can not see whether their funds are being used for investment or consumption, their incentive compatibility constraint restricts them from lending that optimal amount and can only form contracts based on observables such as output. Indeed, to induce the developing country to invest, the contingent claim will be structured such that the sovereign incurs substantial costs when a bad signal is revealed in terms of observables in relation to

developing countries have feared that ICP results, which show higher gross domestic product (GDP) estimates . . . may be used to the detriment of their standing in multilateral lending agencies. Third, the statistical capabilities of some of these countries have not readily supported a full-scale ICP survey.” Yet this can also be analyzed as a reputational variable – just as private-sector creditors may add a premium to their loans, public-sector creditors may offer concessional loans at lower interest rates with bad data quality that shows a country being poorer than it actually is. However, I find the correlation between concessional debt as a percentage of total external debt and data quality to be -0.0252 . Running regressions with concessional debt as the dependent variable also showed lack of any effect of data quality. Therefore, I conclude that countries do not benefit from bad data quality in concessional lending and continue with the analysis of *good* data quality being a possible “good” reputational variable.

investment. This logic has been used to explain the seemingly counter-intuitive phenomenon of capital *outflows* in times of crises in developing markets.

It is difficult to map the repayment ratio into the framework of defaults and repayment ratios as contingent claims is a contract that is enforced *contingent* on something happening. However, if we were to interpret a non-maximum payment as a default occurrence in a two-state setup, Gertler and Rogoff (1990) provide empirical implications for the default probability. If bad information quality were somehow related to information asymmetry, with the implication that developing countries can use bad data to hide and falsify information, then the incentive compatible constraint deters the parties from agreeing to a higher level of level of investment than otherwise. Since investment is directly linked to output the following period, the more likely is it that the country will declare default with asymmetric information.

However, this is not what was confirmed in the empirical findings. As the estimates based on various cutoff levels and robustness tests confirm, there is no sign of bad data quality leading to greater probabilities of default. This may mean two things – one is that bad data quality may not be related to asymmetric information, and the other is that the theory connecting asymmetric information to investment is incorrect. Further analysis is necessary to decouple this question. It is important to point out that the two hypotheses set forth based on better data quality leading to greater bargaining power for creditors or lower search costs for creditors may be related to asymmetric information as well.

CHAPTER 4

CONCLUSION

This essay attempted to explain the statistical link between information quality of macro aggregates and sovereign risk. To answer this question I first constructed a cross-country panel data of repayment ratios to find a statistical relationship between data quality, the repayment ratio and the default probability. The main findings from the empirical investigation confirmed that better data quality increases the repayment ratio while having a positive but statistically insignificant effect on the default probability. Results were robust to controlling for various governance measures and income levels as well. This endeavor enabled me to capture other variables that were linked to sovereign risk, such as warfare, which had a negative effect on repayment ratios. The results for other political factors and governance indicators may provide further scope for research concerning the political economy and sovereign risk.

Policy implications abound regarding information quality and sovereign risk. A direct interpretation of my conclusion is that by enhancing data quality, possibly through better incentives for National Statistical Organizations (NSOs) and better coordination with International Organizations, we can reduce sovereign risk and increase the welfare of the country concerned that is open to international capital. Not only should the IMF, the World Bank, and other International Financial Institutions (IFIs) worry about transparency, they should induce policies to enhance the accuracy of the information also such as enhancing the IMF's DQAF.

Finally, we have witnessed how the problem of information *quality* should be considered as vital as the problems concerning information *asymmetry* when it comes to sovereign debt/default issues. It is important to note that the empirical implications from Gertler and Rogoff (1990) do not match the empirical findings I find, if bad information quality was somehow related to information asymmetry. In their study, information asymmetry leads to an increase in the default probability as foreigners will not lend to the developing country as much. This unambiguously hurts the output prospects in a contingent claims framework, which leads to the empirical implication that asymmetric information leads to a higher probability of default. However, this is not what I found to be true with a decrease in information quality. Still, the relationship between information quality and asymmetry would be important if it were to be found that the former helps alleviate the latter. Better game-theoretical models may provide further understanding of the possible interactions between the two concepts. Further cost-benefit analysis of having bad information or hiding information will allow us to give us a better idea of more tangible policy implications as well. This will be the subject for further research.

APPENDIX I – COUNTRIES IN REGRESSION SAMPLE

Data Quality Index (Variance Measure)

from PWT6.1 (in parentheses)

Algeria (0) 1989 – 1992	Madagascar (5) 1989 – 2002
Angola (0) 1997 – 2002	Malawi (4) 1989 – 2002
Argentina (5) 1989 – 2002	Malaysia (4) 1989 – 2002
Bangladesh (3) 1990 – 2002	Mali (4) 1992 – 1996
Bolivia (4) 1989 – 2002.	Mauritius (4) 1989 – 2002
Botswana (1) 1989 – 2002	Mexico (4) 1989 – 1995, 1997 – 2002
Brazil (4) 1989 – 2002	Morocco (3) 1990 – 2002
Burkina Faso (4) 1989 – 1995, 2001 – 2002	Mozambique (1) 1991 – 1998, 2000 – 2002
Cambodia (0) 1998 – 1999	Nepal (4) 1989 – 2002
Cameroon (3) 1989 – 1996	Nicaragua (4) 1995, 1997 – 2002
Chile (5) 1989 – 2002	Niger (3) 1989 – 1994
China (3) 1990 – 2002	Nigeria (5) 1989 – 2002
Colombia (5) 1989 – 2002	Oman (0) 1994 – 2002
Congo, Democratic Rep. of (0)1995 – 2002	Pakistan (4) 1989 – 2002
Congo, Republic of (1) 1989 – 1998, 2002	Panama (4) 1989 – 2002
Costa Rica (4) 1989 – 2002	Paraguay (5) 1989 – 2002
Côte d'Ivoire (3) 1989 – 2002	Peru (3) 1989 – 2002
Dominican Republic (5) 1989 – 2001	Philippines (3) 1989 – 2002
Ecuador (2) 1989 – 1994, 1996 – 2002	Senegal (5) 1989 – 2002
Egypt (4) 1989 – 2002	Sierra Leone (3) 1989 – 1996
El Salvador (5) 1989 – 2002	Sri Lanka (4) 1989 – 2002
Ethiopia (4) 1989 – 2002	Sudan (0) 1997 – 2001
Gabon (0) 1989 – 2001	Syria (0) 1989
Gambia (4) 1989 – 1996	Tanzania (2) 1992 – 2002
Ghana (5) 1989 – 2002	Thailand (3) 1989 – 2002
Guatemala (5) 1989 – 1994, 1996 – 2002	Togo (0) 1989 – 1997
Guinea-Bissau (3) 1991 – 1998	Trinidad and Tobago (2) 1989 – 2002
Haiti (0) 1989 – 1995	Tunisia (1) 1989 – 2002
Honduras (5) 1989 – 2002	Turkey (5) 1990 – 1995, 1997 – 2002
India (5) 1989 – 2002	Uganda (1) 1989 – 2002
Indonesia (5) 1989 – 2002	Uruguay (5) 1989 – 2002
Jamaica (3) 1989 – 2002	Venezuela (3) 1989 – 2002
Jordan (4) 1989 – 2002	Vietnam (4) 1999 – 2002
Kenya (4) 1989 – 2002	Zambia (5) 1989 – 1992, 1998, 2000 – 2002
	Zimbabwe (2) 1989 - 1995

APPENDIX II – SUPPLEMENTARY FIGURES

Figure A.1. Repayment Ratios Conditional on Default According to Data Quality
(cutoff – a repayment ratio of at least 99% is considered non-default)

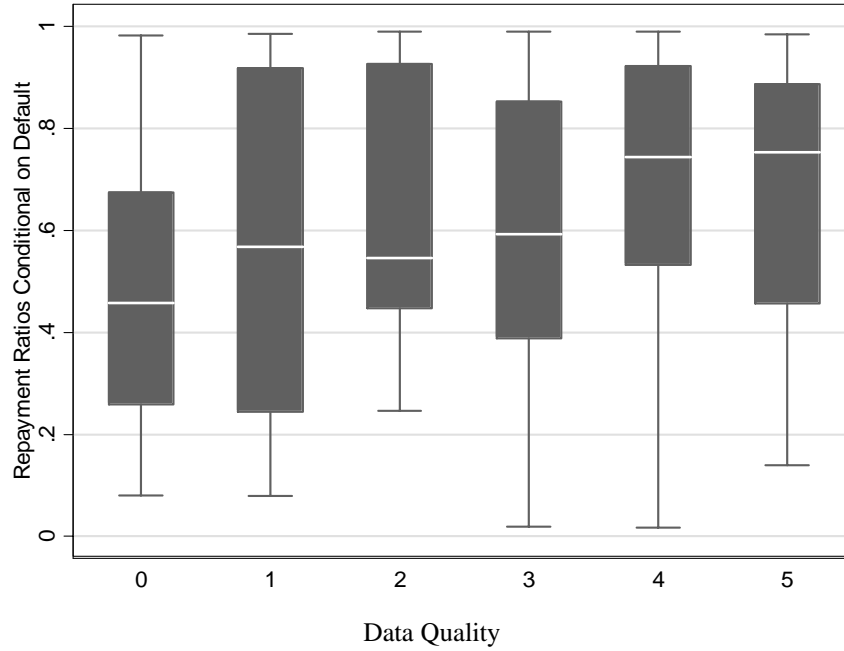


Figure A-2. Repayment Ratios Conditional on Default According to Data Quality
(cutoff – a repayment ratio of at least 95% is considered non-default)

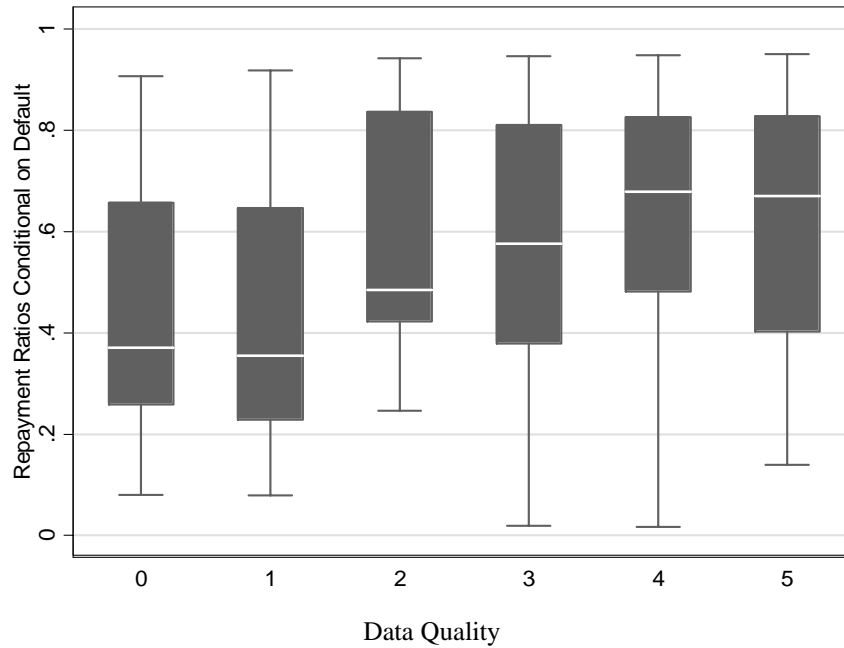


Figure A.3. Repayment Ratios Conditional on Default According to Data Quality
 (cutoff – a repayment ratio of at least 90% is considered non-default)

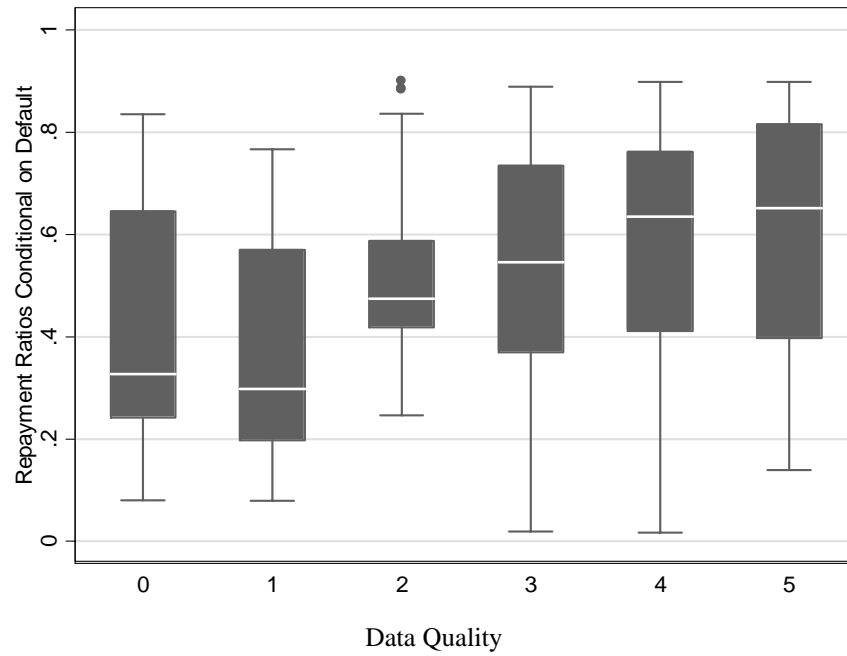
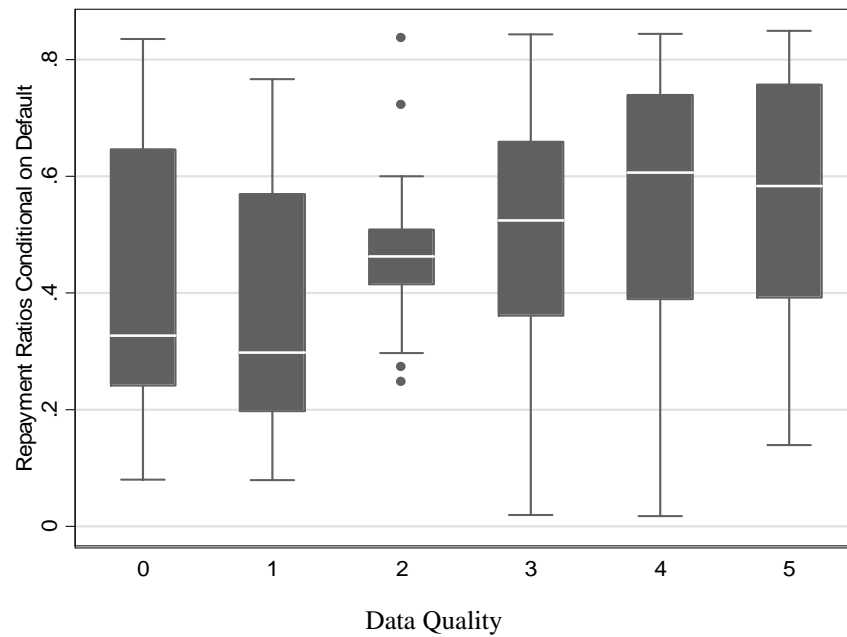


Figure A.4. Repayment Ratios Conditional on Default According to Data Quality
 (cutoff – a repayment ratio of at least 85% is considered non-default)



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