Studies in Debt Valuation Adjustments

Thesis submitted to Lancaster University in fulfilment of the requirements of the degree of Doctor of Philosophy in Accounting and Finance

by

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Abstract

This thesis consists of two self-contained studies in Debt Valuation Adjustments (DVAs). The first study is motivated by the debate about the introduction of the Fair Value Option for financial Liabilities (FVOL) and the requirement to recognize and separately disclose DVAs in financial statements. This study investigates what we can learn regarding own credit risk from DVAs. Using a sample of U.S. bank holding companies that adopt the FVOL, we show that DVAs generally cannot be explained by the same factors that explain contemporaneous changes in the credit quality of these institutions. These results may be driven by the opportunistic use of the FVOL or the superior ability of managers to estimate own credit risk. Further tests indicate that DVAs for fair value Level 3 reporters can explain future changes in credit risk, providing support for the latter explanation.

The second study compares the reported Debt Valuation Adjustments provided by managers with the estimated DVAs based on market information. To obtain the estimated DVAs we use two structural credit risk models: the Merton (1974) model and the Leland (1994) model. We find that the private information contained in the reported DVAs causes a significant deviation of the estimated DVAs from the reported DVAs. This deviation is more pronounced for the banks with high volatile creditworthiness and gets better for the banks with stable credit standing. Findings suggest that the reported DVAs reflect more private information on credit risk when the economy is volatile rather than stable. In addition, the comparison of estimation errors shows that the Merton model outperforms the Leland model with regard to the estimation of DVAs over the sample period, suggesting that the incorporation of additional information in structural models does not improve the performance of pricing DVAs.

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Declaration of Authorship

I hereby declare that this thesis is my own work, and has not been submitted in substantially the same form for the award of a higher degree elsewhere.

Chapter 2 is based on: Lin, W., Panaretou, A., Pawlina, G., and Shakespeare, C. (2020), What can we learn about credit risk from Debt Valuation Adjustments?, *Review of Accounting Studies*, Revise and Resubmit.

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Chapter 1

Introduction

Over the past decades, the International Accounting Standard Board (IASB) and the Financial Accounting Standards Board (FASB) have been working on projects examining the feasibility of extending fair value measurement to more financial instruments. This is because the current mixed-attribute accounting model (part at fair values and part at historical cost) has led to criticisms from both practitioners and investors. Financial Accounting Standards (SFAS) No. 159, *The Fair Value Option for Financial Assets and Liabilities* (FASB 2007) states that measuring related assets and liabilities differently without having to apply complex hedge accounting standards would cause high volatility in accounting earnings, which does not represent the economics of a firm's activities.[1]

To mitigate this concern, the FASB and the IASB introduced fair value option (FVO) in SFAS No. 159 and IAS No. 39 in 2007 and 2006, respectively, to allow

[1]Prior studies consider the earning volatility as an important issue because higher earnings volatility are perceived as higher likelihood of bankruptcy (Kim et al. 2001), and are associated with lower market valuation (Hodder et al. 2006; Barnes 2001; Easton and Zmijewski 1989).

firms to voluntarily measure a broad scope of financial instruments (including financial liabilities) at fair value, with recognition of quarterly changes in fair value in reported earnings. Although the FVO is not mandatory, the decision to adopt FVO is irrevocable at the inception of financial instruments or upon adoption of this option if the inception is prior to it. The election of FVO is made on an instrument-by-instrument basis and is applied only to the entire financial instruments.

The fair value measurement of financial liabilities for which the fair value option has been elected is governed by the guidance set forth in SFAS No. 157, *Fair Value Measurements*, issued in 2006.[2] Specifically, SFAS No. 157 requires that the changes in the fair value of liabilities due to the changes in the firm's own credit risk should be reported in accounting earnings. Therefore, an entity recognizes a loss when its own credit risk decreases and a gain when its own credit risk increases. The standard-setters define these unrealized gains or losses as the Debt Valuation Adjustments (DVAs).

Critics argue that recognizing DVAs in net income is counterintuitive and misleading to investors. The main concern is that the firm recognizes DVA gains in reported earnings, although the firm's credit risk increases. Analogously, improvements in the firm's credit quality would result in recognition of DVA losses. For example, during the recent financial crisis 2008, Morgan Stanley flipped $3.3

[2] To date, SFAS No. 157 and SFAS No. 159 have been incorporated into the FASB Accounting Standard Codification in Topics 820-10 and 825-10, respectively. SFAS No. 159 is effective after the beginning of an entity's first fiscal year that begins as of November 15, 2007. Early adoption is permitted after the beginning of a fiscal year that begins on or before November 15, 2007.

billion losses into a $1.7 billion gains by recognizing the DVA gains as the credit quality deteriorated. By contrast, Citigroup recognized a $4.2 billion DVA losses during the recovery period of 2009. Given this counterintuitive accounting effect, regulators and analysts pay close attention to the effect of DVA on reported accounting earnings to mitigate the concern of earning management.[3] Besides, Basel III requires banks to derecognize the DVAs in the calculation of the regulatory capital by derecognizing.[4]

Apart from the practitioners, academics have also debated whether the DVAs should be removed from the net income in order to avoid the counterintuitive accounting results. Most empirical research has focused on the valuation relevance and risk relevance of fair value option on liabilities (FVOL). The opponents provide evidence that some early adopters of SFAS No. 159 have a tendency to exploit the standard's transition adjustment provision in order to meet and beat target earnings (Chang et al. 2011; Gutherie et al. 2011; Henry 2009; Song 2008). The transition provision of SFAS No. 159 requires that firms which elect the FVO to report the effect of the first remeasurement to fair value as a cumulative-effect adjustment to the opening balance of retained earnings. This provision creates an opportunity for firms to avoid recognizing a loss arising from underwater securities in the income statement. Specifically, at adoption, unrealized losses on securities for which the firm elected FVO can be "moved" directly from the accumulated other comprehensive income (AOCI) section of shareholders' equity to retained

[3]"...booking such gains...erode earnings quality and possibly open a new way for executives to massage earnings"(Reilly D. The Wall Street Journal, Sep. 28, 2007); "...can produce counterintuitive and misleading results"(Moody's 2017).

[4]The Basel Committee initially issued the Basel III rules in December 2010 and then issued the revised rules in June 2011.

earnings without passing through the income statement. Therefore, on the one hand, there is no loss in the income statement resulting from the sale of the securities subsequent to the fair value election. On the other hand, any subsequent increase in the value of the securities would result in the gain recognized in the income statement. Gilman (2007) states no rule specifically prohibits this provision that might be used to aim at having losses bypass the income statement. Given this possible concern caused by the early adopters of SFAS No. 159, Couch et al. (2017) examine whether adoption of SFAS No. 159 effectively reduces earnings volatility, which is the intent and spirit of the standard. They find that SFAS No. 159 failed to systematically reduce earnings volatility.[5]

However, none of these studies considers the election of fair value option for financial liabilities and its relationship with a firm's own credit risk. Wu et al. (2016) complement these current studies by investigating the motivation and characteristics of FVOL during the financial crisis. They conclude that adverse selection occurs among adopters of FVOL. Specifically, they find that financially vulnerable firms are systematically more likely to adopt the FVOL and these firms underperform nonadopters in terms of long-run stock returns. In line with the concern from opponents for recognizing DVAs in accounting earnings, Gaynor et al. (2011) conduct an experiment with CPAs as participants to test whether these professionals correctly interpret the DVA gains or losses reported in net income. They find that 70% of the participants are misled by the reported DVA gains and losses as they incorrectly associated DVA gains (losses) with a(n) decrease (increase) in

[5]In contrast, in analyzing the FVO in IAS 39, Fiechter (2011) concludes that firms' use of the option successfully mitigated earnings volatility.

credit risk. Dong et al. (2016) provide evidence that banks exercised discretion over DVAs to smooth earnings during the recent financial crisis but not afterwards. In contrast, the proponents state that reporting DVAs in accounting earnings is informative to financial statements users. Chung et al. (2012) assess the valuation and risk implications of reporting DVA gains and losses. They find that these controversial gains and losses are positively related to stock returns and income volatility and also positively associated with market-based risk measures. These findings indicate that recognizing DVAs in accounting earnings are value-relevant and risk-relevant to investors. Fontes et al. (2018) find that fair value measurement of assets is associated with noticeably lower information asymmetry and that this reduction is larger when banks also recognize DVAs. This finding is consistent with DVAs providing investors with important information on how gains and losses are shared between equityholders and debtholders (Merton 1974). In line with this finding, Cedergren et al. (2019) find that DVAs are positively related to equity returns for banks with low unrecognized assets.

To contribute the arguments over the recognitions of DVAs in accounting earnings, Chapter 2 examines whether the information (including the private information) in the reported DVAs correctly reflect (or are at least positively correlated to) changes in the credit quality of the entity. Indeed, prior studies focus on the value and information asymmetry implications of DVAs and associated disclosures without addressing this question. This is because few entities reported DVAs and voluntary adoption of FVOL loses the comparability across both time and entities. However, we believe the investigation on the reliability of reporting DVAs in accounting earnings matters to investors given the findings in the prior studies that reported DVAs are value and risk-relevant to investors (Chung et al. 2012). Moreover, both FASB and IASB have invested considerable time and resources in introducing and amending the FVOL accounting standard, providing evidence as to whether this process leads to more informative financial statements or not is important.

We firstly express these gains/losses into changes in credit spreads (DVA-estimated changes in credit spreads). Having DVAs expressed as a change in credit spreads, rather than gains/losses, allows us to understand better the magnitude of these changes and to use the regression model specifications developed in the literature to investigate the determinants of changes in credit spreads.

Then, we investigate whether DVA-estimated changes in credit risk can be explained by the same factors that explain changes in CDS and/or bond spreads. This will provide an indication of whether DVAs reflect market information on the credit quality of the entities. Our expectation is that DVA-estimated changes in credit spreads are not explained by the same factors that explain changes in market-based measures of credit spreads. This is because DVAs may incorporate not only the market but also private managerial information about the credit standing of the entity.

Second, in order to distinguish between public and private information incorporated in DVAs, we use the information on the fair value Level of the financial instruments measure under the FVOL.[6] If financial liabilities under the FVOL are measured at fair value Level 1 and 2, then DVAs are based mainly on market information. In this case, we expect changes in bond, and CDS spreads to be significant in explaining DVA-estimated changes in credit spreads. If financial liabilities under the FVOL are measured at fair value Level 3, valuation is based mainly on entity-supplied inputs, and therefore, DVAs incorporate private information about the credit quality of the entity. In this case, we expect to find that DVA-estimated changes in credit spreads can predict future changes in CDS and bond spreads. If managers manipulate fair values of liabilities to report biased numbers, then DVA-estimated changes in credit spreads are expected to have no predictive ability.

We find that changes in bond and credit spreads are statistically significant in explaining DVA-estimated changes in credit spread for banks that report liabilities at fair value Level 1 and 2. These results provide evidence that market inputs are used in the DVAs estimation process for Level 1 and 2 reporters. When we investigate whether reported DVAs convey private information about the credit quality of the entity, we find that lagged DVA-estimated changes in credit spreads are significant in explaining changes in bond and CDS spreads for Level 3 reporters. These results indicate that managers have superior information in estimating own credit risk. The results are robust if we use only the discretionary portion of DVA-estimated changes in credit spreads or control for the propensity of the firm to use

[6]In SFAS No. 157, Level 1 inputs are quoted prices in active markets and hence require no judgment. Level 2 inputs are data-adjusted from similar items traded in active markets or from identical or similar items in markets that are not active. Level 3 inputs are considered "unobservable" and are based on the models or assumptions of management, valuation specialists, or both. These inputs are the most subjective and are difficult to verify.

Level 3 fair values.

Our results support the view that managers have an information advantage in estimating DVAs, and that the fair value measurements based on managerial inputs better reflect the credit risk of liabilities in our sample. We believe that our results improve our understanding of managerial decision-making with respect to fair value accounting, contributing to the literature that examines the equity and risk relevance of fair value Levels. Our findings indicate that managers use their discretion in computing Level 3 fair values to provide information to the market that is useful to predict future risk. We also contribute to the debate about the role of fair value accounting in generating decision-useful financial information (Fontes et al. 2018; Blankespoor et al. 2013; Koonce et al. 2011).

Given the findings in Chapter 2, Chapter 3 investigates the informativeness of reported DVAs to investors. Following the guidance set forth in SFAS No. 157, management requires to apply complex approaches and data resources in the measurement process of DVAs. Moreover, the disclosure on the DVAs is voluntary and usually reported in footnotes. This opaque DVAs reporting allows management to exercise discretion over DVAs. Therefore, the reported DVAs may reasonably attract stakeholders' concerns about the private information exploited by management in the estimation of DVAs.

To address the concern mentioned above, we compare the reported DVAs provided by management with the estimated DVAs based on market information, denoted as market information-estimated DVAs. If the market information-estimated DVAs differ from the reported DVAs significantly, we could state the internal credit risk assessment reflects private information that is not covered by the external credit risk assessment. Alternatively, if the market information-estimated DVAs are close to the reported DVAs, we could conclude that the external credit risk assessment timely capture the information on credit risk through financial reports. To estimate the DVAs, we rely on structural credit risk models rather than the widespread market measures of credit risk (i.e., CDS spreads, bond spreads) for two primary reasons. First, the market measures of credit risk are expressed in the credit spreads rather than gains/losses that are not comparable with the reported DVAs. Second, bond spreads are not perceived as a cleaner measure because they are also influenced by factors as tax, liquidity, and duration. CDS spreads are only available for large financial institutions so that using this measure would significantly reduce our sample.[7]

To generate the precise measure of credit risk with the compatible format to reported DVAs, we rely on structural credit risk models for several reasons. First, structural models can provide guidance about the theoretical determinants of default risk and offer an unique structure to extract default-related information from the equity market. Second, the estimated results from structural models represent pure default risk of the counterparty in financial contracts. However, other credit assessments CDS spreads and bond prices can be noisy due to existence of other risk factors (Leland 2009; Tang and Yan 2007; Ericsson et al. 2006; Blanco et al. 2005). Third, the option theory-based default probability is particularly

[7]Out of 38 bank holding companies in our sample, 13 banks issue CDS.

attractive because the resulting formula is a function of 'observable' variables including leverage ratio, asset market value and asset volatility.[8] Beside, models use equity market information to make a forward-looking prediction of the default risk. Krainer and Lopez (2004) suggest that market information, especially equity market information, should be included in the oversight of financial institutions. Fourth, structural credit risk models have been successfully implemented in the industry. A benchmark in the application of structural credit risk model is the KMV model (Crosbie and Bohn 2003). Even though a few studies attempt to criticize the implementation of structural models in financial institutions due to their high leverage and complex liability structure (Eom et al. 2004), many prior studies have appropriately used modified structural credit risk models in banks for the purpose of some interesting questions.[9] Furthermore, model misspecification could largely cancel out in computing the intertemporal difference of bond prices due to the changes in firms' own credit risk over two subsequent periods, which is denoted as DVAs.

In this Chapter, we first compare the distribution of market information-estimated DVAs and the reported DVAs. This is necessary to analyze the dispersion of both the estimated and observed DVAs over the sample period due to large standard deviation of estimated DVAs. Then, we compute the measure of estimation errors to investigate the extent to which the market information-estimated DVAs deviate

[8]The asset market value and asset volatility are 'quasi-observable' variables, because these two values are generally estimated based on equity value and equity volatility.

[9]Tsesmelidakis and Merton (2012) implement the CreditGrade model, which is based on the work of Merton 1976 by assuming stationary leverage, to value the "too big to fail" (TBTF) premium in financial institutions. Chen et al. (2014) use a flexible, lattice-based structural credit risk model to examine the term structure of default probabilities for Lehman Brothers. These empirical applications provide strong support of the feasibility of structural models in banks.

from the reported DVAs. Specifically, we compute the signed differences between the estimated and reported DVAs as a measure of bias (*Errors*) and unsigned differences between the estimated and reported DVAs as a measure of accuracy (*Absolute Errors*). The positive (negative) *Errors* indicate that structural models overestimate (underestimate) the DVAs. Large *Absolute Errors* indicate the market information-estimated DVAs remarkably deviate the reported DVAs, suggesting the reported DVAs convey private information which is not reflected in the capital market. Alternatively, small *Absolute Errors* indicate the capital market could capture the information contained in the reported DVAs timely through financial reports. To investigate whether the *Absolute Errors* between the estimated and reported DVAs are driven by the model misspecification, we compare the performance of pricing DVAs between the Merton model and the Leland model, as the Leland model incorporates certain additional information.[10] Finally, we examine whether estimation errors are prone to systematic errors. In particular, we conduct multivariate regressions of estimation errors on factors that represent the firm-specific variables, bond-specific variables and macroeconomic variables. The significant variables suggest the estimation errors from structural models are associated with them.

We find that the market information-estimated DVAs by structural models deviate the reported DVAs significantly, especially when banks' own creditworthiness is volatile. Specifically, the Merton and Leland models tend to overestimate

[10]The Leland model relaxes some assumptions in the Merton model by considering the endogenous default barrier, tax rate and default costs.

the DVAs on average. However, the analysis of estimation errors by year suggests that both the Merton and Leland models tend to underestimate the DVAs when the banks' own creditworthiness is volatile (i.e., the extremely high or low estimates are clustered around the 2008 financial crisis and 2011 sovereign debt crisis). Conversely, in stable credit risk conditions, these two models have a tendency of overestimation and their performance with regard to DVA estimations gets better. The results in analyzing the systematic estimation errors also provide consistent evidence that structural models lead to larger estimation errors for banks with higher market leverage and asset volatility. In both the Merton and Leland models, the leverage ratio and asset volatility are two main channels of default risk. These results suggest reported DVAs convey more private information during the deterioration of creditworthiness.

Further, we investigate the estimation errors in four sub-samples: zero DVA reporters, non-zero DVA reporters, positive DVA reporters and negative DVA reporters. We compare the pricing performance over these four sub-samples due to their different effects on accounting earnings. Specifically, unlike zero DVAs, the reported non-zero DVAs could result in unrealized DVA gains and DVA losses. Furthermore, we split non-zero DVAs into positive DVAs and negative DVAs, as positive (negative) DVAs result from deterioration (improvement) of firms' credit risk that could in fact lead to economic losses (gains). Cedergren et al. (2012) find that compensation committees place different weights on positive DVAs and negative DVAs. Therefore, we compare the estimation errors between positive and negative DVA reporters to investigate whether management estimate DVA gains and DVA losses differently.

We find that the estimates for zero DVA and non-zero DVA reporters are significantly different. In particular, the Merton and Leland models underestimate the DVAs on average for zero DVA reporters, but overestimate the non-zero DVAs. Moreover, comparing to non-zero DVAs, the *Absolute Errors* for zero DVAs are immaterial, suggesting the estimation errors in full sample are mainly attributed to zero DVA reporters. Further, we split non-zero DVAs into positive and negative DVAs due to their opposite accounting effects — DVA gains and DVA losses. The insignificant t-statistics of equality test indicate that the *Absolute Errors* between these two groups are equal. However, the measure of *Error* suggests the Merton and Leland models underestimate DVA gains but overestimate DVAs losses. The results suggest that management estimate positive DVAs and negative DVAs differently, while the capital market treats them indifferently.

Finally, we compare the *Absolute Errors* between the Merton model and the Leland models. The smaller *Absolute Errors* for the Merton model suggest the Merton model outperforms the Leland model in terms of pricing DVAs, especially when the firms' credit risk increases. This finding indicates that incorporation of additional information in structural models does not improve the performance of estimating DVAs.

The rest of the thesis is organized as follows: Chapter 2 examines whether the reported DVAs correctly reflect the changes in the firms' own credit risk. Chapter 3 compares the reported DVAs with the market information-estimated DVAs by implementation of structural credit risk models. Chapter 4 presents the main conclusions of the thesis.

Chapter 2

What can we learn about credit risk from debt valuation adjustments?

2.1 Introduction

The introduction of the Fair Value Option for financial Liabilities (FVOL) has been one of the most controversial issues in the fair value accounting project. An entity electing the FVOL, either under SFAS No. 159 "The Fair Value Option for Financial Assets and Financial LiabilitiesIncluding an amendment of FASB Statement No. 115" (FASB 2007) or IFRS 9 "Financial instruments" (IASB 2014), is required to measure financial liabilities at fair value and to recognize and separately disclose in the financial statements Debt Valuation Adjustments (DVAs). DVAs represent changes in the fair value of the financial liabilities measured under the FVOL that result from the change in the ability of the firm to settle these liabilities in full. Therefore, an entity recognizes a loss (negative DVAs) when its own credit risk decreases and a gain (positive DVAs) when its own credit risk increases.

The FVOL was introduced in order to simplify the use of hedge accounting, enabling the firms to eliminate or reduce accounting mismatch that arise from the measurement of assets at fair value. However, the recognition of DVAs in the financial statements stirred the debate regarding its effect on the usefulness and informativeness of accounting numbers. On the one hand, it has been argued that the resulting gains and losses are counterintuitive to the way in which gains and losses are typically viewed (Chasteen and Ransom 2007; Lipe 2002). As the market value of liabilities decreases when the entitys credit quality deteriorates, a gain is recognised when a bad economic event occurs. Similarly, a loss is recognized when a good economic event occurs. Resulting changes in reported income are considered by some to be misleading and difficult to explain to investors (Lipe 2002). On the other hand, Barth et al. (2008) argue that DVAs are consistent with debtholders partially absorbing shocks to the firm value (Merton 1974).

A number of empirical studies investigate the effects of DVAs recognition. Barth et al. (2008) use changes in credit ratings times the debt-to-assets ratio as a proxy for DVAs. Using a sample of non-financial firms, they find that the effect of own credit risk changes on equity returns is attenuated by the presence of debt. The study concludes that DVAs should be candidates for inclusion in accounting income if the objective is the faithful representation of the firms liabilities and economic performance. Fontes et al. (2018) find that fair value measurement of assets is associated with noticeably lower information asymmetry and that this reduction is larger when banks also recognize DVAs. This finding is consistent with DVAs providing investors with important information on how gains and losses are shared between equityholders and debtholders (Merton 1974). In line with this finding, Cedergren et al. (2019) find that DVAs are positively related to equity returns for banks with low unrecognized assets.

The above studies investigate the value and informational asymmetry implications of DVAs and associated disclosures, assuming that DVAs correctly reflect (or are at least positively correlated to) changes in the credit quality of the entity and/or that DVAs reflect changes in credit spreads captured by the market. In this paper, we contribute to the debate in this accounting policy area by investigating if reported DVAs indeed reflect changes in credit spreads captured by the market and whether incremental information about the entity's own credit risk (beyond information that can be inferred from the market) is conveyed, i.e., private information. **If reported DVAs can be explained by the market information of credit risk, we state managers faithfully reflect the changes in the fair value of liabilities due to the changes in the firm's own credit risk captured by the market. Otherwise, we have two non-mutually exclusive explanations. The first is that managers may use reported DVAs for opportunistic purpose. Managers may have incentives to use DVAs to manage earnings, especially during our sample period that DVAs are reported in net income. For example, Dong et al. (2019) find managers used DVAs to meet earnings targets during the 2008 financial crisis. However, exercising of discretion over DVAs to smooth earnings disappeared when the economy recovers. This finding is not unexpected. First, managers have to rely on internal models and inputs to estimate DVAs when the financial markets are illiquid. In addition, auditors have more difficulties to evaluate whether significant assumptions used by management in periods of high uncertainty are correct (Bell et al., 2012). In line with this, Wu et al. (2016) find firms with higher credit risk, lower profitability, and negative abnormal stock returns are more likely to opportunistically elect the FVOL. The second explanation is that managers may use private information about banks' own credit risk**

to estimate DVAs and credibly communicate the internal credit risk information to the capital market through DVAs disclosure. Although deterioration in credit quality led banks to recognize gains in earnings, the FVOLs irrevocability reverses this effect for adopting firms when credit quality improves. For this reason, according to the adverse selection hypothesis, firms with good financial conditions should have more tendency to comply with the intent and spirit of SFAS No. 159 than vulnerable banks. For example, Altamuro et al. (2013), find that managers generate higher quality fair value estimates than market inputs due to their information advantage, especially in larger banks, as larger banks have more resources to measure the fair value for sophisticated financial instruments. In this paper, we shed light on the second explanation to examine whether incremental information about the entitys own credit risk (beyond information that can be inferred from the market) is conveyed.

For the implementation of this study, we use a sample of U.S. bank holding companies. We focus on banks, as they are the main users of financial instruments for which the FVOL is applicable. Therefore, the effects of DVAs recognition and disclosure are expected to be more pronounced, compared to industries that make only limited use of financial instruments. Second, large U.S. banks have listed bonds and/or CDS, enabling us to obtain market-based measures of credit risk. Finally, we focus on a single country in order to make sure that our results are not driven by differences in the institutional environment. Our sample covers the period 2007-2017, and includes 38 unique banks. Out of the 887 bank-quarters for which FVOL is adopted, banks report a positive (negative) Debt Valuation Adjustment (DVA) in 171 (176) quarters. In more than half of the quarters the banks report a zero DVA, indicating that the effect of own credit risk changes on the fair value of liabilities was considered to be zero or immaterial.

DVAs are changes in the fair value of liabilities (gains or losses), calculated based on internal estimates about the entitys own credit risk. We firstly convert these gains/losses into changes in credit spreads (DVA-estimated changes in credit spreads). Having DVAs expressed as a change in credit spreads, rather than gains/losses, allows us to understand better the magnitude of these changes and to use the regression model specifications developed in the literature to investigate the determinants of changes in credit spreads. As a first step, we investigate whether DVA-estimated changes in credit spreads can be explained by the same factors that determine the changes in CDS and bond spreads. This provides us with an indication whether DVAs reflect market information on the credit quality of the entities. We find that, on average, DVAs cannot be explained by the same factors that explain changes in bond and CDS spreads. We have two possible, non-mutually exclusive explanations for this finding. The first is that on average, DVAs do not reflect changes credit quality of the entity, and therefore FVOL is used by entities for opportunistic reasons. The second explanation is that DVAs reflect management assessment of the credit quality of the bank, providing insider information on the expected cash flows of the bank that it is not captured by the market.

To investigate whether incremental information about the entity's own credit risk (beyond information that can be inferred from the market) is conveyed, we use information on the Level of fair value of liabilities under the FVOL. This enables us to distinguish between DVAs that reflect mainly market information and DVAs that reflect private managerial information about the credit risk of the entity. Using different cut-off levels, we classify our banks into Level 1 and 2 reporters and Level 3 reporters.[1] We group together Level 1 and 2 reporters, as only a small

[1]For the results presented in the paper, a bank is considered Level 1 and 2 (Level 3) reporter, if it reports 80% or more of its financial liabilities under the FVO at Level 1 and 2 (Level 3). The inference of our results does not change if we use a 100% or a 70% cut-off.

proportion of liabilities under the fair value option (FVO) is reported at Level 1. We find that changes in bond and CDS spreads are statistically significant in explaining DVA-estimated changes in credit spread for banks that report liabilities at fair value Level 1 and 2. These results are consistent with the principle that market inputs are used in the DVAs estimation process for Level 1 and 2 reporters. When we investigate whether reported DVAs convey private information about the credit quality of the entity, we find that lagged DVA-estimated changes in credit spreads are a significant determinant of changes in bond and CDS spreads for Level 3 reporters. These results are consistent with managers having superior information in estimating own credit risk, and they are robust if we control for the propensity of the firm to use Level 3 fair values. However, these results cannot rule out the use of DVAs for opportunistic reasons.

Our results support the view that managers have an informational advantage in estimating DVAs, and that the fair value measurements based on managerial inputs offer additional information about the credit risk of liabilities in our sample. We believe that our results improve our understanding of managerial decision-making with respect to fair value accounting, contributing to the literature that examines the equity and risk relevance of fair value Levels. Our findings indicate that managers use their discretion in computing Level 3 fair values to provide information to the market that is useful to predict future risk. We also contribute to the debate about the role of fair value accounting in generating decision-useful financial information (Fontes et al. 2018; Blankespoor et al. 2013; Koonce et al. 2011).

Although the US bank holding companies setting offers several advantages, there are caveats that should be considered when interpreting the results of this study. First, it is unclear whether our findings generalize to industries with more limited use of the FVOL. Second, the limited number of observations does not allow us to explore the cross-sectional variation within the groups of Level 1 and 2 reporters and Level 3 reporters or whether DVAs can predict default better than market-based measures of credit risk. **Third, when we estimate our DVAs-estimated changes in credit risk, we make a number of simplication assumptions regarding liabilities under the FVO. This simplification assumptions are driven by the aggregate disclosure of those instruments. Therefore, we cannot exclude that some of our results are driven, at least partly, by estimation error.**

The remainder of the paper is organized as follows. Section 2 provides information on the recognition and disclosure of DVAs, presents the related literature and explains our research questions. This is followed by section 3 discussing the sample and research design. Section 4 presents our results, while, section 5 summarizes the findings and contains concluding remarks.

2.2 Background and hypothesis development

2.2.1 Fair value option for liabilities and debt valuation adjustments

Financial liabilities can be recognized either at amortized cost or at fair value. The financial liabilities that can be recognized at fair value includes financial liabilities held for trading, derivatives or other financial instruments that qualify for hedge accounting treatment as well as financial instruments for which the FVOL is elected (see Figure 1). The election of FVOL is made on an instrument-by-instrument basis, it is irrevocable at the inception or upon adoption of this option if the inception is prior to it. The option can be applied only to the entire financial instrument, i.e., unlike hedge accounting the manager cannot fair value only that part of the instrument that might be exposed to the hedged risk. DVAs are recognized and disclosed for financial liabilities that are measured under the FVOL.

DVAs represent changes in the fair value of the financial liabilities under the FVO that result from the change in the ability of the firm to settle these liabilities in full. Under SFAS No. 159 (ASC 825), for our sample period, DVAs are reported in the net income. For fiscal years beginning after 15 December 2017, DVAs are reported in other comprehensive income (ASC 825-10-45-5).

In order to estimate changes in own credit risk and resulting DVAs, entities apply a range of valuation techniques. Kengla and De Jonghe (2012) present survey results on how DVAs are estimated by financial institution. Out of the 19 financial institutions, 4 reported that they were using CDS spreads, 4 were using primary issuances data (based on the latest issuances), 4 were using secondary market data (as for example bond spreads), 5 were using curves set internally by treasury and/or asset-liability management departments, while the rest were using a blended approach (a combination of information including observable inputs and internal data). Note, that from the market one can observe credit spreads, which are driven not only by the credit risk of the company but also by other factors (as for example, liquidity and duration). If the characteristics of the liabilities under the FVO are different to the instruments that are traded, the firm will make adjustments to the observed credit spreads.

Although annual reports provide little information on how DVAs are estimated,[2] financial liabilities under the FVO are disclosed in accordance with the three-level measurement hierarchy (FASB 2006). Therefore, financial statement users are able to differentiate between varying degrees of reliability regarding the valuation inputs. Level 1 fair value estimates are based on quoted prices for identical assets or liabilities in active markets. Level 2 estimates are based on quoted market prices

[2]When DVAs are significant, SFAS 159 (ASC 825) requires that the entities disclose qualitative information about the reasons for instrument-specific credit risk changes as well as how DVAs are determined. However, when we read this information in the financial statements of banks in our sample, we find that it is often very brief and that important steps in the calculation process are not provided. Therefore, it is difficult for financial statement users to understand how DVAs are estimated.

for similar assets or liabilities and inputs other than quoted prices, as for example interest rates and yield curves, while, Level 3 estimates are based on unobservable entity-supplied inputs for the asset/liability. FASB required that the entity use market inputs whenever they can be obtained without undue cost and effort.

2.2.2 Related literature

Two streams of literature are relevant to our study. The first stream looks at the informational effects and value implications of DVAs recognition. Lipe (2002) uses an example of a firm that experiences severe financial distress to show that ratios computed using net income adjusted by DVAs do not faithfully depict the firms negative performance. In a study that uses Certified Public Accountants as participants, Gaynor et al. (2011) shows that disclosures about DVAs are not sufficient to avoid misleading interpretations. The participants are unable to associate a gain (loss) arising from changes in the fair value of liabilities to an increase (decrease) in credit risk. Using archival data, Schneider and Tran (2015) examine the informational effects of DVAs recognition. For a sample of European IFRS banks, they provide evidence that DVAs recognizers exhibit lower bid-ask spread compared to non-adopters of the FVOL, consistent with FVOL mitigating information asymmetry. Fontes et al. (2018) find that fair value measurement of assets is associated with lower information asymmetry and that this reduction is larger when banks also recognize DVAs. This finding is consistent with DVAs providing investors with important information on how gains and losses are shared between equityholders and debtholders (Merton 1974).

A number of studies investigate the value relevance of DVAs. Using a sample that includes both financial and non-financial entities, Chung et al. (2017) report a positive relationship between DVAs and current period stock returns, suggesting that DVAs are value relevant. The study of Cedergren et al. (2019) investigates the value relevance of DVAs, considering the level of unrecognized assets. They find that, when the level of unrecognised assets is low, DVAs are positively associated to stock returns. However, this relation becomes less positive as the level of unrecognized assets increases, and eventually it becomes negative. This result suggests that investors understand the influence of unrecognised assets on the value relevance of DVAs.

More closely to our study, Dong et al. (2019) investigate the determinants of DVAs and banks exercise of discretion over DVAs. The study finds that DVAs are positively associated with changes in bond spreads and provides evidence that abnormal DVAs are negatively associated with pre-managed earnings, consistent with banks exercising discretion over DVAs to smooth earnings. However, the study does not address the question of what the market learns about credit risk from DVAs.

The second stream of related literature investigates the value and risk relevance of different fair value Levels. Song et al. (2010) find that the association between share prices and fair values of assets and liabilities is higher for Levels 1 and 2 than for Level 3 fair values. This result suggests that investors place less weight on the fair value of assets and liabilities that are based on unobservable inputs. The fair value hierarchy is also shown to influence information asymmetry between the managers of a firm and the external capital market participants. Magnan et al. (2015) report that Level 3 fair values increase forecast dispersion, and Riedl and Serafeim (2011) provide evidence that firms with greater exposure to Level 3 assets have higher costs of capital, as measured by equity betas. In line with these results, Iselin and Nicoletti (2017) provide evidence that banks change the asset composition of their portfolios to avoid disclosure of Level 3 assets.

While the above studies indicate that fair values based on inputs corresponding to higher levels in the fair value hierarchy are more useful, this is not always the case. For example, Altamuro and Zhang (2013) find that Level 3 mortgage servicing rights reflect better the risk of the underlying servicing portfolios than Level 2 mortgage servicing rights. Their results indicate that managers have an information advantage in estimating the fair value of instruments that are not traded in active markets. Furthermore, Lawrence et al. (2016) report that the association between share prices and Level 3 fair values is similar to the association between share prices and Level 1 and Level 2 fair values. Their results are based on a sample of close-end funds where all assets are measured at fair value. Their study attributes the results of earlier studies to problems with research design, as prior studies draw conclusions from samples where only a small proportion of assets are measured at fair value.

2.2.3 Research questions

Most of the studies that investigate the effects of DVAs recognition and associated disclosures make the assumption that DVAs correctly reflect (or at least positively correlated to) changes in the credit quality of the entity and/or that DVAs reflect changes in credit spreads captured by the market. This paper contributes to the debate in this accounting policy area by investigating if reported DVAs indeed reflect changes in credit spreads captured by the market, and whether incremental information about the entity's own credit risk (beyond information that can be inferred from the market) is conveyed.

First, we investigate whether DVA-estimated changes in credit risk can be explained by the same factors that explain changes in CDS and/or bond spreads. This will provide an indication whether DVAs reflect market information on the credit quality of the entities. Our expectation is that DVA-estimated changes in credit spreads are not necessarily explained by the same factors that explain changes in market-based measures of credit spreads. This is because DVAs incorporate not only market but also private managerial information about the credit standing of the entity.

Second, in order to distinguish between public and private information incorporated in DVAs, we use information on the fair value Level of the financial instruments measure under the FVOL. If financial liabilities under the FVOL are measured at fair value Level 1 and 2, then DVAs are largely based on market information. In this case, we expect changes in bond and CDS spreads to be significant in explaining DVA-estimated changes in credit spreads. If financial liabilities under the FVOL are measured at fair value Level 3, valuation is largely based on entity-supplied inputs, and therefore, DVAs incorporate private information about the credit quality of the entity. In this case, we expect to find that DVA-estimated changes in credit spreads can predict future changes in CDS and bond spreads.

2.3 Sample selection and research design

2.3.1 Sample selection

Our sample includes U.S. bank holding companies that file quarterly FR Y-9C reports with the Federal Reserve. We focus on financial companies, as DVAs are not economically relevant in other industries.[3] This can be driven by the limited use of financial instruments by non-financial firms and the complexity of the fair value option application. We restrict our sample to bank holding companies because, as opposed to other financial institutions (e.g., mutual funds, credit unions), they provide detailed and standardized disclosures on FVOL election and DVAs in their regulatory filings. The sample period is 2007:Q1 to 2017:Q4. We choose to include

[3]Using a sample of all non-financial firms with available 10-K documents in EDGAR in 2009 (year with the highest number of FVOL adopters in our sample), we find that only 11 adopted the FVOL. None of these 11 non-financial firms reports non-zero DVAs.

observations from 2007 because FASB allows early adoption of SFAS No.159 (ASC 825) on eligible financial instruments, although the effective date of the standard is January 1, 2008 for regular adopters.[4]

Once bank holding companies elect the FVOL, they are required to report two data items in quarterly FR Y-9Cs. One is total gains/losses on liabilities under the FVO (BHCKF553), and the second is gains or losses on liabilities under the FVO attributable to changes in own credit risk (BHCKF554). These items are downloaded from Bank Regulatory database. We require that banks report BHCKF553 or BHCKF554 at least once over our sample period. This process leaves us with 85 bank holding companies. For some bank -quarters, data on DVAs are missing from the database. To increase the size of our sample, we hand-collect DVAs from 10Q/10K filings for the selected bank holding companies.[5] An example of such disclosures is provided in Appendix 2.3. DVAs reported in Bank Regulatory occasionally differ from those in the 10Q/10K filings.[6] In such a case, in line with Cedegreen et al. (2019), we use entries from the 10Q/10K filings, as these amounts are likely more scrutinized by auditors.

We also require that banks are publicly traded, with 150 trading-day observations available, in order to estimate our explanatory variables (asset values and volatility), and that they have positive book value of liabilities (Eom et al. 2004). This reduces our sample to 46 unique banks. Finally, we hand-collect information on maturity, fair value and principal of liabilities under the FVOL from financial reports, removing from our sample the banks that do not provide this information. This information is needed in order to calculate the DVA-estimated changes in credit spreads. This process yields a sample of 887 bank-quarter observations, representing 38 unique banks. Appendix 2.4 provides a list of all the banks in our

[4]Our results are robust if we exclude from our analyses the early adopters.
[5]Firms are required to report DVAs in 10Q/K filings if these are material.
[6]This is the case for only 6 bank-quarters, and our results are robust to the exclusion of these observations from our sample.

sample. The sample selection process is summarized in Table 1.

Table 2 provides detailed information on the number of FVOL adopters that recognize DVAs per year. The downloaded quarterly data on DVAs from Bank Regulatory database report the total DVA since the beginning of the financial year. In order to obtain quarterly DVA, we need to take the difference between two quarters. The number of bank-quarter observations is quite low for 2007, as it includes only early adopters of the FVOL. Out of the 887 bank-quarter observations, banks report positive (negative) DVA in 171 (176) quarters. This indicates that in 171 (176) quarters the banks experienced a deterioration (an improvement) in their credit quality. In more than half of the quarters the banks report zero DVA, despite the fact that they adopt the FVOL, indicating that the effect of own credit risk changes in the fair value of liabilities was zero or immaterial. **Managers in our sample banks need to disclose DVAs in FR Y-9C regardless of their materiality. Meanwhile, managers only disclose material DVAs in 10K/Q reports. For each quarter we consider the first date that any of the two types of reports became available as the date that DVA information is publicly available (release day).[7] There is no rigid threshold of the materiality of DVAs to be reported. Cedergren et al. (2019) show that banks adopting large amounts of liabilities under FVO reported larger magnitudes of DVAs than banks adopting few amounts of liabilities under FVO given the same changes in credit risk. Consistently, we find large banks with large amounts of FVOL in our sample are the main reporters of non-zero DVAs. Indeed, the magnitudes of reported DVAs do not affect the inference from results because the reliability is of interest in this paper.**

[7]**The statutory due dates are the 60th for 10K filings and 35th day for 10Q filings. For FR 9Y-C reports the due day is the 40th day following interim quarter-ends and the 45th day following the fourth quarter-end. Reports can be released earlier than the due date, so some times FR 9Y-C is released earlier than 10Q/K.**

Among early adopters, there are 16 positive DVA recognizers and only 1 negative DVA recognizer, which coincides with the growing deterioration in creditworthiness during early 2008. However, a similar number of banks report positive and negative DVAs over financial crisis. This is not in line with our expectation, as entities typically experience a credit deterioration during such a period. One possible explanation for this result is that changes in credit quality were also more volatile during this period. Appendix 2.4 provides information on the number of quarters where zero, positive and negative DVAs are reported per bank. In Panels B and C we report information on DVAs for large banks and other banks respectively. We classify a bank as a large bank if it has a book value of assets greater than \$50 billion.[8] As we can see from Panel B, most of the positive and negative DVAs are driven by large banks. When we look at other banks, in 92% of bank-quarters that the FVOL was adopted, a zero DVA is reported.

2.3.2 DVA-estimated changes in credit spreads

DVAs are based on internal estimates of the entitys credit risk. In order to investigate what determines DVAs, and whether they provide new information on the credit quality of the banks, we firstly convert reported DVA amounts from financial statements into changes in credit spreads. Expressing DVAs as changes in credit spreads, rather than reporting them as dollar gains/losses, allows us to arrive at a unit-free standardized measure that is directly comparable across different observations, as it already takes into account relevant credit information embedded in bonds yield as well as its maturity and coupon structure. This measure, which we label DVA-estimated spread, is interpreted in the same way as market-based credit spreads and, as such, its magnitude can be directly compared to that of the latter. Furthermore, DVA-estimated spreads can be directly used in regression model specifications developed to investigate the determinants of changes in

[8] \$50 billion is used as a threshold for most requirements of enhanced supervision by the Federal Reserve.

credit spreads. A positive DVA (gain) indicates an increase in DVA-estimated credit spreads, whereas a negative DVA (loss) indicates a decrease. In order to be able to express these gains/losses as changes in credit spreads, we use information on liabilities under the FVO from financial statements.

The amount and/or type of liabilities under the FVO can change from one reporting period to the other, because new liabilities may occur and/or some liabilities may extinguish. Therefore, in order to get the DVA-estimated changes in credit spreads we need to rely on information from the same reporting period. We denote with $\widehat{FVL_t}$ the hypothetical value of liabilities under the FVO at the end of quarter t, in the absence of DVAs. DVA_t is the change in fair value of liabilities due to fluctuations in creditworthiness in quarter t, while FVL_t is the actual fair value of liabilities under the FVO at the end of the same quarter after DVAs are considered. Because a negative DVA (loss) indicates an increase in the value of liabilities, while a positive DVA (gain) indicates a decrease in the value of liabilities, the actual fair value of liabilities at time t (FVL_t), equals to the value of liabilities in the absence of own credit risk changes ($\widehat{FVL_t}$) minus DVA_t:

$$FVL_t = \widehat{FVL_t} - DVA_t \tag{2.1}$$

FVL_t and DVA_t are provided in the financial statements, therefore, we use equation (1) to estimate $\widehat{FVL_t}$. If DVA_t is zero, the actual fair value of liabilities equals to the hypothetical fair value of liabilities ($FVL_t = \widehat{FVL_t}$). If there is an improvement in the credit quality (decrease in credit spread), the entity will have a loss, indicated by a negative DVA. In this case, the actual fair value of liabilities will be higher than the hypothetical fair value of liabilities ($FVL_t > \widehat{FVL_t}$). This is because the cash flows of liabilities are discounted at a lower rate (decrease in credit spread) than the rate that they would have been discounted in the absence of credit quality improvement. Similarly, in case of deterioration in credit quality (positive DVA), the actual fair value will be lower than the hypothetical fair value

$(FVL_t < \widehat{FVL_t})$.

Next, we estimate the discount rate applied to obtain the actual fair value of liabilities and the discount rate applied to obtain the hypothetical fair value of liabilities. To do this, we assume that liabilities under the FVO consist of one type of bond that pays coupon semi-annually.[9] Based on the bond valuation formula:

$$FVL_t = B\left[\frac{c}{y_t}(1 - \frac{1}{(1+\frac{y_t}{2})^{2T}}) + \frac{1}{(1+\frac{y_t}{2})^{2T}}\right] \tag{2.2}$$

$$\widehat{FVL_t} = B\left[\frac{c}{\widehat{y_t}}(1 - \frac{1}{(1+\frac{\widehat{y_t}}{2})^{2T}}) + \frac{1}{(1+\frac{\widehat{y_t}}{2})^{2T}}\right] \tag{2.3}$$

where y_t ($\widehat{y_t}$) is the semiannually compounded actual (hypothetical under no own credit risk changes) yield to maturity, and B is the face value of liabilities under FVO. To estimate the two yields (y_t, $\widehat{y_t}$), we hand-collect information on face value (B) and maturity (T) of FVL_t from financial statements. If we do not have more precise information, we assume that debt maturing in 5 years and beyond has a maturity of 10 years.[10] We also use the price weighted average coupon rate (c) on straight coupon bonds issued by each bank in U.S. dollars.

The yield to maturity is equal to the risk free rate plus the credit spread. Given that the risk free rate for the specific quarter is the same, the DVA-estimated change in credit spread ($Delta\_DVA\_CS$) is given by the difference between the actual yield to maturity and the hypothetical yield to maturity:

$$Delta\_DVA\_CS_t = y_t - r - (\widehat{y_t} - r) = y_t - \widehat{y_t} \tag{2.4}$$

[9]**We need to make this simplification assumption, as financial reports do not provide this information for all the individual liabilities under the FVO. Chang et al. (2011) investigate banks FVO elections for different types of financial instruments. They find only early adopters likely to elect AFS securities under FVO in order to exploit the SFAS No. 159s transition adjustments. This characteristic of instruments does not apply to liabilities and then our results. In addition, we also estimate DVA-estimated changes in credit spreads assuming zero-coupon debt. The conclusions based on the revised results remain the same.**

[10]Our results do not change if we assume debt matures in 20 years.

where r is the risk free rate with consistent maturity with liabilities under the FVO, estimated by fitting Nelson and Siegel (1987) curve. Appendix 2.5 provides the time-line of accounting and market information as well as a numerical example on how the variables are measured based on equations (1-4). The numerical example is based on the DVA disclosures provided in Appendix 2.3.

Descriptive statistics on the inputs and DVA-estimated changes in credit spreads are presented in Table 3. The average change in credit spreads estimated for the whole sample as well as for non-zero DVAs is negative. The table also includes information on changes in CDS spreads as well as on changes in bond spreads.[11]

We obtain CDS and bond credit spreads from Thomson Reuters Datastream. We use CDS spreads for identical maturities to the liabilities of the banks under FVOL using linear interpolation. We have CDS spreads for 13 banks in our sample, resulting in 379 quarterly observations. For bond spreads, we identify publicly traded bonds without inherent option rights issued by banks in the sample from 1996 to 2017, as the database starts to disclose bond-related information in 1996. Bond spread is defined as the corporate bond yield minus the yield of the benchmark Treasury rate. If there is no benchmark bond with the same maturity, then linear interpolation is used to estimate the yield of the equivalent benchmark. For bonds with a maturity longer than the longest benchmark, the equivalent benchmark yield is always the yield of the longest Treasury bond. The same holds for bonds with maturities shorter than the shortest benchmark, where the yield of the shortest Treasury bond is used. We include quarterly bond yield spreads for the same period as with DVAs data (2007 to 2017). This process yields to a final sample of 1,313 bonds from 27 bank holding companies and 21,514 quarter

[11]We use CDS spreads as they are a cleaner measure of the credit risk compared to bond spreads. Bond spreads are influenced by factors as tax, liquidity, and duration. However, using bond spreads enables us to increase the number of observations for our tests and to check the robustness of our results. For some entities in the sample we have available both CDS and bond spreads.

credit spreads. We define changes in bond credit spreads ($Delta\_Bond\_CS$) as the difference in credit spreads between two consecutive quarters. We also estimate changes in bond-spreads at bank-level ($Delta\_Bond\_CS\_Mean$). As in Barth et al. (2012), we measure spread as the averages of the spread for each of the banks bonds, weighted by the bond price. To avoid the effect of outliers, we winsorize changes in bond spreads at 1 and 99 percent (Blankespoor et al. 2013; DeFond et al. 2011).[12]

2.3.3 Research design

Firstly, we investigate whether DVA-estimated changes in credit spreads ($Delta\_DVA\_CS$) can be explained by the same factors that explain changes in CDS or bond spreads. This will provide us with an indication whether DVAs reflect market information on the credit quality of the entities. For our multivariate analysis we estimate the following linear regression model:

$$Delta\_DVA\_CS_t = \alpha + \sum \beta_j ExplanatoryVariables_{jt} + \varepsilon \tag{2.5}$$

In structural credit risk models, the value of debt is obtained using contingent-claims pricing techniques. Investing in risky debt is equivalent to holding an otherwise identical riskless debt and having a short position in a put option on the firm's assets with exercise price equal to the face value of debt (Merton 1974). In this framework, the credit spread (CS), is a function of the face value of debt, the market value and volatility of the firm's assets, the riskless interest rate and debt maturity. In line with Collin-Dufresne et al. (2001), we expect changes in credit spreads to be positively associated with changes in leverage ($Delta\_Lev$), changes

[12]Descriptive statistics confirm that there are some potentially non-valid observations in the data, resulting in extreme positive or extreme negative changes in credit spreads. These non-valid observations may be a result of error entry in the database, illiquid bonds, and/or bonds of very long or short maturity. Our results are robust to (1) using not winsorized data, (2) using the log form of bond spreads and (3) deleting observations that are candidates for data errors (Bessembinder et al. 2006; Helwege et al. 2014).

in asset volatility (*Delta_Sigma*) and changes in the probability or magnitude of downward jump (*Delta_Jump*), and negatively associated with changes in the spot rate (*Delta_r*10), changes in the slope of the yield curve (*Delta_Slope*) and changes in business climate (*Delta_Climate*). Appendix 2.7 provides a detailed description of the explanatory variables.

In order to control for the panel data structure of our sample we estimate regressions results adjusted to account for correlation within firm clusters and we include firm fixed effects. Estimating regressions using a within-year control design does not change the inference of our results.[13]

2.4 Empirical results

2.4.1 Descriptive statistics

Table 4 presents descriptive statistics for all bank-quarters (Panel A) as well as for the bank-quarters that non-zero DVA is reported (Panel B). The largest quarterly gain (loss) from DVAs during our sample period is \$3,410 (\$3,135) million, while the average DVA is \$-14.7 million.[14] We also provide the ratio DVA to lagged liabilities under the FVO (DVA/FVL_lag). The mean DVA/FVL_lag is 0.0008 for all FVOL adopters, whereas for non-zero DVA reporters is 0.0021.

Table 5 reports Pearson correlation coefficients for all the variables that are used in the regression analysis. The correlation between the control variables is relatively

[13] In the main analysis, we do not include time fixed effects because macro-economic variables do not vary enough over quarters and because of the small sample size for some of the analyses (Li and Prabhala 2005). The results are robust for our larger subsample of bond spreads when we (1) use year fixed effects, (2) remove the macro-economic control variables and include quarter fixed effects and (3) include indicator variables for first, second and third quarter.

[14] **These DVA gains (losses) greatly affected the net incomes of the largest U.S. bank holding companies in 2008, exemplified by Morgan Stanleys DVA gains flipping the 3.3 billion losses into 1.7 billion profits attributable to credit deterioration.**

low, indicating no multicollinearity between explanatory variables. As, expected, the correlation between DVA-estimated changes in credit spreads and changes in bond and CDS spreads is positive, however, it is small. The correlation between *Delta_DVA_CS* and *Delta_Bond_C*S is 0.13, while the correlation between *Delta_DVA_CS* and *Delta_CDS_CS* is 0.08. This is another indication that DVAs may provide different information about the credit quality of the entities than the market-based measures of credit risk. The correlation between changes in CDS spreads and (mean) bond spreads is 0.48 (0.66). This less than perfect correlation is not unexpected. Literature provides evidence that CDS spreads contain credit risk information that is not captured by bonds of the same firm, and that CDS spreads lead bond spreads (Blanco et al. 2005; Lee et al. 2018).[15]

2.4.2 Determinants of DVA-estimated changes in credit spread

Table 6 presents regression results on the determinants of DVA-estimated changes in credit spreads. The first column presents results for all FVOL adopters, including bank-quarter observations where zero DVA is reported. Only *Delta_Slope* is statistically significant in explaining DVA-estimated changes in credit spreads and the adjusted R-squared is low, indicating limited explanatory power of the model. In the second column, we only consider bank-quarter observations in which non-zero DVA is reported. The only significant variable for the results presented in the second column is *Delta_Jump*.

[15] The fact that CDS spreads lead bond spreads, as documented in the extant literature, is immaterial for our analysis. Lags in the CDS spreads-bond spreads lead-lag relationship are measured in days (e.g., the lag order in Lee et al. 2018 is three days), whereas, due to the nature of accounting data, the relevant duration of a lag in our setting is one month/a quarter.

To assess the explanatory power of the control variables in our model, we run regressions on changes in CDS and bond yield spreads.[16] These results are presented in the last three columns of Table 6. For changes in CDS spreads, *Delta_Lev*, *Delta_Jump* and *Delta_Climate* are statistically significant. The adjusted R-squared increases to 12.10%. In the last two columns, where the dependent variables are the change in bond spreads and the average change in bond spreads, most of the coefficients have the predicted sign, and a number of them are statistically significant. The explanatory power of the model is also much higher, with an adjusted R-squared between 13% and 34%. Similarly to Blanco et al. (2005) and Collin-Dufresne et al. (2001), our models leave significant variance both in changes in CDS spreads and changes in bond spreads unexplained. According to Collin-Dufresne et al. (2001), this may be a results of spreads being driven by market-wide supply and demand shocks.

One concern is that our results are driven by the way we estimate our dependent variable (*Delta_DVA_CS*). Although we incorporate all available information on the characteristics of the instruments under the FVO, as we explained in subsection 3.2, we had to impose some assumptions in our estimation process. To check robustness of the results to these assumptions, we use a number of alternative dependent variables. We scale *DVA_t* by (1) assets, (2) mean value of liabilities under the FVO, (3) liabilities under the FVO at the beginning of the period (4) total liabilities, and we also use the natural logarithm of DVA as well as the annual DVA. The results are very similar to these presented in Table 6 (untabulated results). Most of the control variables are not significant and the explanatory power of the regression models is low. This is also the case if we repeat our analysis after splitting the sample into positive and negative reported DVA (untabulated results). We also investigate whether our insignificant results in the

[16] An alternative market-based measure of changes in credit risk is changes in credit ratings. However, because in our sample we have only a small number of changes in actual and estimated credit ratings, we are unable to meaningfully use this measure.

first two columns in Table 6 are driven by observations for which we do not have market-based measures of credit risk available. To do this, we run our regressions, firstly, using only the observations for which we have available changes in CDS spreads and secondly, using only observations for which we have available changes in bond spreads. The inference of our results do not change. Untabulated findings indicate that most of the variables are insignificant in explaining DVA-estimated changes in credit spreads.

The above analysis shows that reported DVAs are not explained on average by the factors that explain changes in credit spreads. This result can be driven by the fact that DVAs incorporate both market and private information on the credit risk of the entity. The use of private information in the estimation of DVAs can result in entities using FVOL for opportunistic behaviour and/or in order to provide insider information on the credit standing of the bank that it is not captured by the market.

The study of Dong et al. (2019), provides evidence consistent with banks exercising discretion over DVAs to smooth earnings. While we cannot rule out this possibility, the incentives for earnings management in our sample are likely to be lower than in Dong et al. (2019). Firms in our sample report DVAs in a standardised way in their machine-readable FR Y-9C, resulting to higher transparency associated with these gains/losses. In addition, incentives for earnings management are likely to further decrease after 2017 due to DVAs no longer be reported in net income. Therefore, in the subsequent analysis we focus on investigating whether DVAs reflect managements assessment of the credit quality of the bank, providing insider information on its credit standing to the market.

2.4.3 Fair value Level

In order to investigate whether DVAs convey incremental information about the entity's own credit risk (beyond information that can be inferred from the market), we distinguish between public and private information incorporated in DVAs. To do this, we use information on the fair value Level of liabilities under the FVO (FVL). Table 7 provides information on the percentage of liabilities under the FVO at Level 1 and 2 and Level 3 (Panel A), as well as the number of observations classified as Level 1 and 2 or Level 3 reporters using different cut-offs (Panel B). Because only a small percentage of liabilities under the FVOL is measured at fair value Level 1, we had to group Level 1 and 2 reporters together.[17] For the results presented in the paper, a bank is considered Level 1 and 2 (Level 3) reporter, if it reports 80% or more of its financial liabilities under the FVO at Level 1 and 2 (Level 3) in a specific quarter. The inference of our results does not change if we use a 100% or a 70% cut-off.

The table provides information for the whole sample, as well as the sub-samples for which we have available changes in CDS and bond spreads. Note, that if the inputs used to measure the fair value of liabilities under the FVO fall into different levels of the hierarchy, then the Level employed for measurement and presentation is based on the lowest Level input. Therefore, it is possible for banks to have CDS spreads and/or traded bonds and report their liabilities under the FVO at Level 3. Similarly, a Level 2 reporter may not have CDS spreads and/or traded bonds available, but use quoted market prices for similar instruments issued by another company. When we use the 80% cut-off, 433 bank-quarter observations are classified as Level 1 and 2 reporters, while, 306 bank-quarter observations are classified as Level 3 reporters. When we look at the observations for which we have CDS data available, the number of bank-quarter observations decreases significantly,

[17] Only 3 bank holding companies in our sample are classified as Level 1 reporters when we use the 80% cut-off.

only 228 bank-quarter observations are classified as Level 1 and 2 reporters and 49 bank-quarter observations are classified as Level 3 reporters.

For Level 1 and 2 reporters, we expect DVA-estimated changes in credit spread to be better explained by the factors that explain market-based measures of changes in credit spreads than for Level 3 reporters, because market inputs are used for the estimation of DVAs. Regression results presented in Table 8 suggest that DVA-estimated changes in credit spreads are still not well explained by the factors that explain market-based measures of changes in credit spreads for Level 1 and 2 reporters (columns 1). The only significant variables are changes in business climate and probability of downward jump. For Level 3 reporters, none of the explanatory variables is significant. The adjusted R-squared is negative for both Level 1 and 2 and Level 3 reporters, indicating that the models contain terms that do not help to predict the DVA-estimated changes in credit spreads.[18]

The results for Level 1 and 2 category can be largely driven by the Level 2 reporters. If liabilities under the FVO are traded, the market-based measure of changes in credit risk and the DVA-estimated credit risk should be tautological, and therefore, explained by the same factors. However, this is rarely the case in our sample. Only 3 bank holding companies (33 bank-quarters) report more than 80% of liabilities under the FVO at fair value Level 1. The rest of bank holding companies in the Level 1 and 2 category are Level 2 reporters. For the valuation of their liabilities under the FVO, Level 2 reporters use quoted market prices from similar instruments that are traded, and inputs other than quoted prices. From the market, one can observe the credit spread of the instrument, which is driven not only by the credit risk of the company but also by other factors (as for example, liquidity and duration). If the characteristics of the liabilities under the FVO are different to the instruments that are traded, the firm will make adjustments to the

[18] Unadjusted R-squared is positive but very low for both regressions.

credit spreads. Because of these adjustments and potential measurement error, the observed credit spreads can differ from the DVA-estimated credit spreads for Level 2 reporters.

In columns 3-11, we include some additional explanatory variables, the changes in CDS and bond spreads. The coefficients on the changes in CDS spreads and bond spreads are statistically significant for Level 1 and 2 reporters. The adjusted R-squared of the models also increases significantly. These results are consistent with the fact that, for liabilities measured at fair value Level 1 and 2, market inputs are used in the DVAs estimation process. We find no such evidence for Level 3 reporters.

Next, we investigate whether reported DVAs convey private information about the credit quality of the entity. To do this, we look at the ability of reported DVAs to predict future changes in credit spreads. To generate results presented in Table 9, we include in the models explaining the market-based measures of changes in credit spreads the contemporaneous DVA-estimated changes in credit spreads ($Delta\_DVA\_CS\_t$) as well as the one-quarter leading DVA-estimate change in credit spreads ($Delta\_DVA\_CS\_t + 1$) and the one-quarter lagged DVA-estimate change in credit spreads ($Delta\_DVA\_CS\_t - 1$). If managers provide insider information to the market through DVAs and associated disclosures, we expect lagged DVA-estimated changes in credit spreads to be significant in explaining changes in CDS and bond spreads. We expect this to be particularly the case for Level 3 reporters, as Level 3 fair values are based on managerial inputs. The number of observations decreases, as we need data on CDS spreads and bond spreads as well as one-quarter lead and lagged data on DVA-estimated changes in credit spreads.

The leading DVA-estimated change in credit spreads coefficient is not significant, indicating that future DVA-estimated changes in credit spreads and current market-based measures of changes in credit spreads are uncorrelated. The coefficient of the contemporaneous DVA-estimated change in credit spreads is significant for Level 1 and 2 reporters. This result is in line with the results presented in Table 8, and consistent with market inputs used for the estimation of DVAs for Level 1 and 2 reporters. The lagged DVA-estimated changes in credit spreads are significant in explaining changes in the bond and CDS spreads for Level 3 reporters. In addition, the explanatory power of our models, captured by adjusted R-squared, increases significantly. This result is consistent with managers providing insider information to the market through DVAs and associated disclosures. To investigate further the ability of DVA-estimated changes in credit spreads to lead market-based measures of credit risk, we also estimate a panel vector autoregressive (PVAR) model that describes the dynamic evolution of our variables (Holtz-Eakin et al. 1988). Untabulated findings confirm that DVA-estimated changes in credit spreads lead market-based measures of credit risk for Level 3 reporters. Using the model and moment selection criteria of Andrews and Lu (2001), we find that the optimal number of lags in the PVAR model is one (quarter), in line with the model presented in Table 9.

For the results presented in Table 9, the choice of one quarter as the length of a (single) lag is driven by the structure and limitations of our data. While market spreads can be measured almost continuously, we can only measure DVA-implied spreads with quarterly frequency (as they are based on accounting data). Therefore, faced with time series for two variables with a different sampling frequency, we need to settle for the lag length that corresponds to the sampling frequency of the variable that is measured less often. However, if the reported DVAs and associated disclosures are informative to the market, we expect these to influence credit spreads as soon as they becomes available. In the regressions presented in Table

10, we examine the predictive ability of DVA-estimated changes in credit spreads using one-month window. Due to the data frequency limitations explained above, we include in our analyses only the one-quarter lagged DVA-estimate change in credit spreads ($Delta\_DVA\_CS\_t-1$). As information on DVAs is available both in FR 9Y-C and 10Q/K, we consider the one-month window after the end of the quarter as a reasonable approximation of the release of the information without imposing strict assumptions on the release date, or reducing the power of our results because of the thin trading of bonds/CDS. We expect $Delta\_DVA\_CS\_t-1$ to explain changes in credit risk in the first month of the following quarter, and this effect to disappear in the following months.

The first 3 columns of Table 10 present results for the first month of the quarter. Results for the second and third month are presented in columns 4-6 and 7-9 respectively. The explanatory variables are re-estimated to correspond to the specific one-month window. We only include results for changes in bond spreads, but results are very similar if we use the mean change in bond spreads.[19] In line with our expectation, $Delta\_DVA\_CS\_t-1$ is only significant in explaining changes in bond spreads in the first month for Level 3 reporters.

2.4.3.1 Additional endogeneity control

The classification of the bank-quarter observations as Level 1 and 2 or Level 3 reporters is based on the liabilities for which the bank adopts the FVO. If the banks that adopt the FVOL at Level 3 are different from the banks that adopt the FVOL at Level 1 and 2, we have a selection bias. In order to control for the time invariant unobservable characteristics that affect the changes in credit spreads, we include in all our regressions bank fixed effects. To control for potential time varying unobservable characteristic, we use the two-stage Heckman (1979) correction

[19] The coefficient of $Delta\_DVA\_CS\_t-1$ is positive put insignificant in the first month if we use CDS spreads. This is likely to be driven by the small number of observations for the CDS tests.

procedure. First, we use a probit model to explain the use of fair value Level 3 reporting. Following the reasoning of Altamuro and Zhang (2013) and Iselin and Nicoletti (2017), we expect that Level 3 reporting is associated with the size of the bank ($Size$), the auditors ($Big4$), the use of the FVO for assets ($FVOA$) and the importance of liabilities under FVO (FVL/TA). Appendix C provides a detailed description of the explanatory variables.

The results from estimating the probit model are presented in Panel A of Table 11. As in Table 10, we look at the predictive ability of DVAs, using one-month window. The $pseudo-R^2$ is around 61 percent indicating a good fit. The coefficients on $Size$ and FVL/TA are negative and significant, in line with larger firms having liabilities that are traded, and therefore reported at Level 1 and 2. The coefficient on $FVOA$ is positive and statistically significant, while, the coefficient on $Big4$ has the opposite sign to our expectation. In the second stage, reported in Panel B of Table 11, we add the self-selection parameter (λ) calculated from the probit regression to our main regression models. We only include results for changes in bond spreads, but results are very similar if we use the mean change in bond spreads. In line with our results in Table 10, $lag\_Delta\_DVA\_CS$ is only significant in explaining changes in bond spreads in the first month for Level 3 reporters.

The predictive ability of DVAs appears to be driven by the superior ability of managers to estimate own credit risk. This result contributes to the fair value literature, and in particular to the studies that examine the equity and risk relevance of fair value Levels. Our findings indicate that managers use their discretion in computing Level 3 fair values to provide information to the market that is useful to predict future risk. The study also contributes to the small group of studies that consider the effects of fair valuing liabilities (Fontes et al. 2018; Koonce et al. 2011; Blankespoor et al. 2013).

2.4.4 Further sensitivity analyses

To investigate the robustness of our findings, we conduct several additional analyses. The effective date of FVO standard is January 1, 2008 for regular adopters, however, early adoption from 2007 is allowed. To test if our results are driven by early adopters, we run our regressions deleting 2007 observations from the sample. Untabulated findings show that the inference or our results do not change. The lagged DVA-estimated changes in credit spread are significant in explaining future changes in bond and CDS spreads for Level 3 reporters. We also run our models using explanatory variables from the accounting literature. Following the Correia et al. (2018) and Correia et al. (2012), we add to our regression models the change in firm size, return on assets, distance to default, and book to market ratio as additional control variables. The results are in line with those of our main models.

2.5 Conclusions

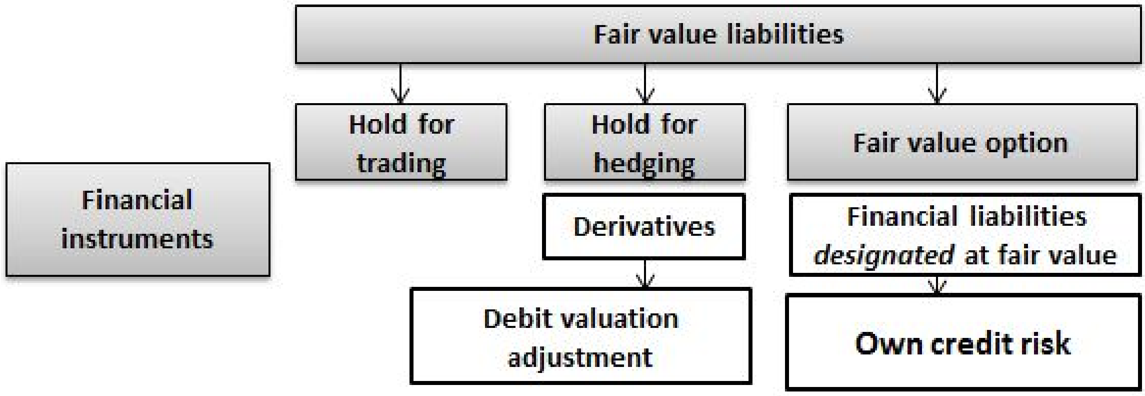
Motivated by the debate that occurred in the accounting policy area regarding the introduction of the FVOL, this paper investigates whether reported DVAs indeed reflect changes in credit spreads captured by the market and whether incremental information about the entity's own credit risk (beyond information that can be inferred from the market) is conveyed. While accounting standards have introduced the FVOL to enable the firms to eliminate or reduce accounting mismatch that arise from the measurement of assets at fair value, concerns have been raised that firms may opt for opportunistic election of the FVOL.

Using a sample of U.S. bank holding companies we find that, on average, DVAs cannot be explained by the same factors that determine changes in credit risk. We propose a number of non-mutually exclusive explanations for this result. The first of them is that, on average, DVAs do not reflect changes in credit quality of the entity, and therefore FVOL is used by managers for opportunistic reasons. The other explanation is based on the conjecture that managers may possess information about institutions' own credit risk that are not fully embedded in bond market data.

When we investigate the ability of reported DVA to predict future changes in credit spreads we find that lagged DVA-estimated changes in credit spreads are significant in explaining changes in CDS and bond spreads. This result is driven by banks that report liabilities at fair value Level 3, providing support that managers provide insider information to the market through DVAs and associated disclosures. These results however, cannot exclude the use of DVAs for opportunistic reasons. Overall, our results improve our understanding of managerial decision-making with respect to fair value accounting and contribute to the debate about the role of fair value accounting for financial liabilities in generating decision-useful financial information.

Appendix 2.1 Accounting Recognition of Financial Liabilities

Figure 2.1: Accounting recognition of financial liabilities



The figure provides information on the accounting recognition of financial liabilities.

Appendix 2.2 Empirical Results

Table 2.1: The sample selection procedure

Banks that report net gains or losses on liabilities (bhckf553) or net gains or losses on liabilities attributable to changes in their own credit risk (bhckf554) at least once during sample period 2007: Q1 to 2017: Q4	85
Banks that match with COMPUSTAT and CRSP with publicly available stock price and positive book value of liabilities	46
Banks that report fair value and principal value of liabilities under fair value option	38
All bank-quarters of selected banks	887

The table provides information on sample selection. In the sample we include U.S. bank holding companies for the period 2007-2017 that have available data. This process leads to 887 bank-quarter observations.

Table 2.2: FVOL adopters and DVA recognizers per year

Number of bank-quarters

	DVA<0		DVA=0		DVA>0		Total		Number of banks DVA!=0
Panel A: All banks									
2007	1	*1%*	36	*7%*	16	*9%*	53	*6%*	5
2008	19	*11%*	68	*13%*	21	*12%*	108	*12%*	13
2009	24	*14%*	65	*12%*	13	*8%*	102	*11%*	12
2010	19	*11%*	68	*13%*	18	*11%*	105	*12%*	10
2011	15	*9%*	50	*9%*	21	*12%*	86	*10%*	9
2012	23	*13%*	47	*9%*	10	*6%*	80	*9%*	9
2013	24	*14%*	46	*9%*	8	*5%*	78	*9%*	8
2014	13	*7%*	42	*8%*	19	*11%*	74	*8%*	8
2015	8	*5%*	40	*7%*	24	*14%*	72	*8%*	8
2016	14	*8%*	42	*8%*	14	*8%*	70	*8%*	8
2017	16	*9%*	36	*7%*	7	*4%*	59	*7%*	6
Total	**176**	*100%*	**540**	*100%*	**171**	*100%*	**887**	*100%*	
Panel B: Large banks (total assets ¿ $50 billion)									
2007	1	*1%*	0	*0%*	13	*9%*	14	*3%*	
2008	10	*6%*	3	*3%*	16	*11%*	29	*7%*	
2009	22	*14%*	3	*3%*	7	*5%*	32	*7%*	
2010	16	*10%*	15	*13%*	17	*11%*	48	*11%*	
2011	13	*8%*	13	*11%*	19	*13%*	45	*10%*	
2012	23	*14%*	12	*10%*	9	*6%*	44	*10%*	
2013	24	*15%*	16	*14%*	8	*5%*	48	*11%*	
2014	13	*8%*	14	*12%*	19	*13%*	46	*11%*	
2015	8	*5%*	12	*10%*	24	*16%*	44	*10%*	
2016	14	*9%*	17	*15%*	13	*9%*	44	*10%*	
2017	16	*10%*	12	*10%*	7	*5%*	35	*8%*	
Total	**160**	*100%*	**117**	*100%*	**152**	*100%*	**429**	*100%*	
Panel C: Other banks (Total assets ¡ $50 billion)									
2007	0	*0%*	36	*9%*	3	*16%*	39	*9%*	
2008	9	*56%*	65	*15%*	5	*26%*	79	*17%*	
2009	2	*13%*	62	*15%*	6	*32%*	70	*15%*	
2010	3	*19%*	53	*13%*	1	*5%*	57	*12%*	
2011	2	*13%*	37	*9%*	2	*11%*	41	*9%*	
2012	0	*0%*	35	*8%*	1	*5%*	36	*8%*	
2013	0	*0%*	30	*7%*	0	*0%*	30	*7%*	
2014	0	*0%*	28	*7%*	0	*0%*	28	*6%*	
2015	0	*0%*	28	*7%*	0	*0%*	28	*6%*	
2016	0	*0%*	25	*6%*	1	*5%*	26	*6%*	
2017	0	*0%*	24	*6%*	0	*0%*	24	*5%*	
Total	**16**	*100%*	**423**	*100%*	**19**	*100%*	**458**	*100%*	

The table provides information on the number of bank-quarters for which FVOL was adopted, and the recognition of positive and negative DVA each year. Panel A provides information for all the banks, while Panels B and C provide information for large banks (total assets more than $50 billion) and other banks respectively. The sample includes all U.S. bank holding companies which have available data for the period 2007-2017 (887 bank-quarter observations).

Table 2.3: DVA-estimated changes in credit spreads, bond spreads and CDS spreads

Variable	Obs	Mean	Std.Dev.	Min	Q1	Median	Q3	Max
Panel A: Inputs for DVA-estimated changes in credit spreads								
Coupon rate	887	0.0566	0.0179	0.0113	0.0439	0.0547	0.0671	0.1164
Maturity	887	8.0267	7.1085	1.0000	3.1834	4.8017	10.0000	39.0000
Risk-free rate	887	0.0205	0.0123	0.0014	0.0103	0.0186	0.0282	0.0517
Fair value ('000)	887	21,689,588	44,049,942	1,250	41,429	159,787	10,392,000	358,827,000
Principal value ('000)	887	21,896,584	44,471,600	1,500	61,900	192,900	8,042,000	357,997,000
DVA ('000) (all observations)	887	-14,651	374,937	-3,134,715	0	0	0	3,410,000
DVA ('000) (non-zero DVA)	347	-37,450	599,267	-3,134,715	-143,000	-162	87,000	3,410,000
Panel B: DVA-estimated changes in credit spreads								
Delta_DVA_CS (all observations)	887	-0.0008	0.0147	-0.1591	0.0000	0.0000	0.0000	0.1918
Delta_DVA_CS (non-zero DVA)	347	-0.0019	0.0234	-0.1591	-0.0018	-0.0001	0.0009	0.1918
Panel C: Market-based measures of changes in credit spreads								
Delta_CDS_CS	379	-0.0002	0.0144	-0.0841	-0.0022	-0.0003	0.0010	0.1451
Delta_Bond_CS	21,514	0.0006	0.0087	-0.0257	-0.0018	-0.00002	0.0015	0.0587
Delta_Bond_CS_Mean	540	0.0008	0.0073	-0.0235	-0.0020	-0.0001	0.0018	0.0334

The table provides descriptive statistics of the inputs used for the estimation of DVA-estimated changes in credit spreads (Delta_DVA_CS) as well as information on Delta_DVA_CS (Panel B), and market based measures of changes in credist spreads (Panel C). Market-based measures include changes in CDS spreads of identical maturities to the liabilities of the banks under the FVO (Delta_CDS_CS), changes in bond spreads (Delta_Bond_CS) and changes in the mean bond spread (Delta_Bond_CS_Mean) for the period 2007-2017. We have CDS spreads for 13 banks in our sample, resulting in 379 quarterly observations. For bond spreads, we identify all publicly traded bonds without inherent option rights issued by the banks in the sample. We have 1,313 bonds from 27 banks, resulting in 21,514 quarter credit spreads. Delta_Bond_CS_Mean captures the changes in bond-spreads at bank-level.

Table 2.4: Descriptive statistics on DVAs and determinants

Variable	Obs	Mean	Std.Dev.	Min	Q1	Median	Q3	Max
Panel A: All FVOL adopters								
DVA ('000)	887	-14,651	374,937	-3,134,715	0.0000	0.0000	0.0000	3,410,000
DVA/FVL_lag	887	0.0008	0.0346	-0.1296	0.0000	0.0000	0.0000	0.6522
DVA/FVL_mean	886	0.0001	0.0269	-0.1282	0.0000	0.0000	0.0000	0.4675
DVA/Asset_lag	886	0.0000	0.0004	-0.0037	0.0000	0.0000	0.0000	0.0041
Delta_Lev	887	0.0003	0.0152	-0.0556	-0.0075	-0.0003	0.0075	0.0658
Delta_r10	887	-0.0005	0.0044	-0.0102	-0.0038	-0.0010	0.0020	0.0104
Delta_Slope	887	0.0002	0.0035	-0.0078	-0.0025	-0.0003	0.0023	0.0101
Delta_Sigma	887	-0.0002	0.0133	-0.0660	-0.0040	-0.0005	0.0035	0.1066
Delta_Climate	887	0.0193	0.0851	-0.2190	-0.0257	0.0312	0.0635	0.1569
Delta_Jump	887	-0.0005	0.0325	-0.0635	-0.0263	-0.0003	0.0263	0.0783
Panel B: Non-zero DVA								
DVA ('000)	347	-37,450	599,267	-3,134,715	-143,000	-162	87,000	3,410,000
DVA/FVL_lag	347	0.0021	0.0553	-0.1296	-0.0052	-0.0001	0.0026	0.6522
DVA/FVL_mean	347	0.0003	0.0431	-0.1282	-0.0055	-0.0001	0.0026	0.4675
DVA/Asset_lag	347	0.0000	0.0006	-0.0037	-0.0001	0.0000	0.0001	0.0041
Delta_Lev	347	-0.0003	0.0146	-0.0556	-0.0073	-0.0006	0.0069	0.0658
Delta_r10	347	-0.0006	0.0043	-0.0102	-0.0038	-0.0011	0.0020	0.0104
Delta_Slope	347	0.0001	0.0034	-0.0078	-0.0025	-0.0003	0.0023	0.0101
Delta_Sigma	347	0.0007	0.0127	-0.0603	-0.0028	-0.0002	0.0029	0.0600
Delta_Climate	347	0.0187	0.0849	-0.2190	-0.0257	0.0312	0.0635	0.1569
Delta_Jump	347	-0.0010	0.0330	-0.0635	-0.0263	-0.0010	0.0263	0.0783

The table reports descriptive statistics of the variables used in the analysis. Panel A reports descriptive statistics for all the sample, including bank-quarters where zero DVA were reported. Panel B, includes only the bank-quarters that non-zero DVA were reported. Accum_DVA is the annual DVA and DVA/FVL_lag is the ratio of DVA to one quarter lagged liabilities under the FVO. Delta_Lev is the change in the ratio book value of liabilities to market value of assets. Delta_r10 is the change in the 10-year Treasury rate. Delta_Slope is the change in the slope of the yield curve. Delta_Sigma is the change is asset volatility. Delta_Climate is captured by quarterly S&P returns. Delta_Jump captures the changes in the probability or magnitude of downward jump.

Table 2.5: Pearson Correlation Coefficients

Panel A: All bank-quarters

		1	2	3	4	5	6	7	6	7	8	9	10
1	Delta_DVA_CS												
2	Delta_Bond_CS	0.1330***											
3	Delta_Bond_CS_Mean	0.1020**	0.5877***										
4	Delta_CDS_CS	0.0818	0.4808***	0.6561***									
5	DVA/FVL_lag	0.5229***	0.2526***	0.1978***	0.2202***								
6	DVA/FVL_mean	0.6635***	0.2493***	0.1607***	0.2697***	0.8115***							
7	DVA/Asset_lag	0.2603***	0.2896***	0.3424***	0.3538***	0.3864***	0.4116***						
6	Delta_Lev	0.0303	0.2476***	0.2750***	0.2744***	0.0431	0.0214	0.1406***					
7	Delta_r10	-0.0815**	-0.2302***	-0.3423***	-0.1292**	-0.0211	-0.0408	-0.1531***	-0.2783***				
8	Delta_Slope	-0.0742**	-0.1972***	-0.1122***	-0.1563***	-0.0230	-0.0465	-0.0565*	-0.1517***	0.4412***			
9	Delta_Sigma	0.0107	0.0285***	0.1480***	-0.0667	-0.0002	0.0207	0.0613*	-0.4639***	-0.1066***	0.0702**		
10	Delta_Climate	-0.0862**	-0.3030***	-0.5022***	-0.3085***	-0.0462	-0.0230	-0.2197***	-0.4347***	0.5456***	0.0958***	-0.096***	
11	Delta_Jump	0.0370	0.1261***	0.1694***	0.2043***	0.0161	0.0181	0.0980***	-0.0084	-0.2571***	-0.2898***	0.1271***	-0.1127***

Panel B: Non-zero DVA

		1	2	3	4	5	6	7	6	7	8	9	10
1	Delta_DVA_CS												
2	Delta_Bond_CS	0.1353***											
3	Delta_Bond_CS_Mean	0.1311**	0.5774***										
4	Delta_CDS_CS	0.0836	0.4821***	0.7114***									
5	DVA/FVL_lag	0.5262***	0.2569***	0.2554***	0.2227***								
6	DVA/FVL_mean	0.6652***	0.2535***	0.2072***	0.2740***	0.8117***							
7	DVA/Asset_lag	0.2590***	0.2946***	0.4416***	0.3581***	0.3877***	0.4120***						
6	Delta_Lev	0.0471	0.2507***	0.3937***	0.2778***	0.0733	0.0360	0.2320***					
7	Delta_r10	-0.1337**	-0.2287***	-0.3413***	-0.1233**	-0.0336	-0.0660	-0.2486***	-0.3446***				
8	Delta_Slope	-0.1229**	-0.2000***	-0.1673***	-0.1533***	-0.0365	-0.0754	-0.0928*	-0.223***	0.4683***			
9	Delta_Sigma	0.0238	0.0256***	0.0723	-0.0741	-0.0030	0.0341	0.1053*	-0.464***	-0.0511	0.1234**		
10	Delta_Climate	-0.1391***	-0.2971***	-0.5052***	-0.3036***	-0.0739	-0.0369	-0.3528***	-0.4646***	0.5659***	0.1019*	-0.1129**	
11	Delta_Jump	0.0574	0.1290***	0.2018***	0.2215***	0.0260	0.0286	0.1540***	0.0642	-0.2564***	-0.2944***	0.0913*	-0.1082*

The table reports Pearson correlation coefficients. All variables are defined in Table 4.

Table 2.6: Determinants of DVA-estimated changes in credit spreads, CDS spreads changes and bond spreads changes.

	Pred. Sign	Delta_DVA_CS All FVOL	Delta_DVA_CS Non-zero DVA	Delta_CDS_CS	Delta_Bond_CS	Delta_Bond CS_Mean
Intercept		-0.0004*	-0.0010	0.0016	0.0016***	0.0015***
t		(-1.83)	(-1.42)	(1.09)	(3.31)	(3.07)
Delta_Lev	+	-0.0332	-0.1197	0.1478***	0.0974***	0.0577**
		(-1.16)	(-1.34)	(2.70)	(2.90)	(2.35)
Delta_r10	-	-0.0370	-0.0838	0.7608	0.0015	-0.0866
		(-0.25)	(-0.20)	(1.22)	(0.01)	(-0.54)
Delta_Slope	-	-0.3378*	-0.8164	-0.5777	-0.2344	-0.0689
		(-1.65)	(-1.42)	(-1.12)	(-1.04)	(-0.40)
Delta_Sigma	+	-0.0072	-0.0418	-0.0664	0.0876**	0.0758
		(-0.24)	(-0.55)	(-1.46)	(2.06)	(1.01)
Delta_Climate	-	-0.0140	-0.0463	-0.0557**	-0.0306***	-0.0295***
		(-1.28)	(-1.57)	(-2.02)	(-3.20)	(-3.48)
Delta_Jump	+	0.0035	0.0327***	0.0775*	0.0091	0.0246
		(0.25)	(2.83)	(1.65)	(1.02)	(1.56)
Firm FE		Yes	Yes	Yes	Yes	Yes
Observations		887	347	379	21514	540
Adj. R-squared		6.20%	27.40%	12.10%	13.37%	34.07%

The table presents regression results on the determinants of DVA-estimated credit spreads changes, CDS spreads changes and bond spreads changes. The first column presents results for all FVOL adopters, whereas for the regression results presented in the second column, we only include bank-quarters that a non-zero DVA is reported. The third column presents regression results for changes in CDS spreads with identical weighted average maturities to liabilities under FVOL. The last two columns present results on the determinants of changes in bond spreads. All variables are defined in Table 4. The coefficient estimates and t-statistics (in parenthesis) are based on robust standard errors that are clustered by bank and quarter. *,**, and *** indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Table 2.7: Liabilities under the FVO in different Levels

Panel A: Percentage of liabilities in different Levels

		Obs	Mean	Std.Dev.	Min	Q1	Median	Q3	Max
All observations	Level 1 and 2	887	57.45%	43.89%	0.00%	0.00%	78.48%	100.00%	100.00%
	Level 3	887	42.55%	43.89%	0.00%	0.00%	21.52%	100.00%	100.00%
Observations with bond_spreads available	Level 1 and 2	540	63.86%	40.86%	0.00%	0.00%	84.49%	97.00%	100.00%
	Level 3	540	36.14%	40.86%	0.00%	3.00%	15.51%	100.00%	100.00%
Observations with CDS_spreads available	Level 1 and 2	379	74.10%	31.75%	0.00%	72.27%	87.10%	96.00%	100.00%
	Level 3	379	25.90%	31.75%	0.00%	4.00%	12.90%	27.73%	100.00%

Panel B: Observations classified as Level 1 and 2, and Level 3 reporters

		Obs. for different cut-off		
		100%	>80%	>70%
All observations	Level 1 and 2 reporters	231	433	507
	Level 3 reporters	285	306	317
Observations with bond_spreads available	Level 1 and 2 reporters	92	292	357
	Level 3 reporters	140	146	150
Observations with CDS_spreads available	Level 1 and 2 reporters	28	228	293
	Level 3 reporters	43	49	53

The table presents information on the percentage of liabilities under the FVO at Level 1 and 2 and Level 3 (Panel A), as well as the number of observations classified as Level 1 and 2 or Level 3 reporters using different cut-offs (Panel B). With the 100% cut-off a bank is considered Level 1 and 2 (Level 3) reporter, if it reports 100% or more of its financial liabilities under the FVOL at Level 1 and 2 (Level 3) in the particular quarter. Similarly, with the 80% (70%) cut-off a bank a bank is considered Level 1 and 2 reporter, if it reports 80% (70%) or more of its financial liabilities under the FVOL at Level 1 and 2 in the particular quarter. The bank is considered as Level 3 reporter, if it reports 80% (70%) or more of its financial liabilities under the FVOL at Level 3 in the particular quarter. The table provides information for the whole sample, as well as for the sub-samples for which we have available information on changes in bond and CDS spreads.

Table 2.8: Determinants of DVA-estimated changes in credit spreads: Fair value levels

	Pred. Sign	Level1&2	Level 3	All obs.	Level1&2	Level 3	All obs.	Level1&2	Level 3	All obs.	Level1&2	Level 3
Intercept		-0.0003***	0.0008***	-0.0012***	-0.0001	0.0009	0.0002	0.0001	0.0020*	-0.0004	-0.0003***	0.0037**
t		(-35.35)	(4.25)	(-3.87)	(-0.85)	(0.37)	(1.08)	(1.18)	(1.79)	(-0.96)	(-6.70)	(2.32)
Delta_CDS_t	+			0.0280***	0.0570**	1.2642						
				(8.30)	(2.15)	(0.86)						
Delta_Bond_CS_t	+						0.0381**	0.1363***	-0.1759			
							(2.00)	(4.42)	(-1.08)			
Delta_Bond_CS_Mean_t	+									0.1311***	0.1559**	-0.4360
										(2.62)	(2.56)	(-1.07)
Delta_Lev	+	-0.0235	-0.0306	-0.0907	0.0133	-0.4713**	0.0190	0.0202	-0.1329	-0.0567	0.0186	-0.1371
		(-0.47)	(-1.46)	(-0.79)	(0.63)	(-2.47)	(0.83)	(0.70)	(-0.90)	(-0.90)	(1.10)	(-1.35)
Delta_r10	-	-0.2568	0.1169	-0.1032	-0.1315*	-1.3461*	-0.1185*	0.0178	0.0214	0.2058	0.0078	0.0024
		(-1.06)	(0.68)	(-0.41)	(-1.90)	(-1.86)	(-1.95)	(0.58)	(0.02)	(1.08)	(0.16)	(0.01)
Delta_Slope	-	-0.1075	-0.4860	-0.5028	0.0475	0.3645**	-0.0178	0.0063	-0.6551	-0.5688	-0.0330	-0.9359
		(-1.24)	(-1.15)	(-1.34)	(0.94)	(2.15)	(-0.24)	(0.46)	(-0.64)	(-1.35)	(-0.93)	(-1.04)
Delta_Sigma	+	-0.0411	0.0305	-0.0422	-0.0108	-0.3632	0.0511***	-0.0130	0.2571	-0.0078	-0.0170	0.3477
		(-1.08)	(0.71)	(-0.48)	(-0.54)	(-0.77)	(2.97)	(-1.11)	(1.07)	(-0.13)	(-1.35)	(0.86)
Delta_Climate	-	-0.0093***	-0.0112	-0.0350	-0.0122***	-0.0871	-0.0161**	-0.0165***	-0.0482	-0.0294	-0.0079***	-0.0752
		(-2.93)	(-0.86)	(-1.33)	(-2.61)	(-0.83)	(-2.56)	(-6.63)	(-1.18)	(-1.25)	(-3.31)	(-1.28)
Delta_Jump	+	0.0191*	-0.0430	0.0176**	0.0088	-0.0928**	-0.0045*	0.0061	-0.0503	-0.0051	0.0044	-0.1189
		(1.72)	(-1.16)	(2.27)	(1.44)	(-2.05)	(-1.89)	(1.16)	(-1.12)	(-0.25)	(0.95)	(-1.19)
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		433	306	379	228	49	21514	17754	914	540	292	146
Adj. R-squared		-3.48%	-2.80%	11.50%	39.88%	-18.27%	19.33%	41.41%	4.02%	9.61%	37.57%	-4.71%

The table presents regression results of the determinants of DVA-estimated credit spreads for different fair value levels. The first and second columns present results for DVA determinants for Level 1,2 reporters and Level 3 reporters, respectively. The next columns report results after controlling for changes in CDS and bond spreads. All other variables are defined in Table 5. The coefficient estimates and t-statistics (in parenthesis) are based on robust standard errors that are clustered by bank and quarter. *,**, and *** indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Table 2.9: The effect of lagged DVA-estimated changes in **quarterly changes of** credit spreads

		Delta_CDS_CS			Delta_Bond_CS			Delta_Bond_CS_Mean		
	Pred. Sign	All obs.	L1&2	L3	All obs.	L1&2	L3	All obs.	L1&2	L3
Intercept		0.0018	0.0039**	0.0003	0.0014***	0.0018***	0.0007***	0.0014***	0.0019***	0.0009**
t		(1.13)	(2.29)	(0.72)	(2.83)	(3.70)	(5.05)	(3.44)	(3.56)	(2.14)
Delta_DVA_CS_t+1	+	-0.0182	-0.2493	-0.0353	0.1003	0.2064	-0.0013	0.0071	-0.0974	0.0057
		(-0.68)	(-0.35)	(-1.14)	(0.84)	(0.90)	(-0.78)	(0.67)	(-0.40)	(1.20)
Delta_DVA_CS_t	+	0.0085	1.5238***	0.0234	0.0968	1.0459***	-0.0210	0.0166	1.2695***	-0.0037
		(0.28)	(5.35)	(1.11)	(1.07)	(9.26)	(-1.46)	(1.23)	(9.36)	(-0.43)
Delta_DVA_CS_t-1	+	0.0274	-0.1655	0.0441***	0.0098	0.1240	0.0136**	0.0081	0.0772	0.0078**
		(1.39)	(-0.96)	(3.87)	(0.36)	(0.96)	(2.02)	(1.58)	(0.95)	(2.05)
Delta_Lev	+	0.1585*	0.1765	-0.2380	0.1165***	0.0462	-0.0180	0.0513	0.0326	-0.0589
		(1.67)	(1.08)	(-0.92)	(3.60)	(1.44)	(-0.46)	(1.52)	(0.63)	(-1.28)
Delta_r10	-	0.8756	0.5350	0.1700	0.0831	-0.1348	-0.5720	0.0560	0.1174	-0.5360*
		(1.21)	(1.27)	(0.58)	(0.35)	(-0.80)	(-1.11)	(0.24)	(0.73)	(-1.68)
Delta_Slope	-	-0.6685	-0.0032	-0.5311	-0.2466	0.0955	0.3894	-0.1444	-0.0700	0.2904
		(-1.00)	(-0.01)	(-0.98)	(-0.88)	(0.57)	(0.62)	(-0.53)	(-0.38)	(0.74)
Delta_Sigma	+	-0.0660	-0.0280	-0.0850	0.1313***	0.0855**	0.0801	0.0694	0.0543	0.0575
		(-1.12)	(-0.31)	(-0.88)	(3.46)	(2.33)	(0.83)	(0.97)	(0.68)	(0.62)
Delta_Climate	-	-0.0565**	-0.0668**	-0.0331	-0.0295***	-0.0268***	-0.0333***	-0.0313***	-0.0259*	-0.0290***
		(-2.02)	(-2.38)	(-1.05)	(-3.21)	(-3.54)	(-6.34)	(-2.83)	(-1.85)	(-3.75)
Delta_Jump	+	0.0812*	0.0327	-0.0274**	0.0082	0.0034	-0.0095	0.0263	0.0224	-0.0082
		(1.72)	(1.21)	(-2.02)	(0.92)	(0.46)	(-1.00)	(1.62)	(1.37)	(-1.08)
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		352	211	43	18828	15624	684	491	264	129
Adj. R-squared		11.42%	30.68%	33.74%	17.09%	25.75%	45.98%	27.54%	48.10%	64.87%

The table presents regression results on the effect of DVA-estimated changes in credit spread on market-based measure of risk. The first three columns present results on **quarterly** changes in CDS spreads, the next six columns present results for **quarterly** changes in bond spreads. Delta_DVA_CS_t+1 is the one-period leading DVA-estimated change in credit spreads. Delta_DVA_CS_t is the contemporaneous DVA-estimated change in credits spreads, while, Delta_DVA_CS_t-1 is the one-period lagged DVA-estimated change in credits spreads. All other variables are defined in Table 5. The coefficient estimates and t-statistics (in parenthesis) are based on robust standard errors that are clustered by bank and quarter. *,**, and *** indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Table 2.10: The effect of lagged DVA-estimated changes in **monthly changes of** credit spreads on bond spreads for months 1-3

	Pred. Sign	Delta_Bond_CS_M1 All obs.	Delta_Bond_CS_M1 L1&2	Delta_Bond_CS_M1 L3	Delta_Bond_CS_M2 All obs.	Delta_Bond_CS_M2 L1&2	Delta_Bond_CS_M2 L3	Delta_Bond_CS_M3 All obs.	Delta_Bond_CS_M3 L1&2	Delta_Bond_CS_M3 L3
Intercept		0.0001	0.0002**	-0.0003***	0.0009***	0.0011***	0.0004**	0.0012***	0.0014***	0.0005***
t		(0.61)	(2.22)	(-3.55)	(4.88)	(5.15)	(2.55)	(3.41)	(3.67)	(3.73)
lag_Delta_DVA_CS	+	0.0093	0.0135	0.0175***	-0.0165	-0.0900	0.0028	-0.0025	-0.0436	-0.0035
		(1.23)	(0.42)	(3.68)	(-0.43)	(-0.64)	(0.34)	(-0.29)	(-0.51)	(-0.89)
Delta_Lev	+	0.0523	0.0690*	0.0319*	-0.0309	-0.0354	-0.0078	0.0890	0.0846	-0.0905
		(1.42)	(1.66)	(1.68)	(-0.70)	(-1.24)	(-0.23)	(1.42)	(1.11)	(-1.62)
Delta_r10	-	-0.4021***	-0.2458	0.2237	-0.3529*	-0.3533***	-0.6433**	-0.7800**	-0.9391**	-0.3501
		(-2.63)	(-1.45)	(0.81)	(-1.74)	(-2.71)	(-2.28)	(-2.11)	(-2.28)	(-1.43)
Delta_Slope	-	0.0479	-0.0564	-0.3809	0.1638	0.1376	0.5632	0.9234	0.9591	0.0095
		(0.29)	(-0.34)	(-1.15)	(0.82)	(1.22)	(1.60)	(1.29)	(1.31)	(0.04)
Delta_Sigma	+	0.0463	0.0700	0.0947	0.0332	0.0151	0.0527	0.1143**	0.1247*	0.1003
		(0.63)	(1.01)	(1.39)	(0.53)	(0.31)	(0.75)	(2.01)	(1.78)	(1.24)
Delta_Climate	-	-0.0024	-0.0071	-0.0108**	-0.0326***	-0.0374***	-0.0151**	-0.0408**	-0.0447***	-0.0226***
		(-0.39)	(-1.13)	(-2.45)	(-3.67)	(-3.76)	(-2.57)	(-2.50)	(-2.66)	(-6.12)
Delta_Jump	+	-0.0030	0.0008	0.0010	0.0105*	0.0125*	-0.0013	-0.0030	-0.0081	-0.0146**
		(-0.51)	(0.14)	(1.33)	(1.95)	(1.95)	(-0.47)	(-0.47)	(-1.05)	(-2.06)
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		20619	17075	850	20807	17161	846	21422	17741	849
Adj. R-squared		5.67%	5.64%	13.04%	10.42%	10.91%	24.82%	9.46%	10.05%	26.61%

The table presents regression results on the effect of lagged DVA-estimated changes in credit spreads on bond spreads using different time window. The first three columns presents results on the effect of lagged DVA-estimated changes in credit spreads on changes in bond spreads in the first month of the bank-quarter (Delta_Bond_CS_M1). Columns 4-6 (7-9) present results on the effect of lag_Delta_DVA_CS on changes in bond spreads in the second month (third month) of the bank-quarter. All other variables are defined in Table 5. The coefficient estimates and t-statistics (in parenthesis) are based on robust standard errors that are clustered by bank and quarter. *,**, and *** indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Table 2.11: The effect of lagged DVA-estimated changes in credit spreads on bond spreads for months 1 - 3: Controlling for self-selection

Panel A: Probit estimates for Level 3 measurement

	Pred.	First Month		Second Month		Third Month	
	Sign	Probit	Chi-square	Probit	Chi-square	Probit	Chi-square
Constant		9.2066***	(369.79)	9.3158***	(388.09)	9.3086***	(379.08)
Size	?	-0.5274***	(391.25)	-0.5327***	(408.44)	-0.5316***	(392.44)
Big4	+	-0.9679***	(18.75)	-1.0757***	(19.45)	-1.0794***	(19.62)
FVOA	+	1.6071***	(23.81)	1.6873***	(24.50)	1.6807***	(24.40)
FVL/TA	?	-0.3277***	(462.25)	-0.3279***	(454.54)	-0.3271***	(454.97)
Pseudo R-squared		61.44%		61.75%		62.15%	
LR Chi square		4940.7***		4929.08***		5011.98***	
Pearson		4078.24***		4132.8***		4096.68***	
Observations		20,619		20,807		21,422	

Panel B: Including self-selection parameter

	Pred.	Delta_Bond_CS_M1			Delta_Bond_CS_M2			Delta_Bond_CS_M3		
	Sign	All obs.	L1&2	L3	All obs.	L1&2	L3	All obs.	L1&2	L3
Intercept		0.0030**	0.0041***	-0.0011	0.0017	0.0029**	-0.0011**	0.0024	0.0030	0.0004
t		(2.46)	(3.96)	(-0.85)	(1.51)	(2.08)	(-2.50)	(1.28)	(1.51)	(0.35)
lag_Delta_DVA_CS	+	0.0080	-0.0043	0.0176***	-0.0170	-0.0919	0.0028	-0.0027	-0.0447	-0.0035
		(1.31)	(-0.17)	(3.76)	(-0.45)	(-0.67)	(0.34)	(-0.33)	(-0.55)	(-0.89)
Delta_Lev	+	0.0463	0.0596**	0.0321*	-0.0288	-0.0305	-0.0111	0.0896	0.0850	-0.0906
		(1.48)	(2.06)	(1.74)	(-0.65)	(-0.94)	(-0.31)	(1.45)	(1.13)	(-1.59)
Delta_r10	-	-0.4465***	-0.3385***	0.2249	-0.3605*	-0.3722***	-0.6846**	-0.7840**	-0.9461**	-0.3502
		(-4.62)	(-3.98)	(0.81)	(-1.75)	(-2.70)	(-2.27)	(-2.09)	(-2.27)	(-1.43)
Delta_Slope	-	0.1328	0.1142	-0.3814	0.1771	0.1669	0.6162*	0.9302	0.9665	0.0094
		(1.29)	(1.25)	(-1.14)	(0.87)	(1.30)	(1.69)	(1.29)	(1.30)	(0.04)
Delta_Sigma	+	0.0445	0.0720	0.0944	0.0353	0.0153	0.0523	0.1134**	0.1210*	0.1000
		(0.61)	(1.11)	(1.41)	(0.57)	(0.31)	(0.74)	(1.99)	(1.73)	(1.23)
Delta_Climate	-	-0.0016	-0.0052	-0.0109**	-0.0330***	-0.0388***	-0.0148***	-0.0405**	-0.0438**	-0.0226***
		(-0.31)	(-1.04)	(-2.54)	(-3.67)	(-3.87)	(-2.64)	(-2.44)	(-2.50)	(-6.11)
Delta_Jump	+	-0.0036	0.0002	0.0011	0.0108**	0.0136**	-0.0017	-0.0031	-0.0082	-0.0146**
		(-0.61)	(0.04)	(1.11)	(2.06)	(2.13)	(-0.57)	(-0.49)	(-1.13)	(-2.05)
Lambda	?	-0.0009**	-0.0011***	0.0009	-0.0003	-0.0005	0.0018**	-0.0004	-0.0004	0.0001
		(-2.44)	(-3.76)	(0.65)	(-0.72)	(-1.30)	(2.57)	(-0.60)	(-0.74)	(0.06)
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations		20619	17075	850	20807	17161	846	21422	17741	849
Adj. R-squared		6.23%	6.67%	13.01%	10.48%	11.16%	24.95%	9.51%	10.13%	26.53%

The table presents regression results controlling for self-selection. Panel A presents probit estimates on the determinants of Level 3 reporting. Size is the natural logarithm of total assets, Big4 equals to 1 if the bank is audited by a big 4 auditor and zero otherwise. FVOA is an indicator variable for the use of the FVO for assets. FVL/TA is the ratio of liabilities under the FVO to total assets. The first two columns presents results for the first month of the quarter, while columns 3-4 (5-6) present results for the second (third) month of the quarter. Panel B presents results on the effect of lagged DVA-estimated changes in credit spreads on bond spreads using different time window, including the self-selection parameter (Lambda). The first three columns presents results on the effect of lagged DVA-estimated changes in credit spreads on changes in bond spreads in the first month of the bank-quarter (Delta_Bond_CS_M1). Columns 4-6 (7-9) present results on the effect of lag_Delta_DVA_CS on changes in bond spreads in the second month (third month) of the bank-quarter. All other variables are defined in Table 5. The coefficient estimates and t-statistics (in parenthesis) are based on robust standard errors that are clustered by bank and quarter. *,**, and *** indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Appendix 2.3 An Example of DVA Disclosure

The Appendix provides an example of DVA disclosure by JP Morgan Chase & Co as of September 31, 2015.

Figure 2.2: Example of DVA disclosure from FR Y-9C report

Dollar Amounts in Thousands	BHCK		
Memorandum item 14 is to be completed by holding companies that have elected to account for assets and liabilities under a fair value option.			
14. Net gains (losses) recognized in earnings on assets and liabilities that are reported at fair value under a fair value option:			
a. Net gains (losses) on assets	F551	3105000	M.14.a.
(1) Estimated net gains (losses) on loans attributable to changes in instrument-specific credit risk	F552	273000	M.14.a.(1)
b. Net gains (losses) on liabilities	F553	3747000	M.14.b.
(1) Estimated net gains (losses) on liabilities attributable to changes in instrument-specific credit risk	F554	492000	M.14.b.(1)
15. Stock-based employee compensation expense (net of tax effects) calculated for all awards under the fair value method	C409	1262000	M.15.

The 10Q report provides the following note (page 105) :

”Total changes in instrument-specific credit risk (DVA) related to structured notes were \$169 million and \$190 million for the three months ended September 30, 2015 and 2014, respectively, and \$492 million and \$209 million for the nine months ended September 30, 2015 and 2014, respectively. These totals include such changes for structured notes classified within deposits and other borrowed funds, as well as long-term debt.”

Appendix 2.4 List of Banks

Table 2.12: List of Banks

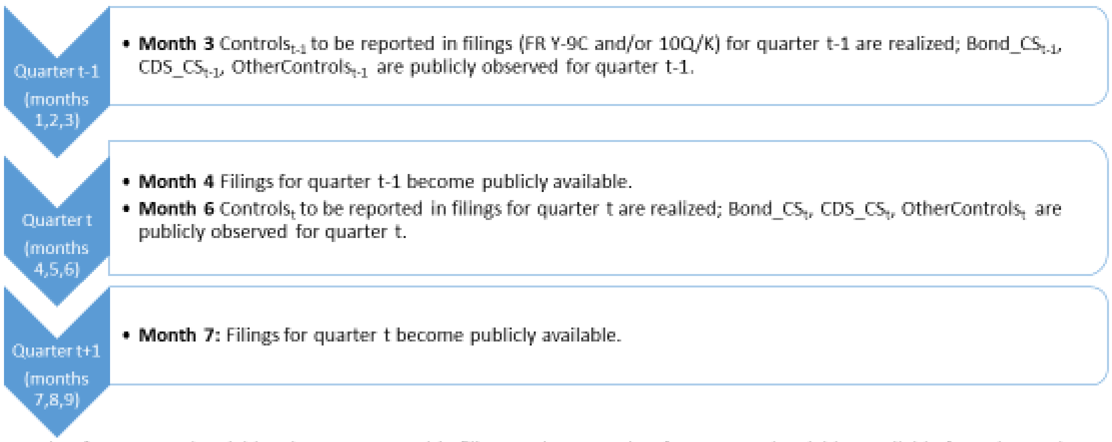
Name	Gvkey	Quarters	DVA¡0	DVA¿0	DVA=0
American International Group Inc.	001487	40	22	18	0
Popular Inc.	002002	4	2	0	2
Bank of Hawaii Corp.	002005	3	0	0	3
Bank of New York Mellon Corp.	002019	6	2	1	3
JP Morgan Chase & Co.	002968	44	19	25	0
Citigroup Inc.	003243	44	22	22	0
Bank of America Corp.	007647	39	22	17	0
Wells Fargo & Co.	008007	5	0	1	4
P N C Finanical Service Group Inc.	008245	23	0	0	23
Keycorp	009783	18	0	0	18
Suntrust Bank Inc.	010187	44	20	16	8
Valley National Bancorp	011861	23	0	0	23
Morgan Stanley	012124	42	19	23	0
Synovus Financial Corp.	013041	5	0	0	5
Fulton Financial Corp.	014172	1	1	0	0
First Bancorp	016821	21	7	12	2
National Penn Bancshares Inc.	017070	11	0	0	11
Old National Bancorp	017095	5	2	3	0
W Holding Company Co Ltd	017157	4	0	0	4
Tompkins Financial Corp.	017240	34	2	0	32
Irwin Financial Corp.	018928	4	2	2	0
VIST Financial Corp.	021595	17	0	0	17
BOK Financial Corp.	024447	12	0	0	12
Cascade Financial Corp.	025719	17	0	1	16
Banner Corp.	061487	44	0	0	44
Flushing Financial Corp.	061585	44	0	1	43
Community Central Bank Corp.	064142	15	0	0	15
First Mariner Bancorp	064194	10	0	0	10
United Security Bankshares	064228	44	0	0	44
Flagstar Bancorp Inc.	064699	19	0	0	19
Umpqua Holdings Corp.	065228	44	0	0	44
First Community Corp.	112295	10	0	0	10
Goldman Sachs Group Inc.	114628	36	18	18	0
Metlife Inc.	133768	28	0	0	28
Principal Financial Group Inc.	145701	28	16	11	1
Alliance Bankshares Corp.	146354	23	0	0	23
Western Alliance Bancorporation	163920	44	0	0	44
Ameriprise Financial Inc.	164708	32	0	0	32

This Appendix provides the list of banks in our sample. It also provides information on the quarters that positive, negative and zero DVA is reported.

Appendix 2.5 Time-line of Market and Accounting Information

This Appendix provides a figure that indicates the time-line that market and accounting information becomes available, as well as a numerical example on how we calculate DVA-estimated changes in credit spreads. The example is based on the DVA disclosures provided in Appendix A (JP Morgan Chase & Co, 2015) and the process is explained in Section 2.3.2.

Figure 2.3: The time-line of market and accounting information



Controls refer to control variables that are reported in filings, *OtherControls* refer to control variables available from the market. Bond(CDS)_CS refers to bond spread (CDS spread).

Calculations:

Delta_Control1$_t$=(Control1$_t$-Control1$_{t-1}$)

Delta_Bond(CDS)_CS$_t$=Bond(CDS)_CS$_t$ –Bond(CDS)_CS$_{t-1}$

Delta_DVA_CS$_t$ (see example below)

Appendix 2.6 Illustration of DVA-estimated Changes In Credit Spreads Calculation

Figure 2.4: Numerical example on how DVA-estimated changes in credit spreads are calculated

Steps	Information from financial reports	Calculations and assumptions
Step 1: Estimate the hypothetical value of liabilities under the FVO in the absence of own credit risk changes ($\widehat{\boldsymbol{FVL}_t}$).	At the end of the accounting period $\boldsymbol{t}$, the fair value of the bond ($\boldsymbol{FVL_t}$) under the FVO is \$62,501 million. The entity discloses debt valuation adjustments ($\boldsymbol{DVA_t}$) of \$169 million.	$FVL_t = \widehat{FV}L_t - DVA_t$ (1) $\widehat{FV}L_t$= 62,501 + 169 = \$62,670 million
Step 2: Estimate the yield to maturity applied to obtain the fair value of liabilities under the FVO ($\boldsymbol{y_t}$).	Principal value of the bond ($\boldsymbol{B}$) is \$63,734 million, the time to maturity ($\boldsymbol{T}$) is 3.18-years, and the coupon rate ($\boldsymbol{c}$) 6.75%. The fair value of the the bond ($\boldsymbol{FVL_t}$) under the FVO is \$62,501 million.	**Assumptions:** A single bond that pays semi-annual coupon $FVL_t = B\left[\frac{c}{y_t}\left(1-\frac{1}{\left(1+\frac{y_t}{2}\right)^{2T}}\right)+\frac{1}{\left(1+\frac{y_t}{2}\right)^{2T}}\right]$ (2) $62{,}501 = 63{,}734 \times$ $\left[\frac{6.75\%}{y_t}\times\left(1-\frac{1}{\left(1+\frac{y_t}{2}\right)^{2\times 3.18}}\right)+\frac{1}{\left(1+\frac{y_t}{2}\right)^{2\times 3.18}}\right]$ $y_t = 7.45\%$
Step 3: Estimate the hypothetical (under no credit risk changes) yield to maturity applied to obtain the hypothetical value of liabilities under the FVO ($\boldsymbol{\hat{y}_t}$).	The principal value of the bond ($\boldsymbol{B}$) is \$63,734 million, the time to maturity ($\boldsymbol{T}$) is 3.18-year, and the coupon rate ($\boldsymbol{c}$) is 6.75%. From step 1 $\widehat{FV}L_t$=\$62,670 million.	$\widehat{FVL_t} = B\left[\frac{c}{\hat{y}_t}\left(1-\frac{1}{\left(1+\frac{\hat{y}_t}{2}\right)^{2T}}\right)+\frac{1}{\left(1+\frac{\hat{y}_t}{2}\right)^{2T}}\right]$ (3) $62{,}670 = 63{,}734 \times$ $\left[\frac{6.75\%}{y_t}\times\left(1-\frac{1}{\left(1+\frac{y_t}{2}\right)^{2\times 3.18}}\right)+\frac{1}{\left(1+\frac{y_t}{2}\right)^{2\times 3.18}}\right]$ $\hat{y}_t = 7.35\%$
Step 4: Calculate the DVA-estimated changes in credit spread (**Delta_DVA_$\boldsymbol{CS_t}$**).	The yield to maturity is equal to the risk free rate plus the credit spread. Given that, the risk free rate of the specific quarter $\boldsymbol{t}$ is the same, the difference between $\boldsymbol{y_t}$ and $\boldsymbol{\hat{y}_t}$ is the change in yield to maturity driven by changes in own credit risk.	Delta_DVA_$CS_t = y_t - r - (\hat{y}_t - r) = y_t - \hat{y}_t$ (4) Delta_DVA_CS_t = 7.45% - 7.35% = 0.10%

Appendix 2.7 Variable Definitions

This Appendix provides definition of the variables used in our analysis, as well as information on the sources.

Explanatory variables used in the main models

- Changes in leverage ($Delta_Lev$): Default is triggered when the leverage ratio becomes sufficiently high. Hence, an increase in leverage is expected to increase credit spreads. We define leverage as the ratio of the book value of liabilities (LTQ) (source: Compustat) to the market value of equity (CSHOQ*PRCCQ) (source: CRSP) plus the book value of liabilities.

- Changes in the spot rate ($Delta_r10$): A higher spot rate leads to a higher growth rate of the value of the firm's assets (or, its risk-neutral drift rate). This results in a reduction in the credit spreads because of lower default probability. We use the quarterly series of 10-year Treasury rate as a proxy for the spot rate (source: Federal Reserve).

- Changes in the slope of the yield curve ($Delta_Slope$): The slope of the term structure positively affects the future spot rates. An increase in the slope, increases the expected future spot rate leading to a decrease in credit spreads. We define the slope of the yield curve as the difference between the 10-year and 2-year Treasury rates (source: Federal Reserve).

- Changes in asset volatility ($Delta_Sigma$): Since option value increases with volatility, we expect a positive relationship between changes in asset volatility and changes in credit spreads. We estimate equity volatility using the standard deviation of daily stock returns over the past 150 days. Then, we use Merton model to estimate the value and volatility of assets simultaneously. We assume a maturity of 0.25 and use 3-month Treasury yield as a proxy for the risk free rate (source: CRSP).

- Changes in business climate ($Delta_Climate$): Changes in credit spreads can be a result of changes in the expected recovery rate, even if the default probability remains the same. As the expected recovery rate is an increasing function of business climate, we expect business climate to negatively affect credit spreads. We use the quarterly S&P returns from CRSP as a proxy for changes in the business climate (source: CRSP).

- Changes in the probability or magnitude of downward jump ($Delta_Jump$): Given that implied volatility smiles in observed option prices, the market seems to account for negative jumps in the value of the firm. Therefore, an increase in the probability or the magnitude of a downward jump is expected to increase the credit spreads. We use changes in the slope of the implied volatility of options on S&P500 index future to capture the changes in the probability of such a jump (source: Datastream).

Variables used in the first-stage of Heckmans model

- Size of the bank ($Size$): On the one hand, larger firms are more likely to have liabilities that are traded, and therefore reported at Level 1 and 2. On the other hand, larger banks have more resources to develop internal models for valuation, making them more likely to carry Level 3 assets and liabilities. To measure size, we use the natural logarithm of the total assets (source: Compustat).
- Audited by big 4 ($Big4$): If the bank is using big four auditors are more likely to use firm-specific model inputs to classify the liabilities under the FVO as Level 3. Big4 is a variable that takes the value 1 if the bank uses a Big 4 auditor and zero otherwise (source: Bank Regulatory).
- Use of FVO for assets ($FVOA$): Firms that use the FVO for assets choose to report firm specific inputs, so they are more likely to value liabilities at Level 3. FVOA is an indicator variable that takes the value 1 if the bank uses the FVO for assets in the particular quarter and zero otherwise (source: Bank Annual Reports).
- Importance of liabilities under FVO (FVL/TA): If liabilities under the FVO are important for the banks, we expect that the banks invest more in resources to develop internal models for valuation, making it more likely to measure liabilities at Level 3. However, it is possible that the FVOL is used more frequently by larger banks. Larger banks are more likely to have liabilities traded, and therefore reported at Level 1 and 2. We use the ratio fair value of liabilities under the fair value option to total assets to capture the importance of this item to the balance sheet (source: Bank Annual Reports).

Chapter 3

Evidence on information differences in reported DVAs and market information-estimated DVAs

3.1 Introduction

In recent decades, accounting standard-setters the Financial Accounting Standards Board (FASB) and the International Accounting Standard Board (IASB) have increased the use of fair value measurement for financial instruments. However, the recent financial crisis led to a vigorous debate surrounding whether the use of fair value accounting (FVA) in financial statements is more representative of an entity's financial position than other accounting measurement bases (Ryan 2008). A critical evaluation of FVA's relevance and reliability, which includes both academics and professionals, is motivated by the issuing of Financial Accounting Standards (SFAS) No. 159, *The Fair Value Option for Financial Assets and Liabilities* (FASB 2007).[1] SFAS 159 provides firms with an option to irrevocably expand the scope of financial instruments accounted

[1] Prior to FASB, the International Accounting Standard Board (IASB) adopted the fair value option in the IAS No. 39 (IASB 2006).

for using fair value, with unrealized gains or losses flowing to earnings.[2] The adopter records unrealized gains (losses) in bottom-line net income that are attributable to the deterioration (improvement) in firms' creditworthiness. These gains and losses driven by the fair value option of liabilities (FVOL) are commonly referred to as debt valuation adjustments (DVAs).[3]

The recognition of DVAs in net income has lead to competing arguments about whether the accounting results of DVAs are counterintuitive or not. This concern is driven by the fact that DVA gains (losses) would be recognized in accounting earnings as result of negative (positive) economic effect. Specifically, according to SFAS No. 159, the DVAs are computed as differences between the fair value of liabilities at the beginning and the end of one period that is attributable to the changes in firms' own credit risk. If credit risk increases, absent the changes in the interest rates, the fair value of liabilities decreases, yielding unrealized gains. Among existing research, Barth et al. (2008) use changes in credit rating multiplied by the debt-to-assets ratio as a proxy for DVAs. They find that the reduction in equity returns associated with increases in credit risk is attenuated by the presence of debt. Their findings imply that DVAs should be candidates for inclusion in earnings if the objective of financial statements is the faithful representation of the firm's liabilities and economic performance. However, opponent believe that recognizing DVAs in accounting earnings results in counterintuitive gains and losses, which misrepresents real economic condition and entail that outcomes are difficult to interpret (Gaynor et al. 2011).[4] Moreover, there are indications that banks manipulate DVAs to smooth earnings during the recent financial crisis (Dong et al. 2016).

Despite its relevance for financial institutions during the last financial crisis, research on the recognition of DVAs is limited for two primary reasons.[5] First, few entities, mainly large financial institutions, adopt the fair value option so that the observations of reported DVAs are limited. Second, the relevant information on DVAs is optionally disclosed in the footnotes in a way that is opaque compared to other accounting items with standardized disclosures.

[2]The intent for issuing this standard is well discussed in Guthrie et al. (2011). The rationale is 1) to mitigate artificial earnings volatility created by the mismatch between assets and liabilities; 2) to expand the use of fair value measurement for financial instruments; 3) to better reflect inherent economic influence without using complicated hedging accounting.

[3]From December 2017, DVAs are no longer recognised in the net income, but in other comprehensive income.

[4]These counterintuitive gains (losses) greatly affected the net incomes of the largest U.S. bank holding companies in 2008, exemplified by Morgan Stanleys DVA gains flipping the \$3.3 billion losses into \$1.7 billion profits attributable to credit deterioration.

[5]Prior research mostly examine the valuation and risk implications of recognizing DVAs (Fonte et al. 2019; Gaynor et al. 2011; Lipe 2002).

Understanding the information contained in the reported DVAs is helpful to stakeholders to understand the underlying economic performance of adopters, considering the counterintuitive accounting effects of DVAs recognition. Specifically, stakeholders only access public available information. However, the reported DVAs by management require complex approaches and data resources in the measurement process. According to SFAS No. 157, the valuation of financial instruments suggests managers to employ observable and/or unobservable market data in a range of valuation techniques, dependent on the instrument type.[6] Kengla and Jonghe (2012) surveyed 19 financial institutions in 2012, and obtained information on current practices for managing and measuring DVAs on liabilities designated under the fair value option. They highlighted that four were using CDS spreads, four were using primary issuances data (based on the latest issuances), four were using secondary market data (as for example bond spreads), five were using curves set internally by treasury and/or asset-liability management departments, while the rest were using a blended approach (a combination of information including observable inputs and internal data). Therefore, the reported DVAs attracts stakeholders' concerns about the private information used by management in the estimation of DVAs,[7] especially an opportunistic and adverse selection behavior that may exist in the adoption of FVOL (Wu et al. 2016; Henry 2009).

To address these concerns, we compare the reported DVAs provided by managers with the estimated DVAs based on market information, denoted as market information-estimated DVAs. If the market information-estimated DVAs differ from the reported DVAs significantly, we could state the internal credit risk assessment reflects private information not covered by the external credit risk assessment efficiently, as the guidance of DVAs calculation permits management to use the private information if the market for the underlying liabilities is illiquid. Alternatively, if the market information-estimated DVAs are close to the reported DVAs, we could state the external credit risk assessment captures the information on credit risk through financial reports in a timely manner.

To estimate the market information-based DVAs we rely on the structural credit risk models rather than the widespread market measures of credit risk (i.e., CDS spreads, bond spreads) for

[6]FASB (2006) requires financial liabilities under the FVOL to be disclosed in accordance with the three-level measurement hierarchy. Level 1 fair value estimates are based on quoted prices for identical assets or liabilities in active markets. Level 2 estimates are based on quoted market prices for similar assets or liabilities and inputs other than quoted prices, as for example interest rates and yield curves, while Level 3 estimates are based on unobservable entity-supplied inputs for the asset/liability.

[7]There are extant literature stating that the management may exploit the internal information at the cost of stakeholders by selectively reporting information, and in turn, mislead stakeholders if the interest of management is not identical to that of stakeholders (Beyer et al. 2010; Healy and Palepu 2001)

two primary reasons. First, the market measures of credit risk are expressed by a unit-free standardized measure (i.e., basis points) rather than dollar gains/losses that are non-compatible to the reported DVAs when we compare their magnitudes. Second, bond spreads are not perceived as a clean measure of credit risk because they are also influenced by factors like tax, liquidity, and duration. CDS spreads are only available for large financial institutions so that using this measure would decrease our sample size considerably.[8]

To generate a clear measure of credit risk with the compatible format to the reported DVAs, we rely on structural credit risk models for several reasons. First, structural models are able to provide guidance about the theoretical determinants of default risk and the unique structure that can extract default-related information from the equity market.[9] Second, the estimated results from structural models represent the pure default risk of counterparty in financial contracts. However, other credit assessments CDS spreads and bond prices can be noisy due to the existence of other risk factors (Leland 2009; Tang and Yan 2007; Ericsson et al. 2006; Blanco et al. 2005). Third, the option theory-based default probability is particularly attractive because the final formula is a function of 'observable' variables including leverage ratio, asset market value and asset volatility.[10] Fourth, structural models use equity market information to make a forward-looking prediction of the default risk.[11] Fifth, structural models have been successfully implemented into industry. A benchmark in the application of structural credit risk models is the KMV model (Crosbie and Bohn 2003).

To the best of our knowledge, this is the first paper to investigate the information contained in DVAs by comparing its magnitude to market information-estimated DVAs. Partly, this reflects the fact that the large sample of firms reporting DVA data has only recently become available in common database. Our investigation allows us to discuss the extent to which the external credit risk assessment captures the information on credit risk exploited by the internal measurement, that is, whether estimated DVAs from structural credit risk models are informative to regulators and investors.

[8]Out of 38 bank holding companies in our sample, 13 banks issue CDS.

[9] Leland (2012) examines the ability of structural credit risk models to capture the historical default frequencies across bonds with different ratings. He concludes that the structural models fit the empirical long-term default frequencies quite accurately for investment-grade and speculative-grade bonds. This paper uses the default frequencies reported in Moody's (2001). The investment grade bonds in this credit rating system are rated above "Baa" and "Baa"; the non-investment grade otherwise is rated below "Baa".

[10]The asset market value and asset volatility are in fact 'quasi-observable' variables, because these two values are generally estimated based on equity value and equity volatility.

[11] Krainer and Lopez (2004) suggest that market information, especially equity market information, should be included in the oversight of financial institutions.

In this work, we implement the Merton (1976) and Leland (1994) models to estimate the market information-estimated DVAs, using a sample of U.S. bank holding companies with 887 bank-quarter observations over the period of 2007-2017. We focus on banks, as they are the main users of financial instruments for which the FVOL is applicable. Therefore, the effects of DVAs recognition and disclosure are expected to be more pronounced, compared to industries that make only limited use of financial instruments.

We first compare the distribution of market information-estimated DVAs and the reported DVAs. This is necessary to discuss the dispersion of both the estimated and observed DVAs over the sample period due to large standard deviation of estimated DVAs. Then, we compute the measure of estimation errors to investigate the extent to which the market information-estimated DVAs deviate from the reported DVAs. Specifically, we compute the signed differences between the estimated and reported DVAs as a measure of bias and unsigned differences between the estimated and reported DVAs as a measure of accuracy. The positive (negative) signed differences indicate that structural models overestimate (underestimate) the DVAs. Large unsigned differences indicate the market information-estimated DVAs remarkably deviate the reported DVAs, suggesting the reported DVAs convey private information which is not reflected in the capital market. Alternatively, small unsigned differences indicate that the capital market could capture the information contained in the reported DVAs timely through financial reports. To investigate whether the unsigned differences between the estimated and reported DVAs are driven by the model misspecification, we compare the performance of pricing DVAs between the Merton model and the Leland model, as the Leland model incorporates some additional information.[12] Finally, we examine whether estimation errors are prone to systematic errors. In particular, we conduct multivariate regressions of estimation errors on factors that represent the firm-specific variables, bond-specific variables and macroeconomic variables. The significant variables suggest the estimation errors from the structural models are associated with them.

We find that the market information-estimated DVAs by structural models deviate the reported DVAs significantly, especially when the banks' own creditworthiness is volatile. Specifically, the Merton and Leland models tend to overestimate the DVAs on average. However, the analysis of estimation errors by year suggests that both the Merton and Leland models tend to underestimate the DVAs when the banks' own creditworthiness is volatile (i.e., the extremely high or low estimates are clustered around the 2008 financial crisis and 2011 sovereign debt crisis).

[12] The Leland model relaxes some assumptions in the Merton model by considering the endogenous default barrier, tax rate and default costs.

Conversely, in stable credit risk conditions, these two models have a tendency of overestimation and their performance with regard to DVA estimations gets better. The results in analyzing the systematic estimation errors also provide consilient evidence that structural models lead to larger estimation errors for banks with higher market leverage and asset volatility. In both the Merton and Leland models, the leverage ratio and asset volatility are two main channels of default risk. These results suggest reported DVAs convey more private information during the deterioration of creditworthiness.

Further, we investigate the estimation errors in four sub-samples: zero DVA reporters, non-zero DVA reporters, positive DVA reporters and negative DVA reporters. We compare the pricing performance over these four sub-samples due to their different effects on accounting earnings. Specifically, unlike zero DVAs, the reported non-zero DVAs could result in unrealized DVA gains and DVA losses. Furthermore, we split non-zero DVAs into positive DVAs and negative DVAs, as positive (negative) DVAs result from deterioration (improvement) of firms' credit risk that could in fact lead to economic losses (gains). Cedergren et al. (2012) find that compensation committees place different weights on positive DVAs and negative DVAs. Therefore, we compare the estimation errors between positive and negative DVA reporters to investigate whether management estimate DVA gains and DVA losses differently.

We find that the estimates for zero DVA and non-zero DVA reporters are significantly different. In particular, the Merton and Leland models underestimate the DVAs on average for zero DVA reporters, but overestimate the non-zero DVAs. Moreover, comparing to non-zero DVAs, the unsigned differences for zero DVAs are immaterial, suggesting the estimation errors in full sample are mainly attributed to zero DVA reporters. Further, we split non-zero DVAs into positive and negative DVAs due to their opposite accounting effects — DVA gains and DVA losses. The insignificant t-statistics of equality test indicate that the unsigned differences between these two groups are equal. However, the measure of signed differences suggests the Merton and Leland models underestimate DVA gains but overestimate DVAs losses. The results suggest that management estimate positive DVAs and negative DVAs differently, while the capital market treats them indifferently.

Finally, we compare the unsigned differences between the Merton and Leland models. The smaller unsigned differences by the Merton model suggest the Merton model outperforms the Leland model in terms of pricing DVAs, especially when the firms' credit risk increases. This finding indicates that incorporation of additional information in structural models does not improve the performance of estimating DVAs.

This chapter is organized as follows. Section 3.2 provides informaiton on the disclosure and recognition of DVAs. We also introduce structural credit risk models and their empirical applications. Section 3.3 discusses the sample selection and provides descriptive statistics. Section 3.4 presents the implementation of structural credit risk models and estimates the market information-estimated DVAs. Section 3.5 provides empirical results and discusses the performance of models. Finally, we summarize the main findings of this chapter in Section 3.6.

3.2 Literature review and research questions

3.2.1 Fair value liabilities and debt valuation adjustments (DVAs)

In recent decades, the FASB has adopted fair value measurement for a wide range of financial instruments. In 2006, the FASB issued SFAS No. 157 *Fair Value Measurements* that provided a unified definition of fair value and established a framework for the disclosures of fair value measurements. Further, SFAS No. 159 *The Fair Value Option for Financial Assets and Financial Liabilities* extended the scale of financial instruments measured on a fair value basis, with unrealized gains and losses going to net income. This standard permits firms to elect the FVO for eligible financial instruments on an instrument-by-instrument basis at the inception of the instruments or upon adoption of SFAS No. 159 if the inception of the instrument proceeds the adoption date. This adoption is irrevocable, suggesting that firms cannot stop the use of fair value measurement unless the selected instruments expire or are sold.

Debt valuation adjustments stems from the application of SFAS No.157 and SFAS No. 159 on eligible financial liabilities. Specifically, the application of SFAS No. 157 requires adopters to reflect changes in their own credit risk in the measurement of the fair value of liabilities and then any resulting adjustments are recognized in the accounting earnings. The adoption of SFAS No. 159 allows firms to measure eligible financial liabilities at fair value that would otherwise be measured at historical amortized costs. The changes in the fair value of liabilities under the adoption of SFAS No. 159 attributable to the changes in firms' own credit risk are referred to as DVAs.

Firms have discretion over the estimation of DVAs, especially when underlying financial liabilities are illiquid. Specifically, SFAS No.157 allows firms to rely on unobservable entity-supplied inputs for measurements if no same or similar liabilities are traded in the market. Moreover, we find a few banks that provide the relevant information, although the SFAS No. 159 requires banks to disclose information on DVAs in SEC filings when they are significant. Therefore, users of financial statements have difficulty in understanding how DVAs are estimated, although prior studies provide strong evidence on the value-relevance of DVAs (Fontes et al., 2018; Chung et al., 2012; Barth et al., 2008). Therefore, understanding the information contained in the reported DVAs is important for financial statement users to understand the underlying economic performance of adopters.

3.2.2 Structural credit risk models

In this study, we compare the reported DVAs with the market information-estimated DVAs to investigate the extent to which the information in the reported DVAs is different from the one provided by the market. The market information-estimated DVAs are estimated by implementing structural credit risk models originated by Merton (1974), in which securities are priced as contingent claims on the process of firm value. In the framework of Merton (1974), the debt value is considered as the put option on the assets of the firm. The default risk is driven by business risk (asset volatility) and financial risk (leverage).

Despite the innovative nature of the Merton model, its simplified assumptions lead to shortcomings in its application (Anginer et al., 2014; Hovakimian et al., 2012; Sonke et al., 2007; Bongini et al., 2002). It assumes that the liability structure of a firm consists of a single zero-coupon bond, and the bankruptcy is only triggered at maturity. Prior research find that the Merton model has a tendency towards the underestimation of bond spreads. Following its publication several articles, including Leland (1994), Longstaff and Scheartz (1995) (LS) and Colline-dufresne et al. (2001) (CDG), have relaxed the assumptions in the Merton model to incorporate more realistic conditions. Specifically, Leland (1994) extends the Merton model by considering an endogenous default barrier, bankruptcy costs and tax savings of the debt. Holding other assumptions the same as the Merton model, the LS model considers stochastic interest rates rather than the flat form of the term structure. The CDG model extends the LS model to incorporate a stationary leverage ratio, allowing the firm leverage to be mean reversed to its target leverage ratio over the long run. Appendix 3.1 provides a discussion of the Merton and Leland models with regards to their assumptions.

Among these four classical structural credit risk models, we only apply the Merton and Leland models to estimate DVAs, as these two structural models took major step in pricing debt by incorporating exogenous and endogenous default barrier respectively. Moreover, empirical results indicate the Leland model **is an exception in that it overpredicts spreads on most bonds, although it also share the problem of inaccurate estimation** (Eom et al., 2004). Therefore, we denote the estimation errors from the Merton model as the benchmark, and compare them with the estimation errors from the Leland model to investigate whether the deviations between the reported DVAs and market information-estimated DVAs are driven by model misspecification.

In this paper, we denote the estimated DVAs from the Merton and Leland models as the market information-estimated DVAs, as the nature feature of structural credit risk models rely on public available information to price DVAs. Specifically, structural models consider credit risk as a function of financial leverage, asset value and asset volatility, which are computed from the information from financial reports and capital market. Thus, the changes in the fair value of liabilities due to changes in credit risk estimated by structural models — market information-estimated DVAs — are influenced by market information.

Even though a few studies attempt to criticize the implementation of structural models in financial institutions due to their high leverage and complex liability structure (Eom et al. 2004), many papers have appropriately used modified structural credit risk models in banks to investigate a number of interesting questions. Tsesmelidakis and Merton (2012) implement the CreditGrade model, which is based on the work of Merton (1976) by assuming a stationary leverage, to value the "too big to fail" (TBTF) premium in financial institutions. Chen et al. (2014) use a flexible, lattice-based structural credit risk model to examine the term structure of default probabilities for Lehman Brothers. These empirical applications provide strong support for the feasibility of structural models in banks. Moreover, in pricing DVAs, the estimation errors due to model misspecification could largely cancel out in computing the intertemporal differences of bond prices due to the changes in firms' own credit risk. In particular, the proportion of bond price that is overestimated by structural models could be offset after computing the differences of bond price between two subsequent periods.

3.3 Sample selection and descriptive statistics

3.3.1 Sample selection

Our sample focuses on U.S. bank holding companies that filed quarterly FR Y-9C with the Federal Reserve from 2007 to 2017. We start with 2007 because FASB allowed early adoption of SFAS 159 under certain conditions, and the effective date of standard for all fiscal period begins after November 15, 2007.[13] We restrict our sample to bank holding companies because they are required to report detailed and standardized disclosures on Fair Value Option for Financial Liabilities (FVOL) election and DVAs in their regulatory filings.[14] Data of the FVOL and DVAs are downloaded from the Bank Regulatory database. For those banks reporting missing value in FVOL and/or DVAs we also hand-collect the items from SEC filings.

Table 3.4 provides the sample selection procedure. Bank holding companies that select certain eligible liabilities under FVOL report two data items in FR Y-9C reports. One is the total gains and losses on fair-valued liabilities under FVOL (bhckf553), and the second is the gains and losses on fair-valued liabilities under FVOL attributable to changes in banks' own credit risk (bhckf554). Figure 3.1 in Appendix 3.2 provides an example of such reporting.[15] A bank holding company that reported bhckf553 suggests that this bank has adopted the fair value option to measure certain liabilities and has to consider the effect of changes in banks' own credit risk in measuring the fair value of selected liabilities. Thus, if the bank holding company reports bhckf553, it will also report bhckf554 unless the amount is zero or immaterial.[16] In our sample selection, we require bank holding companies to report bhckf553 or bhckf554 at least once over the sample period from the first quarter they adopted FVOL through to the fourth quarter of 2017. This process gives us 85 bank holding companies. We also require that banks are publicly

[13] SFAS No. 159 is effective for fiscal years beginning after November 15, 2007. The early adoption is permitted with the requirement of making adoption decision within 120 days after the beginning of the fiscal year and prior to the issuance of any financial statements. We hand-collected each bank holding company's adoption date in its 10-K filings.

[14] Following the Bank Holding Act of 1956, we define a bank holding company as a company which controls one or more banks. In order to regulate the activities of bank holding companies, FR Y-9C reports are required to be disclosed quarterly by the Federal Reserve Bank of Chicago.

[15] An example of the relevant disclosure in SEC filings is also reported in Appendix 3.2. Comparing the DVAs reported in SEC filings and FR Y-9C, we find FR Y-9C reports the cumulative DVAs of the year. In the following empirical tests, we compute the quarterly amount of DVAs from the reported cumulative magnitudes.

[16] In some unusual cases, bank holding companies report bhckf554 but miss bhckf553. We consider those banks electing FVOL, and those missing observations are erroneous entries. The missed bhckf533 does not affect our empirical tests because they are only used in the sample selection procedure.

traded, with 150 trading-day observations available before the end of each quarter over the sample period to estimate our explanatory variables. This process reduces our sample to 46 banks. Finally, we hand-collect information on maturity, fair value and principal of liabilities under the FVOL from SEC filings, removing from our sample the banks that do not provide this information. This information is used as the model input to estimate the market information-estimated DVAs. This sample selection procedure yields a sample of 887 bank-quarter observations, representing 38 unique banks. Table 3.5 provides a list of all the banks in our sample.[17] The vast majority of our sample are traditional commercial banks based on SIC codes (31 unique bank holding companies or 71.82% of bank-quarter observations).[18]

3.3.2 Descriptive statistics

Table 3.6 provides information on the average value of fair value and principal value of liabilities under FVOL per year. Early adopters accounted for the greatest amounts of liabilities under FVOL on average, whereas the bank-quarter observations stay the lowest level in our sample period. After the effective adoption date, the bank-quarter observations in the following three years are two times more than the early adopters and then decrease gradually, together with the reduction in the magnitudes of the balanced principal value of liabilities under the FVOL.

In Table 3.7, Panel A summarizes the frequency of bank-quarter DVAs per year over the sample period with the decomposition of negative, zero, and positive DVA groups. In our sample, 60.88% of bank-quarters (540 observations) report zero DVAs. The remaining 39.12% of bank-quarter observations (347) have non-zero values, consisting of 176 negative DVAs and 171 positive DVAs. This indicates that the effect of own credit risk changes in the fair-valued liabilities was zero or immaterial in more than half of bank-quarters. Over the sample period, few banks reported DVAs in 2007, as it includes only early adopters of the FVOL.[19] The number of bank-quarters increases from the effective year of 2008 and decreases after 2010. As the adoption of FVOL is irrevocable, the reduction in the DVA recognizers is due to the existence of liabilities measured

[17]In this table, the bank-quarter observations (N), the amounts of reported DVAs (DVAs), fair value of liabilities under FVOL (FV) and the face value of liabilities under FVOL (PV) are reported for each bank.

[18]The remainder of the sample includes 7.67% life insurance and 20.52% brokers and dealers. They must run at least some banking activities because they are regulated by Federal Reserve and file FR Y9-C reports.

[19]Out of 38 bank holding companies in our sample, 14 banks are early adopters.

under the fair value option (e.g., bonds expired).[20]

To detect the magnitudes of FVOL adoption, we report information on DVAs for large banks (Panel B) and other banks (Panel C) respectively in Table 3.7. We classify a bank as a large bank if it has a book value of assets greater than $50 billion.[21] The number of bank-quarters is almost equally split into large banks (429 observations) and other banks (458 observations). In addition, we find that large banks are prone to report non-zero DVAs, with 72.73% of bank-quarter observations have non-zero value (312 out of 429). By contrast, the reported zero DVAs are mainly from other banks, of which 92.36% of DVA bank-quarters are zero (423 out of 458).

Descriptive statistics on the characteristics of liabilities account for FVOL are presented in Table 3.8. Panel A presents the information on all sample banks (887 bank-quarters). Panel B includes only the bank-quarters that non-zero DVAs were reported (347 bank-quarters), and Panel C reports bank-quarters that only zero DVAs were reported (540 bank-quarters). We hand-collect information on maturity, fair value and principal of liabilities under the FVOL from financial statements.[22] We download coupon rates of straight bonds from Datastream. If a bank adopts multiple bonds under FVOL, we measure maturity and coupon as the weighted average of maturity and coupon respectively, for each of banks' liabilities, weighted by the fair value of liabilities at the end of the period.

On average, the non-zero DVA recognizers adopted the FVOL for more liabilities than zero DVA recognizers. In particular, the average principal value of liabilities under FVO in non-zero DVA recognizers is$55,000,173,000, which is 88 times higher than those in zero DVA recognizers ($624,464,000). It is consistent with Cedergren et al. (2014), who express DVAs as an increasing function of the amount of liabilities under FVOL and the changes in credit risk (i.e., asset risk). That is, the level of reported DVAs is also affected by the amount of liabilities under FVOL apart from the changes in credit risk. Therefore, the large magnitude of liabilities account for FVOL could lead to the large magnitude of DVAs given the small changes in banks' own credit

[20]The FVOL is made on an instrument-by-instrument basis upon inception of the instrument or upon adoption of SFAS No. 159 if inception was earlier. A bank may not necessarily adopt new eligible liabilities under FVOL in each quarter after adoption. Therefore, the liabilities under FVOL may exist if the adopted liabilities was expired without rolling over new liabilities.

[21]$50 billion is used as a threshold for most requirements of enhanced supervision by the Federal Reserve.

[22]In Appendix 3.2, using JP Morgan Chase & Co as an example, Table 3.1 provides information on the disclosure of the fair value of financial liabilities under FVOL. Table 3.2 provides information on the differences between fair value and principal value of liabilities under FVOL. Table 3.3 provides information on maturity distribution across various liabilities.

risk. Besides, the term to maturity varies from 1 year up to 39 years, and the average coupon rate is similar in non-zero and zero DVA recognizers.

3.4 DVAs Estimation

In this section, we implement the Merton model and the Leland model to estimate market information-estimated DVAs. Consistent with the framework of Black and Scholes (1973), equity and debt in the Merton model represent two different claims on the firm value. Equity-holders have the legal ownership of the firms' assets, owe a fixed amount of zero-coupon debt and effectively hold a put option on the firms' assets with the exercise price equal to the face value of debt. Debt-holders own the face value of debt and have a short position in the put option on the firm. The value of the two claims sum up to the unlevered value of the firms' assets, so the capital structure irrelevance principle holds (Modigliani and Miller, 1958). Debt valuation can be undertaken using standard methods of option pricing. The risk and the return distribution of debt are inferred from the market value of assets, asset volatility, risk-free rate, time to maturity and the face value of outstanding liabilities. Since all the inputs in structural models are solely determined by market information, debt value estimated from a structural credit risk model can be seen as the market information-estimated valuation.[23] Thus, after controlling for the effect of changes in the risk-free rate, the estimated changes in the value of *same* debt between two subsequent periods are referred to as the market information-estimated or estimated DVAs.

The Leland model relaxes the assumptions in the Merton model by introducing corporate taxes and bankruptcy risk. Instead of the zero-coupon debt structure, the Leland model considers a perpetual continuous coupon bond which leads to tax shields from debt. Bankruptcy costs occur when the firm value breaks the default threshold. By contrast with the exogenous default threshold in the Merton model, the Leland model derives the endogenous default barrier within the optimal capital structure. By explicitly introducing tax savings and bankruptcy costs, the levered firm value is not equal to the unlevered firm value. Rather, the levered firm value increases with tax shields and decreases with bankruptcy costs, which allows a classic trade-off in this model. In the Leland model, the debt value is inferred from the market value of assets, asset volatility, risk-free rate, perpetual coupon rate, tax rate and recovery rate. Similar to the Merton

[23] The market value of assets and asset volatility are simultaneously estimated by solving two systems of equations which only involve the stock price, stock volatility and firm liability structure.

model, asset value and asset volatility are determined by market information on the stock price. The pricing formulas of these two models are discussed in Appendix 3.1.

3.4.1 Implementation

This section presents the information on the calibration procedure that estimates the parameters of structural credit risk models. In Table 3.9 we discuss the calibration methods and data sources that are used to estimate these parameters.

3.4.1.1 Term Structure of Risk-Free Rate

In order to calibrate the structural credit risk models, it is necessary to estimate a term structure for the risk-free rate. Several methods can be used to model the risk-free yield curves: for example, the Nelson and Siegel (1987) model and the Vasicek (1977) model. In Eom et al. (2004), these two models were applied, and the estimated term structures were very similar. In this paper, we choose to implement the Nelson and Siegel curve to fit the risk-free yield curve.

In the Nelson and Siegel model, let $r(t, T; \Theta)$ denote the spot rate at time t with a term equal to $T - t$ predicted by a particular model characterized by a parameter set Θ. At the end of each quarter, we use the constant maturity treasury (CMT) rates, obtained from the Federal Reserve Board's website, to fit the model on the day t. We choose parameters in Θ to minimize the sum of squared errors, where the error is measured as the deviation between the model yield and the market yield. The specific model in the Nelson and Siegel (1987) is:

$$r(t, T; \Theta) = \beta_0 + \delta_1(\beta_1 + \beta_2)\frac{(1 - e^{-(T-t)/\delta_1})}{T - t} - \beta_2 e^{-(T-t)/\delta_1} \tag{3.1}$$

where $\Theta = (\beta_0, \beta_1, \beta_2, \delta_1)$, and β_0 and δ_1 need to be positive.

3.4.1.2 The Merton (1974) Model

The Merton model requires the use of five parameters: asset value, asset volatility, the face value of debt, the maturity of the debt and risk-free rate. The points below demonstrate the estimation process for these parameters.

- *Maturity of liabilities under FVOL* (T_B): The Merton model prices appropriately a single specific corporate debt — zero-coupon debt. However, all banks in our sample not only adopted multiple types of debt measured under FVOL, but also traded debt with coupon payments. Therefore, some assumptions have to be adopted in order to convert 'real debt' into 'synthetic Merton debt'. We consider the duration of each bond as the proxy for the maturity of Merton zero-coupon debt.[24] By definition, the duration of a bond discounts the weighted average of the maturity of each coupon payment and the final principal at the yield to maturity, with the weights by using the present value of each payment. Because banks in our sample only disclose the maturity distribution of various debt in their SEC filings,[25] we first estimate the weighted average maturities of portfolio debt, with the weights being based on the debt value. Then we convert these weighted average maturities into the duration of a portfolio. This approach takes the time to maturities of each payment into consideration, which returns a 'synthetic maturity' of Merton zero-coupon debt. By using this approach, we implicitly assume that the liability structure will remain the same over time and that no bankruptcy will happen before this portfolio duration.

- *Balanced principal value of liabilities under FVOL* (B): We hand-collect the remaining principal value of financial liabilities under FVOL from SEC filings.[26] In our sample, we implicitly assume all debt under FVOL to be strict bonds with constant coupon rates, which is the main type of debt account for FVOL. Then, the balanced principal value of bonds in the Merton model is computed as follows. We discount all the coupons and principal of each bond at the corresponding risk-free rate — term structure of risk-free rate from Nelson and Siegel model — to time zero, and then compound the sum of their present value to the 'synthetic maturity' of the Merton zero-coupon debt. This final value is denoted as the balanced principal value of 'synthetic Merton debt', which incorporates all payments of bonds. The balanced principal value is determined by solving the two following equations:

$$PV = \sum_{t=1}^{T} \frac{C \times F}{(1+r_t)^t} + \frac{F}{(1+r_T)^T} \tag{3.2}$$

$$B = PV \times (1 + r_{T_B})^{T_B} \tag{3.3}$$

[24] Eom et al. (2004) develop the Merton model with considering each coupon as a separate zero-coupon bond and then value them by using the Merton model separately.

[25] The Table 3.3 in Appendix 3.2 provides the presentation of the maturity distribution of debt under FVOL.

[26] In Appendix 3.2, Table 3.2 provides the presentation of the difference between aggregate fair value and the aggregate remaining contractual principal balance outstanding by JP Morgan Chase & Co as of September 31, 2015.

where C, T and F is the price-weighted average coupon rate, price-weighted average term to maturity and principal value of debt under FVOL. And here, r_t is the risk-free rate of Nelson and Siegel curve with the term t.

- *Asset value* (V) *and asset volatility* (σ): We estimate the quarterly asset value (unlevered firm value) and asset return volatility by undertaking an option theory-based method introduced by Black and Scholes (1973) and Merton (1974). By using the option nature of equity, we can express the asset value and asset volatility associated with the equity value and equity volatility.[27] This procedure is similar to the process used to determine the implied volatility of an option from the observed option price. This calibration is illustrated as follows. Given that V and E represent a bank's market value of asset and equity value, σ and σ_E denote as a bank's asset volatility and equity volatility, TL denotes the book value of total liabilities with maturity of T and r is the risk-free rate, we use the following system of equations to describe their relations:

$$E = V_0 N(d_1) - Be^{-rT} N(d_2) \tag{3.4}$$

$$\sigma_E = \frac{V}{E} N(d_1)\sigma \tag{3.5}$$

where d_1 and d_2 are defined in Eq. 3.24 in Appendix 3.1. Eq. 3.4 expresses the equity value as a function of the asset value and Eq. 3.5 describes the relationship between the asset volatility and equity volatility. To reflect the relevant horizon, we set the maturity T as 0.25,[28] and the 3-month CMT yield as a proxy for the corresponding risk-free rate. Moreover, the annual equity volatility is estimated as the standard deviation of daily return over 150 days before the observation date times the square root of 252. Having observed or estimated E, σ_E, r, T and B, we can compute the asset value V and asset volatility σ by numerically solving the system of equations.

3.4.1.3 The Leland (1994) Model

Similar to the calibration procedure in the Merton model, the Leland model requires six parameters: risk-free rate, perpetual coupon rate, corporate tax rate, recovery rate, unlevered firm value

[27] Vassalou and Xing (2004) use an interactive process to obtain a time series of asset values that allows the further computation of asset volatility.

[28] This maturity assumption follows Liao et al. (2009), it is reasonable to set the maturity of debt as 0.25 year because all data-type used in the estimation of these two variables is quarterly. Moreover, the financial data in SEC filings need to be audited by public investors, indicating the public investors could make a decision on holding or selling securities in the review process quarterly (i.e., the exercise date).

and asset volatility.

- *Leland model-implied risk-free rate* (r_{Leland}): The Leland model modified the Merton model by considering a single perpetual coupon debt, and it is considered reasonable to use a continuous rate to discount the perpetual coupon payments. The risk-free rate obtained from the Nelson and Siegel model only reflects the spot rate with the corresponding term. Therefore, we construct an alternative flat interest rate as follows. We compute the Leland model-implied risk-free rate (r_{Leland}) which makes the present value of a 30-year annuity discounted at r_{Leland} equal to the present value of the same annuity discounted at the corresponding risk-free rates obtained from the Nelson and Siegel model. The Leland model-implied single risk-free rate follows the equation:

$$\sum_{t=1}^{30} \frac{C \times F}{(r_{Leland})^t} = \sum_{t=1}^{30} \frac{C \times F}{(r_t)^t} \tag{3.6}$$

  This continuous rate captures the information for both short-term and long-term risk-free rates.

- *Leland model perpetual debt coupon payment* (C_{Leland}): Following the same method used in the Merton model, we transform all payments of debt — periodic coupon payments and a final principal payment at maturity – into perpetual coupon debt. This makes the present value of 'synthetic Merton debt' discounted at the corresponding risk-free rate from the Nelson and Siegel curve equal to the present value of 'synthetic Leland model' discounted at the Leland model-implied risk-free rate. The perpetual coupon is determined by solving the equation

$$Be^{-r_{T_B} T_{T_B}} = \frac{C_{Leland}}{r_{Leland}} \tag{3.7}$$

- *Corporate tax rate* (τ): Following Eom et al. (2004), we assume a corporate tax rate of 35% by incorporating the tax-deductibility of interest payments in the model.

- *The bankruptcy cost* (α): The bankruptcy cost parameter is defined as one minus the recovery rate which is assumed as 51.31% following Eom et al. (2004).

- Asset volatility (σ_{Leland}) and unlevered firm value (V_{Leland}): Similar to the method used in the Merton model, we have two equations for numerically solving these two parameters. The first equation is the equity valuation equation which describes the relationship between equity value and unlevered firm value:

$$\begin{aligned} E &= v_{Leland} - D = V_{Leland} - BC + TS - D \\ &= V_{Leland} - (1-\tau)\frac{C_{Leland}}{r_{Leland}} + [(1-\tau)\frac{C_{Leland}}{r_{Leland}} - V_B]P_B \end{aligned} \tag{3.8}$$

where E is the market value of equity. In addition, v_{Leland} is the levered firm value equal to the unlevered firm value V_{Leland} minus the bankruptcy costs BC in Eq. 3.31 in Appendix 3.1 and add the tax shields TS in Eq. 3.32 in Appendix 3.1. V_B in Eq. 3.29 in Appendix 3.1 is the endogenously determined optimal bankruptcy threshold. P_B in Eq. 3.28 is interpreted as the risk-neutral default probability, and in Eq. 3.8, the market value of equity is the residual of levered firm value v_{Leland} after paying off all liabilities D.

The second equation describes the relationship between equity volatility σ_E and asset volatility σ_{Leland}

$$\sigma_E = \frac{V_{Leland}}{E}\frac{\partial E}{\partial V_{Leland}}\sigma_{Leland} \tag{3.9}$$

where $\partial E/\partial V_{Leland}$ is now the partial derivative of the equity value with respect to the unlevered firm value, instead of asset value (levered firm value) V in the Merton model. Based on the equity valuation in the Leland model, the partial derivative $\partial E/\partial V_{Leland}$ is not $N(d_1)$ as before but is given by

$$\frac{\partial E}{\partial V_{Leland}} = 1 + \left[\frac{C_{Leland}(1-\tau)}{r_{Leland}} - V_B\right]\lambda\frac{V_{Leland}^{\lambda-1}}{V_B^{\lambda}} \tag{3.10}$$

where λ equals to $-\frac{2r}{\sigma^2}$. It is interpreted as the elasticity of the default probability with respect to the unlevered firm value.

3.4.2 Estimation methodology

By definition, the reported DVAs equal the changes in the fair value of liabilities due to the changes in the firms' own credit risk. However, net gains or losses on the same amounts of fair-valued liabilities can arise both from changes in market risk and the issuer's own credit risk. Thus, we need to control for the effect of fluctuations in market risk on the debt value when estimating the market information-estimation DVAs at t ($\widehat{DVA_t}$). To do this, we follow these steps:

Step 1: Compute the value of liabilities designated under FVOL by applying structural credit risk models at the end of audit period $t-1$ (i.e., the last quarter-end date). In the Merton model, the market value of liabilities is a function of asset volatility, asset value, risk-free rate, time-to-maturity and principal value of liabilities at time $t-1$. To avoid the changes in the fair value of debt due to the changes in the principal value, we use the balanced principal value of liabilities under FVOL at t (B_t). We denote the debt value in the Merton model at $t-1$ as $D(B_t; \sigma_{t-1}, r_{t-1}, T_{t-1}, V_{t-1})$. In the Leland model, the market value of liabilities is a function of the Leland perpetual coupon rate, asset volatility, unlevered firm value, the Leland model-implied risk-free rate, tax rate and recovery rate at time $t-1$. Similar to the Merton model, the Leland model uses the perpetual coupon rate at t as the input to value debt at $t-1$. The corporate tax rate and recovery rate maintain the same level over time in our calibration procedure. Thus, the debt value in the Leland model at $t-1$ is denoted as $D(C_{Leland,t}, \tau, \alpha; \sigma_{Leland,t-1}, V_{Leland,t-1}, r_{Leland,t-1})$. We are then able to calculate the internal rate of return (R_{t-1}) given the debt value estimated by the Merton and Leland models respectively.

Step 2: To control for the effect of fluctuations in market risk on the debt value, we first compute the credit spread at $t-1$ by deducting the risk-free rate at $t-1$ from yield to maturity (R_{t-1}), arriving at an instrument-specific credit risk of the internal rate of return. In the Merton model, the credit spread is determined by solving the Eq. 3.11 below:

$$\begin{aligned} CS_{t-1} &= R_{t-1} - r_{t-1} \\ &= -\frac{1}{T_{t-1}} \ln \frac{D(B_t; \sigma_{t-1}, r_{t-1}, T_{t-1}, V_{t-1})}{B_t} - r_{t-1} \end{aligned} \tag{3.11}$$

where the risk-free rate r_{t-1} is obtained from the Nelson and Siegel model with term to maturity T_{t-1}.

In the Leland model, the credit spread is calculated as follows:

$$CS_{Leland,t-1} = \frac{C_{Leland,\ t}}{D(C_{Leland,t}, \tau, \alpha; \sigma_{Leland,t-1}, V_{Leland,t-1}, r_{Leland,t-1})} - r_{Leland,t-1} \tag{3.12}$$

where the risk-free rate $r_{Leland,t-1}$ is the Leland model-implied risk-free rate at $t-1$. This implied risk-free rate captures the short-term and long-term market risk at time $t-1$.

Step 3: Estimate the discount rate at time t ($\widehat{R_t}$) equal to the sum of the risk-free rate at time t and the credit spread at time $t-1$ as determined in Step 2. This discount rate reflects the firms' own credit risk at $t-1$ and market risk at t. In the Merton model, the discount rate is:

$$\widehat{R_t} \quad = \quad CS_{t-1} + r_t \tag{3.13}$$

This step in the Leland model is similar to the Merton's. Eq. 3.13 in the Merton model is replaced by:

$$\widehat{R_{Leland,\ t}} = CS_{Leland,\ t-1} + r_{Leland,\ t} \tag{3.14}$$

Step 4: Estimate the market value of debt at time t ($\widehat{D_t}$) by calculating the present value of the cash flows associated with the liabilities under FVOL, with the discount rate determined in Step 3. In the Merton model, the debt value is below:

$$\widehat{D_t}(\widehat{R_t}, T_t, B_t) \quad = \quad B_t e^{-\widehat{R_t} T_t} \tag{3.15}$$

We obtain the yield to maturity at t based on the credit risk at $t-1$ from Eq. 3.13, and we then estimate the debt value by discounting the balanced principal value of synthetic zero-coupon debt with this rate.

Since the debt in Leland model is assumed to be paid perpetually, the value of debt is given as:

$$\widehat{D_t}(\widehat{R_{Leland,\ t}}, C_{Leland,\ t}) = \frac{C_{Leland,\ t}}{\widehat{R_{Leland,\ t}}} \tag{3.16}$$

The debt value determined in this step reflect the firms' credit risk at $t-1$ and market risk at t.

Step 5: Similar to Step 1, we first implement structural credit risk models to estimate the debt value under FVOL at t. The fair value of liabilities at the end of the period t is denoted as $D(B_t; \sigma_t, r_t, T_t, V_t)$ in the Merton model and $D(C_{Leland,\ t}, \tau, \alpha; \sigma_{Leland,\ t}, V_{Leland,\ t}, r_{Leland,\ t})$ in the Leland model. Then, we compute the market information-estimated DVAs as the differences between the debt value determined in Step 3 and Step 4, as the changes in these two debt value is only attributable to changes in the firms' own credit risk. In the Merton model, the market information-estimated DVAs are obtained by solving the equation below:

$$\widehat{DVA_t} = \widehat{D_t}(\widehat{R_t}, T_t, B_t) - D(B_t; \sigma_t, r_t, T_t, V_t) \tag{3.17}$$

The market information-estimated DVAs in the Leland model is given as:

$$\begin{aligned} DV\widehat{A_{Leland,\ t}} &= \widehat{D_t}(R\widehat{_{Leland,\ t}}, C_{Leland,\ t}) & (3.18) \\ &- D(C_{Leland,\ t}, \tau, \alpha; \sigma_{Leland,\ t}, V_{Leland,\ t}, r_{Leland,\ t}) & (3.19) \end{aligned}$$

Appendix 3.3 provides the summarized illustration of market information-estimated DVAs calculation, together with a numerical example of the calculation.

3.5 Empirical Results

This section is organized into three parts. In Section 3.5.1 we discuss the estimated parameters in the Merton and Leland models after adjusting the real liabilities into the synthetic Merton zero-coupon bond and synthetic Leland perpetual coupon bond. In Section 3.5.2 we examine the ability of structural credit risk models to fit reported DVAs. We first compare the distribution of estimated and reported DVAs, and then compute the measures of bias and accuracy to investigate the extent to which the market information-estimated DVAs deviate from the reported DVAs. In Section 3.5.3 we evaluate the performance of the Merton and Leland models by investigating whether the estimation errors are determined by systematic factors.

3.5.1 Estimation of parameters

Table 3.10 summarizes the descriptive statistics of parameters in the Merton model. Panel A and Panel B present the estimation of parameters at the end of audit period $t-1$ and t respectively. Comparing the distribution of equity value (E) and equity volatility (σ_E) in these two panels, our results suggest the equity value and equity volatility are far closer over two subsequent periods. The average equity volatility and equity value are around 47% and \$36 billion. Given the one-quarter interval between time $t-1$ and t, we do not expect such extreme fluctuations in the equity market.

Following the calibration of the Merton model in Section 3.4.1.2, the average asset value (V)

and asset volatility (σ_V) are \$464,759,496,200 (\$463,146,281,300) and 3.49% (3.51%) at t ($t-1$). Given the average book value of total liabilities (TL), the average financial leverage is approximately 92%, consistent with the feature of financial institutions that are in the business of facilitating leverage for others. The risk-free rate (r) with term to maturity equal to the liabilities under FVOL are computed by the Nelson and Siegel model (around 1.9%). The liabilities accounted for FVOL in our sample banks are implicitly assumed to be straight bonds with periodic coupon payments. In order to be compatible with the zero-coupon bond assumption in the Merton model, we adjust the real bonds into synthetic Merton zero-coupon bond. The average synthetic face value of bonds (B) is about \$25 billion, whereas the real balanced face value of bonds is about \$21 billion. The increased amounts are attributable to the value of total coupon payments. Besides, the average real term-to-maturity shrinks from an 8-year to 6-year duration (T_B).

In the Leland model, the estimations of parameters are reported in Table 3.11. Similarly, we convert the real straight bonds into synthetic Leland perpetual coupon bonds so that the assumptions in the Leland model are necessarily adapted. The average Leland model-implied risk-free rate (r_{Leland}) is 3.14% (3.46%) at time t ($t-1$), reflecting both the short-term and long-term market risk. In contrast with the average real coupon rate of 5.66% at time t, the average Leland model-implied coupon rate (C_{Leland}) is reduced to more or less 2.56% after conversion. Correspondingly, the average annual Leland model-coupon payments ($Coupon_{Leland}$) decrease to \$654,094,700. The reduction in annual coupon payments is because the total coupon payments are spread over from the finite maturity into the perpetual maturity after conversion. Solving the two system equations in the Leland model calibration, the average unlevered asset value (V_{Leland}) and asset volatility (σ_{Leland}) are near \$50 billion and 3.44%. Furthermore, the average levered asset value (v_{Leland}) increases to near \$57 billion after taking into account the tax shields (TS) and bankruptcy costs (BC). Contrast to the tax shields (\$7,283,934,400 in audit period t and \$7,298,774,300 in audit period $t-1$), the bankruptcy costs are immaterial (\$11,870 in audit period t and \$12,810 in audit period $t-1$), indicating that the default risk is extremely low.[29] The low average lambda (λ) and low default probability (P_B) also provide evidence that the banks in our sample have low default risk.

[29] The bankruptcy costs depend on the default probability, recovery rate and bond value at the default date. Given the constant recovery rate 51.31% and the same bond value in the calculation of tax shields, the extreme low bankruptcy costs but high tax shields imply that the default probability in bankruptcy costs calculation is low.

3.5.2 Model performance measure

In this section we discuss the performance of structural credit risk models in pricing DVAs. Firstly, we compare the distribution of market information-estimated DVAs and reported DVAs. Secondly, we analyze the estimation errors by using structural credit risk models in the estimation of DVAs.

3.5.2.1 Distribution analysis of market information-estimated DVAs

First we compare the reported DVAs with the market information-estimated DVAs estimated by the Merton and Leland models for total observations, as illustrated in Panel A in Table 3.12. On average, the sign of Merton model-estimated DVAs is same as the reported DVAs, whereas the sign of Leland model-estimated DVAs is opposite to the reported DVAs. Both the Merton and Leland models overestimates DVAs ($-5,628,000 and $42,401,000 against $-14,651,000). Furthermore, the distribution of Merton model-estimated DVAs is similar to the reported DVAs, with same median value of zero. By contrast, the distribution of Leland model-estimated DVAs differs from the reported DVAs, revealing a substantial dispersion in estimated DVAs (standard deviation of 703,416,000 against 374,937,000 of reported DVAs).

To investigate further, we split our sample into four subsamples in accordance with the categories of reported DVAs (i.e., non-zero DVAs, positive and negative DVAs, and zero DVA reporters). We find that the distribution of estimated DVAs by the Merton and Leland models for non-zero DVA reporters, shown in Panel B of Table 3.12, appears to be close to the distribution of reported DVAs for total observations. Figure 3.2 plots the market information-estimated DVAs from the Merton and Leland models versus the reported DVAs over the sample period (2007 - 2017) for non-zero DVA reporters. The Merton model performs well on the reported DVAs with small magnitude. However, the estimates deviate significantly from the DVAs with large magnitude, which are clustered into the periods 2008, late 2011 and 2012. Unlike the Merton model, the Leland model has many examples of extreme overestimation and underestimation of DVAs before 2011, but the estimates converge to the reported DVAs afterwards. This pattern implies that the performance of pricing DVAs by structural models tends to be less well when the firms' own creditworthiness is volatile, but improves when the firms are in a stable credit risk condition.

Panel C and D in Table 3.12 show the information on positive and negative DVA reporters, respectively. The average estimates in Panel C indicate both the Merton and Leland models underestimate the positive DVAs. By contrast, the average estimates in Panel D indicate both the Merton and Leland models overestimate the negative DVAs. From Figure 3.3 and Figure 3.4, we find the average Merton model-estimated DVAs are positive (negative) for the positive (negative) DVA reporters, although some exceptional cases show the opposite in the year 2009 and 2012. However, the estimates for the Leland model in Figure 3.3 and Figure 3.4 have a tendency to oppose the reported DVAs — over 53% (70%) of Leland model-estimated DVAs are negative (positive) for the positive (negative) DVA reporters. This pattern results in the average estimates by the Leland model being opposite to the reported DVAs (the average Leland model-estimated DVAs of $-170,610,000 and $382,278,000 versus the average reported DVAs of $259,153,000 and $-325,628,000). Morover, the dispersion of the estimates from the Leland model, as illustrated by the standard deviation in Panel C and D of Table 3.12, is substantially spread over the sample period, especially in 2008. In particular, the estimated DVAs range from $-7,052,019,000 to $4,549,972,000 for positive DVA reporters, and from $-4,158,417,000 to $4,191,246,000 for negative DVA reporters.

In contrast to non-zero DVA reporters, the estimates for zero DVA reporters in panel E of Table 3.12 reveal a tendency toward underestimation of DVAs. Figure 3.5 indicates the Merton model outperforms the Leland model significantly because the reported DVAs are almost overlapped by the estimates by the Merton model, but the Leland model is way off the mark. The estimated DVAs from the Leland model range from $-446,221,000 to $362,901,000, although the reported DVAs are zero in this case.

From the distribution analysis of market information-estimated DVAs and reported DVAs, we find on average both the Merton and Leland models overestimate the DVAs for non-zero DVA reporters, but underestimate the DVAs for zero DVA reporters. From the comparison of estimates between positive DVAs and negative DVAs, we find the Merton and Leland models underestimate the DVA gains but overestimate the DVA losses, suggesting the sign direction of reported DVAs matters in estimates. In addition, the distribution of market information-estimated DVAs and reported DVAs over the sample period shows the estimates from the Merton and Leland models have a tendency to deviate wildly from the reported DVAs during the financial crisis, indicating that the pricing performance of DVAs by structure models is sensitive to the macroeconomic environment.

3.5.2.2 Estimation errors analysis

This section sheds light on the examination of the performance of structural credit risk models to fit the reported DVAs. Prior studies examine the valuation performance of structural models through computing the measure of relative percentage errors in order to allow them to be comparable among different size of firms (Liao et al., 2009; Eom et al., 2004). However, we do not rely on this widely used measure in our main test, as zero DVAs could generate missing value when they are the denominator of percentage error. Therefore, we consider the difference errors and the absolute difference errors in DVAs to be the most informative measures of model performance as follows:

Error = Market information-estimated DVAs - Reported DVAs

Absolute Error = | Market information-estimated DVAs - Reported DVAs |

Error captures the signed difference between the estimated DVAs and the reported DVAs. The negative (positive) *Error* implies structural credit risk models underestimate (overestimate) the DVAs.[30] In addition, the *Absolute Error* is denoted as the absolute value of *Error*, which captures the unsigned difference between the estimated DVAs and the reported DVAs. All positive *Absolute Error* would mitigate the problem arisen from being off-set by negative values when we compute the mean. The lower (higher) *Absolute Error* indicates the more (less) accurate the model estimates DVAs. In addition, we also pay particular attention to the standard deviation of these two measures because all structural credit risk models have substantial dispersion in estimated DVAs.

Table 3.13 summarizes the estimation errors (*Error* and *Absolute Error*) of the Merton and Leland models. Two measures are reported for total observations and four subsamples (i.e., zero DVAs reporter, non-zero DVA reporters, positive DVA and negative DVA reporters). For each measure, we report the average value and the standard deviation in parentheses.

The measure of *Error* in Table 3.13 shows that both the Merton and Leland models overestimate the reported DVAs. Identical to the implications from distribution of estimated DVAs in Section 3.5.2.1, the standard deviation of estimation errors is relatively high, suggesting extreme over-estimates or under-estimates of DVAs appear in our sample. Then, we split our total

[30] The distribution of DVAs is unlike the benchmark used in previous literature (Eom et al., 2004; Liao et al., 2009). The benchmarks in these papers are credit spreads, default probability, and the debt value, which are always positive.

observations into zero DVA reporters and non-zero DVA reporters. The positive pricing errors imply the Merton and Leland models overestimate the DVAs for non-zero DVA reporters, while the negative errors for zero DVA reporters show an underestimation. Therefore, the pattern of overestimation appeared in total observations is mainly driven by the non-zero DVA reporters, although the number of observations for non-zero DVAs is less than zero DVAs (347 versus 540). Accordingly, the mean errors for non-zero DVA reporters are \$23,187,000 and \$147,268,000 by the Merton and Leland models respectively, which are remarkably higher than these for zero DVA reporters (\$-79,000 by the Merton model and \$-921,000 by the Leland model). Moreover, the mean absolute errors for non-zero DVA reporters also largely contribute to the pricing absolute errors in total observations because the mean absolute errors for zero DVA reporters are immaterial.

Further, we split non-zero DVA reporters into positive DVA reporters and negative DVA reporters to investigate whether the estimation errors are relevant to the sign direction of reported DVAs. Table 3.13 shows that the observations of non-zero DVA reporters are almost equally divided into positive DVA reporters (171) and negative DVA reporters (176). However, the sign direction of mean errors for positive and negative DVA reporters are opposite. Specifically, the mean *Error* for positive DVA reporters is negative but positive for negative DVA reporters, suggesting the Merton and Leland models underestimate positive DVAs but overestimate negative DVAs. In contrast, the mean *Absolute Error* are almost identical for these two groups.

Another conclusion that we could draw from Table 3.13 is whether incorporation of additional information in structural credit risk model could improve the performance in the estimation of DVAs. Comparing the two measures between the Merton and Leland models, we find the Merton model outperforms the Leland model regarding the accuracy of DVA estimations, although the Leland model has considered additional economic information.[31] In full sample, the magnitude of mean *Error* for the Leland model (\$57,051,000) is significantly greater than that for the Merton model (\$9,023,000). The mean *Absolute Error* for the Leland model is three times higher than that for the Merton model (\$325,958,000 versus \$113,716,000). This pattern persists in the other four sub-samples.[32]

[31] Appendix 3.1 gives all the assumptions and pricing formulas of the Merton and Leland models. The Leland model relaxes some conservative assumptions in the Merton model by considering early default, cost of financial distress, interest payments savings, and the optimal endogenously determined default barrier. Teixeira (2007) finds that the Leland model outperforms the Merton model in pricing credit spreads of bonds.

[32]**The inference still holds if we use median deviations to examine the pricing performance.**

Next, we examine the model effectiveness over the year in our sample period. Panel A in Table 3.14 suggests that the estimation errors from the Merton model are clustered in the period 2007 to 2012, covering both the 2008 financial crisis and the 2011 sovereign debt crisis. However, the results of the Leland model in Panel B indicate that the tendency toward overestimation appears to spread over the entire sample period, although the occasional underestimation did happen. Interestingly, both Merton and Leland models tend to underestimate the reported DVAs in years 2007, 2008 and 2011 in which creditworthiness deteriorates. Merton (1974) states that the debt value tends to be more sensitive to the changes in the firms' credit risk when the default probability is high. Thus, the loss of accuracy occurs in both the Merton and Leland models, as bonds become even riskier. To further illustrate the impact of high own credit risk on the accuracy of the estimated DVAs, we compare the estimations in zero DVA reporters and non-zero DVA reporters because the zero DVAs imply no change or immaterial changes in the credit risk of bond issuers. Under the similar economic condition (i.e., in the same year), the structural credit risk models perform far better in pricing DVAs for zero DVA reporters (columns 4 and 5) than non-zero DVA reporters (columns 6 and 7) due to the stability of credit environment.

Parallel to analyzing estimation errors we also test whether the mean *Error* (*Absolute Error*) for the Merton and Leland models differ from zero, and whether the Merton model mean *Error* (*Absolute Error*) equal to that for the Leland model. Panel A in Table 3.15 reports the p-values for the mean zero of *Error* and *Absolute Error* for the Merton model and the Leland model. The results indicate the mean *Absolute Error* for these two models are significantly different from zero. Panel B in Table 3.15 reports the p-values for the mean equality test of *Error* and *Absolute Error* between the Merton model and the Leland model. The significant results of mean *Absolute Error* imply that the Leland model-estimated DVAs significantly differ from the estimated DVAs by the Merton model. This is essentially due to the consideration of more real economic information in the Leland model.

Considering the inconsistent estimation errors across the four sub-samples, illustrated in Table 3.13, the equality test might depend on the types of reported DVAs. In addition, Table 3.7 shows that large banks appear to disclose non-zero DVAs whereas small banks report zero DVAs. In order to detect any size effects we divide the sample into two groups in accordance with their firm size. Table 3.16 reports the p-values for the mean equality of estimation errors according to the types of reported DVAs and the firm size. Considering a 5% significance level, we fail to reject the null hypothesis of no difference in the *Absolute Error* between positive DVA and negative DVA reporters, but the mean *Error* differ significantly across these two sub-samples (see Panel A). These results indicate the sign direction of reported DVAs does not affect the accuracy of DVA estimations by structural models. However, the estimation bias between these two groups are statistically different — underestimation of positive DVAs and overestimation of negative DVAs. The results in Panel B show that both the mean *Error* and mean *Absolute Error* for zero DVA reporters differ significantly to non-zero DVAs reporters. The results in Panel C reveal the significant effects in *Error* and *Absolute Error* according to the size of banks in our sample. This result is consistent with the implications from Panel B, as large banks tend to report non-zero DVAs and vice versa.

The analysis of estimation errors in this section provides consilient evidence with the findings in the distribution analysis. On average, both the Merton and Leland models overprice DVAs. This pattern of overestimation is driven by non-zero DVA reporters, as the estimation errors for zero DVA reporters are immaterial. Dividing the sample of non-zero DVAs into positive and negative DVAs, we find both the Merton and Leland models overprice negative DVAs, but underprice positive DVAs. From the descriptive statistics of estimation errors by year, we find the estimation errors for the Merton model are more pronounced in the 2008 financial crisis and 2011 sovereign debt crisis, while the estimation errors for the Leland model appear to spread somewhat over the entire sample period. Further, the mean zero test shows the *Absolute Error* are significantly different from zero for both the Merton and Leland models, indicating the market information-estimated DVAs remarkably deviate from the reported DVAs. The significant results of mean equality test of *Absolute Error* suggest the Merton model and the Leland model fit the reported DVAs differently. The measure of *Absolute Error* is not affected by the sign direction of reported DVAs, but is significantly affected by the magnitude of reported DVAs.

3.5.3 Systematic estimation errors

In this section we investigate in more detail issues in line with the poor job of pricing DVAs by structural credit risk models. First, we estimate a multi-variable regression on the logarithm value of *Absolute Error* to detect the factors that might lead to systematic valuation errors. These factors are classified as firm-specific variables, bond-specific variables and macroeconomic variables. Then, we test the relationship between the logarithm value of *Absolute Error* and the systematic factors by type of reported DVAs.

3.5.3.1 Multivariate regression analysis

Similar to Eom et al. (2004), we use the measures of leverage and capital structure (e.g., market leverage ratio, the absolute differences between market leverage and book leverage), and the measures of firm value and its riskiness (e.g., the bank size, the market-to-book ratio, the asset volatility and tangible assets ratio) to reflect the firms' economic condition. In terms of the bond-specific variables, we consider the variables related to bond features such as the weighted average maturity, weighted average coupon rate and balanced principal value of liabilities under FVOL. Since structural credit risk models (i.e., the contingent claim theory) price the debt in risk-neutral environment, which indicates the asset value grow at the risk-free rate, we consider two macroeconomic variables related to the term structure (e.g., the ten-year CMT and the difference between the ten and two years yield). The significant relation between the absolute error and factors indicates these factors play an essential role in improving the performance of structural credit risk models regard to the estimation of DVAs.

Table 3.17 and Table 3.18 display the Pearson correlations between regressors and the *Absolute Error* by implementation of the Merton and Leland models respectively. The results show market leverage, firm size and principal value of liabilities under FVOL might explain variations in the absolute errors. Moreover, the low correlations across regressors indicate no multicollinearity issues in our test specification.

Table 3.19 shows six sets of regressions. The first and the second columns report the results of regressions for total observations by implementation of the Merton and Leland models respectively. Given the implications from Table 3.16 that the *Absolute Error* for the Merton and Leland models are significantly different between zero DVA reporters and non-zero DVA reporters, we also conduct the same regressions for these two groups. The results are displayed in the remaining columns. Unsurprisingly, both the Merton and Leland models have systematic errors related to market leverage. The positive t-statistics implies that the market information-estimated DVAs significantly deviate the reported DVAs on average for the banks with a higher market leverage ratio. This is consistent with the findings in the previous sections that structural credit risk models do a poor job of pricing DVAs in the risky banks. This systematic factor markedly affects the accuracy of estimation. However, the effect of market leverage disappears for zero DVAs reporters.

Like leverage, asset volatility also positively and significantly explain the variations in *Absolute*

Error for these six regression specifications. In addition, the explanatory power of regressions is clearly reduced once asset volatility is removed (untabulated). This result is consistent with the inference from the analysis of estimation errors that banks with high business risk typically receive severe estimation errors in all models. Moreover, given the fact that these two factors have been incorporated in these two structural models (they should lead to white noise other than the systematic errors), the positive and significant coefficients on both leverage and asset volatility suggest that the structural credit risk models would suffer fewer estimation errors if they include more information of leverage and asset volatility.[33]

Unlike our expectation indicated from the Pearson correlation, we do not observe a consistently significant effect of firm size on the *Absolute Error*, especially the Leland model. The insignificant t-statistics in the Leland model indicates the impact of bank size on the estimation errors is less pronounced. This result is consistent with the high dispersion of estimation errors by the Leland model. However, the untabulated results show firm size is significantly associated with the *Absolute Error* if we replace to control for time effect instead of firm effect. Therefore, including the firm fixed effect captures the firm-specific information that is incorporated in the firm size. Moreover, the positive coefficient provides evidence that structural credit risk models tend to overestimate (underestimate) the DVAs for large (small) firms. The reason is large (small) banks tend to disclose the non-zero (zero) DVAs, and the distribution analysis shows that non-zero DVAs suffer more severe estimation bias. Further, we use the market-to-book ratio as the proxy of banks' growth opportunities. Banks with higher growth opportunities tend to be safer than banks with lower growth opportunities; thus, the estimation errors are less pronounced in the safe banks. However, we do not find the significant effect of market-to-book ratio on the*Absolute Error*.

The t-statistic for variables related to recovery rates are strongly consistent in the Merton and Leland models. The negative coefficients reveal that structural models fit the DVAs much better for banks with higher tangible assets ratios. Banks with higher tangible assets are perceived as low default risk premiums because these assets can be used as collateral in a potential bankruptcy. In addition, the tangible assets only significantly explain the *Absolute Errors* by the Merton model, suggesting that consideration of bankruptcy costs in the Leland model somewhat improve the performance of pricing DVAs.

[33] In both the Merton and Leland models, they assume the constant leverage ratio and asset volatility. The prior studies find that the models incorporating the mean reversion in leverage (Pierre Collin-Dufresne, 2001) extremely improve the prediction errors in bond spreads.

Regarding the bond-specific variables, maturity is a major factor in both the Merton and Leland models, suggesting the careful treatment of maturity in structural credit risk models may help the accuracy of estimations. Further, the negative t-statistic reveals that the shorter maturity bonds are subject to higher estimation errors issue, which was raised initially by Duffie et al. (2001). In contrast, the coupon rate does not influence the accuracy of structural models in terms of pricing DVAs. This is because the coupon payments have been incorporated into the face value of liabilities under FVOL after transferring the 'real' bonds into the 'synthetic' bonds. The variable of the principal value of liabilities under FVOL positively and significantly affects the *Absolute Errors*, suggesting greater amounts of liabilities accounted for FVOL lead to higher estimation errors. Apparently, given the same changes in the firms' own credit risk, the greater magnitude of liabilities under FVOL would generate higher DVAs. Moreover, the findings in Table 3.13 show that the estimation errors in total observations is contributed mainly by non-zero DVA reporters. Therefore, the principal value of liabilities under FVOL should be positively associated with *Absolute Errors.* In addition, the adjusted R^2 rises considerably when the principal value of liabilities under FVOL is considered.

Considering the macroeconomic variables, we find no evidence that the slope of the term structure is significantly related to the systematic errors in both the Merton and Leland models. In addition, there is no tendency for the level of the term structure to come into play in the estimation of DVAs by the Leland model, even though the changes in firm value occurs with interest rates (the risk-neutral drift of the firm value Brownian motion process). In contrast, the significant negative t-statistic in the Merton model implies that the high level of interest rates reduces the estimation errors of pricing DVAs. Following Collin-Dufresne et al. (2001), the higher drift in the firm value process decreases the default probability, and in return, improves the creditworthiness. This finding confirms the estimation errors are less pronounced in banks with more healthy credit condition.

3.6 Conclusions

This paper directly tests whether the information contained in the Debt Valuation Adjustments (DVAs) can be captured by market efficiently by using a sample of 887 bank-quarter observations between 2007 and 2017. In particular, we compare the reported DVAs to the market information-estimated DVAs which are estimated by the Merton (1974) model and Leland (1994) model.

We first analyze the distribution of reported DVAs and market information-estimated DVAs over the sample period. We find the distribution of estimated DVAs from the Merton model appears to be similar to that of the reported DVAs, whereas the estimates from the Leland model deviate wildly from the reported DVAs over the entire sample period. Overall, the Merton model outperforms the Leland model when the banks' own credit risk is considerable low, although the Leland model incorporates the additional information.

Then, we compute the signed difference (*Error*) between the reported DVAs and the estimated DVAs as the measures of bias, and unsigned difference (*Absolute Error*) between the reported DVAs and the estimated DVAs as the measures of accuracy. We find that both the Merton and Leland models tend to overestimate the DVAs on average. However, the average *Errors* is a rather poor summary of a model's ability in fitting reported DVAs, because the dispersion of market information-estimated DVAs in our sample is remarkably high. Therefore, we analyze the estimation errors by year. Interestingly, we find that both the Merton and Leland models reverse their performance on average to the underestimation of DVAs when banks' own creditworthiness was volatile, and the estimated DVAs gradually converge to the reported ones when their credit risk improves. The results indicate that the poor economic condition exacerbates the weakness of pricing DVAs by structural models.

Finally, we consider whether the estimation errors are associated with some systematic factors. The results reveal that banks with high market leverage and asset volatility lead to high estimation errors. In both the Merton and Leland models, leverage ratio and asset volatility are two main channels of default risk. This pattern of high estimation errors in banks with poor credit condition may stem from the fact that the debt value tends to be more sensitive to the changes in the firm's credit risk when default probability is high.

All analysis incorporate a decomposition of banks in accordance with the categories of reported DVAs due to the different economic impacts on accounting earnings (i.e., non-zero DVAs, zero DVAs, positive DVAs and negative DVAs). The estimates for zero DVA and non-zero DVA reporters are significantly different. In particular, the Merton and Leland models underestimate the DVAs on average for zero DVA reporters, but overestimate the non-zero DVAs. Moreover, comparing to non-zero DVAs, the *Absolute Errors* for zero DVAs are immaterial, suggesting the loss of accuracy in full sample are mainly attributed to zero DVA reporters. Further, we split non-zero DVAs into positive and negative DVAs due to their opposite accounting effects — DVA gains and DVA losses. The insignificant t-statistics of equality test indicate that the *Absolute*

Errors between these two groups are equal. However, the measure of *Error* suggests the Merton and Leland models underestimate DVA gains but overestimate DVAs losses. The results imply that management estimate positive DVAs and negative DVAs differently, while the capital market treats them indifferently.

Overall, the results in this chapter indicate that the reported DVAs contain private information and the ignorance of private information in structural credit risk models limit their ability in the replication of reported DVAs. Further, the reported DVAs reflect more private information on credit risk when the economy is volatile rather than stable.

Appendix 3.1 Formulas for Structural Credit Risk Models

In this appendix we summarize the main assumptions and formulas for firm value, equity value, debt value and credit spread of the Merton (1974) and Leland (1994) models.

3.6.1 The Merton (1974) model

The Merton (1974) model assumes that the dynamics for the asset value, V_t, to be the geometric Brownian motion (GBM) process as follows:

$$dV_t = rV_t dt + \sigma V_t dW_t \tag{3.20}$$

where σ is the constant variance of the return on the underlying assets, and W_t is a standard Brownian motion under the risk-neutral measure Q. In this extended Merton model we include the payout ratio, as most firms pay both interests to debtholders and dividends to equity-holders.

The Merton model assumes that a firm issues a single class of debt, a zero-coupon bond, with a face value B payable at maturity T. A default is triggered by the market value of the firm's assets being lower than the face value B, and such credit events can only occur at the finite maturity T of this bond, i.e. $V_T \leq B$. If a default occurs, debt-holders receive the remaining asset V_T without incurring any distress costs. The payoff to debt $D(V_T)$ is given as

$$D(V_T) = \min(V_T,\ B) = B - \max(B - V_T,\ 0) \tag{3.21}$$

The representation of the payoff to debt-holders makes it clear that the debt-holders are short a put option written on the assets of the borrowing firm with a strike price equal to B, the face value of debt. In addition, according to the assumptions in the Merton model the value of the firm and the asset value are identical and are not affected by the capital structure (i.e., MM theory). The asset value is thus given by the sum of risky debt and equity. With this framework, equity is a call option on the assets of the borrowing firm with a strike price equal to B, the face value of debt. We can therefore express equity as follows:

$$E(V_T) = \max(V_T - B,\ 0) \tag{3.22}$$

Equity and debt values are therefore given by Black and Scholes (1973) formulas:

$$\begin{aligned} E &= Call_{BS}(V_0, B, r, T, \sigma) \\ &= V_0 N(d_1) - Be^{-rT} N(d_2) \qquad (3.23) \\ D &= Be^{-rT} - Put_{BS}(V_0, B, r, T, \sigma, \delta) \\ &= V_0 N(-d_1) + Be^{-rT} N(d_2) \qquad (3.24) \\ d_1,\ d_2 &= \frac{\ln \frac{V_0}{B} + (r \pm \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} \end{aligned}$$

where $N(.)$ is the cumulative standard normal distribution.

The yield to maturity YTM is computed as

$$YTM = -\frac{\ln(D/F)}{T} \qquad (3.25)$$

Hence, the credit spread CS is the difference between the yield to maturity YTM and the risk-free rate r as follows:

$$CS = YTM - r = -\frac{1}{T} \ln \left[N(d_2) + \frac{V_0}{Be^{-rT}} N(-d_1) \right] \qquad (3.26)$$

3.6.2 The Leland (1994) model

The Leland (1994) extends the results of Merton (1974) by including bankruptcy costs and corporate costs as endogenous cases. In other words, the option-based pricing models assume the Modigliani-Miller theorem in corporate capital structure, which the firm's asset value is only split into debt and equity and invariant to the capital structure. In practice, however, it is unrealistic to develop a default model without considering the corporate capital structure. In this model, the firm issues perpetual security with a long period to maturity, which pays a nonnegative coupon C before infinite maturity T when the firm is solvent. Therefore, these securities are time-homogeneous, which means they are time-independent $F_t(V,\ t) = 0$.

Considering a constant corporate tax rate τ, the firm obtains tax shields from its debt at a rate $C\tau$ until default. Bankruptcy occurs when the firm value reaches a threshold V_B. In this case, the bankruptcy costs are αV_B, where α is defined as the bankruptcy cost rate or one minus the recovery rate. Because of these new "real world features" the levered firm value, V_{Leland}, differs from the unlevered firm value V (i.e., the asset value in the Merton model). Rather, the firm value increases by the tax shield, TS, and decreases by the bankruptcy costs, BC. After incorporating these new assumptions, the debt value is

$$D = \frac{C}{r}(1 - P_B) + P_B(1 - \alpha)V_B \quad (3.27)$$

$$P_B = (\frac{V}{V_B})^\lambda \quad (3.28)$$

where P_B is $(\frac{V}{V_B})^\lambda$ and the endogenously determined bankruptcy threshold is given by

$$V_B = \frac{C(1 - \tau)}{r} \frac{-\lambda}{1 - \lambda} \quad (3.29)$$

The parameter λ in the bankruptcy trigger solution is

$$\lambda = -\frac{2r}{\sigma^2} \quad (3.30)$$

P_B can be interpreted as the risk-neutral default probability and λ as the elasticity of the probability of default with respect to the value of the assets of the firm. As such, it is negative and increases with the volatility of the assets of the firm.

The bankruptcy costs resemble a zero-coupon bond with the face value equal to the bankruptcy costs αV_B at $V = V_B$. The value of bankruptcy costs BC therefore is derived as

$$BC = \alpha V_B \left[\frac{V}{V_B}\right]^\lambda = P_B \alpha V_B \quad (3.31)$$

Similarly, the tax benefits resemble the security of paying a constant coupon equal to the tax-sheltering value of interest payment τC if the firm is solvent and paying nothing if the firm goes bankruptcy. The value of tax advantage TB is obtained

$$TS = \frac{\tau C}{r} - \left(\frac{\tau C}{r}\right)\left(\frac{V}{V_B}\right)^\lambda = \frac{\tau C}{r}\left(1 - P_B\right) \quad (3.32)$$

The total firm value therefore is

$$V_{Leland} = E + D = V + TS - BC \quad (3.33)$$

The equity value is the residual of total firm value after paying off all liabilities

$$E = V_{Leland} - D = V + TS - BC - D \quad (3.34)$$

The credit spread is

$$CS = \frac{C}{D} - r \tag{3.35}$$

Appendix 3.2 An Example of DVA Disclosure

The Appendix provides an example of DVA disclosure by JP Morgan Chase & Co as of September 31, 2015.

Figure 3.1: Example of DVA disclosure from FR Y-9C report

Dollar Amounts in Thousands	BHCK		
Memorandum item 14 is to be completed by holding companies that have elected to account for assets and liabilities under a fair value option.			
14. Net gains (losses) recognized in earnings on assets and liabilities that are reported at fair value under a fair value option:			
a. Net gains (losses) on assets	F551	3105000	M.14.a.
(1) Estimated net gains (losses) on loans attributable to changes in instrument-specific credit risk	F552	273000	M.14.a.(1)
b. Net gains (losses) on liabilities	F553	3747000	M.14.b.
(1) Estimated net gains (losses) on liabilities attributable to changes in instrument-specific credit risk	F554	492000	M.14.b.(1)
15. Stock-based employee compensation expense (net of tax effects) calculated for all awards under the fair value method	C409	1262000	M.15.

In the 10-Q form the following information was provided regarding the DVA and financial liabilities under FVOL : "Total changes in instrument-specific credit risk (DVA) related to structured notes were \$169 million and \$190 million for the three months ended September 30, 2015 and 2014, respectively, and \$492 million and \$209 million for the nine months ended September 30, 2015 and 2014, respectively. These totals include such changes for structured notes classified within deposits and other borrowed funds, as well as long-term debt."

Table 3.1: Presentation of the fair value of financial liabilities at fair value in the statement of financial statement

(in millions)

Liabilities		**Sep 30, 2015**
Deposits (include **$11, 062** and $8,807 at fair value)	**$**	**1,273,106**
Federal funds purchased and securities loaned or sold under repurchase agreements (included **$3,565** and $2,979 at fair value)		**180,319**
Other borrowed funds (included **$9,665** and $14,739 at fair value)		**27,174**
Accounts payable and other liabilities (included **$5,850** and $4,155 at fair value)		**187,986**
Beneficial interests issued by consolidated variable interest entities (included **$1,199** and $2,162 at fair value)		**48,733**
Long-term debt (included **$31,160** and $30,226 at fair value)		**292,945**

The table provides information on the disclosure of the fair value of financial liabilities under fair value option (FVO) by JP Morgan Chase & Co as of September 31, 2015. According to the disclosure requirements from SFAS No. 159, adopters need to present the aggregate of fair value amounts in the same line item in the statement of financial position and parenthetically disclose the amount measured at fair value included in the aggregate amount. JP Morgan Chase & Co parenthetically reported the current fair value of financial liabilities under FVOL in bold front as of September 30, 2015 (page 87).

Table 3.2: Presentation of the fair value of financial liabilities at fair value in the financial report

Difference between aggregate fair value and the aggregate remaining contractual principal balance outstanding
The following table reflects the difference between the aggregate fair value and the aggregate remaining contractual principal balance outstanding as of September 30, 2015, for long-term debt for which the fair value option has been elected.

		September 30, 2015		
(in millions)		Contractual principal outstanding	Fair value	Fair value over/(under) contractual principal outstanding
Long-term debt				
Principal-protected debt	**$**	16753 (b)	15,520	(1233)
Nonprincipal-protected debt (a)		NA	15,640	NA

(a): Remaining contractual principal is not applicable to nonprincipal-protected notes. Unlike principal-protected structured notes, for which the firm is obligated to return a stated amount of principal at the maturity of the note, nonprincipal-protected structured notes do not obligate the firm to return a stated amount of principal at maturity, but to return an amount based on the performance of an underlying variable or derivative feature embedded in the note. However, investors are exposed to the credit risk of the firm as the issuer for both nonprincipal-protected and principal protected notes.
(b): Where the Firm issues principal-protected zero-coupon or discount notes, the balance reflects the contractual principal payment at maturity or, if applicable, the contractual principal payment at the Firm's next call date.

The table from 10-Q filing includes the differences between aggregate fair value and aggregate remaining contractual principal balance outstanding for liabilities. JP Morgan Chase & Co only displayed the differences between fair value and contractual principal balance of principal-protected debt. This is because this type of debt has relatively long-term maturity. For the rest of liabilities under FVO (i.e., nonprinciple-protected debt), JP Morgan did not report the differences of these liabilities. On the one hand, they probably do not have principal value. On the other hand, these liabilities have relatively short-term maturity so that the differences between fair value and contractual principal are immaterial. According to the Table 3.1 "Fair value disclosure", the fair value of liabilities under FVO was 62,501 millions, therefore, the principal value of liabilities under FVO should be 63,734 millions (62,501 millions + 1,233 millions), page 106.

Table 3.3: Presentation of maturity of financial liabilities at fair value in the financial report

Contractual cash obligations

		2015				
By remaining maturity at December 31, (in millions)		2016	2017-2018	2019-2020	After 2010	Total
On-balance sheet obligations						
Deposits (a)	$	1,262,865	5,166	3,553	4,555	1,276,139
Federak funds purchased and securities loaned or sold under repurchase agreements		151,433	811	3	491	152,738
Other borrowed funds (a)		11,331	0	0	0	11,331
Beneficial interests issued by consolidated variable interest entities		16,389	18,480	3,093	3,130	41,092
Long-term debt (a)		45,972	82,293	59,669	92,272	280,206

(a) Excludes structured notes on which the Firms is not obligated to return a stated amount of principal at the maturity of the notes, but is obligated to return an amount based on the performance of the structured notes.

This table displays the maturity distribution across various liabilities by JP Morgan Chase & Co as of September 31, 2015 (page 78). This data is used to compute the priced weighted average maturities.

Appendix 3.3 Illustration of Market Information-estimated DVAs Calculation

1. Steps for determining the market information-estimated DVAs.

Step 1: Determine the fair value of liabilities at the end of period $t-1$
We implement structural credit risk models — the Merton model and the Leland model — to compute the fair value of liabilities at the end of audited period $t-1$.

Step 2: Determine the instrument-specific component at the end of period $t-1$
Given the fair value of liabilities determined in Step 1, we compute the yield to maturity in accordance with the zero-coupon bond and perpetual coupon bond pricing formula in the Merton and Leland model respectively. Deducting from yield to maturity the observed (benchmark) interest rate at the end of audited period $t-1$, we arrive at an instrument-specific component of the yield to maturity, which reflects the credit risk at the end of audited period $t-1$.

Step 3: Determine the discount rate at the end of the period t
In order to control for the fluctuation in fair value of liabilities between $t-1$ and t due to the changes in interest rate, we compute the discount rate (i.e., yield to maturity) equal to the sum of (i) the observed (benchmark) interest rate at the end of the period t and (ii) the instrument-specific component as determined in Step 2.

Step 4: Determine the fair value of liabilities at the end of the period t
According to the zero-coupon bond and perpetual coupon bond pricing formula, we compute the fair value of liabilities at the end of the period using the discount rate as determined in Step 3. This estimated bond value reflects the firm's own credit risk at the end of audited period $t-1$ and the interest rate at the end of the period t.

Step 5: Determine the market information-estimated DVAs at the end of the period
Again, we implement structural credit risk models — the Merton model and the Leland model — to compute the fair value of liabilities at the end of audited period t. Accordingly, the estimated fair value reflects both the firm's own credit risk and the interest rate at the end of the period t.The differences in the bond value determined in Step 3 and Step 4 are denoted as the market information-estimated DVAs, as these are the changes in fair value that is only attributable to changes in the firm's own credit risk.

2. Numerical example of calculation of market-implied DVAs by JP Morgan Chase & Co for September 31, 2015

Step 1	At the start of the third quarter in 2015 (July 1, 2015), the synthetic Merton zero-coupon bond has duration 2.72-year with balanced principal value \$74,407,512 thousand, and the synthetic Leland perpetual coupon bond has coupon rate 2.62%$^{(b)}$, the fair value of liabilities are estimated by using Merton model and Leland model as:	Merton-model(000): \$72, 570, 860	Leland-model(000): \$61, 749, 359
Step 2	Given the fair value of liabilities as determined in **Step 1**, the Merton interest rate 0.918% and the Leland interest rate 2.70%, the instrument-specific components of synthetic Merton zero-coupon bond and synthetic Leland perpetual coupon bond equal to the yield to maturity minus interest rate:	Merton-model(bps): $-\frac{1}{2.72} \times \ln(\frac{72,570,860}{74,407,512}) -0.918\% = 0.0012$	Leland-model(bps): $\frac{2.62\% \times 74,407,512}{61,749,359} -2.70\% = 46$
Step 3	Given the Merton interest rate 0.917% and Leland interest rate 2.43% at the end of the third quarter in 2015 (September 31, 2015), the synthetic Merton discount rate and Leland discount rate equal to the instrument-specific components determined in **Step 2** plus their interest rate:	Merton-model(bps): $0.0012 + 0.9167\% = 91.6712$	Leland model(bps): $46 + 2.43\% = 289$
Step 4	Given the synthetic Merton discount rate and Leland discount rate as determined in **Step 3**, the Synthetic Merton zero-coupon bond with balanced principal value \$76,570,328 thousand and duration 2.94-year, and the Synthetic Leland perpetual coupon bond with coupon rate 2.35% at the end of the third quarter, the fair value of synthetic Merton zero-coupon bond and synthetic Leland perpetual bond:	Merton-model(000): $76,570,328 \times \exp(-0.917\% \times 2.94) = 74,534,243$	Leland-model(000): $\frac{2.35\% \times 76,570,328}{2.89\%} = 62,558,200$
Step 5	Using Merton and Leland mode, we estimate the fair value of the same liabilities at the end of the third quarter in 2015. The difference from the debt value determined in **Step 4** is market-implied DVAs:	Merton-model(000): $74{,}534{,}243 - 74{,}536{,}499 = 38.46$	Leland-model(000): $62{,}558{,}200 - 61{,}776{,}252 = 781{,}947.02$

(a): At the start of the third quarter in 2015 (July 1, 2015), the balanced principal value of liabilities under FVOL by JP Morgan Chase & Co was \$63,734,000 thousands with the term to maturity 3.18-year and coupon rate 6.75%.

Appendix 3.4 Empirical Results

Table 3.4: Sample selection procedure

Banks that report net gains or losses on liabilities (bhckf553) or net gains or losses on liabilities attributable to changes in their own credit risk (bhckf554) at least once during sample period 2007: Q1 to 2017: Q4	85
Banks that match with COMPUSTAT and CRSP with publicly available stock price and positive book value of liabilities	46
Banks that report fair value and principal value of liabilities under fair value option	38
All bank-quarters of selected banks	887

The table provides information on the number of bank-quarters for which FVOL was adopted, and the recognition of positive and negative DVA each year. The sample includes all U.S. bank holding companies which have available data for the period 2007-2017 (887 bank-quarter observations).

Table 3.5: List of bank holding companies

Name	**GVKEY ID**	**N**	**DVAs ('000)**	**FV ('000)**	**PV ('000)**
American International Group Inc.	001487	40	-16,750	17,142,875	15,718,700
Popular Inc.	002002	4	-2,500	181,830	264,156
Bank of Hawaii Corp.	002005	3	0	120,400	118,971
Bank of New York Mellon Corp.	002019	6	-1,500	3,197,833	3,210,833
JP Morgan Chase & Co.	002968	44	7,227	70,885,159	71,324,932
Citigroup Inc.	003243	44	-17,182	146,456,318	146,779,145
Bank of America Corp.	007647	39	-234,431	92,550,410	95,136,026
Wells Fargo & Co.	008007	5	200	296,800	340,000
P N C Finanical Service Group Inc.	008245	23	0	124,522	160,478
Keycorp	009783	18	0	2,440,056	2,845,889
Suntrust Bank Inc.	010187	44	2,000	3,383,067	3,320,874
Valley National Bancorp	011861	23	0	153,843	155,641
Morgan Stanley	012124	42	-34,429	49,792,905	50,735,595
Synovus Financial Corp.	013041	5	0	100,433	100,433
Fulton Financial Corp.	014172	1	-35	7,517	7,458
First Bancorp	016821	21	243	1,201,995	1,204,352
National Penn Bancshares Inc.	017070	11	0	61,132	65,200
Old National Bancorp	017095	5	34	39,084	38,880
W Holding Company Co Ltd	017157	4	0	49,756	49,596
Tompkins Financial Corp.	017240	34	-59	15,175	13,824
Irwin Financial Corp.	018928	4	2,232	82,616	82,616
VIST Financial Corp.	021595	17	0	19,240	20,200
BOK Financial Corp.	024447	12	0	239,227	246,167
Cascade Financial Corp.	025719	17	236	10,733	12,647
Banner Corp.	061487	44	0	151,219	201,336
Flushing Financial Corp.	061585	44	17	60,906	87,092
Community Central Bank Corp.	064142	15	0	16,037	22,620
First Mariner Bancorp	064194	10	0	56,581	55,000
United Security Bankshares	064228	44	0	10,665	14,318
Flagstar Bancorp Inc.	064699	19	0	115,415	165,629
Umpqua Holdings Corp.	065228	44	0	148,653	216,026
First Community Corp.	112295	10	0	2,291	2,250
Goldman Sachs Group Inc.	114628	36	-36,250	77,700,917	78,803,222
Metlife Inc.	133768	28	0	2,448,214	2,393,857
Principal Financial Group Inc.	145701	28	-2,871	88,739	160,136
Alliance Bankshares Corp.	146354	23	0	65,743	64,505
Western Alliance Bancorporation	163920	44	0	51,143	71,780
Ameriprise Financial Inc.	164708	32	0	4,555,563	4,924,094

The table lists the bank holding companies in our sample, together with COMPUSTAT identifier (GVKEYI ID), the bank-quarter observations, the arithmetic mean of reported DVAs (DVAs), the arithmetic mean of fair value of liabilities under FVOL (FV) and the arithmetic mean of the balanced principal value of liabilities under FVOL (PV) for each bank.

Table 3.6: DVAs, Fair value (FV) and Principal value (PV) of liabilities under FVOL by year

Year	N	DVAs('000)	FV('000)	PV('000)
2007	53	48,852	31,581,826	31,544,489
2008	108	105,683	17,777,179	17,982,122
2009	102	-160,467	18,979,335	19,508,684
2010	105	-14,389	19,641,662	19,992,953
2011	86	96,295	23,724,618	24,225,617
2012	80	-155,362	25,129,710	25,126,753
2013	78	-36,649	23,288,955	23,155,473
2014	74	18,526	18,956,872	18,805,129
2015	72	13,054	18,873,678	18,990,011
2016	70	-29,572	20,368,417	20,544,875
2017	59	-53,061	27,347,615	27,838,602

The table provides information on the bank-quarter observations, the arithmetic mean of reported DVAs (DVAs), the arithmetic mean of fair value of liabilities under FVOL (FV) and the arithmetic mean of principal value of liabilities under FVOL (PV) by year in our sample period.

Table 3.7: Number of negative, positive and zero DVAs by year

	Number of bank-quarters			
	DVA<0	DVA=0	DVA>0	Total
Panel A: All banks				
2007	1	36	16	53
2008	19	68	21	108
2009	24	65	13	102
2010	19	68	18	105
2011	15	50	21	86
2012	23	47	10	80
2013	24	46	8	78
2014	13	42	19	74
2015	8	40	24	72
2016	14	42	14	70
2017	16	36	7	59
Total	**176**	**540**	**171**	**887**
Panel B: Large banks (total assets > $50 billion)				
2007	1	0	13	14
2008	10	3	16	29
2009	22	3	7	32
2010	16	15	17	48
2011	13	13	19	45
2012	23	12	9	44
2013	24	16	8	48
2014	13	14	19	46
2015	8	12	24	44
2016	14	17	13	44
2017	16	12	7	35
Total	**160**	**117**	**152**	**429**
Panel C: Other banks (Total assets < $50 billion)				
2007	0	36	3	39
2008	9	65	5	79
2009	2	62	6	70
2010	3	53	1	57
2011	2	37	2	41
2012	0	35	1	36
2013	0	30	0	30
2014	0	28	0	28
2015	0	28	0	28
2016	0	25	1	26
2017	0	24	0	24
Total	**16**	**423**	**19**	**458**

The table provides information on the number of bank-quarters for which FVOL was adopted, and the recognition of positive and negative DVA each year. Panel A provides information for all the banks, while Panels B and C provide information for large banks (total assets more than $50 billion) and other banks respectively. The sample includes all U.S. bank holding companies which have available data for the period 2007-2017 (887 bank-quarter observations).

Table 3.8: Descriptive statistics of characteristics of liabilities under FVOL

Variable	Obs	Mean	Std.Dev.	Min	Q1	Median	Q3	Max
Panel A: All bank-quarter observations								
Fair value of liabilities under FVOL('000)	887	21,689,588	44,049,942	1,250	41,429	159,787	10,392,000	358,827,000
Principal value of liabilities under FVOL ('000)	887	21,896,584	44,471,600	1,500	61,900	192,900	8,042,000	357,997,000
Maturity	887	8.03	7.11	1.00	3.18	4.80	10.00	39.00
Coupon	887	5.66%	1.79%	1.13%	4.39%	5.47%	6.71%	11.60%
Panel B: Non-zero DVAs recognizers								
Fair value of liabilities under FVOL('000)	347	54,549,423	56,453,525	3,341	4,050,000	54,387,000	79,685,000	358,827,000
Principal value of liabilities under FVOL ('000)	347	55,000,173	57,059,240	5,890	4,050,000	55,293,000	80,602,000	357,997,000
Maturity	347	4.44	4.10	1.07	2.95	3.84	4.81	39.00
Coupon	347	5.76%	1.09%	2.95%	4.85%	6.00%	6.46%	11.60%
Panel C: Zero DVAs recognizers								
Fair value of liabilities under FVOL('000)	540	574,102	1,391,548	1,250	25,037	68,720	172,266	7,129,000
Principal value of liabilities under FVOL ('000)	540	624,464	1,467,050	1,500	25,000	95,750	215,568	7,302,000
Maturity	540	10.33	7.66	1.00	3.65	8.11	17.62	27.62
Coupon	540	5.59%	2.12%	1.13%	4.19%	5.15%	6.79%	11.60%

This table reports descriptive statistics of the characteristics of liabilities account for under the FVOL . Panel A provides information on all the sample, including bank-quarters where zero DVA were reported. Panel B includes only the bank-quarters that non-zero DVA were reported. Panel C reports bank-quarters that only zero DVA were reported. Maturity is computed as the price-weighted average of the term to maturity across liabilities account for FVOL for each bank. The coupon rate is computed as the price-weighted average of coupon rate of all straight bonds issued by each bank.

Table 3.9: Estimation of model parameters

Panel A: Merton model (1974)			
Parameters	**Description**	**Estimation method**	**Data source**
Firm characteristics	V Unlevered firm value	Merton (1974) approach	Compustat and CRSP
	σ_V Asset volatility	Merton (1974) approach	Compustat and CRSP
	TL Default barrier	Total book value of liabilities	Compustat
Interest rate	r Risk-free rate	Nelson-Siegel (1987)	CMT
Debt related information	T_B Maturity	Duration of bonds	Hand-collection from 10-K/10-Q filings
	B Balanced principal value of liabilities under FVOL	Synthetic Merton zero-coupon face value	Hand-collection from 10-K/10-Q filings
Panel B: Leland model (1994)			
Parameters	**Description**	**Estimation method**	**Data source**
Firm characteristics	V_{Leland} Unlevered firm value	Leland (1994) approach	Compustat and CRSP
	σ_{Leland} Asset volatility	Leland (1994) approach	Compustat and CRSP
	τ Corporate tax rate	Assumed at 35%	
Interest rate	r_{Leland} Risk-free rate	Implied risk-free rate from Nelson-Siegel (1987)	CMT
Debt related information	C_{Leland} Perpetual debt coupon rate	Implied coupon rate	Datastream
	α Recovery rate	Assumed at 51.31%	Moody's

This table reports the summary of the estimation of model parameters. Panel A summarizes the parameters needed in Merton's model (1974); Panel B summarizes the parameters needed in Leland's model (1994). The data sources include COMPUSTAT, COMPUSTAT BANK, CRSP, Federal Reserve Board's website, and Data hand-collected from 10K/10Q filings.

Table 3.10: Inputs for market information-estimated DVAs (Merton 1974)

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Panel A: Inputs for Merton model at t-1								
σ_E	887	47.42%	38.34%	12.40%	23.25%	32.51%	54.50%	235.99%
E ('000)	887	36,135,439.80	59,195,982.10	4,259.00	467,129.90	3,591,340.50	48,549,136.00	336,100,000.00
r_{3month}	887	0.63%	1.22%	0.01%	0.05%	0.12%	0.29%	5.04%
TL ('000)	887	427,596,479.80	663,392,165.30	468,363.00	4,381,285.00	21,291,457.00	742,291,000.00	2,341,284,000.00
σ_V	887	3.51%	2.46%	0.23%	2.09%	2.87%	4.05%	20.81%
V ('000)	887	463,146,281.30	717,106,790.20	496,118.90	4,981,018.70	24,799,569.50	773,866,554.10	2,634,690,000.00
r	887	1.94%	1.24%	0.14%	0.90%	1.75%	2.75%	5.09%
B ('000)	887	25,485,378.50	50,269,458.10	1,625.90	70,586.40	280,600.30	11,312,666.90	379,261,725.90
T_B	887	5.9511	4.3853	0.7371	2.7543	4.1517	7.3814	19.203
Panel B: Inputs for Merton model at t								
σ_E	887	47.93%	39.17%	12.40%	22.98%	32.34%	55.36%	235.99%
E ('000)	887	36,527,099.50	60,144,531.20	2,505.80	471,597.60	3,650,342.00	49,539,048.00	371,100,000.00
r_{3month}	887	0.53%	1.04%	0.01%	0.05%	0.12%	0.29%	5.04%
TL ('000)	887	428,764,165.50	665,918,391.60	468,946.00	4,439,590.00	21,387,391.00	742,291,000.00	2,341,284,000.00
σ_V	887	3.49%	2.45%	0.23%	2.08%	2.84%	4.00%	20.81%
V ('000)	887	464,759,496.20	720,477,655.40	496,118.90	5,009,298.20	24,926,168.00	773,866,554.10	2,641,110,000.00
r	887	1.91%	1.16%	0.14%	0.96%	1.76%	2.63%	5.09%
B ('000)	887	25,770,806.90	50,969,467.00	1,667.80	70,584.40	281,061.30	11,434,833.10	389,891,857.80
T_B	887	6.1446	4.3579	0.9754	2.9763	4.3653	7.5328	19.0490

This table reports the descriptive statistics on inputs used to estimate market-implied DVAs by Merton model (1973). Panel A and Panel B report the information on same variables but at the end of quarter t-1 and t, respectively. σ_E is annual equity volatility estimated as the standard deviation of daily return over 150 days before the end of the quarter. E the market value of equity.r_{3_month} is the three-month CMT yield. TL is the total book value of liabilities. σ_V is Merton model-estimated annual asset volatility. V is Merton model-estimated unlevered firm value. r is estimated by the Nelson-Siegel model with a term equal to the duration of synthetic Merton zero-coupon bonds. B is defined as the face value of synthetic Merton zero-coupon bonds. T_B is defined as the duration of synthetic Merton zero-coupon bonds.

Table 3.11: Inputs for market information-estimated DVAs (Leland 1994)

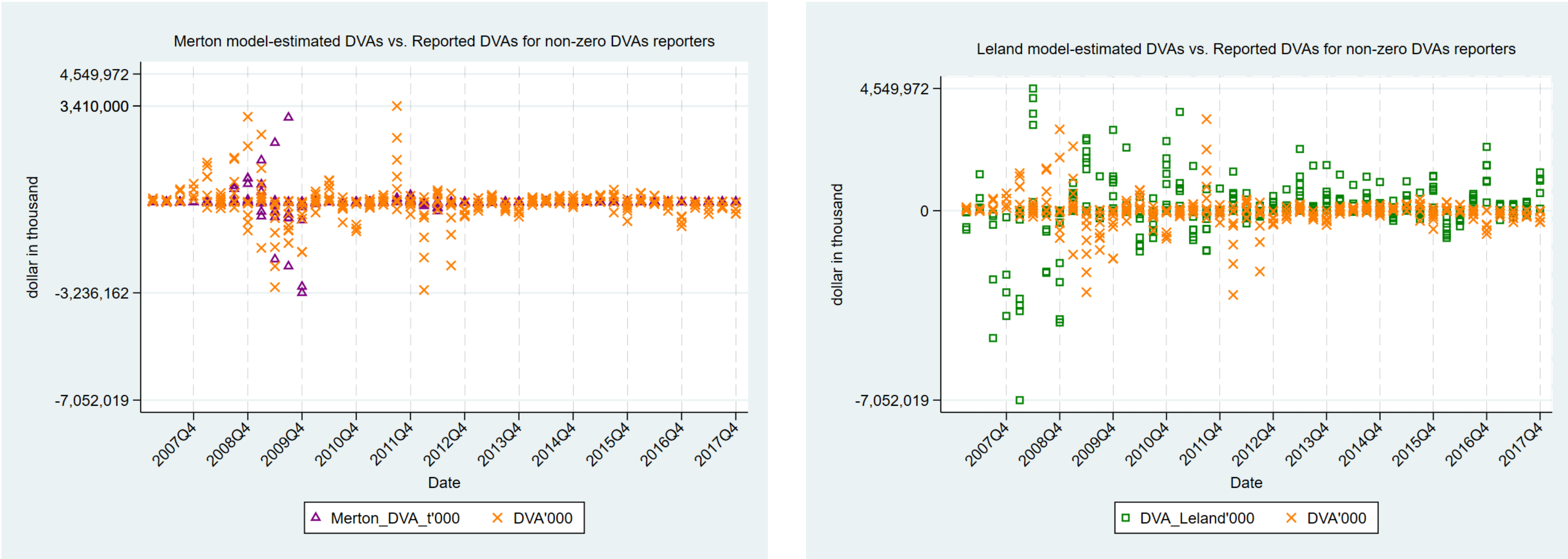
Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Panel A: Inputs for Leland model at t-1								
r_{Leland}	887	3.20%	0.81%	1.87%	2.46%	3.06%	3.91%	5.10%
$Coupon_{Leland}$ ('000)	887	664,768.80	1,556,153.30	64.07	1,217.20	5,525.80	268,756.90	16,907,720.40
C_{Leland}	887	2.61%	0.81%	0.71%	2.06%	2.53%	3.22%	4.72%
σ_{Leland}	887	3.46%	2.39%	0.21%	2.06%	2.85%	3.96%	19.80%
V_{Leland} ('000)	887	49,717,832.00	81,233,059.00	9,621.70	491,746.50	3,767,363.90	66,511,703.50	469,348,055.60
v_{Leland} ('000)	887	57,016,593.50	94,356,082.10	12,357.00	526,723.60	4,091,219.80	71,819,936.10	585,466,239.40
λ	887	-198	730	-13891	-138	-73	-38	-2
V_B ('000)	887	13,387,920.80	27,461,856.00	881.80	24,268.40	107,451.50	4,711,894.80	214,846,326.50
P_B	887	0.0005%	0.0089%	0	4.24E-117	5.7E-64	1.11E-35	0.2330%
BC ('000)	887	12.81	324.10	0	2.83E-112	6.59E-58	3.76E-30	9,591.10
TS ('000)	887	7,298,774.30	14,944,777.90	476.20	13,862.10	58,892.60	2,597,720.00	116,118,183.80
Panel B: Inputs for Leland model at t								
r_{Leland}	887	3.14%	0.78%	1.87%	2.46%	2.97%	3.86%	5.10%
$Coupon_{Leland}$ ('000)	887	654,094.70	1,519,972.10	59.84	1,186.10	5,498.20	263,819.60	15,842,051.70
C_{Leland}	887	2.56%	0.78%	0.68%	2.06%	2.49%	3.11%	4.72%
σ_{Leland}	887	3.44%	2.37%	0.21%	2.05%	2.84%	3.94%	19.80%
V_{Leland} ('000)	887	50,051,014.30	81,827,536.40	9,600.80	505,133.10	3,890,415.20	65,177,944.10	450,929,097.30
v_{Leland} ('000)	887	57,334,936.90	94,819,025.50	12,207.50	528,492.90	4,141,960.30	71,993,246.90	568,706,303.50
λ	887	-203	746	-13891	-138	-73	-37	-2
V_B ('000)	887	13,359,122.50	27,439,157.10	881.90	24,568.10	106,275.20	4,667,050.70	217,517,401.80
P_B	887	0.0005%	0.0087%	0	3.93E-116	2.2E-63	3.99E-36	0.2300%
BC ('000)	887	11.87	270.30	0	5.13E-110	6.72E-57	9.32E-31	7,740.10
TS ('000)	887	7,283,934.40	14,941,225.70	476.20	13,823.00	57,379.10	2,564,336.70	117,777,206.20

This table reports the descriptive statistics on inputs used to estimate market-implied DVAs by Leland model (1979). Panel A and Panel B report the information on the same variables but at the end of quarter t-1 and t, respectively. r_{Leland} is defined as the Leland model-implied risk-free rate. $Coupon_{Leland}$ is defined as the Leland model perpetual debt coupon payment. The Leland model perpetual debt coupon rate (C_{Leland}) is calculated by dividing $Coupon_{Leland}$ over the face value of liabilities under FVOL. σ_{Leland} is the Leland model-estimated asset volatility. V_{Leland} is the Leland model-estimated unlevered firm value. v_{Leland} is defined as the levered firm value. λ is the bankruptcy trigger solution, meaning the elasticity of the probability of default with respect to the value of the asset value.V_B is the endogenously determined optimal bankruptcy threshold. P_B is interpreted as the risk-neutral default probability. BC is defined as the bankruptcy costs, and TS is defined as the tax shields.

Table 3.12: Descriptive statistics of DVAs and market information-estimated DVAs

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Panel A: Total observations								
DVAs ('000)	887	-14,651	374,937	-3,134,715	0	0	0	3,410,000
DVAs_Merton ('000)	887	-5,628	237,950	-3,236,161	-30	0	2	3,003,049
DVAs_Leland ('000)	887	42,401	703,416	-7,052,019	-2,721	89	7,366	4,549,972
Panel B: Non-zero DVA reporters								
DVAs ('000)	347	-37,450	599,267	-3,134,715	-143,000	-162	87,000	3,410,000
DVAs_Merton ('000)	347	-14,264	380,606	-3,236,161	-972	-1	57	3,003,049
DVAs_Leland ('000)	347	109,817	1,120,764	-7,052,019	-91,925	1,546	431,864	4,549,972
Panel C: Positive DVA reporters								
DVAs ('000)	171	259,153	516,821	12	6,000	92,000	231,300	3,410,000
DVAs_Merton ('000)	171	15,089	141,951	-581,161	-82	0	173	845,538
DVAs_Leland ('000)	171	-170,610	1,231,645	-7,052,019	-276,198	-248	181,570	4,549,972
Panel D: Negative DVA reporters								
DVAs ('000)	176	-325,628	530,167	-3,134,715	-383,000	-129,000	-14,300	-35
DVAs_Merton ('000)	176	-42,783	514,953	-3,236,161	-10,331	-29	0	3,003,049
DVAs_Leland ('000)	176	382,278	926,500	-4,158,417	-938	115,187	656,870	4,191,246
Panel E: Zero DVA reporters								
DVAs ('000)	540	0	0	0	0	0	0	0
DVAs_Merton ('000)	540	-79	1,548	-18,189	-3	0	1	13,729
DVAs_Leland ('000)	540	-921	46,836	-446,221	-1,451	8	1,290	362,901

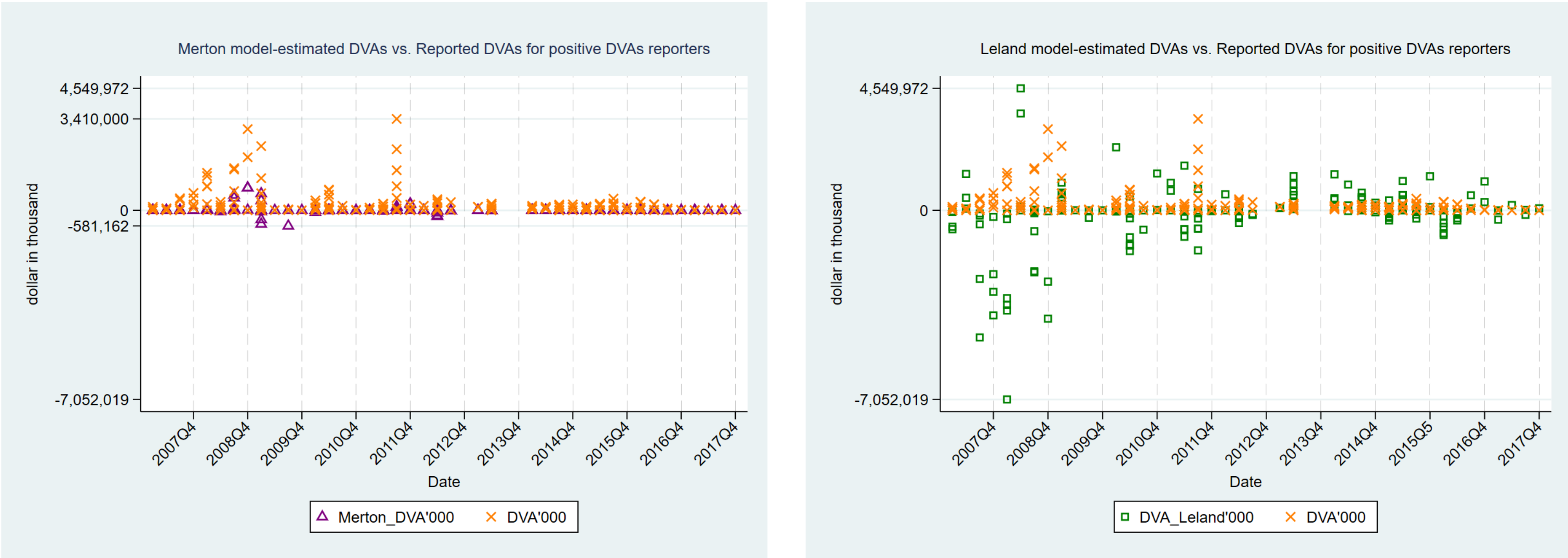
This table reports the descriptive statistics on reported DVAs, Merton model-estimated DVAs and Leland model-estimated DVAs. Panel A provide the information on total observations. Panel B provides the information on non-zero DVA reporters. The information on positive DVAs and negative DVA reporters are displayed in Panel C and Panel D. Panel E reports the information on zero DVA reporters.



(a) (b)

Figure 3.2: The market information-estimated DVAs versus the reported DVAs for non-zero DVA reporters.

This figure shows the market-implied DVAs by the Merton and Leland models versus the reported DVAs against the sample period (2007 - 2017) for non-zero DVA reporters. The bank-quarter observations for non-zero DVA reporters are 347. The Merton model-estimated DVAs are marked with a trangle and the reported DVAs are denoted with an sterisk in the left graph. The Leland model-estimated DVAs are marked with a square and the reported DVAs are denoted with an sterisk in the right graph. DVAs are calculated in thousand.



(a) (b)

Figure 3.3: The market information-estimated DVAs versus the reported DVAs for positive DVA reporters

This figure shows the market-implied DVAs by the Merton and Leland models versus the reported DVAs against the sample period (2007 - 2017) for positive DVA reporters. The bank-quarter observations for non-zero DVAs reporters are 171. The Merton model-estimated DVAs are marked with a trangle and the reported DVAs are denoted with an sterisk in the left graph. The Leland model-estimated DVAs are marked with a square and the reported DVAs are denoted with an sterisk in the right graph. DVAs are calculated in thousand.

(a) (b)

Figure 3.4: The market information-estimated DVAs versus the reported DVAs for negative DVA reporters

This figure shows the market-implied DVAs by the Merton and Leland models versus the reported DVAs against the sample period (2007 - 2017) for negative DVA reporters. The bank-quarter observations for non-zero DVA reporters are 176. The Merton model-estimated DVAs are marked with a trangle and the reported DVAs are denoted with an sterisk in the left graph. The Leland model-estimated DVAs are marked with a square and the reported DVAs are denoted with an sterisk in the right graph. DVAs are calculated in thousand.

(a) (b)

Figure 3.5: The market information-estimated DVAs versus the reported DVAs for zero DVA reporters

This figure shows the market-implied DVAs by the Merton and Leland models versus the reported DVAs against the sample period (2007 - 2017) for the zero DVA reporters. The bank-quarter observations for non-zero DVA reporters are 540. The Merton model-estimated DVAs are marked with a trangle and the reported DVAs are denoted with an sterisk in the left graph. The Leland model-estimated DVAs are marked with a square and the reported DVAs are denoted with an sterisk in the right graph. DVAs are calculated in thousand.

Table 3.13: Descriptive statistics of *Error* and *Absolute Error* for the Merton and Leland models

	Total observations		Zero DVA reporters		Non-zero DVA reporters		Positive DVA reporters		Negative DVA reporters	
	Error ('000) mean (std. dev.)	Absolute error ('000) mean (std. dev.)	Error ('000) mean (std. dev.)	Absolute error ('000) mean (std. dev.)	Error ('000) mean (std. dev.)	Absolute error ('000) mean (std. dev.)	Error ('000) mean (std. dev.)	Absolute error ('000) mean (std. dev.)	Error ('000) mean (std. dev.)	Absolute error ('000) mean (std. dev.)
Merton	9,023	113,716	-79	336	23,187	290,157	-244,064	251,066	282,845	328,137
	(401,692)	(385,347)	(1,547)	(1,512)	(642,535)	(573,547)	(480,856)	(477,216)	(673,833)	(652,855)
Leland	57,051	325,958	-921	13,530	147,268	812,158	-429,763	791,827	707,906	831,912
	(925,919)	(868,456)	(46,835)	(44,844)	(1,475,984)	(1,240,472)	(1,505,067)	(1,349,196)	(1,210,492)	(1,128,385)

This table reports the means and standard deviations of the estimation errors from the Merton and Leland models. It presents the results of model effectiveness for total observations and other four subsamples (i.e. zero DVA reporters, non-zero DVA reporters, positive DVA reporters and negative DVA reporters). The difference (**Error**) and the absolute difference (**Absolute error**) between market-implied DVAs from the Merton and Leland models and the reported DVAs are reported. The error is calculated as the estimated market-implied DVAs minus the actual DVAs. The absolute error is calculated as the absolute value of the **Error**.

Table 3.14: Descriptive statistics of *Error* and *Absolute Error* for the Merton and Leland models by year

	Total observations		Zero DVA reporters		Non-zero DVA reporters		Positive DVA reporters		Negative DVA reporters	
	Error ('000)	Absolute error ('000)	Error ('000)	Absolute error ('000)	Error ('000)	Absolute error ('000)	Error ('000)	Absolute error ('000)	Error ('000)	Absolute error ('000)
	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
Panel A: The Merton model										
2007	-50,806	51,379	3	7	-158,401	160,166	-169,238	169,238	15,000	15,000
2008	-71,297	144,209	416	481	-193,208	388,546	-552,212	555,891	203,586	203,586
2009	77,012	266,642	-920	979	213,918	733,346	-413,400	465,163	553,716	878,611
2010	9,837	85,145	-40	153	27,988	241,348	-217,763	217,763	260,804	263,691
2011	-81,712	131,303	570	631	-195,993	312,792	-425,456	446,747	125,255	125,255
2012	139,419	195,592	-765	771	339,075	473,065	-215,131	215,131	580,034	585,211
2013	33,879	59,814	-11	15	82,595	145,774	-126,358	126,358	152,246	152,246
2014	-18,440	34,379	-4	5	-42,637	79,495	-102,849	102,849	45,364	45,364
2015	-13,040	61,703	-0.28	7	-29,339	138,823	-112,107	112,107	218,968	218,968
2016	27,731	66,553	6	126	69,318	166,195	-96,877	96,877	235,512	235,512
2017	52,567	53,907	-12	14	134,864	138,261	-5,580	5,580	196,308	196,308
Panel B: The Leland model										
2007	-376,812	448,998	-4,696	5,485	-1,164,824	1,388,203	-1,246,018	1,466,573	134,278	134,278
2008	-308,443	613,137	-1,739	4,751	-829,839	1,647,393	-1,736,888	2,474,898	172,689	732,782
2009	401,863	451,714	2,269	2,803	1,103,853	1,240,341	-141,930	246,536	1,778,652	1,778,652
2010	43,073	264,039	-6,067	30,486	133,383	693,271	-327,499	699,506	570,009	687,364
2011	-79,047	338,282	-16,065	25,926	-166,521	772,111	-544,520	855,756	362,676	655,007
2012	215,782	288,896	746	14,056	522,045	680,336	-218,199	304,158	843,891	843,891
2013	224,654	226,768	18,652	18,652	520,782	525,935	382,626	403,238	566,834	566,834
2014	103,005	125,052	-5,496	8,610	245,412	277,881	221,223	265,113	280,764	296,543
2015	95,404	191,733	3,144	17,880	210,729	409,050	28,289	284,600	758,049	782,400
2016	97,541	308,905	864	13,238	242,557	752,407	-242,884	516,063	727,998	988,751
2017	153,694	181,974	946	2,295	392,778	463,211	-37,769	119,637	581,142	613,525

This table reports the average estimation errors from the Merton and Leland models by year. It presents the results of model effectiveness for total observations and other four subsamples (i.e. zero DVA reporters, non-zero DVA reporters, positive DVA reporters and negative DVA reporters). The difference (**Error**) and the absolute difference (**Absolute error**) between market-implied DVAs from the Merton and Leland models and the reported DVAs are applied as the measures of model effectiveness. The error is calculated as the estimated market-implied DVAs minus the actual DVAs. The absolute error is calculated as the absolute value of the **Error**. The results from the Merton and Leland models are reported in panel A and panel B respectively.

Table 3.15: Mean zero and mean equality tests of *Error* and *Absolute Error* for the Merton and Leland models

	All observations		Zero DVA reporters		Non-zero DVA reporters		Positive DVA reporters		Negative DVA reporters	
	Error ('000***)	Absolute error ('000***)	Error ('000***)	Absolute error ('000***)	Error ('000***)	Absolute error ('000***)	Error ('000***)	Absolute error ('000***)	Error ('000***)	Absolute error ('000***)
	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value
Panel A: Test mean zero of the Merton and Leland models estimation errors										
Merton	0.5037	0.0000***	0.2386	0.0000***	0.5019	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Leland	0.0668	0.0000***	0.6479	0.0000***	0.0639	0.0000***	0.0003***	0.0000***	0.0000***	0.0000***
Panel B: Test equality of means of the Merton and Leland models estimation errors										
Equality	0.0694	0.0000***	0.6773	0.0000***	0.0661	0.0000***	0.0594	0.0000***	0.0000***	0.0000***

This table reports the P-values for a two-tailed test, which test the mean zero of the estimation errors from the Merton and Leland models in panel A and equality of the Merton and Leland model mean estimation errors in panel B. The hypothesis for the mean estimation errors is H_0: $\mu = 0$ and $H_1 : \mu \neq 0$. The hypothesis for the equality of the mean estimation errors from the Merton and Leland models is $H_0 : \mu^{Merton} - \mu^{Leland} = 0$ and $H_1 : \mu^{Merton} - \mu^{Leland} \neq 0$. All tests hold for a 5% significance level.

Table 3.16: Mean equality tests of *Error* and *Absolute Error* for the Merton and Leland models by type of DVAs and firm size

	The Merton model		The Leland model	
	Error ('000***)	Absolute error ('000***)	Error ('000***)	Absolute error ('000***)
	P-value	P-value	P-value	P-value
Panel A: For the positive and negative DVA reporters				
Equality	0.0000***	0.2112	0.0000***	0.7639
Panel B: For the zero DVAs and non-zero DVA reporters				
Equality	0.0402**	0.0000***	0.0199**	0.0000***
Panel C: For the large and small banks				
Equality	0.0403**	0.0000***	0.0500**	0.0000***

This table reports the P-values for a two-tailed test, which test the equality of the Merton and Leland model mean estimation errors according to the types of reported DVAs and the size of the sample banks. Panel A compares the estimation errors between the positive and negative DVA reporters from the Merton and Leland models respectively. The hypothesis is $H_0 : \mu^{Positive} - \mu^{Negative} = 0$ and $H_1 : \mu^{Positive} - \mu^{Negative} \neq 0$. Panel B reports the P-values to test the equality of the estimation errors between the zero DVAs and non-zero DVA reporters. The hypothesis is $H_0 : \mu^{Zero} - \mu^{Non-zero} = 0$ and $H_1 : \mu^{Zero} - \mu^{Non-zero} \neq 0$. Applying the threshold ($50 billion) of large banks used in Table **??**, we provide the information on the equality of the mean estimation errors between the large banks and the small banks. The hypothesis is $H_0 : \mu^{Large} - \mu^{Small} = 0$ and $H_1 : \mu^{Large} - \mu^{Small} \neq 0$. The values in bolt refer to cases where the quality of means does hold for a 5% significance level.

Table 3.17: Pearson correlation for the Merton model

	Absolute estimation errors	Market Leverage	Abs Diff.	Size	Market to Book	Asset volatility	Maturity	Coupon	PV_FVOL	Tangible assets	10r
Market Leverage	0.2204										
	0.0000										
Abs Diff.	0.0291	-0.1591									
	0.3870	0.0000									
Size	0.3599	0.0985	-0.1666								
	0.0000	0.0033	0.0000								
Market to Book	-0.1868	-0.7693	0.1844	-0.1790							
	0.0000	0.0000	0.0000	0.0000							
Asset volatility	0.0189	-0.4273	0.2504	-0.2681	0.3503						
	0.5731	0.0000	0.0000	0.0000	0.0000						
Maturity	-0.1798	-0.2790	0.1642	-0.4501	0.1454	0.3318					
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000					
Coupon	0.0573	0.1751	0.0979	-0.0565	-0.1246	0.0612	-0.1389				
	0.0882	0.0000	0.0035	0.0929	0.0002	0.0684	0.0000				
PV_FVOL	0.4701	0.2119	-0.1044	0.6219	-0.1582	-0.1811	-0.3234	0.0561			
	0.0000	0.0000	0.0018	0.0000	0.0000	0.0000	0.0000	0.0948			
Tangible assets	-0.0389	0.0117	0.2219	-0.2650	-0.1453	0.1291	0.2347	-0.1171	-0.1984		
	0.2466	0.7268	0.0000	0.0000	0.0000	0.0001	0.0000	0.0005	0.0000		
10r	-0.0110	0.0629	0.0890	-0.2157	0.0951	0.1636	0.0491	0.3031	0.0137	0.1543	
	0.7437	0.0610	0.0080	0.0000	0.0046	0.0000	0.1439	0.0000	0.6846	0.0000	
Slope	0.0461	0.2938	-0.0350	-0.0190	-0.2636	-0.0031	-0.0112	0.0811	-0.0385	0.0605	0.1896
	0.1701	0.0000	0.2972	0.5710	0.0000	0.9269	0.7398	0.0157	0.2519	0.0718	0.0000

This table reports the Pearson correlation between explanatory variables for the Merton model.

Table 3.18: Pearson correlation for the Leland model

	Absolute estimation errors	Market Leverage	Abs Diff.	Size	Market to Book	Asset volatility	Maturity	Coupon	PV_FVOL	Tangible assets	10r
Market Leverage	0.2089										
	0.0000										
Abs Diff.	-0.0677	-0.1591									
	0.0439	0.0000									
Size	0.4562	0.0985	-0.1666								
	0.0000	0.0033	0.0000								
Market to Book	-0.1375	-0.7693	0.1844	-0.1790							
	0.0000	0.0000	0.0000	0.0000							
Asset volatility	-0.0603	-0.4273	0.2504	-0.2681	0.3503						
	0.0725	0.0000	0.0000	0.0000	0.0000						
Maturity	-0.2232	-0.2790	0.1642	-0.4501	0.1454	0.3318					
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000					
Coupon	0.0645	0.1751	0.0979	-0.0565	-0.1246	0.0612	-0.1389				
	0.0547	0.0000	0.0035	0.0929	0.0002	0.0684	0.0000				
PV_FVOL	0.6818	0.2119	-0.1044	0.6219	-0.1582	-0.1811	-0.3234	0.0561			
	0.0000	0.0000	0.0018	0.0000	0.0000	0.0000	0.0000	0.0948			
Tangible assets	-0.0842	0.0117	0.2219	-0.2650	-0.1453	0.1291	0.2347	-0.1171	-0.1984		
	0.0121	0.7268	0.0000	0.0000	0.0000	0.0001	0.0000	0.0005	0.0000		
10r	0.1039	0.0629	0.0890	-0.2157	0.0951	0.1636	0.0491	0.3031	0.0137	0.1543	
	0.0019	0.0610	0.0080	0.0000	0.0046	0.0000	0.1439	0.0000	0.6846	0.0000	
Slope	0.0222	0.2938	-0.0350	-0.0190	-0.2636	-0.0031	-0.0112	0.0811	-0.0385	0.0605	0.1896
	0.5098	0.0000	0.2972	0.5710	0.0000	0.9269	0.7398	0.0157	0.2519	0.0718	0.0000

This table reports the Pearson correlation between explanatory variables for the Leland model.

Table 3.19: Regressions of logarithm of *Absolute Error* on firm, bond and macroeconomic characteristics

	Logarithm of Absolute error					
	Total observations		Zero DVAs reporters		Non-zero DVAs reporters	
	Merton	Leland	Merton	Leland	Merton	Leland
Intercept	-71.5447***	-4.1615	23.7654	6.6889	-14.8103	-3.4985
t	(-4.35)	(-0.71)	(0.61)	(0.63)	(-1.14)	(-0.29)
Market leverage	23.6888**	4.8652*	-2.7101	1.8000	21.2415***	5.5794***
	(2.49)	(1.66)	(-0.14)	(0.35)	(4.73)	(3.28)
Size	1.9532**	0.3285	0.4689**	0.7301	0.4470	0.4527
	(2.41)	(1.26)	(2.48)	(0.22)	(0.62)	(0.71)
Market/Book	4.6947	0.5274	-27.5548	-1.0908	5.3498	-1.5982
	(0.51)	(0.19)	(-1.60)	(-0.24)	(0.91)	(-0.35)
Asset volatility	109.0310***	9.4290***	158.9584***	10.8134***	17.7037***	8.0548*
	(10.50)	(4.01)	(8.86)	(3.94)	(3.59)	(1.82)
Years to maturity	-0.0621**	-0.0167**	-0.1245	-0.0085	-0.1970*	-0.3119***
	(-2.49)	(-2.58)	(-0.90)	(-0.29)	(-1.92)	(-2.82)
Coupon	20.9901	-3.2174	16.6173	-6.7137	17.4585*	6.6778
	(1.31)	(-0.72)	(0.85)	(-1.23)	(1.78)	(0.73)
PV_FVOL	0.9186***	1.0008***	1.3985***	1.0299***	0.4548***	1.1122***
	(4.14)	(15.54)	(3.91)	(11.81)	(3.52)	(8.29)
PPE/assets	-2.6535**	-7.0441	-237.6725***	-4.6232	-27.3416***	-8.3491
	(-2.22)	(-1.10)	(-2.75)	(-0.19)	(-3.69)	(-1.12)
10-year CMT	-1.4179***	0.0922	-2.1204***	-0.0496	-0.2213*	0.2493
	(-5.75)	(1.30)	(-6.39)	(-0.50)	(-1.74)	(0.42)
Slope of CMT	0.5368**	0.0063	0.2634	-0.0334	0.2070	0.0191
	(2.16)	(0.10)	(0.76)	(-0.36)	(1.53)	(0.19)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	883	887	536	540	347	347
Adj. R-square	77.64%	88.00%	57.85%	73.53%	73.81%	82.20%

This table reports regression coefficients and their t-statistics (in parentheses) of the logarithm value of model absolute estimation errors by applying the Merton and Leland models, respectively. The first two columns display the results in total observations. We divide our full sample into zero DVA reporters and non-zero DVA reporter. Their regression results are shown in the column (3), (4), (5) and (6). Market leverage is the book value of total liabilities over the market value of total assets. Market to book ratio is defined as the market value of total assets over the book value of total assets. PV_FVOL is defined as the balanced principal value of liabilities under FVOL. PPE/assets is the proxy for the recovery rate when firms go bankruptcy, which is defined as the plant, property, and equipment over assets. The slope is the difference between the 10-y CMT minus the 2-year CMT. The coefficient estimates and t-statistics are based on robust standard errors. *, **, and *** of the t-statistics indicate statistical significance at 10%, 5% and 1% levels (two-tailed) respectively.

Chapter 4

Conclusions

To date, fair value accounting (FVA) has become a crucial measurement principle in both IFRS and U.S. GAAP. In order to promote FVA as the future basis for measurement, IASB and FASB issued IAS 39 and SFAS No. 159 respectively, which allow firms to adopt the fair value option (FVO) to measure eligible assets and/or liabilities at fair value. Following the disclosure guidance set forth in SFAS No. 157, firms need to recognize the changes in fair value of liabilities under FVO due to the changes in firms' own credit risk in accounting earnings, referred as Debt Valuation Adjustments (DVAs).

Although the counterintuitive accounting results of recognizing DVAs attract remarkably attention from both financial statements-users and standard setters, there is a limited theoretical analysis and empirical evidence regarding DVAs. This thesis aims to contribute to the mixed arguments over the recognition of DVAs in accounting earnings.

The first study (Chapter 2) examines whether the information (including the private information) in the reported DVAs correctly reflect (or are at least positively correlated to) changes in the credit quality of the entity. Indeed, prior studies focus on the value and information asymmetry implications of DVAs and associated disclosures without answering this question. However, we believe the investigation on the reliability of reporting DVAs in accounting earnings really matters to investors given the findings in the prior studies that reported DVAs are value and risk-relevant to investors (Chung et al. 2012). Moreover, both FASB and IASB have invested considerable time and resources in introducing and amending the FVOL accounting standard, providing evidence as to whether this process leads to more informative financial statements or not is important.

The mandatory disclosure of fair value estimates in accordance with a three-level hierarchy based on the nature of the inputs used in the estimation provides a perfect research specification to examine the reliability of DVAs. We find that changes in bond and credit spreads are statistically significant in explaining DVA-estimated changes in credit spread for banks that report liabilities at fair value Level 1 and 2. These results provide evidence that market inputs are used in the DVAs estimation process for Level 1 and 2 reporters. When we investigate whether reported DVAs convey private information about the credit quality of the entity, we find that lagged DVA-estimated changes in credit spreads are significant in explaining changes in bond and CDS spreads for Level 3 reporters. These results indicate that managers have superior information in estimating their own credit risk and credibly communicate this information through financial reports to the market.

Our results support the view that managers have an information advantage in estimating DVAs, and that the fair value measurements based on managerial inputs better reflect the credit risk of liabilities in our sample. We believe that our results improve our understanding of managerial decision-making with respect to fair value accounting, contributing to the literature that examines the equity and risk relevance of fair value Levels. Our findings indicate that managers use their discretion in computing Level 3 fair values to provide information to the market that is useful to predict future risk. We also contribute to the debate about the role of fair value accounting in generating decision-useful financial information (Fontes et al. 2018; Blankespoor et al. 2013; Koonce et al. 2011).

The second study (Chapter 3) is motivated by the empirical evidence on the informativeness of reported DVAs in net income. Following the guidance set forth in the SFAS No. 157, the disclosure on DVAs is voluntary and usually reported in the footnotes. This opaque disclosure gives management an opportunity to exercise discretion over DVAs. Furthermore, the survey on the data sources and methodologies used in DVAs estimation procedure suggests management employ observable and/or unobservable market data in a range of valuation techniques. Therefore, the reported DVAs attracts the investors' concerns about the extent to which the privacy information exploited by management in the estimation of DVAs.

This study compares the reported DVAs provided by management with the estimated DVAs based on market information, denoted as market information-estimated DVAs. If the market information-estimated DVAs differ from the reported DVAs significantly, we could state the internal credit risk assessment reflects private information not covered by the external credit risk assessment efficiently, as the guidance of DVAs calculation permits management to use the private information if the market for the underlying liabilities is illiquid. Alternatively, if the market information-estimated DVAs are close to the reported DVAs, we could state the external credit risk assessment captures the information on credit risk through financial reports in a timely manner. We find that the structural credit risk models do a poor job of pricing DVAs, especially when the banks' own creditworthiness is volatile. Our results support the view that the reported DVAs contain private information and the ignorance of private information in structural credit risk models limit their ability in the replication of reported DVAs. Further, the private information in the reported DVAs surges when the economy is volatile rather than stable.

This paper contributes the debate over the recognition of DVAs in accounting earnings in terms of its informativeness to investors. Our investigation allows us to discuss the extent to which market information-implied credit risk capture the information contained in the banks' internal risk measure. That is, whether estimates from structural credit risk models are informative to the regulators and investors who mainly rely on the public information to understand the underlying economic performance of an entity. Our results suggest that the reported DVAs reflect more internal information of credit risk if an entity suffers from poor economic condition.

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