The Relationship Between Fiscal Opacity and Credit Spreads: A Biased Information Model

JUE WANG*, JIRI SVEC AND MAURICE PEAT

School of Business,

The University of Sydney, NSW 2006, Australia

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Abstract

Duffie and Lando (2001) were the first to show, under a structural framework, how opacity is priced into credit risk. However, their model is shown to produce results conflicting intuition and empirical observations. In the first part of this study, we propose a biased information model that incorporates skewness into the conditional asset density function. In the second part, we validate our model predictions using two established measures of fiscal opacity and sovereign credit default swaps spreads. Both sections of this study contribute to our understanding of the consequences of opacity on the cost of government external debt financing.

*Corresponding author

1. Introduction

Models for pricing defaultable claims have become more important given today's expanding debt market and volatile environment. One main type of such models is the structural models beginning with Black and Scholes (1973) and Merton (1974), which postulates that firm leverage, volatility and risk-free rate jointly determine credit spreads.[1] This class of model assumes that the parameters such as leverage are observed with certainty. However, in practice, investors rarely know the precise leverage at any point in time (Ericsson and Reneby (2002)), since accounting reports are mere periodic snapshots of a continuous process, and are subject to statistical errors or management biases. Another limitation of structural models is that they predict zero credit spread at short maturity, whereas empirical observations reveal that bond investors seem to account for the probability of instantaneous default (Zhou (2001)). In recent years, a class of models were developed to specifically generate non-zero short-term credit spreads by allowing for uncertainty in the parameters. For example, the CreditGrades model by Finger, Finkelstein, Lardy, Pan, Ta and Tierney (2002), and the I^2 model by Giesecke and Goldberg (2004) allow uncertainty in the level of debt. Nevertheless, neither model provides an economic explanation for the uncertainty mechanism.

Duffie and Lando (2001) proposed an incomplete information model that addresses parameter uncertainty by considering asset measurement errors due to noisy accounting reports. The Duffie and Lando (2001) model is the first to relate financial opacity to credit spreads and is a cornerstone credit risk model that unifies the structural framework with the reduced form framework via informational assumptions (Jarrow and Protter (2004)). In spite of the model's economic and statistical elegance, when the model parameters are calibrated to real world values, the model implies counter-intuitively that investors perceive firms with noisy accounting reports

[1] Further extensions include the possibility of early default introduced by Black and Cox (1976), stochastic interest rates modelled by Shimko, Tejima and Deventer (1993), and endogenous default boundary developed by Leland and Toft (1996). Reduced form models, which originated with Jarrow and Turnbull (1995), form the second class of credit risk models.

safer than firms with transparent accounting reports, all else being equal. As argued by Yu (2005), bond price is a positive function of transparency and this result would not have occurred if accounting bias was considered.

In the first part of this paper, we propose a biased information model that incorporates skewness in the original model's conditional asset density function to address the unintended consequences of unbiased accounting reports in the original model. We show via simulation that the biased information model predicts consistently an "S" or sigmoid-shaped relationship between opacity and credit spreads. In contrast to the Duffie and Lando (2001) model, our model predicts an uncertainty premium over the whole credit term structure. We then formulate four testable hypotheses and validate our model predictions using fiscal opacity and sovereign credit default swaps (CDS) spreads in a similar manner as Yu (2005).

One reason for focusing on sovereigns instead of firms for validating model predictions pertains to the measurement opacity.[2] Like other model parameters, opacity is unobservable. An ideal proxy would be one that is free from endogeneity problem. In the accounting literature, such proxy exists prior to 1998, which is the commonly used survey-based AIMR (Association for Investment Management and Research) ranking of corporate disclosure quality. Yu (2005) for example, adopted the AIMR rankings as a proxy for firm opacity. Another set of popular proxies is the analyst forecast attributes (dispersion and accuracy) proposed by Lang and Lundholm (1996). However, this set of proxies is not completely free from endogeneity, and therefore it may not be possible to disentangle uncertainty due to opacity from pure heterogeneity of beliefs. Moreover, analysts are under no obligation to update forecasts in synchronisation with their peers or even update at all. The potential staleness of forecasts biases forecasts dispersion as a proxy for opacity. As for forecast accuracy, it has been shown that managers manipulate earnings towards analysts' targets (Mulford and Comiskey (2002)).

[2] Hassan and Marston (2010) provide a review of disclosure proxies used in the accounting literature.

On the other hand, we have for sovereigns the Open Budget Index, developed by the International Budget Partnership, a publicly available survey-based, exogenous measure of fiscal transparency covering 100 countries. As a robustness check, we calculate stock-flow adjustments publicly available data following von Hagen and Wolff (2006), which has been shown to indicate accounting gimmickry used by many governments.

Although the role of corporate financial transparency on the cost of capital has been well researched since Diamond and Verrechia (1991), the impact of government financial transparency has attracted less scrutiny until recently. Accordingly our second motivation is gained from the Eurozone sovereign debt crisis, during which questions were raised about the transparency of fiscal positions of governments in years prior to the crisis. Understanding the role of government transparency in the financial market is important due to its broad implications. For a government, its perceived degree of transparency may have implications for its short and long term borrowing costs. From its electorate's perspective, if the financial market creates the incentive for making forthcoming disclosure, then the private sector is able to make better informed consumption or investment decisions. Furthermore, governments that are aware of its own underlying fiscal position are less susceptible to adverse exogenous shocks. (IMF (2012))

Empirical testing of the effect of opacity on sovereign credit risk is quite limited. Examples include Arbatli and Escolano (2012), who show that fiscal transparency is associated with better credit ratings, Bernoth and Wolff (2008), who find that creative accounting activities in the European Union increase government risk premia, and Glennerster and Shin (2008), who show sovereign bond spreads fall after adopting transparency reforms. We extend this literature in three ways. Firstly, our study benefits from large panel datasets, which allow us to apply panel techniques. Our sample covers a period during the financial crisis, when the incentive to be opaque is at the highest. Secondly, unlike studies using bond data, our use of sovereign CDS circumvents issues relating to tax, optionality, shortening maturity and the appropriate benchmark rate. (Houweling and Vorst (2005)) Thirdly, we test four hypotheses, with each examining the effect of fiscal opacity on CDS spreads from a different angle.

Our results show that the credit market does demand a higher credit premium for sovereigns with higher fiscal opacity. In particular we confirm a nonlinear effect of fiscal opacity on credit spreads, which is the highest between an OBI score of 17 to 46 and between 0.47 to 2.43 percent of GDP for stock-flow adjustments. The market, however, appears to be indifferent to macro-volatility. Finally we show that opacity premium is prevalent over the entire credit spreads term structure.

The remainder of the paper is organised as follows. We first present the biased information model and analyse model implications. Section 3 formulates testable hypotheses. Section 4 describes two measures of fiscal opacity and the control variables. Section 5 describes the method. In Section 6 we report the regression results and check for endogeneity. Section 8 concludes.

2. Biased information model

2.1. Model setup

This section develops the biased information model which builds on the DL model. In contrast to classical structural models that assume the firm value is continuously observable by investors, the DL model assumes that since its last known true position, the asset value has evolved stochastically to a position which is obscured by some noise. Expressed mathematically,

$$Y_t = Z_t + U_t \tag{1}$$

where Y_t is the log of the reported asset value, Z_t is the log of the actual asset value and U_t is the accounting noise, all at time t. Intuitively, the actual asset value may lie somewhere closer to the default boundary than the reported asset value, and if close enough, default may occur instantaneously. This idea ensures that default pro bability at short maturities is positive.

The biased information model differs from the DL model in the distributional assumption of U. While the DL model assumes U is normally distributed, we assume that U follows a skew normal distribution with a location parameter $\bar{u}$, a scale parameter a and a shape parameter ω. The shape parameter, ω, can also be expressed as $\frac{\delta}{\sqrt{1-\delta^2}}$, so that the skewness (δ) is bounded by -1 and 1. In the DL model, the standard deviation of the noise (a) is the only factor that determines the distribution of accounting noise. A lower a represents less noise and therefore less uncertainty about the true asset value. In our model, there is an additional shape parameter that determines the skewness of accounting noise distribution.

Here, we offer an intuitive interpretation for the role played by the scale and shape parameters in the accounting noise distribution. We decompose accounting noise into two sources. One source is entirely random, which may arise as an artefact of an accounting system or it may simply be statistical errors. Being random, this particular source of error either over- or understates the actual asset value. Accordingly, we model it as the dispersion of the noise distribution captured by the scale parameter and we refer to it as opacity. The other source is directional, which may arise from deliberate misreporting or withholding material adverse information as in the case of discretionary disclosure. We model this directional bias as the skewness of the noise distribution captured by the shape parameter. [3]

Conditional on the last known true asset value, its diffusion process, the current reported asset value and a perceived distribution of noise, investors then derive a posterior probability density function for the current true asset value via Bayes' rule:

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[3] Note that unlike the normal distribution, the location parameter is not equivalent to the mean of a skew normal. We set the location parameter to zero, so that in the absence of a directional bias, the noise distribution is symmetrical around zero.

$$b(x|Y_t, z_0, t) = \frac{SN(Y_t - x)\ \psi(z_0 - \underline{v}, x - \underline{v}, \sigma\sqrt{t})\ \phi_Z(x)}{\phi_Y(Y_t)} \tag{2}$$

where:

x	is the actual asset value
Y_t	is the reported asset value
z_0	is the last known actual asset value
$\underline{v}$	is the default boundary
σ	is the asset diffusion
$SN(.)$	is the skew normal density function[4]
ϕ	is the normal probability density function

$\psi(z_0 - \underline{v}, x - \underline{v}, \sigma\sqrt{t}) = 1 - \exp\left(\frac{-2(z_0 - \underline{v})(x - \underline{v})}{\sigma^2 t}\right)$ is an adjustment to the unconditional asset density $\phi_Z(x)$ such that it is bounded below by the default barrier

Expanding the density functions in equation 2 yields:

$$b(x|Y_t, z_0, t) =$$

$$\frac{\sqrt{a^2 + \sigma^2 t}}{\sqrt{2\pi a^2 \sigma^2 t}} \exp\left[-\frac{(\tilde{y} - \tilde{x})^2}{2a^2} - \frac{(\tilde{z}_0 + mt - \tilde{x})^2}{2\sigma^2 t}\right]\left[1 - \exp\left(\frac{-2\tilde{z}_0\tilde{x}}{\sigma^2 t}\right)\right]\left[\text{erfc}\left(\frac{-\omega(\tilde{y} - \tilde{x})}{\sqrt{2}a}\right)\right] \tag{3}$$

where $\tilde{y} = y - \underline{v}$, $\tilde{x} = x - \underline{v}$, $\tilde{z}_0 = z_0 - \underline{v}$, and erfc(.) denotes the complimentary error function.

Next, following Duffie and Lando (2001), the asset density conditional on no prior default is expressed as:

$$g(x|Y_t, z_0, t) = \frac{b(x|y, z_0, t)}{\int_{\underline{v}}^{+\infty} b(z|y, z_0, t)dz} \tag{4}$$

An interesting point to note is the interplay between normal and lognormal distributions. While the log of asset value is normally distributed, asset value is lognormally distributed. This implies that by exponentiating equation 2 and taking the expectation,

[4] Skew normal distribution has a pdf: $\frac{\exp(-(x-\overline{u})/2a^2)\ erfc(-\omega(x-\overline{u})/\sqrt{2}a)}{\sqrt{2\pi}\ a}$

$E(\exp(Y_t)) = E(\exp(Z_t))E(\exp(U_t))$, where the amount of bias is given by $E(\exp(U_t))$ with $U_t \sim SN(0, a^2, \omega)$. In order to visualise the amount of bias for different levels of a and ω, we simulated $E(\exp(U_t))$ by sampling from the skew normal distribution 1000 times with 10000 independent draws in each sample. The result is plotted against δ [5] as shown in Figure 1. It can be seen that the level of bias increases almost linearly as δ increases and the slopes are proportional to the scale parameter. The grey horizontal line reveals that δ needs to be negative for no bias. It turns out that when $\delta \approx -0.53$, the DL model is recovered, therefore it is in this regard that the DL model is a special case of the biased information model.

[Insert Figure 1]

While investors may be aware of the degree of opacity associated with the reporting entity, bias (if any) would not be revealed to the public ex-ante. We postulate that the amount of bias increases proportionally to the level of opacity, i.e. we let $\omega = \lambda a$, where λ is a constant. It is conceivable that under a low opacity environment, the possibility of misreporting is quite low since the public has all the relevant information allowing them to discover any untruthfulness. As the level of opacity increases due to reasons such as the inability to value complex structured financial products or to account for complex transactions, the likelihood of bias increases. Theory on discretionary disclosure shows that given the choice, firms have the tendency to withhold sensitive information from the public that can have adverse implications on the firm/manager (E.g. Shin (2003) and Verrecchia (1983)). Furthermore, Lev (2003) presented anecdotal evidence showing that in the late 1990s, over 90% of financial report restatements revised earnings downward. This sharp increase in downward revision coincided with a major move by the SEC to curb earnings manipulations. It was also reported that of the 1,068 cases of restatements, 232 firms faced securities class action lawsuits in the wake of the restatement, 193 firms had their management replaced, and 108 companies replaced their auditors. These facts

[5] Recall that ω can also be expressed as $\frac{\delta}{\sqrt{1-\delta^2}}$

support the argument that reported firm asset value may be upward biased, unbeknown to the investors. When opacity falls, as in the case of SEC enforcement, bias diminishes.

Similar to firms, a lack of transparency provides governments the opportunity to manipulate financial accounts. As maintained by Kopits and Craig (1998), fiscal opacity may arise due to a government's technical inability to report. Evidence for accounting manipulation has emerged with Buti, Martins and Turrini (2007) showing that European Economic and Monetary Union (EMU) governments employed accounting tricks and exotic transactions to meet the fiscal rules of EMU during the early years of EMU. Irwin (2012) also reports a range of common accounting devices employed by governments of economies battered by the sovereign debt crisis, in order to window-dress fiscal performance.

Figure 2 contrasts the effect of opacity on the conditional asset density function given by the DL model to that given by the biased information model. The reported asset value is 86, and λ is arbitrarily set to 30 to accentuate the skewness. As opacity increases, the density function given by the biased information model becomes more skewed to the right. This is consistent with the argument presented earlier, whereby given the opportunity, reported firm value may be upward biased. Consequently, the true asset value is more likely to lie below the reported level. Without the effect of discretionary disclosure however, the DL model implies that greater opacity leads investors to knowingly infer higher asset values.

[Insert Figure 2]

Finally, we derive the risk neutral survival probability to time *s* by solving for the weighted average probability of survival, whereby the weights are given by the conditional density function $g(x|Y_t, z_0, t)$:

$$p(t,s) = \int_{\underline{v}}^{\infty} \Big(1 - \pi\big(s - t, x - \underline{v}\big)\Big)\, g(x|Y_t, z_0, t)dx \tag{5}$$

with

$$\pi(t,x) = \Phi\left(\frac{x-mt}{\sigma\sqrt{t}}\right) + \exp\left(\frac{2mx}{\sigma^2}\right)\Phi\left(\frac{x+mt}{\sigma\sqrt{t}}\right) \tag{6}$$

where equation 6 is the probability of first passage of a Brownian motion and Φ denotes the standard normal cumulative distribution function.

2.2. Implications

To be comparable with the DL model, we use the same parameter values as Duffie and Lando (2001) unless stated explicitly otherwise. This means a leverage of 90 percent (Debt/Asset= 78/86), a risk-free rate of 6 percent, asset drift of 1 percent, and a recovery rate of 70 percent. Figures 3a and 3b plot the relationship between opacity (a) with the probability of default and 5-year credit spreads. The DL model predicts a positive relationship when asset diffusion remains low at 5 percent. However, as asset diffusion increases to 10 percent (an asset diffusion of 30 percent is not uncommon in the current economic environment) the model implies that investors perceive higher noise as safer. The same effect can be observed in terms of credit spreads by increasing the time to maturity from 1-year to 5-year. By contrast, when investors account for the possibility for misreporting due to a lack of transparency, the biased information model predicts a positive relationship.

[Insert Figure 3a, 3b]

Figure 4 illustrates the term structure of credit default swap spreads by varying the degree of opacity. In line with Duffie and Lando (2001) and empirical evidence, short-term credit spreads are bounded above zero. However the biased information model predicts a positive uncertainty premium across the entire term structure, whereas the DL model predicts a positive opacity premium at the short-end, and a negative premium at the long-end.

[Insert Figure 4]

2.3. Default intensity

A major contribution of the DL model is the unification of structural class models with reduced form models. In this section, we follow Duffie and Lando (2001) and show that the limit of default probability from the biased information model, as time to maturity tends to zero is in fact the intensity, or a local default rate. That is, we need to show that $\lim_{h \to 0^+} \frac{1}{h} \int_{\underline{v}}^{\infty} \pi(s - t, x - \underline{v}) g(x|Y_t, z_0, t) dx$ has a non-zero limit. Considering a discrete time random walk with:

1) one time period h,
2) steps of size $\sigma\sqrt{h}$
3) a probability of a $+\sigma\sqrt{h}$ move equal to $(1 - \pi)$
4) a probability of a $-\sigma\sqrt{h}$ move equal to π
5) x has a starting position at $\sigma\sqrt{h}$

Without loss of generality, we assume that $\underline{v} = 0$, and let $g(x)$ denote the conditional asset density. By the approximation of an integral, the probability $= \sigma\sqrt{h} \approx g(\sigma\sqrt{h})\sigma\sqrt{h}$. Accordingly, the conditional probability of x hitting 0 by time h is given by $\pi\, g(\sigma\sqrt{h})\sigma\sqrt{h}$. Taking the limit of h,

$$\lim_{h \to 0^+} \frac{\pi\, g(\sigma\sqrt{h})\sigma\sqrt{h}}{h} = \lim_{h \to 0^+} \frac{\pi\, g(\sigma\sqrt{h})\sigma^2}{\sigma\sqrt{h}} \tag{7}$$

Using the fact that $g(0) = 0$,

$$\lim_{h \to 0^+} \frac{\pi\, g(\sigma\sqrt{h})\sigma^2}{\sigma\sqrt{h}} = \pi\sigma^2 g'(0) \tag{8}$$

Figure 5 shows the rate of convergence of $g'(0)$ for various levels of bias as opacity decreases. As long as opacity is greater than zero, $g'(0) > 0$.

[Insert Figure 5]

3. Hypotheses

In the previous section, we see that our biased information model makes a number of predictions about the relationship between opacity and credit spreads. In light of the growing concerns about sovereign credit risk and drawing on the theory from incomplete information models, we examine the causal relationship between fiscal opacity and sovereign credit default swaps (CDS) spreads. In particular, we perform regression analyses to test the following hypotheses stated in the null form:

H1: Fiscal opacity has no effect on the level of CDS spreads.

H2: The relationship between fiscal opacity and CDS spreads is linear.

H3: credit spreads for countries with higher or lower macroeconomic volatility is equally sensitive to fiscal opacity.

H4: The effect of fiscal opacity is uniform across all maturities of the credit curve

4. Variable selection and data

4.1. Fiscal Opacity Measures

A widely accepted definition of sovereign fiscal transparency is given by Kopits and Craig (1998), which states that fiscal transparency is:

"Openness toward the public at large about government structure and functions, fiscal policy intentions, public sector accounts, and projections. It involves ready access to reliable, comprehensive, timely, understandable, and internationally comparable information on government activities …" [Emphasis added]

This quote highlights that fiscal transparency is a multi-dimensional concept, which can be difficult to reduce into a single measure. Previous studies (e.g. Dabla-Norris, Allen, Zanna, Prakash, Kvintradze, Lledo, Yackovlev and Gollwitzer (2010) and von Hagen and Wolff (2006)) have proposed three leading proxies for it, namely, results from the International Monetary Fund Reports on the Observance of Standards and Codes (ROSCs), the Open Budget Index (OBI) published by the International Budget Partnership, and stock-flow adjustments (SFA).

In 1998, the International Monetary Fund (IMF) approved the Code of Good Practices on Fiscal Transparency that sets out the principles and practices for sound fiscal management. This code forms the basis for fiscal transparency assessment whose results are published in the fiscal transparency modules of the ROSCs.[6] Three limitations of this dataset have prevented us from using it. Firstly, implementation of the codes and reporting by the governments are entirely voluntary, which may potentially introduce selection bias. Secondly, the ROSCs are not produced concurrently. For example, Australia's report has not been revised since 1999, while for the US it was last revised in 2003. Previous studies employing this proxy, such as Arbatli and Escolano (2012), implicitly assumed a static transparency, which may span several years. Thirdly, these reports only contain textual information, thus require subjective transformation into numeric scores.

OBI

The Open Budget Survey is an initiative of the International Budget Partnership that evaluates the extent to which governments make their budget information accessible to the public in a timely manner.[7] Since 2006, there have been four rounds of surveys conducted biannually and the countries covered in the surveys have increased from 59 in 2006 to 100 in 2012. For each country, an independent budget researcher within that country answers 95 ordinal survey questions that constitute the Open Budget Index. The responses are then mapped on to a numerical scale of 0, 33, 67, and 100. The index is a simple arithmetic average of 95 scores that ranges from 0 to 100, where 100 means transparent. According to the International

[6] ROSCs can be accessed from http://www.imf.org/external/np/fad/trans/index.htm
[7] OBI index can be accessed from http://internationalbudget.org/what-we-do/open-budget-survey/

Budget Partnership, the survey results are reviewed by two anonymous peer reviewers and cross checked with IMF's ROSCs. The cut-off date for each round of survey differs[8], therefore for the purpose of matching OBI to other data, we assume that the scores published in 2008 for example applies to the period from November 2005 to September 2007. Finally, in order to have consistent signs in the regression coefficients as SFA, we subtract the original score from 100 to obtain our opacity proxy (100=opaque).

Panel A of Table I describes the properties of the transformed OBI. Although our sample is confined to those with traded CDS, the range of OBI scores sampled is not affected. Notice that the OBI dataset is an unbalanced short panel. There are 24 countries in 2005, increasing to 47 in 2012, with no countries dropping out of the sample. The mean and variance have remained stable over time. By decomposing the total variance into between and within variances as displayed in Panel D, we see that most of the variation is between countries rather than within countries over time. This will have implication for our modelling.

SFA

Our second proxy of fiscal opacity is SFA. Technically, SFA measures the discrepancy between the annual change in government gross debt and budget deficit. However, since von Hagen and Wolff (2006), researchers have associated SFA with fiscal accounting gimmickry used by governments to hide deficits. Hagen and Wolff (2006) find that the stability and growth pact used by the European Union induced governments to use SFA to meet the deficit limit in times of recession. Bernoth and Wolff (2008) find that SFA is positively correlated with the value of known cases of fiscal window-dressing transactions reported in Koen and van den Noord (2005). Using an international sample, Weber (2012) reports a significant relationship between SFA and a static measure of transparency which includes the ROSC.

[8] For the 2006, 2008, 2010 and 2012 surveys, the cut-off months were October 2005, September 2007, September 2009 and December 2011 respectively.

In a recent study, Seiferling (2013) argues the stock-flow adjustments calculated in the past literature is a partial measurement in the sense that it provides an incomplete view of the complete stock-flow adjustments. Using a comprehensive set of government financial data, Seiferling (2013) calculates complete stock-flow adjustments and shows that transparency (based on ROSCs) is highly correlated with partial stock-flow adjustments, but not with complete stock-flow adjustments. This implies that the correlation with transparency must rest within some economic flows between partial and complete stock-flow adjustments. Due to data limitation and considering the scope of this paper, we utilise partial stock-flow adjustments as a proxy for opacity.

Following von Hagen and Wolff (2006), the partial stock-flow adjustment is calculated as,

$$\frac{Debt_t - Debt_{t-1}}{NGDP_t} = \frac{Deficit_t}{NGDP_t} + \frac{SFA_t}{NGDP_t} \tag{9}$$

where:

Debt =	Government gross debt
Deficit =	Revenue – total expenditure
NGDP=	Nominal gross domestic product
SFA=	Stock-flow adjustments

Data for calculating the proxy is obtained from the IMF World Economic Outlook Database. Panel B of Table I describes the properties of stock-flow adjustments, where it is notably a larger panel. Consistent with von Hagen and Wolff (2006), stock-flow adjustments have been consistently positive on average, ranging between 1.11 percent of GDP in 2005 to a peak of 3.07 percent in 2008. In other words, debt levels have risen more than what is implied by the deficits. Weber (2012) argues that an increase is expected during the financial crisis, due to financial support given to the private sector and a possible resurgence of accounting gimmickries such shifting expenditure off balance sheet. In Panel D, by decomposing its variance reveals that unlike OBI, there is similar variation across countries and over time.

4.2. CDS and control variables

CDS is economically equivalent to an insurance contract on the event that the reference entity will default. The spread on CDS reflects the premia protection buyers are willing to pay to the underwriters for protection against default. Although CDS may not provide a perfect measure of credit risk, it nevertheless provides a clearer indication compared to either stocks or bonds. (Ericsson, Jacobs and Oviedo (2009)) Recent evidence shows that during market distress, sovereign CDS dominates sovereign bonds in the price discovery process (Delatte, Gex and López-Villavicencio (2012)), therefore affecting the funding costs for governments.

Data on sovereign CDS spreads is obtained from Credit Market Analysis Ltd (CMA) via Datastream for January 2004 to October 2010, during which the number of sovereign reference entities increased rapidly. CMA collects executable and indicative prices directly from leading market makers, cleans and publishes consensus prices. The dataset available to this study consists of mid-spreads with maturities ranging from 0.5 to 10 years.

For testing hypotheses 1 to 3, we follow the method standard in current literature, which uses contracts with 5 year maturity, as they are the most liquid. For testing hypothesis 4, we complement the sample with contracts of 1 year and 10 year maturities. We log transform the spreads to minimise heteroscedasticity.

Panel C of Table I summarises the properties of CDS spreads. Not shown in the Table is that there is a total of 71 sovereign entities in the dataset, however not every country has active quotes over the whole sample period and across all three maturities. For all three maturities, the variance of CDS spreads has risen sharply since 2007, followed by the levels in 2008 during the onset of the financial crisis. Inferring from the three maturities, the credit term structure has been upward sloping. A Fisher-type test proposed by Choi (2001) is used to test for unit root in our unbalanced panels. This test combines the p-values from individual Augmented Dickey-Fuller tests. The null hypothesis that all panels contain unit roots is rejected at all conventional levels for all three maturities.

[Insert Table I]

To ascertain the effect of fiscal opacity on credit spreads, we need to control for other factors that may impact CDS spreads. Existing literature such as Edwards (1986) and Boehmer and Megginson (1990) have shown strong explanatory power of macroeconomic fundamentals such as public debt ratios on emerging market risk premium. Catão and Sutton (2002) and Genberg and Sulstarova (2008) find that the volatility of macroeconomic variables can explain variations in sovereign spreads. Guided by previous empirical literature and structural credit risk models, we include country specific lagged debt to GDP ratio (L.Debt), deficit to GDP ratio (Deficit), and the standard deviation of annual GDP percentage changes for 10 years (sdΔGDP) to capture idiosyncratic macroeconomic volatility. To control for global effects, we include the Chicago Board Options Exchange VIX index (VIX) that captures time varying US market risk aversion (assuming that US drives world activity) and the 3 month sterling Libor (Libor) as the international interest rate. Bühler and Trapp (2007) and Pu (2009) among others have recognised the existence of a liquidity premium in CDS spreads. Due to insufficient data on issuer-specific CDS bid-ask spread, we calculated the bid-ask spread of Itraxx Europe index (BidAsk) as a measure for market-wide liquidity. Since the sample covers the Eurozone sovereign debt crisis period, Itraxx Europe should be the most sensitive to changes in CDS market liquidity.

Table II presents the cross correlation between spreads, opacity measures and control variables. Spreads are positively correlated with all variables except for lagged debt and Libor. The negative correlation with Libor is mainly due governments' actions to protect banks while their financial health deteriorates. The two opacity measures SFA and OBI are weakly correlated, suggesting that different dimensions of fiscal opacity may be captured. While OBI captures primarily the availability and comprehensiveness aspects, SFA is associated more with the presence of accounting gimmickry. As expected, SFA is negatively correlated with deficit and lagged debt due to variable construction.

[Insert Table II]

5. Statistical modelling

Two considerations are made in designing the model. The first is that OBI and SFA datasets have vastly different characteristics as shown in Table I. Since only a small variation exists in OBI scores over time (for some countries there is only one measurement), we run regressions with year effects controlled by time-varying variables such as VIX, Libor and BidAsk. To gain confidence in the results, we repeat the analysis using between effects models which estimate coefficients based on country-specific means of the dependent and independent variables. The SFA dataset is more balanced, and therefore allowing fixed effects models.

For testing hypothesis 1, the following model is constructed:

$$lspread_{it} = \beta_0 + \beta_1 Opacity_{it} + \sum_j \beta_j Z_{jit} + \alpha_i + \epsilon_{it} \qquad \text{(model 1)}$$

where for country *i* in month *t*:

Opacity = measure of fiscal opacity - OBI or SFA;

$\sum_j \beta_j Z_{jit} = \beta_2 L.Debt_{it} + \beta_3 Deficit_{it} + \beta_4 sd\Delta GDP_{it} + \beta_5 VIX_t + \beta_6 Libor_t + \beta_7 BidAsk_t$;

α = country fixed effects (SFA dataset);

ϵ = the residual.

For model 1, we are interested in the magnitude and significance of β_1. We expect a positive coefficient, which means that higher fiscal opacity leads to higher credit spreads.

To examine the nonlinear effects of fiscal opacity, rather than relying on a specific functional form, we apply a panel piecewise regression with two knots. We divide the opacity measures into deciles and search for a combination of two thresholds that achieve the lowest residual sum of squares. Similar to testing hypothesis 1, a between effects model and a year fixed effects model are used on the OBI dataset and country fixed effects are used on the SFA dataset. The piecewise linear regression is specified as follows:

$$lspread_{it} = \beta_0 + \beta_1 L_{it} + \beta_2 M_{it} + \beta_3 H_{it} + \sum_j \beta_j Z_{jit} + \alpha_i + \epsilon_{it} \qquad \text{(model 2)}$$

where for country *i* in month *t*:

$$\text{L (low opacity)} = \begin{cases} x & \text{if } x \leq \text{c1} \\ \text{c1} & \text{if } x > \text{c1} \end{cases}$$

$$\text{M (medium opacity)} = \begin{cases} 0 & \text{if } x \leq \text{c1} \\ x - \text{c1} & \text{if } x > \text{c1 AND } x \leq \text{c2} \\ \text{c2} & \text{if } x > \text{c2} \end{cases}$$

$$\text{H (high opacity)} = \begin{cases} 0 & \text{if } x \leq \text{c2} \\ x - \text{c2} & \text{if } x > \text{c2} \end{cases}$$

x denotes OBI or SFA value, c1 and c2 denote the estimated thresholds.

Coefficients β_2 and β_3 represent the slope for the respective segments. For the relationship between fiscal opacity and credit spreads to be nonlinear, we expect the magnitude of the betas to be different.

Next, we further split the sample into two groups based on the median volatility of GDP percentage changes, to test whether countries with higher macro-volatility experience greater sensitivity to fiscal opacity. Based on model 2, we include further a dummy variable *Hvol* that equals 1 if a country's GDP volatility in the past 10 years exceeds the sample median and 0 otherwise.

$$lspread_{it} = \beta_0 + \beta_1 L_{it} + \beta_2 M_{it} + \beta_3 H_{it} + \beta_4 Hvol * L_{it} + \beta_5 Hvol * M_{it} + \beta_6 Hvol * H_{it} + \sum_j \beta_j Z_{jit} + \alpha_i + \epsilon_{it} \qquad \text{(model 3)}$$

For the final hypothesis, we follow Yu (2005) regression model specification. However, instead of using Fama and MacBeth (1973) regression estimates are made using panel techniques and robust standard errors. The model fitted is:

$$lspread_{it} = \beta_0 + \beta_1 m_{it}^5 + \beta_2 m_{it}^{10} + \beta_3 Dm_{it}^1 + \beta_4 Dm_{it}^5 + \beta_5 Dm_{it}^{10} + \sum_j \beta_j Z_{ji} + \alpha_i + \epsilon_{it} \qquad \text{(model 4)}$$

where for country *i* in month *t*:

m^k = 1 for maturity k, 0 otherwise; and

D = 1 if Opacity > median opacity, 0 otherwise;

Note that with this specification, the coefficients to opacity and maturity variables represent shifts in the intercept rather than changes in the slope. If fiscal opacity has a positive effect only on the short end as predicted by Duffie and Lando (2001), then we expect β_3 to be significantly positive, while β_4 and β_5 are insignificantly different from zero.

The second consideration one must make is about endogeneity. There are two potential sources of endogeneity in our estimations – omitted variable and simultaneity. As argued by Bhattacharya, Daouk and Welker (2003), panel data estimation with fixed effects can minimise omitted variable bias by washing its effect into the intercepts. For the stock-flow adjustments dataset at least, we believe this assumption is justified since once we have controlled for fiscal factors (i.e. debt, primary balance and GDP) that change from year to year, the remaining institutional factors should be relatively stable over time. Omitted variables then would have no effect on the coefficient estimates in the presence of fixed effects. On the other hand, we suspect simultaneity bias in our estimation because it is possible that higher credit risk forces governments to adopt accounting gimmickry. We control for simultaneity bias in section 6.5.

6. Results

6.1. Effect of fiscal opacity on the level of credit spreads

The estimated effect of fiscal opacity on the level of 5-year credit spreads is shown in Table III. After controlling for debt, deficit, GDP volatility, and other market-wide factors, more opaque countries as measured by higher OBI or SFA, is associated with higher credit spreads across all three specifications. A one point increase in the OBI score as well as a one percent increase in SFA raise 5-year CDS spreads by over 1 basis point. We find that deficit has higher explanatory power than lagged debt, which can be explained by the larger attention paid to budget balance figures than debt figures (Weber (2012)). As predicted by theory, macroeconomic volatility is strongly significant. VIX and BidAsk are both highly significant despite concerns about multicollinearity. Consistent with Bernoth and Wolff (2008), the economic effect of opacity is small. There are two possible explanations. Firstly, there may be specification error whereby a linear line is fitted through a relationship that is nonlinear. To check for possible specification error, we conducted a Ramsey specification test, and the model for OBI is rejected at 5 percent levels, but not for SFA.[9] Another reason as pointed out by Bernoth and Wolff (2008) which only pertains to SFA is that SFA is a noisy measure of opacity and measurement error in regressions tends to bias the coefficient towards zero. Accordingly, it may be argued that the impact of opacity measure by SFA is regarded as the lower bound of the true impact.

[Insert Table III]

6.2. Nonlinear effects

Table IV presents the results for the piecewise linear regressions. The thresholds for OBI and SFA are estimated to be 17-46 and 0.47-2.43 respectively, hence the proportion of

[9] $F(2, 47)=4.62$ for OBI and $F(2, 70)=1.45$ for SFA

observations falling within each segment is 12, 45 and 43 percent for OBI, and 24, 46, and 30 percent for SFA. We first test for model specification error using Ramsey specification test, which fails to reject model misspecification at conventional levels for both OBI and SFA.[10]

Focusing on OBI, only the medium opacity is statistically significant under all three models, and the economic effects are more than three times the magnitude reported earlier in Table III. In terms of spread levels, the magnitude remains small nevertheless, with 1.1 basis point change per OBI score and SFA percent GDP. Neither low nor high levels of opacity appear to have any explanatory power. Therefore, the relationship between opacity and credit spreads is indeed nonlinear, rejecting hypothesis 2.

The sigmoid-shaped relationship implies that low levels of fiscal opacity create little concern in the credit market over the credit risk of these governments. As fiscal opacity grows to the medium range, it catches market attention and there is a sharp rise in the perceived risk of default by those governments. However, when fiscal opacity increases to high levels, the market seems not to respond further.

[Insert Table IV]

6.3. Sensitivity to fiscal opacity

In Table V, we analyse the non-linear effect of opacity by categorising countries into high or low macro-volatility. High macro-volatility countries are typically high risk developing countries, while low macro-volatility countries are considered as low risk countries. We expected the credit spreads of high risk countries to be more sensitive to fiscal opacity, as a small change in their fundamentals could change investors' risk perception completely. To the contrary, we find no statistically significant differences between the two groups using OBI. Setting statistical significance aside, we can see that the signs for Hvol low opacity are positive and for Hvol

[10] F(2, 47)=0.52 for OBI and F(2, 70)=1.62 for SFA

medium opacity coefficients are negative. This tentatively indicates that credit spreads react to the very first signs of fiscal opacity for high risk countries, while opacity only matters to the spreads of low risk countries at the medium level. Results from SFA support this explanation. Nevertheless, due to the lack of statistical significance, we conclude that there is insufficient evidence to reject hypothesis 3.

[Insert Table V]

6.4. Term structure effects

Our analysis has focused on one point in the credit term structure. In this section, we utilise three points on the credit term structure to test for the effect of fiscal opacity at different maturities.

Table VI presents the results for the term structure analysis. Note that models are specified in a way such that the coefficients for opacity and maturity variables represent shifts in the intercepts rather than changes in the slopes. Therefore, their magnitudes are different to those reported in the previous tables. To begin, the first two columns of Table VI show an overall statistically significant positive effect of fiscal opacity as measured by OBI on all three maturities. More specifically, for the group with lower than the medium OBI score, 2.4 basis points and 5.3 basis points are added to yield 5 year and 10 year CDS spreads respectively. For sovereigns with high opacity, further 2 to 3 basis points are added to 1, 5 and 10 year maturities. The effect of SFA is also significant, where opaqueness adds on average 1 basis point to all three maturities. From the magnitude of the coefficients, it can be seen that the implied shape of the term structure is upward sloping and convex. Furthermore, fiscal opacity affects both the short-end and the long-end of the credit term structure. It is most pronounced at the short-end but gradually decreases as time to maturity increases. We therefore reject hypothesis 4 based on the evidence.

[Insert Table VI]

6.5. Endogeneity

To address endogeneity arising from simultaneity, we follow Bhattacharya*, et al.* (2003)'s principle of using one-year lagged opacity measures and rerun models 2 and 4.[11] Model 1 is excluded because we have shown a potential misspecification error, and moreover, one could also test hypothesis 1 with model 2. Model 3 is excluded since we fail to reject hypothesis 3 based on the previous analysis.

Tables VII and VIII present the results using lagged opacity variables. The results using OBI are similar to those reported previously in terms of the shape of nonlinearity and term structure effects. For SFA, we find that only high levels of opacity affects CDS spreads, and opacity affects the short-end of the credit term structure. Overall, this section validates the hypothesis that opacity leads to higher credit spreads.

[Insert Tables VII and VIII]

7. Conclusion

Models for pricing defaultable claims have become more important given today's expanding debt market and volatile environment. A new class of credit risk models have emerged recently that specifically account for parameter uncertainty, which is an inadequacy in traditional structural models. In this paper, we extend a well-known model of this class - the Duffie and Lando (2001) model and empirically validate our model predictions using sovereigns rather than firms. Our use of sovereigns is motivated by the lack of exogenous proxy for corporate opacity and an urgent need to assess the impact of sovereign opacity.

[11] Lagged opacity measures are not used in the main analysis to avoid losing the 2012 round of OBI survey.

What does our biased information model imply about the relationship between opacity and credit spreads? We show that our biased information model overcomes the unintended consequences of unbiased reporting noise as reported in Yu (2005), as a result, the inclusion of potential misreporting in an opaque environment leads to a positive, but nonlinear relationship between opacity and credit spreads. Moreover, our model generates a positive opacity premium over the entire credit spread term-structure, whereas the DL model predicts a negative premium at the longer end.

using two proxies of fiscal opacity.

Consistent with limited studies on this issue, we confirm our model predictions and find that the credit market does penalise governments with high fiscal opacity. However, we produce evidence showing that the impact is non-linear. In particular, the opacity premium can be insignificant at low levels of opacity, but increases sharply once opacity reaches the medium level and flattens again beyond a high threshold. This has major implication for governments already being regarded as opaque, since the marginal change in the credit spread can be severe. Furthermore, we find no difference between countries with high and low macroeconomic volatility in their sensitivity to fiscal opacity. As such, governments of low risk countries are not placed in a safer position. Lastly, we show that opacity premium exists across the credit spread term structure, but the effect is most pronounced in the short-end. Therefore, countries that borrow short-term should not only improve their fundamentals, but also strive to become more transparent, as investors do appear to reward those that have less uncertainty in its ability and willingness to service debt.

Our current measure of fiscal opacity using SFA is by no means perfect. Future studies may benefit from more comprehensive government financial statistics across the world to refine the SFA measure as proposed by Seiferling (2013). Future work can also calibrate and implement our biased information model using real data in the same spirit as the CreditGrades model.

It has been argued that fiscal opacity is considered as one of the factors which have contributed to the current sovereign debt crisis. Looking into the future, for those countries that relied on international emergency loans, their governments will be pressured by their lenders to achieve various binding financial targets and fiscal opacity will once again attract attention.

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Figure 1
Simulated $E(\exp(U_t))$

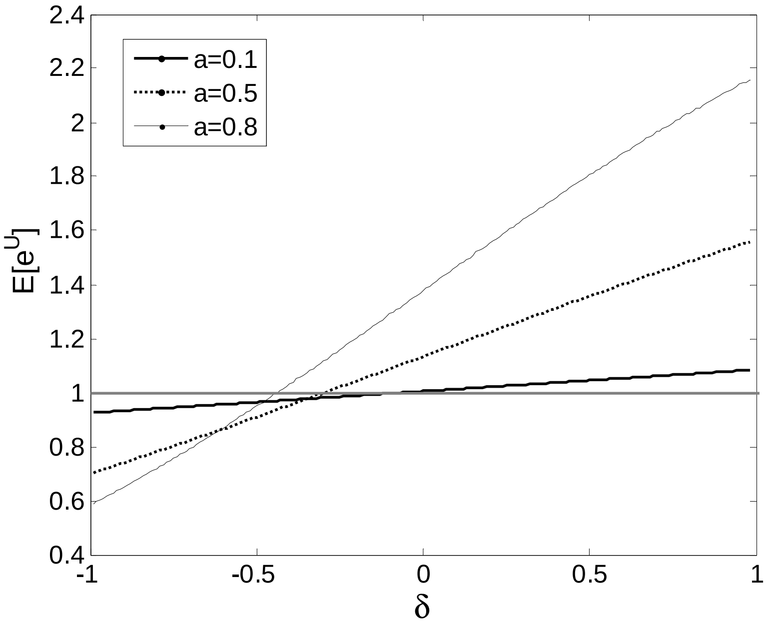

Figure 2
Conditional Asset Density

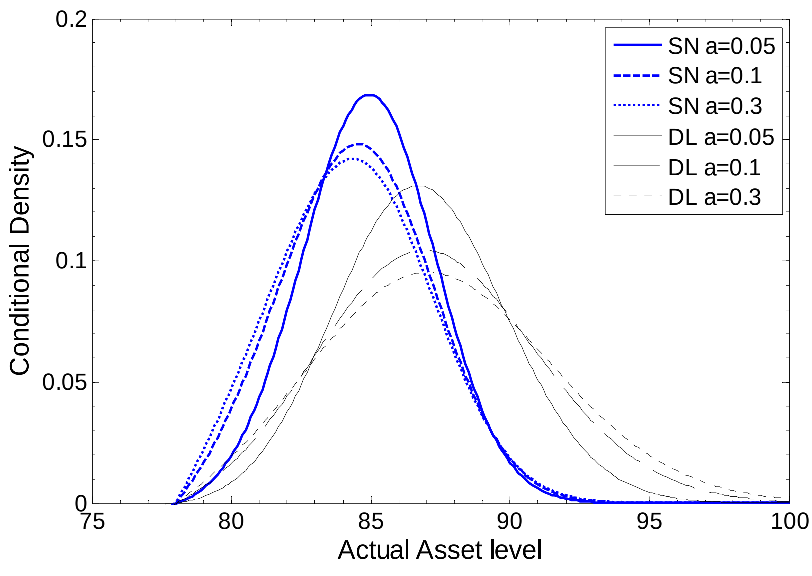

Figure 3a
Opacity and Probability of Default

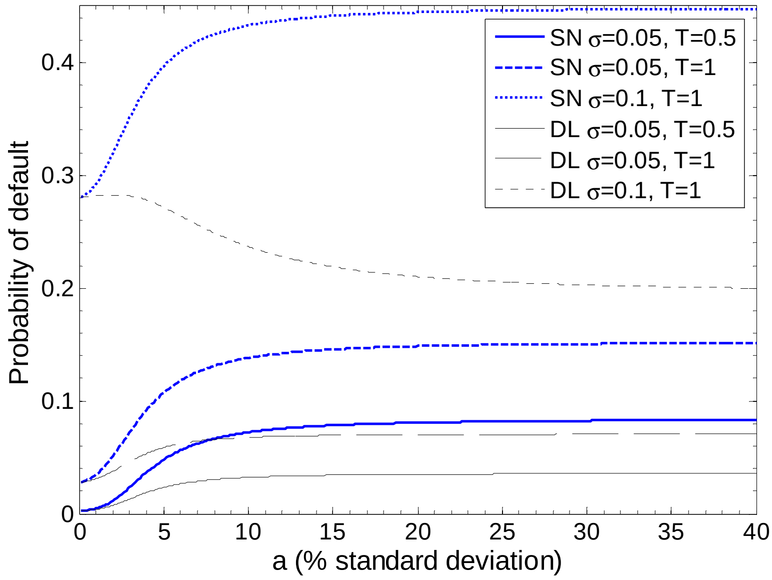

Figure 3b
Opacity and Credit Spread

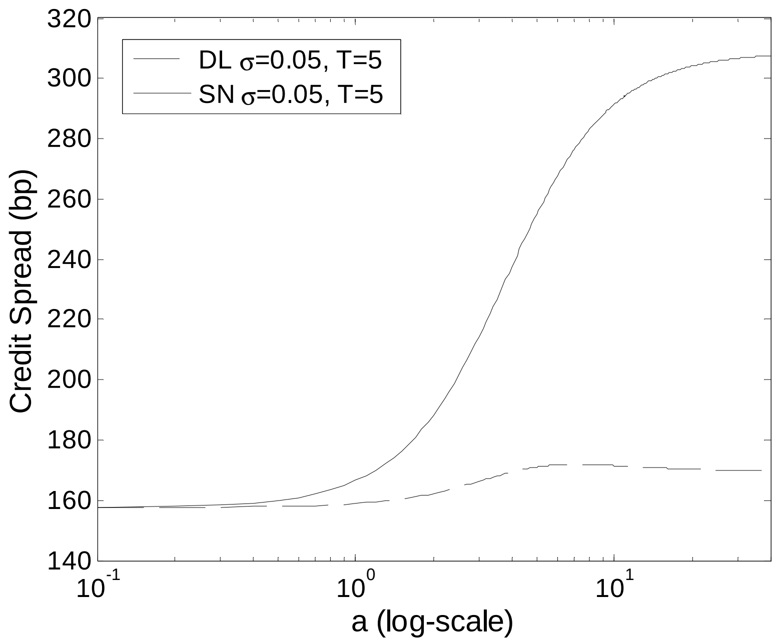

Figure 4
Credit Term Structure

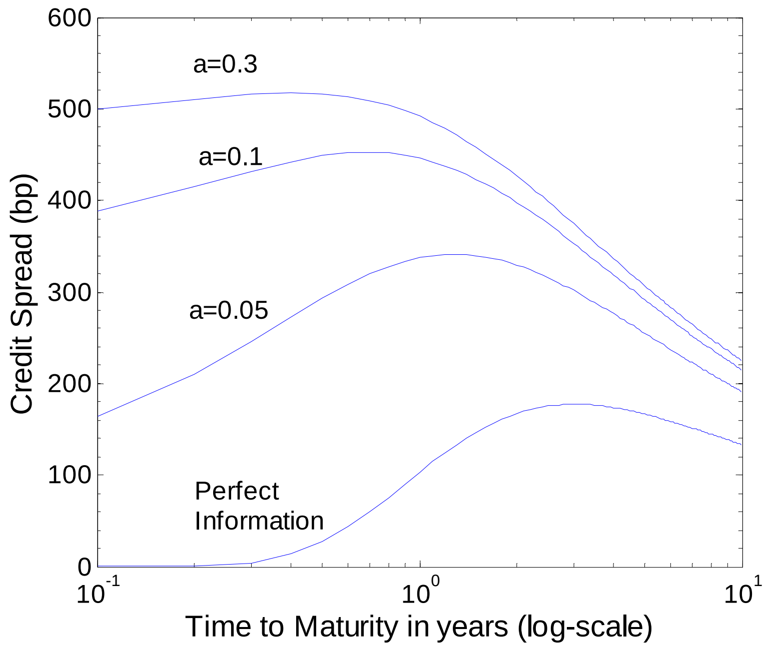

Figure 5

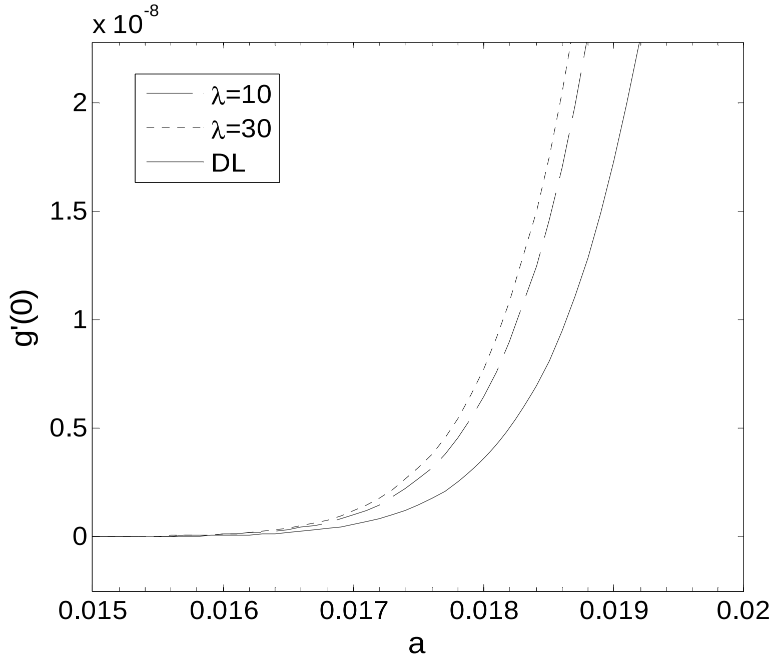

Table I
Descriptive Statistics

OBI refers to the Open Budget Index, which has a range between 0 and 100. We subtract the OBI from 100 to obtain the opacity proxy. 0 = transparent; 100 = opaque. SFA refers to stock-flow adjustment in percentage GDP. It is the difference between year on year change in debt and annual deficit. CDS spreads are monthly CMA quotes in basis points (bp). Lspread=log of CDS spreads, L.Debt=lagged debt to GDP ratio, VIX=CBOE volatility index, sdΔGDP =standard deviation of GDP percentage changes, Libor=3 month UK Libor, BidAsk= bid-ask spread of Itraxx Europe index. Panel unit root test is the Fisher-type test. H_0: All panels contain unit roots.

Panel A: OBI

Release Year	OBI - before merging					OBI - after merging				
	Obs	Mean	Sd	Min	Max	Obs	Mean	Sd	Min	Max
2006	59	53.98	22.23	11	97	24	43.17	21.11	11	97
2008	85	60.27	25.19	12	100	35	44.89	20.01	13	90
2010	94	57.79	24.53	8	100	45	45.09	21.92	8	100
2012	100	57.32	24.22	7	100	47	45.70	23.23	7	100

Panel B: SFA

	SFA (% GDP)				
Year	Obs	Mean	Sd	Min	Max
2004	48	1.73	4.53	-8.93	18.04
2005	54	0.69	4.65	-21.3	17.29
2006	61	1.54	5.75	-9.59	34.28
2007	63	1.58	3.96	-9.37	18.39
2008	68	3.23	6.15	-15.63	32.66
2009	69	1.34	6.29	-25.84	37.59
2010	67	1.58	4.39	-5.62	18.01

Panel C: CDS

	1 Year CDS (bp)		5 Year CDS (bp)		10 Year CDS (bp)	
	Mean	Sd	Mean	Sd	Mean	Sd
2004	45.97	79.94	108.23	161.21	133.29	176.57
2005	30.12	50.69	84.56	113.74	116.50	143.24
2006	20.08	34.07	63.69	90.20	90.32	121.32
2007	31.49	88.09	71.47	132.32	98.89	187.16
2008	140.09	398.83	208.05	375.40	237.51	396.00
2009	307.67	619.36	332.01	521.16	335.30	504.94
2010	154.27	236.36	192.17	211.48	197.04	198.72
Unit root	Reject		Reject		Reject	

Panel D: Decomposed variance

	LSpread	OBI	SFA (% GDP)	Deficit (% GDP)	L.Debt (% GDP)	sdΔGDP (%)
Overall	1.71	21.59	5.24	4.74	34.95	1.87
Between	1.32	23.54	3.68	3.62	35.09	1.65
Within	1.12	5.19	3.74	3.03	8.26	0.84

Obs = number of observations; Sd = standard deviation

Table II
Correlation Matrix

	Lspread	OBI	SFA	Deficit	L.Debt	VIX	sdΔGDP	Libor
Lspread	1							
OBI	0.380*	1						
SFA	-0.075*	0.046	1					
Deficit	0.271*	0.118*	-0.507*	1				
L.Debt	-0.004	0.179*	-0.250*	0.254*	1			
VIX	0.442*	0.024*	0.047*	0.188*	-0.070*	1		
sdΔGDP	0.352*	0.312*	0.081*	-0.143*	-0.142*	-0.067*	1	
Libor	-0.357*	-0.026*	0.045*	-0.361*	0.014	-0.304*	-0.016	1
BidAsk	0.223*	0.005	0.014*	0.095	-0.036*	-0.480*	-0.036*	-0.081*

Lspread=log of CDS spreads, OBI=Open Budget Index, SFA=stock-flow adjustment, L.Debt=lagged debt to GDP ratio, VIX=CBOE volatility index, sdΔGDP =standard deviation of GDP percentage changes, Libor=3 month UK Libor, BidAsk= bid-ask spread of Itraxx Europe index.

Table III
The Effect of Fiscal Opacity on 5 Year Sovereign CDS Spreads

The dependent variable for all regressions in this table is the natural log of 5-year CDS spreads. t-Statistics are given in parentheses (based on robust standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. –BE denotes between effects, –FE fixed effects. Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level.

	Dependent variable: Lspread		
	OBI	OBI, BE	SFA, FE
Opacity	**0.018** **(2.95)**	**0.020** **(3.71)**	**0.032** **(3.59)**
L.Debt	0.002 (0.63)	0.000 (0.03)	**0.019** **(3.14)**
Deficit	**0.056** **(3.06)**	**0.074** **(2.44)**	**0.084** **(5.02)**
sdΔGDP	**0.268** **(5.56)**	**0.240** **(3.30)**	**0.114** **(2.61)**
VIX	**0.044** **(10.29)**		**0.052** **(18.99)**
Libor	**-0.111** **(-4.29)**		**-0.133** **(-6.63)**
BidAsk	**0.070** **(2.49)**		**0.087** **(5.38)**
Constant	**2.073** **(6.05)**	**2.700** **(7.90)**	**1.911** **(5.85)**
Number of Obs.	2725	2725	4535
Clusters	48	-	71
R^2	0.50	0.50 (between)	0.66 (within)
RESET	P>F(2,47)=0.015		P>F(2,70)=0.189

Table IV
Testing Nonlinear Effects of Fiscal Opacity

The dependent variable for all regressions in this table is the natural log of 5-year CDS spreads. t-Statistics are given in parentheses (based on robust standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. –BE denotes between effects, –FE fixed effects. Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level.

	Dependent variable: Lspread		
	OBI	OBI, BE	SFA, FE
Low Opacity	-0.103 (-1.14)	-0.179 (-1.74)	0.023 (1.87)
Medium Opacity	**0.058** **(4.38)**	**0.077** **(4.24)**	**0.103** **(2.01)**
High Opacity	-0.002 (-0.29)	-0.001 (-0.12)	0.022 (1.50)
L.Debt	0.004 (1.31)	0.004 (0.85)	**0.019** **(3.14)**
Deficit	**0.038** **(2.59)**	0.037 (1.24)	**0.083** **(5.03)**
sdΔGDP	**0.215** **(4.77)**	**0.178** **(2.55)**	**0.117** **(2.73)**
VIX	**0.043** **(9.94)**		**0.051** **(19.11)**
Libor	**-0.132** **(-5.20)**		**-0.135** **(-6.70)**
BidAsk	0.061 (2.00)		**0.087** **(5.45)**
Constant	**3.602** **(2.44)**	**5.129** **(3.40)**	**1.861** **(5.47)**
Number of Obs.	2725	2725	4535
Clusters	48	-	71
R^2	0.55	0.60 (between)	0.66 (within)
RESET	P>F(2,47)=0.596		P>F(2,70)=0.166

Table V

Sensitivity of 5 Year Sovereign CDS Spreads to Fiscal Opacity

The dependent variable is the natural log of 5-year CDS spreads. t-Statistics are given in parentheses (based on robust standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. –BE denotes between effects, –FE fixed effects. Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level.

	Dependent variable: Lspread		
	OBI	OBI, BE	SFA, FE
Low Opacity	-0.141	-0.216	-0.026
	(-1.60)	(-1.93)	(-0.90)
Medium Opacity	**0.068**	**0.082**	**0.192**
	(4.32)	**(3.60)**	**(3.67)**
High Opacity	0.002	-0.001	-0.013
	(0.16)	(-0.05)	(-1.31)
HVol*Low Opacity	0.058	0.063	**0.062**
	(1.73)	(1.04)	**(2.30)**
HVol*Medium Opacity	-0.039	-0.031	-0.116
	(-1.63)	(-0.67)	(-1.53)
HVol*High Opacity	-0.007	0.002	**0.057**
	(-0.52)	(0.09)	**(3.18)**
L.Debt	**0.006**	0.005	**0.018**
	(2.07)	(1.01)	**(3.16)**
Deficit	**0.032**	0.036	**0.088**
	(2.39)	(0.14)	**(5.28)**
sdΔGDP	**0.227**	0.133	**0.135**
	(4.34)	(1.24)	**(3.23)**
VIX	**0.044**		**0.051**
	(10.03)		**(18.79)**
Libor	**-0.126**		**-0.129**
	(-5.15)		**(-6.32)**
BidAsk	0.061		**0.084**
	(1.94)		**(5.26)**
Constant	**3.874**	**5.544**	**1.797**
	(2.64)	**(3.51)**	**(5.43)**
Number of Obs.	2725	2725	4535
Clusters	48	-	71
R^2	0.56	0.61 (between)	0.67 (within)

Table VI
The Effect of Fiscal Opacity on Sovereign CDS Term Structure

The dependent variable is the natural log of 1, 5, and 10-year CDS spreads. t-Statistics are given in parentheses (based on robust standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. –BE denotes between effects, –FE fixed effects. Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level.

	Dependent variable: Lspread		
	OBI	OBI, BE	SFA, FE
Constant	**1.605**	**2.281**	**0.874**
	(5.91)	**(10.69)**	**(3.22)**
M5	**0.857**	**0.859**	**0.885**
	(19.76)	**(3.74)**	**(21.28)**
M10	**1.087**	**1.083**	**1.197**
	(20.53)	**(4.71)**	**(24.74)**
D*M1	**0.986**	**1.337**	**0.384**
	(4.03)	**(5.42)**	**(3.98)**
D*M5	**0.888**	**1.172**	**0.245**
	(3.72)	**(4.76)**	**(3.28)**
D*M10	**0.875**	**1.153**	**0.179**
	(3.70)	**(4.68)**	**(2.54)**
L.Debt	0.002	0.001	**0.020**
	(0.61)	(0.26)	**(4.74)**
Deficit	**0.057**	**0.068**	**0.075**
	(2.94)	**(4.07)**	**(4.96)**
sdΔGDP	**0.258**	**0.221**	**0.108**
	(5.79)	**(5.45)**	**(2.74)**
VIX	**0.049**		**0.055**
	(12.30)		**(20.46)**
Libor	**-0.132**		**-0.151**
	(-5.24)		**(-8.33)**
BidAsk	0.092		**0.874**
	(3.13)		**(3.22)**
Number of Obs.	8183	8183	13441
Clusters	48	-	71
R^2	0.58	0.61 (between)	0.70 (within)

Table VII
The Effect of Fiscal Opacity on 5 Year Sovereign CDS Spreads
with Lagged Opacity Measures

The dependent variable for all regressions in this table is the 1 year ahead natural log of 5-year CDS spreads. t-Statistics are given in parentheses (based on robust standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. BE denotes between effects, Year denotes regression with year dummies, FE denotes fixed effects Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level. L12 and L24 denote 12 and 24 month lags.

	Dependent variable: Lspread		
	L24.OBI	L24.OBI, BE	L12.SFA, FE
Low Opacity	-0.021	-0.064	0.041
	(-0.17)	(-0.64)	(1.96)
Medium Opacity	**0.054**	**0.054**	0.074
	(4.28)	**(3.54)**	(1.40)
High Opacity	-0.001	0.005	**0.039**
	(-0.17)	(0.67)	**(3.17)**
L.Debt	0.002	0.001	**0.022**
	(0.65)	(0.40)	**(5.91)**
Deficit	**0.049**	**0.052**	**0.098**
	(3.56)	**(2.09)**	**(6.46)**
sdΔGDP	**0.220**	**0.276**	**0.103**
	(4.86)	**(4.02)**	**(2.84)**
VIX	**0.044**		**0.051**
	(4.86)		**(19.58)**
Libor	**-0.107**		**-0.120**
	(11.75)		**(-6.87)**
BidAsk	0.052		**0.081**
	(1.62)		**(5.26)**
Constant	2.334	**3.581**	**1.705**
	(1.15)	**(2.36)**	**(6.79)**
Number of Obs.	2085	2085	4259
Clusters	46	-	71
R^2	0.63	0.69 (between)	0.69 (within)

Table VIII
The Effect of Fiscal Opacity on Sovereign CDS Term Structure
with Lagged Opacity Measures

The dependent variable is the natural log of 1, 5, and 10-year CDS spreads. t-Statistics are given in parentheses (based on bootstrapped standard errors adjusted for clustering). OBI and SFA refers to models using the Open Budget Index and stock-flow adjustments as the opacity variable respectively. –BE denotes between effects, –FE fixed effects. Results on fixed effects are suppressed. Bold text means statistical significance at 5 percent level. L12 and L24 denote 12 and 24 month lags.

	Dependent variable: Lspread		
	L24.OBI	L24.OBI, BE	L12.SFA, FE
Constant	**1.665**	**2.218**	**1.023**
	(6.34)	**(11.75)**	**(4.51)**
M5	**0.783**	**0.751**	**0.885**
	(15.45)	**(3.86)**	**(22.89)**
M10	**0.978**	**0.954**	**1.194**
	(15.52)	**(4.91)**	**(25.69)**
D*M1	**0.921**	**1.181**	**0.199**
	(3.46)	**(5.68)**	**(2.03)**
D*M5	**0.848**	**1.059**	0.062
	(3.61)	**(5.09)**	(0.90)
D*M10	**0.832**	**1.006**	-0.026
	(3.70)	**(4.84)**	(-0.42)
L.Debt	0.000	0.001	**0.019**
	(0.06)	(0.65)	**(5.55)**
Deficit	**0.057**	**0.067**	**0.070**
	(3.68)	**(4.77)**	**(4.59)**
sdΔGDP	**0.308**	**0.340**	**0.103**
	(5.41)	**(9.07)**	**(2.54)**
VIX	**0.050**		**0.056**
	(12.06)		**(20.81)**
Libor	**-0.139**		**-0.150**
	(-5.56)		**(-8.52)**
BidAsk	**0.096**		**0.111**
	(6.34)		**(7.16)**
Number of Obs.	6233	6233	12691
Clusters	46	-	71
R^2	0.62	0.71 (between)	0.70 (within)

Appendix A

List of Sovereigns

ARGENTINA	LATVIA
AUSTRALIA	LEBANON
AUSTRIA	LITHUANIA
BAHRAIN	MALAYSIA
BELGIUM	MALTA
BRAZIL	MEXICO
BULGARIA	MOROCCO
CHILE	NETHERLANDS
CHINA	NEW ZEALAND
COLOMBIA	NORWAY
COSTA RICA	PAKISTAN
CROATIA	PANAMA
CYPRUS	PERU
CZECH REPUBLIC	PHILIPPINES
DENMARK	POLAND
DOMINICAN REPUBLIC	PORTUGAL
ECUADOR	QATAR
EGYPT	ROMANIA
EL SALVADOR	RUSSIAN
ESTONIA	SAUDI ARABIA
FINLAND	SLOVAKIA
FRANCE	SLOVENIA
GERMANY	SOUTH AFRICA
GREECE	SPAIN
GUATEMALA	SWEDEN
HONGKONG	SWITZERLAND
HUNGARY	THAILAND
ICELAND	TUNISIA
INDONESIA	TURKEY
IRAQ	UKRAINE
IRELAND	UNITED KINGDOM
ISRAEL	UNITED STATES
ITALY	URUGUAY
JAPAN	VENEZUELA
KAZAKHSTAN	VIETNAM
SOUTH KOREA	