Fiscal Opacity and Sovereign Credit Spreads

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Abstract

This study addresses the counterintuitive result produced by the Duffie and Lando (2001) incomplete information model by remodelling its asset density function with added positive bias. We call this new model biased information model. The theory is then applied to study the effect of fiscal opacity on the levels and term structure of sovereign credit spreads. We make use of new panel datasets sourced from Open Budget Survey and IMF World Economic Outlook Database. Using panel data tests, we show that higher fiscal opacity leads to higher credit spreads, and that this relationship is nonlinear. Moreover, we show that fiscal opacity premium exists across the whole credit spread curve. These results have implications for policy setting in economies that are emerging from the debt crisis, since investors demand higher premium when there is high fiscal opacity.

JEL classification: G01; G10

Keywords: Sovereign credit risk, credit default swap, structural model

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1. Introduction

The role of corporate financial transparency[1] on the cost of capital has been widely researched since Diamond and Verrechia (1991). However, the impact of government financial transparency attracted less scrutiny until recently. In particular the Eurozone sovereign debt crisis has seen questions arise over the transparency of fiscal positions of governments in years prior to the crisis. Lack of transparency provides an opportunity to manipulate financial accounts, and it has been argued that fiscal opacity is considered one of the factors which led to the current debt crisis. Evidence for such lack of transparency 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 crisis to window dress fiscal performance. In light of the growing concerns about fiscal mismanagement and sovereign credit risk, this paper makes two contributions to the literature. Firstly, this paper presents a biased information credit risk model that improves upon the incomplete information model of Duffie and Lando (2001), which is known to generate counterintuitive results. Secondly, motivated by the stark parallels between the deliberate manipulation of financial reporting by both governments and corporations due to a lack of transparency, this study tests the theory of biased and incomplete information on sovereign credit spreads.

Our work straddles two strands of literature. The first is the pricing of defaultable bond yields tracing back to the seminal works of Meton (1974) and Black and Cox (1976). Traditional structural models produce credit spreads much lower than observed (the credit

[1] Transparency is regarded as the principle for good disclosure. (White (2007)) Opacity is the opposite of transparency.

spread puzzle). Duffie and Lando (2001) propose an incomplete information model that produces a positive credit spread at zero maturities when there is uncertainty surrounding the true firm value. However, Yu (2005) shows that when one of the parameters deviates from the base case, counterintuitive implications arise. Empirical studies such as Yu (2005) and Arora, Richardson and Tuna (2011) test the theory of Duffie and Lando (2001) on corporate credit spreads and they confirm a positive association between corporate financial transparency and short-end credit spreads.

The second strand relates to literature that focuses on the effects of fiscal transparency from a policy setting perspective. Alt and Lassen (2006) and Hameed (2005) examine the causal relationship between fiscal transparency and fiscal performance, both studies concluding that higher transparency leads to lower public debt, lower deficits and better fiscal outcomes in general. Arbatli and Escolano (2012), Bernoth and Wolff (2008) and Glennerster and Shin (2008) show that fiscal transparency reduces market risk premia and achieves better credit ratings.

In relation to the first strand of literature, this paper asks a key question: Is government financial opacity priced into the sovereign credit spreads as predicted by the incomplete information models? Moreover, this paper complements studies in the second strand by evaluating specifically the level as well as the term structure effects of government financial opacity on sovereign credit default swaps.

In this paper, we examine a sample of 71 countries over 3 to 7 years using panel data tests, a much larger sample compared to prior studies. We use two widely employed proxies for fiscal opacity – the Open Budget Index developed by the International Budget Partnership and stock flow adjustments. Unlike studies using bond data such as Bernoth and Wolff (2008) and Yu (2005), our use of sovereign CDS negates issues relating to tax, optionality, shortening maturity and the appropriate benchmark rate. (Houweling and Vorst (2005))

Our analysis yields a number of theoretical predictions. Our biased information model shows that spreads are monotonically increasing with respect to opacity in the presence of a positive reporting bias and furthermore, our model predicts that opacity premium is present across the entire term structure. In the following empirical part of this paper we find that sovereign bond investors do demand a higher premium when there is high fiscal opacity. Moreover, we show that the opacity premium may not be significant at low levels of opacity, but becomes sensitive to opacity once it reaches a higher range. Finally, we confirm that the opacity premium is prevalent over the entire credit spread term structure, which is also consistent with the findings from Yu (2005).

2. Biased information model

2.1. Review of the Duffie and Lando (2001) model

This section introduces the key principles of the Duffie and Lando (2001) (DL) model, which paves the way for our biased information model.

Traditional structural models of credit risk assume that firm asset value follows a diffusion process and is readily observable. Such assumptions not only produce defaults which are predictable but can also lead to zero credit spread at short maturity if the asset value is far from the default barrier, an anomaly which puzzled early researchers. In contrast, the DL model assumes that the asset value is observed with some error or noise. That is, $y = z + u$, where y is the log of observed asset, z is the log of actual asset and u is the accounting noise. Accordingly, the actual asset value may lie somewhere closer to the default boundary than the observed asset value and default becomes unpredictable. This simple idea ensures that the default probabilities at short maturities are strictly positive.

The main feature of the DL model is a market where bond holders only observe periodic imperfect information about the firm value V, while the owner is well informed. In addition, bond holders also understand the strategic behaviour of the owner, who would liquidate the firm optimally if asset value falls below debt. Denote this informational set available to bond holders by ***F***. Given ***F***, bond holders form expectations of the true asset value represented by the density function $g(x|Y_t, z_0, t)$ [3], which is a function of the log of observed asset value ($\ln(Y_t)$), last period's asset value (z_0), log of the default boundary ($\ln(\underline{V})$), drift and standard deviation of the asset diffusion process (m, σ), and the standard deviation of accounting noise (a). a in the DL model is the only driver that determines the distribution of accounting noise. A lower a represents less noise and therefore less uncertainty about the true asset value. The observed asset value becomes the true value when $a = 0$.

Incorporating asset density with first passage probability, Duffie and Lando (2001) show that the probability of survival to time *s* is:

$$(1) \quad p(t,s) = \int_{\underline{v}}^{\infty} \left(1 - \pi\left(s - t, x - \underline{v}\right)\right) g(x|Y_t, z_0, t)dx$$

given

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

where equation 2 denotes the probability of first passage of a Brownian motion at x. ϕ is the cumulative standard normal distribution function. Note that equation 1 can be interpreted as the weighted average probability of survival, where the weights are given by the density

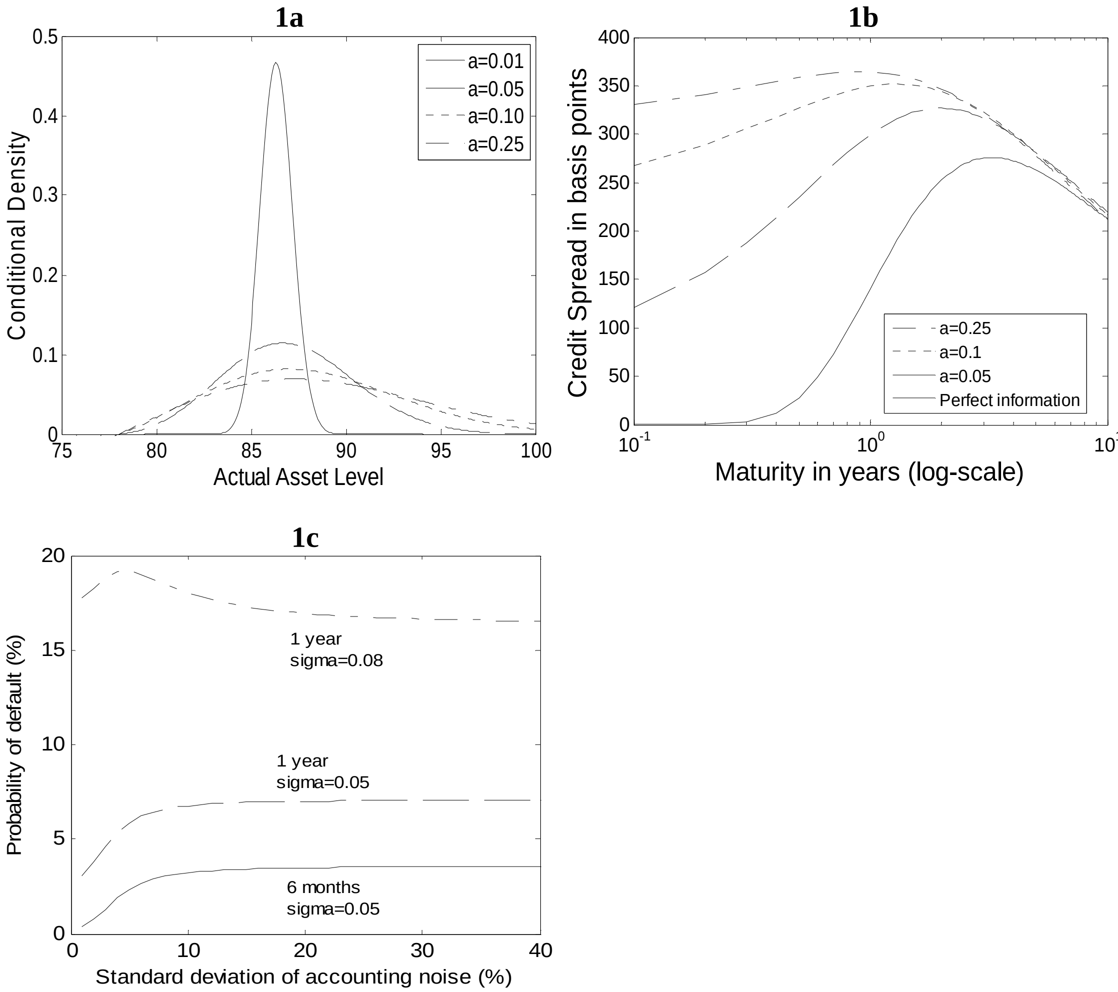
[3] Refer to Duffie and Lando (2001) for details.

function of the asset value. Therefore, the DL model maintains strictly positive short-term spreads by assigning some probability to $\underline{v} + \Delta x$. Figure 1 shows the conditional density of the actual asset value and the term structure of credit spreads as reported in Duffie and Lando (2001). One can observe that the higher the standard deviation of accounting noise, the fatter is the asset density (Figure 1a) and the higher is the credit spread (Figure 1b), but only for maturities of up to about 3 years.

Figure 1c presents a case where the DL model produces a counterintuitive result. As the standard deviation of asset diffusion process is increased by 3 percent from the base case of 5 percent, higher standard deviation of noise is associated with a decreased probability of default. Yu (2005) observes a similar result by lowering the observed asset value from the base case. This is caused by the lower tail of the asset density function being bounded by $\underline{v}$. As the standard deviation of noise rises, the distribution expands only via the upper tail, implying higher asset value and leading to a lower probability of default. Yu (2005) contends that such anomaly would not have evolved under discretionary disclosure whereby firms withhold bad news, because under this scenario it is highly unlikely for the firm's true asset value to be higher than the reported value. It follows that if by increasing the mass of the asset density function below the reported asset level, consistent with discretionary disclosure, the probability of default would instead increase. This is the idea behind our biased information model.

Figure 1
Asset Density and Term Structure of Credit Spreads from the DL Model

Graphs are reproduced using the base case in Duffie and Lando (2001). Observed asset value is 86.3. *a* denotes the standard deviation of a normally distributed noise, sigma is the standard deviation of the asset diffusion process and 1 year refers to the time to maturity. The probabilities of default and credit spreads are obtained by solving numerically the integral in equation 1 in Matlab.



2.2. Biased information model

In this section, we develop the biased information model. We start by assuming that similar to the DL model, the process for firm asset value follows a geometric Brownian motion. Owners of the firm behave strategically and will liquidate firm assets the first time that the asset level falls to a default boundary. In a market with asymmetric information, bond investors are not kept fully informed of the true firm value. Instead, they must infer the true asset value from the current observed amount and the perceived level of uncertainty. Our market is assumed to be efficient, thus asset values observed in the past do not influence current inferences.

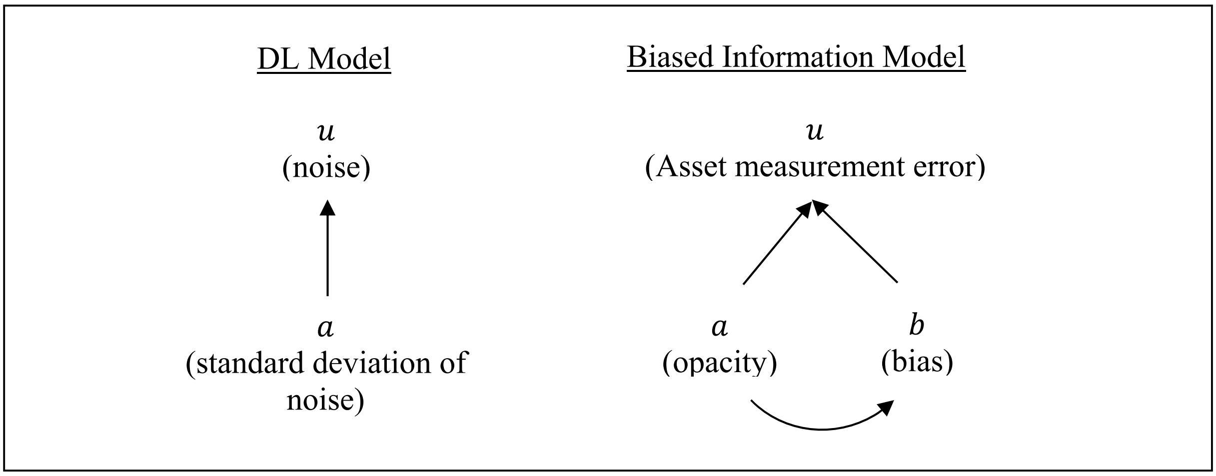
Let u denote asset measurement error, which is the difference between the log of observed asset value y and the log of true asset value x as shown by equation 3. Consistent with Duffie and Lando (2001), u follows a normal distribution with mean b and standard deviation a.

(3) $x = y - u,\ u \sim N(b, a^2)$

Here, we offer an intuitive interpretation for the mean and standard deviation of asset measurement error, which is also critical to the analysis. Consider that there are two sources of asset measurement error. One source is entirely random and is caused by one-off effects such as the nature of accounting, incomplete reports and/or a general level of uncertainty in the reporting environment. This particular source of asset measure error either increases or decreases the observed asset value; hence we model it as the standard deviation and refer to it as opacity. The other source is directional and is caused by deliberate misreporting. We model this source of error as the mean and refer to it as bias.

Is there connection between opacity and bias? We argue that there is a positive relationship between the two components. It is conceivable that under low opacity 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 an inability to account for complex transactions by the firm[6] or an inability to obtain information by the public, the possibility of bias increases. Figure 2 illustrates the conceptual and terminological differences between the DL model and the biased information model. Note that Yu (2005) interprets the standard deviation of noise in the DL model as transparency.

Figure 2



From equation 3, it is clear that the expected actual asset value is expressed as:

(4) $E(X) = \mathrm{y} - \mathrm{b}$

Taking the exponential yields,

(5) $E(X) = \exp(\log(Y) - b + 0.5a^2)$

Equation 5 reveals the follow two conditions,

if $b = 0.5a^2$, then there is no bias since $E(X) = Y$

[6] As maintained by Kopits and Craig (1998) in the context of government accounting, fiscal opacity may arise due to a government's technical inability to report.

if $b > 0.5a^2$, then there is positive bias since $E(X) < Y$

Theory and evidence of discretionary disclosure show that firms have the tendency to withhold sensitive information from the public that can have adverse implications to the firm/manager.[7] As a result of selective disclosure, valuation of firm assets will be upward biased. Buti, *et al.* (2007), amongst others have provided evidence for similar biases at government level accounting. Therefore, we introduce an upward bias in our model. Since there is no *a priori* hypothesis on the exact functional form of reporting bias, we endogenize bias and propose a relationship between opacity and bias[8] given by:

(6) $b = a^2$

Finally, the DL asset density function is replaced by:

(7) $p(t,s) = \int_{\underline{V}}^{\infty} (1 - \pi(s-t, X-\underline{V})\, l(X|a)\, dX$

where

(8) $l(X|a) = \exp\left[-\frac{\left(\ln(X-\underline{V}) - \ln(Y-\underline{V}) + a^2\right)^2}{2a^2}\right] / (X-\underline{V})a\sqrt{2\pi}$

Figure 3a shows that, unlike the original model, the new asset density is significantly positively skewed as opacity increases. At low opacity levels, the asset density surrounds closely the observed asset value at 86.3. Figure 3b shows that our model produces non-zero credit spreads at short maturities, preserving the most important feature of the DL model.

[7] See Yu (2005) for discussion of the relevant literature. Furthermore, Lev (2003) presented anecdotal evidence showing that in the late 1990s, over 90% of restatements revised earnings downward. The sharp increase 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.

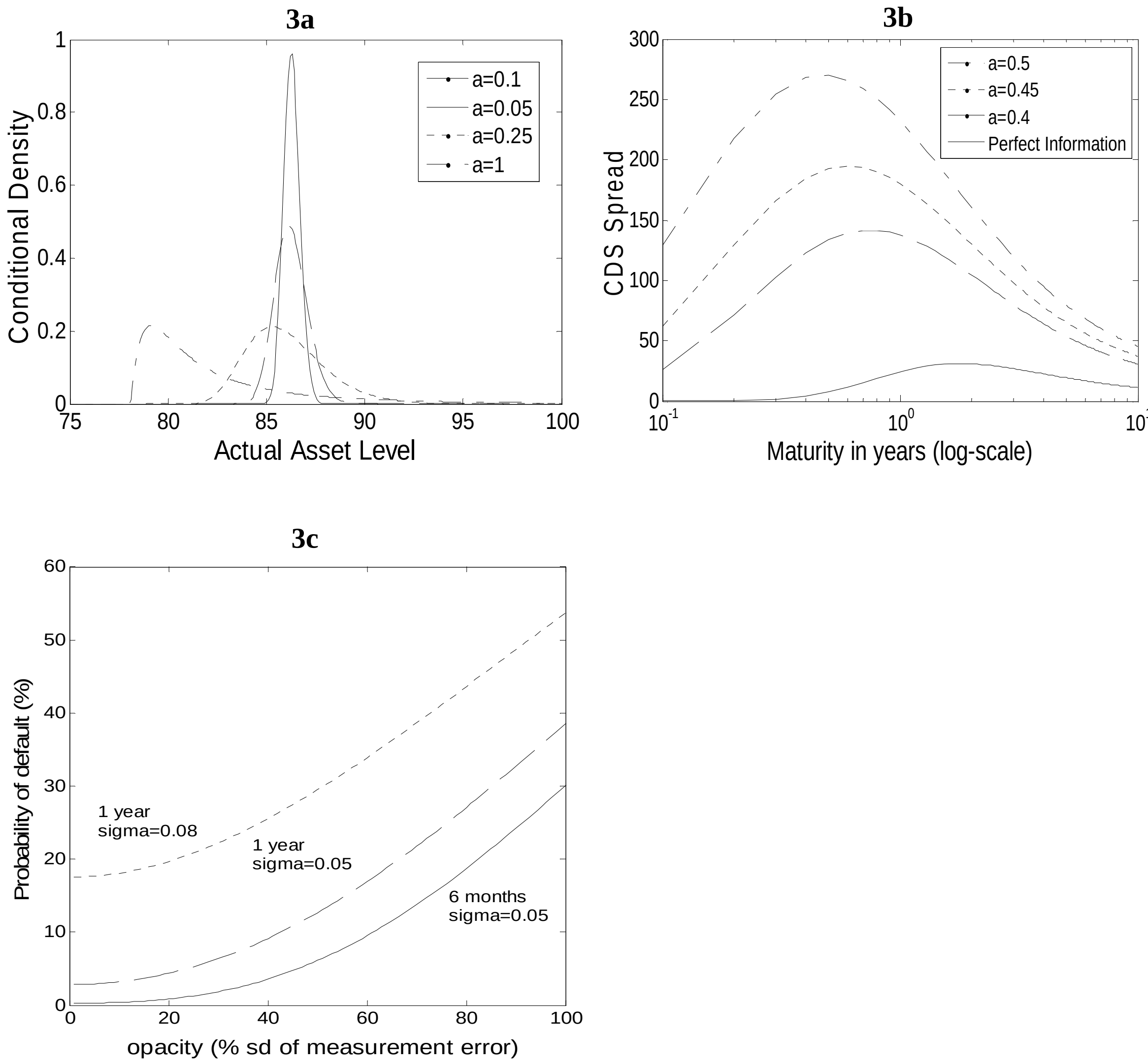
[8] The model is robust to any positive relationship. The only difference it makes is the degree of curvature. For example, a cubic function will produce more convexity than quadratic.

However, our model predicts positive effect of opacity on longer maturities. Finally, Figure 3c depicts an increasing and convex relationship between opacity and credit spreads irrespective of the value assigned to other model parameters. The biased information model has effectively overcome the counterintuitive result from the DL model.

Figure 3

Asset Density and Term Structure of Credit Spreads from Biased Information Model

Graphs are reproduced using the same parameter value as in Duffie and Lando (2001). Observed asset value is 86.3. *a* denotes the level of opacity, sigma is the standard deviation of the asset diffusion process and 1 year refers to the time to maturity. The probabilities of default and credit spreads are obtained by solving numerically the integral in equation 6 in Matlab.



3. Testable Hypotheses

Finance theory establishes that the market value of company assets is the present value of all expected future free cash flows to the firm. Using the same argument the market value of sovereign assets should incorporate the current expectation of all possible future taxation and spending paths. For example, Currie and Velandia (2002) propose a conceptual government balance sheet, where sovereign assets consist of the present value of fiscal revenue and liabilities consist of the present value of fiscal expenditures. Opacity relating to fiscal positions would therefore create uncertainty around the true sovereign asset value and according to our model and DL model, would have term structure effects on sovereign credit spreads.

We consider three hypotheses stated in the null form:

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

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

H3: The effect of fiscal opacity is uniform across all maturities of the credit curve.

Given the predictions in section 2.2, we expect higher fiscal opacity to lead to higher credit spreads and furthermore, the effect to be non-linear. Moreover, as implied by the biased information model, we expect fiscal opacity to affect the entire term structure, but diminish as the maturity increases.

4. Variable selection and data

4.1. Fiscal Opacity Measures

A widely accepted definition of 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 – whether undertaken inside or outside the government sector – so that the electorate and financial markets can accurately assess the government's financial position and the true costs and benefits of government activities, including their present and future economic and social implication." [Emphasis added]

Fiscal transparency is a multi-dimensional concept, which is difficult to reduce into a single measure. Previous studies have proposed three proxies including: an index based on the International Monetary Fund (IMF) 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 IMF approved the Code of Good Practices on Fiscal Transparency that sets out the principles and practices for sound fiscal management. The code forms the basis for fiscal transparency assessment which are published in the fiscal transparency modules of the ROSCs. According to the IMF, 93 countries had posted ROSCs as of September 2012.[11] Three limitations of this dataset have prevented us from using it. Firstly, implementation of the codes and reporting are entirely voluntary, which may potentially introduce selection bias.

[11] More information about the fiscal ROSC can be found at http://www.imf.org/external/np/fad/trans/index.htm

Secondly, the reports for each country are not produced simultaneously. 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 that fiscal transparency remains constant from the time of reporting to the time of analysis. Thirdly, these reports only contain textual information, which requires subjective transformation into numeric scores. Therefore, this study employs both the OBI and SFA as robustness checks. The remaining section provides a brief overview of these two proxies.

OBI

Open Budget Survey is an initiative of the International Budget Partnership (IBP) that evaluates the extent to which governments make their budget documents accessible to the public in a timely manner.[12] Evaluation is undertaken by independent budget experts based on information available to the public and using 92 questions. The main OBI index is based on these survey results, and for each country a score of 0 to 100 is assigned to reflect the public availability and comprehensiveness of key budget documents. According to the IBP, staff also cross check the survey results with other sources that include the IMF's ROSCs.

There are currently three rounds of OBI surveys. Countries covered in the analysis have increased from 59 in 2006 to 85 in 2008, and have risen to 94 in the latest 2010 report. The cut-off date for the 2010 survey was 15 September 2009, and no subsequent information was taken into account. We assume a similar cut-off time for both 2006 and 2008 reports. The next round of survey is expected to be release by early 2013, which is unavailable at the time of writing. Finally, we subtract the transparency score from 100 to obtain our opacity proxy.

SFA

[12] More information about the OBI index can be found at http://internationalbudget.org/what-we-do/open-budget-survey/

Our second proxy of fiscal opacity is stock flow adjustments. Technically, SFA is the discrepancy between the annual change in government gross debt and budget deficit. SFA may arise out of purely technical reasons such as cash versus accrual accounting or one off financial transactions, which should be cancelled out over time. However, Buti*, et al.* (2007) report consistent positive SFA and show that governments in the EMU actively employed SFA to hide the true extent of government deficit.

Following Weber (2012), 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 = Government net lending

NGDP = Nominal gross domestic product

SFA = Stock flow adjustments

The data for calculating SFA is obtained from the IMF World Economic Outlook Database.

The first 6 columns of Table I describe the properties of the OBI and SFA dataset. Notably, the OBI dataset is a heavily unbalanced short panel after merging with CDS data. There are 31 countries left in 2006, increasing to 46 in 2010. However, no countries have dropped out of the sample. The average score and variance of OBI have remained quite stable over time. The SFA is a notably larger dataset. The number of observations is capped at 71 due to the availability of CDS data. In 2010, two countries did not have actual debt and GDP figures. Consistent with Weber (2012), SFA has been consistently positive on average, ranging between 0.4 percent of GDP in 2005 to a peak of 3.7 percent of GDP in 2008. Weber (2012) suggests that this increase could be due to financial support given to the private sector and a resurgence of accounting stratagems. Here we immediately identify a source of endogeneity, which requires further investigation. We address endogeneity issues in section 5.

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. As Longstaff, Mithal and Neis (2005), and Ericsson, Jacobs and Oviedo (2009) have argued, CDS spreads provide a clearer indication of an entity's credit risk compared to either stocks or bonds.

Data on sovereign CDS spreads is obtained from Datastream, which is in turn sourced from Credit Market Analysis Ltd (CMA). Our CDS data spans from January 2003 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 H1 and H2, we follow the method of the current literature and analyse contracts with 5 year maturities, as they are the most liquid. For the term structure effect, we focus on contracts with 1 year and 10 year maturities, since we are interested in the short and long end of credit spread term structure.

The last 3 columns in Table I summarises the properties of 5 year CDS spreads. There are altogether 71 sovereign entities in the dataset, however not every country had active quotes over the whole sample period. Not surprisingly, both the level and variance of CDS spreads have risen sharply since 2007, during the onset of the financial crisis, which peaked in 2009.

Table I
Descriptive Statistics of Fiscal Opacity Proxies and CDS

OBI refers to the Open Budget Index, which has a range from 0 to 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. 5-year maturity sovereign CDS spreads are CMA quotes on 2nd September of each year.

Year		OBI (Score)			SFA (% GDP)			5-Year CDS Spread (as at 2/9/t)	
	Obs	Mean	Sd	Obs	Mean	Sd	Obs	Mean	Sd
2004				70	0.019	0.042	45	108.153	156.163
2005				71	0.004	0.054	53	82.848	113.753
2006	31	43.352	22.445	71	0.017	0.057	59	61.907	94.236
2007				71	0.016	0.039	61	101.580	191.494
2008	40	46.987	22.369	71	0.037	0.077	69	163.155	200.231
2009				71	0.012	0.064	69	238.719	341.040
2010	46	45.984	22.509	69	0.015	0.043	70	202.843	221.543

Obs = number of observations; Sd = standard deviation

To ascertain the effect fiscal opacity has on credit spreads, we need to control for other factors that may impact CDS spreads. Guided by Bernoth and Wolff (2008), Yu (2005) and the credit risk models, we include country specific lagged debt to GDP ratio, deficit to GDP ratio and CBOE VIX index that captures time varying market risk aversion and liquidity. There is of course a long list of other factors such as institutional effects. Nevertheless, the richness of panel data allows us to use fixed effects to control for any unobserved, time-invariant factors.

Table II presents cross correlation between spreads, opacity measures and control variables. Spreads are highly correlated with OBI, SFA, VIX and deficit/GDP ratio, but not with debt measures. The correlation between SFA and OBI is 14.2 percent, which suggest some commonality in the measures. As expected SFA is negatively correlated with deficit and lagged debt due to variable construction.

Table II
Correlation Matrix

	Lnspread	OBI	SFA	Deficit/GDP	Debt/GDP(-1)
Lnspread	1				
OBI	0.412	1			
SFA	0.120	0.142	1		
Deficit/GDP	0.187	-0.002	-0.299	1	
Debt/GDP(-1)	0.097	0.043	-0.049	0.463	1
Debt/GDP	0.070	0.009	0.009	0.547	0.984
VIX	0.184	0.084	0.138	0.304	0.078

Lnspread=log of CDS spreads, OBI=Open Budget Index, SFA=stock flow adjustment, GDP=gross domestic product, (-1) denotes 1 year lag, VIX=CBOE volatility index.

5. Research design

There are two considerations worth making during modelling design. The first is that OBI and SFA datasets have vastly different structures as shown in Table I. Therefore specific econometric models are used for each dataset. The second involves endogeneity issues. Both are discussed in turn.

For testing hypothesis H1, panel regression with between effects (model 1) is used for the OBI dataset due to a short panel and for some countries, only one measurement is taken in 2010. The between effects model estimates coefficients based on country-specific means of the dependent and independent variables, similar to pure cross-section regressions. A disadvantage of such model however is the loss of information along the time dimension. As a robustness check, we also run a panel regression with time fixed effects (model 2). In contrast, the richness of the SFA dataset allows for within effects (model 3).[13] Variation in credit spreads due to changes in risk aversion over time is controlled by VIX. The models are expressed mathematically as follows:

$$\overline{lspread}_i = \beta_0 + \beta_1\overline{OBI}_i + \beta_2\overline{LD}_i + \beta_3\overline{Def}_i + \alpha_i + \bar{\epsilon}_i \qquad \text{(model 1)}$$

[13] Hausman's test rejects random effect at 5 percent level.

$$lspread_{it} = \beta_0 + \beta_1 OBI_{it} + \beta_2 LD_{it} + \beta_3 Def_{it} + \beta_4 y08 + \beta_5 y10 + \epsilon_{it} \qquad \text{(model 2)}$$

$$lspread_{it} = \beta_0 + \beta_1 LD_{it} + \beta_2 Def_{it} + \beta_3 SFA_{it} + \beta_4 VIX_t + \alpha_i + \epsilon_{it} \qquad \text{(model 3)}$$

where for country *i* at year *t*:

lspread = the natural log of CDS spreads;

OBI = Open Budget Index;

SFA = stock flow adjustment;

LD = lagged 1-year debt to GDP ratio;

Def = deficit to GDP ratio;

VIX = CBOE volatility index;

y08/09 = year dummies;

α = country heterogeneity effects; and

ϵ = the residual error term.

For models 1 to 3, 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. Two knots are placed at the 33rd and 66th percentiles of each transparency measures, providing three equal segments. Similar to testing hypothesis H1, a between effects model as well as a year fixed effects model are used for the OBI dataset. A country fixed effects model is used on the SFA dataset. The respective regression models are:

$$\overline{lspread}_i = \beta_0 + \beta_1 \overline{Lobi}_i + \beta_2 \overline{Mobi}_i + \beta_3 \overline{Hobi}_i + \beta_4 \overline{LD}_i + \beta_5 \overline{Def}_i + \alpha_i + \bar{\epsilon}_i \qquad \text{(model 4)}$$

$$lspread_{it} = \beta_0 + \beta_1 Lobi_{it} + \beta_2 Mobi_{it} + \beta_3 Hobi_{it} + \qquad \text{(model 5)}$$

$$\beta_4 LD_{it} + \beta_5 Def_{it} + \beta_6 y08 + \beta_7 y10 + \epsilon_{it}$$

$$lspread_{it} = \beta_0 + \beta_1 Lsfa_{it} + \beta_2 Msfa_{it} + \beta_3 Hsfa_{it} + \qquad \text{(model 6)}$$

$$\beta_1 LD_{it} + \beta_2 Def_{it} + VIX_t + \alpha_i + \epsilon_{it}$$

where for country *i* at year *t*:

Lobi = OBI scores lower than the 33rd percentile (low opacity);

Mobi = OBI scores higher than 33rd percentile and lower than 66th percentile (medium opacity);

Hobi = OBI scores higher than 66th percentile (high opacity);

and the same notation is used for the SFA measure.

Coefficients β_2, and β_3 show the incremental change in the slopes from the previous segment. For the relationship between fiscal opacity and credit spreads to be nonlinear, we expect statistically significant and economically different β_2, and/or β_3. In addition, the signs of β_2 and β_3 indicate the direction of curvature.

For the final hypothesis, we follow Yu (2005)'s empirical specification. However, instead of using the Fama and MacBeth (1973) regression, estimates are made using panel techniques. The models fitted are:

$$\overline{lspread}_i = \beta_0 + \beta_1 m_i^5 + \beta_2 m_i^{10} + \beta_3 d_{obi} m_i^1 + \beta_4 d_{obi} m_i^5 + \qquad \text{(model 7)}$$

$$\beta_5 d_{obi} m_i^{10} + \beta_6 \overline{LD}_i + \beta_7 \overline{Def}_i + \alpha_i + \bar{\epsilon}_i$$

$$lspread_{it} = \beta_0 + \beta_1 m_{it}^5 + \beta_2 m_{it}^{10} + \beta_3 d_{obi} m_{it}^1 + \beta_4 d_{obi} m_{it}^5 + \beta_5 d_{obi} m_{it}^{10} + \beta_6 LD_{it} + \beta_7 Def_{it} + \beta_8 y08 + \beta_9 y10 + \epsilon_{it} \quad \text{(model 8)}$$

$$lspread_{it} = \beta_0 + \beta_1 m_{it}^5 + \beta_2 m_{it}^{10} + \beta_3 d_{sfa} m_{it}^1 + \beta_4 d_{sfa} m_{it}^5 + \beta_5 d_{sfa} m_{it}^{10} + \beta_6 LD_{it} + \beta_7 Def_{it} + \beta_8 VIX_t + \gamma_t + \alpha_i + \epsilon_{it} \quad \text{(model 9)}$$

where for country *i* at year *t*:

m^k = a dummy variable that equals 1 for maturity k;

d = a dummy variable that equals 1 if a country's opacity measure is worse than the median score;

γ = year fixed/random effects; and

α = country fixed/random effects.

If fiscal opacity has a positive and diminishing effect on the credit curve as predicted by our model in Section 2, it must be the case that: $\beta_3 > \beta_4 > \beta_5 > 0$.

Endogeneity is a dangerous problem for regression analysis and 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 country fixed effects can minimise omitted variable bias by washing their effects to country specific intercepts, as long as these country specific heterogeneity are time invariant. We believe this assumption is probable since once we have controlled for fiscal factors (i.e. debt, primary balance and GDP) that changes from year to year, the remaining institutional factors should be relatively stable over time. Their inclusion or non-inclusion has no effect on the coefficient estimates in the presence of fixed effects. (Bhattacharya*, et al.* (2003))

On the other hand, we suspect simultaneity bias in our estimation because it is possible that higher credit risk forces governments to adopt accounting stratagems. Our panel data tests do not address simultaneity bias. Therefore in section 7, we control for simultaneity bias using lagged opacity measures.

6. Results

This section presents the regression results for models 1 to 9. Standard errors robust to clustered data are used where applicable. Results for tests of hypothesis H1 are presented in panel A of Table III. Without exception, higher opacity is associated with higher CDS spreads. Regardless of model specification, the opacity coefficients using the OBI index are identical. Assessing the overall model fit, the coefficients of determination for the three models are high, ranging from 0.31 to 0.54.

One thing worth noting is that the opacity coefficient using SFA is substantially higher than that using OBI. Such difference is potentially due to the multi-dimension nature of fiscal transparency. While OBI captures primarily the availability and comprehensiveness aspects, SFA is associated more with the presence of accounting stratagems. A higher coefficient for SFA suggests that the credit market reacts stronger to signs of accounting stratagems than the unavailability of budget data.

Interestingly, for the OBI dataset, fiscal control variables are insignificantly different from zero. This may be due to high correlation between debt/GDP and deficit/GDP ratios, causing multicollinearity problem. To see whether this is true, we repeated the regressions by excluding debt/GDP from the models. The resulting coefficient for OBI remained the same, while the statistical significance of control variables remained insignificant.[14] For the SFA measure however, deficit/GDP and VIX are statistically significant and have the expected signs. Based on the results, H1 can be rejected conditional on there being no simultaneity bias. We check for simultaneity bias in section 7.

Panel B of Table III presents the results for panel piecewise regression. It reveals that the coefficients for low opacity range are not statistically different from zero at 5 percent level. This is also true for high opacity. On the other hand, medium opacity across all three models is positive and statistically significant. Note that the slope coefficients represent marginal effects. The interpretation of this result is that a low range of fiscal opacity causes little concern in the credit market over the credit risk of these governments. As fiscal opacity increases to the medium range, there is a significant increase in the slope from the low opacity range. However, as fiscal opacity increases to high levels, the impact of opacity on credit spreads (β_3) is not significantly different from the previous slope (β_2). This is unpredicted by both the DL model and biased information model, since the DL model predicts a significantly negative β_3, while our model predicts a significantly positive β_3. Nonetheless, the evidence strongly rejects H2 that the relationship between fiscal opacity and credit spreads is linear. Moreover, the relationship appears to be convex rather than concave. Consistent with H1, the structural change is the greatest with stock flow adjustments, indicating the adverse impact of possible accounting stratagems.

[14] Results not reported but are available upon request from the authors.

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). 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, and –FE denotes fixed effects. Results on fixed effects are suppressed. In Panel A we present the results to hypothesis H1, whereas Panel B presents the results to hypothesis H2. *,**,*** denote statistical significant at 10, 5 and 1 percent respectively.

	OBI-BE	OBI-Year	SFA-FE
Panel A: The Level Effect			
Constant	**3.190***** **(8.10)**	**2.946***** **(7.50)**	1.105 (0.95)
Opacity	**0.028***** **(4.06)**	**0.028***** **(4.75)**	**4.021**** **(2.60)**
Debt/GDP(-1)	-0.105 (-0.19)	-0.029 (-0.07)	1.881 (0.88)
Deficit/GDP	4.779 (1.31)	4.210* (1.87)	**13.608***** **(6.64)**
VIX			**0.080***** **(8.26)**
Y08		0.710 (-0.56)	
Y10		**0.710**** **(2.16)**	
Number of Obs.	103	103	408
R^2	0.31 (between)	0.35	0.54 (within)
Panel B: Testing Nonlinearity			
Constant	**2.763***** **(3.87)**	**2.257***** **(3.33)**	0.983 (0.85)
Low Opacity	0.030 (1.23)	0.040* (1.90)	-0.273 (-0.06)
Medium Opacity	**0.086**** **(2.67)**	**0.076***** **(3.36)**	**17.497**** **(2.58)**
High Opacity	-0.008 (-0.55)	-0.013 (-1.42)	1.137 (0.46)
Debt/GDP(-1)	0.139 (0.27)	0.179 (0.47)	1.910 (0.91)
Deficit/GDP	3.366 (0.97)	2.941 (1.35)	**13.565***** **(6.65)**
VIX			**0.080***** **(8.24)**
Y08		-0.133 (-0.43)	
Y10		**0.828***** **(2.66)**	
Number of Obs.	103	103	408
R^2	0.43 (between)	0.44	0.55 (within)

To gain an understanding of the impact of fiscal opacity on the credit term structure, we include 1 year and 10 year CDS spreads into the sample. Focusing on the OBI measure (columns 1 and 2 of Table IV), the term structure is upward sloping on average, with around 16 basis points for 1 year CDS, 36 basis points for 5 year CDS and 100 basis points for 10 year CDS.[15] The effect of opacity as given by the interaction with dummy variable, *d*, is similar across the two models. Countries with above median opacity add around 4.5 basis points to 1 year CDS, 4 basis points to 5 year CDS and 3.5 basis points on average. This is consistent with our expectation that opacity does affect the whole term structure and that its effect diminishes as maturity increases.

Columns 3 and 4 present the results using the SFA measure with country and year fixed effects and country and year random effects respectively. Again the interactions between maturity and opacity dummies strongly reject H3. Fiscal opacity as measured by stock flow adjustments affects the whole term structure, by adding 1.4 basis points to 1 year CDS, 1.2 basis points to 5 year CDS and 1.1 basis points to 10 year CDS.

[15] The independent variable is the natural log of CDS spreads.

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

The dependent variable for all regressions in this table is the natural log of 1, 5, and 10-year CDS spreads. *t*-Statistics are given in parentheses (based on robust standard errors). 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/FE denotes crossed fixed effects for country and year, and –RE/RE denotes crossed random effects for country and year. Results on fixed effects are suppressed. *,**,*** denote statistical significant at 10, 5 and 1 percent respectively.

	OBI-BE	OBI-Year	SFA-FE/FE	SFA-RE/RE
Constant	**2.871*** (12.36)**	**2.612*** (11.07)**	0.541 (0.90)	-0.464 (-0.87)
M5	**0.767*** (2.73)**	**0.803*** (3.34)**	**0.845*** (19.71)**	**0.843*** (13.85)**
M10	**0.960*** (2.73)**	**1.010*** (4.28)**	**1.137*** (23.24)**	**1.137*** (18.59)**
d*M1	**1.521*** (5.40)**	**1.375*** (6.10)**	**0.311*** (3.35)**	**0.310*** (4.59)**
d*M5	**1.409*** (5.01)**	**1.284*** (6.41)**	**0.213** (2.54)**	**0.216*** (3.22)**
d*M10	**1.391*** (4.94)**	**1.249*** (6.05)**	**0.188** (2.33)**	**0.187*** (2.77)**
Debt/GDP(-1)	0.122 (0.42)	-0.013 (-0.06)	**3.458*** (2.90)**	**2.700*** (10.56)**
Deficit/GDP	**4.378** (2.21)**	**4.091*** (3.09)**	**7.109*** (4.70)**	**7.547*** (9.13)**
VIX				**0.101*** (4.38)**
Year Effects		Yes	Yes	Yes
Number of Obs.	307	307	1208	1208
R^2	0.47(between)	0.46	0.72 (within)	

7. Endogeneity

We have minimised the endogeneity problem due to omitted variables using our panel data tests. However, to address endogeneity arising from simultaneity, we follow Bhattacharya*, et al.* (2003)'s principle of using one-year lagged opacity measures. However, our OBI measure of fiscal opacity lacks yearly observations. Therefore, we use instead 1 year ahead CDS spreads for the OBI dataset as well as for the SFA dataset for consistency. This specification assumes that past opacity can affect present spreads, but not the reverse. For our estimation to suffer from simultaneity, the government must be able to predict its future credit risk in order to affect its current budget reporting practice. Arguably, if the market is efficient, then the government's expectation of future credit risk is also being reflected in the present spreads.

Table V presents the results to hypothesis one using one-year leading CDS spreads. Comparing to earlier results in panel A, Table III, the impact of fiscal opacity as measured by both OBI and SFA are very similar, further substantiating our conclusions.

Table V
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). 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. *,**,*** denote statistical significant at 10, 5 and 1 percent respectively.

Lnspread(t+1)	OBI-BE	OBI-Year	SFA-FE
Constant	**3.314*** (9.62)**	**2.631*** (8.36)**	0.864* (1.87)
Opacity	**0.026*** (4.48)**	**0.024*** (5.70)**	**4.056** (2.59)**
Debt/GDP(-1)	-0.200 (-0.42)	-0.109 (-0.37)	**1.770** (2.28)**
Deficit/GDP	**10.272*** (3.67)**	**8.65*** (5.31)**	**4.115** (2.12)**
VIX			**0.113*** (11.83)**
Y08		**1.014*** (3.54)**	
Y10		**0.984*** (3.63)**	
Number of Obs.	113	113	367
R^2	0.44 (between)	0.46	0.55 (within)

8. Conclusion

This study addresses the counterintuitive result produced by the Duffie and Lando (2001) incomplete information model by remodelling its asset density function with added positive bias. We call this new model biased information model. This study then applies the theory to study the effect of fiscal opacity on the levels and term structure of sovereign credit spreads. Using panel data tests, we find that investors demand higher premium when there is high fiscal opacity. Moreover, there is evidence that such opacity premium can be insignificant at low levels of opacity, but increases sharply once opacity reaches a higher level. In addition, we show that opacity premium exists across the credit spread term structure, but diminishes as maturity increases.

Our result has major policy implications. Countries wanting a lower borrowing cost 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.

9. References

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