The Impact of Government Interventions on CDS and Equity Markets*

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Abstract

We investigate the impact of government guarantees on the pricing of default risk in credit and stock markets in light of the unprecedented wave of rescue actions witnessed in the 2007-09 financial crisis. Using a Merton-type credit model, we provide evidence of a structural break in the valuation of U.S. bank debt in the course of the crisis, manifesting in a lowered default boundary, or, under the pre-crisis regime, in lower credit spreads than if there were no guarantees. The counterfactual is estimated from stock market information, the underlying assumption being that, unlike creditors, shareholders are not the targeted beneficiaries of interventions. The discrepancies are positively related to firm size, default correlation, systemic risk, and high ratings, thus corroborating our too-big-to-fail hypothesis. The framework we develop allows (1) to measure the magnitude of the guarantees, (2) to identify which firms are perceived as TBTF and when guarantees become particularly valuable, and finally (3) to have a better estimator of the standalone financial condition of a firm, and as such opens up interesting avenues for research and policy applications in the area of economic policy and regulation.

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Although the notion of "too big to fail" (TBTF) has been around for a few decades in the context of sporadic government actions targeting individual companies, the existence of this phenomenon has long been the subject of controversy (see, e.g., Meltzer (2004)). The large wave of interventions that accompanied the 2007-2009 economic crisis clearly argues in favor of the TBTF doctrine advocated by Feldman and Stern (2004). Reminded of the Great Depression in the 1930s, policymakers were concerned about the possible scenario of cascading bank failures following the non-rescue of Lehman Brothers in September 2008. As a result, governments and central banks of the leading economies joined their efforts to save the financial system by restoring confidence within markets and stemming the spread of financial contagion. Trading off the need for immediate financial stability against the long-term implications for moral hazard, governments engaged in a proactive policy of saving major financial institutions at all cost. To provide figures, Panetta et al. (2009) estimate that, as of June 2009, the United States had committed to guarantees, capital injections, and asset purchases worth of \$3.5 trillion or 25% of the book value of assets in the national banking sector. Global efforts are reported to be about twice as high. However, the entailed long-term repercussions on incentives, competition, sovereign debt, and the information content of market prices are disastrous in other ways and illustrate that going forward regulation needs to address crises in a more proactive and preventive manner so as to lessen the need for bailouts.

When a government intervenes, its primary focus is on the avoidance of default and thus the service of the debt of the distressed company. Hence, creditors generally see their claims honored, whereas the picture is less favorable for shareholders. While stock prices often climb immediately after the announcement of a bailout and sometimes even outperform their market benchmark (King (2009)), the bounce may not be sufficient to offset previously accumulated losses, and in the worst case the equity is virtually wiped out. Simply put, it appears that interventions by their very nature favor debtholders over shareholders. Bear Stearns is a case in point: On May 30, 2008 the distressed U.S. investment bank was acquired by its competitor JPMorgan Chase for a share price of \$10 (compared to \$150 one year earlier) in a deal arranged and backed by the Federal Reserve that granted a \$30 billion nonrecourse loan to JPMorgan, thereby de facto guaranteeing for Bear Stearns' risky assets. This begs the question whether markets picked up this "scheme," i.e., considered the Bear Stearns bailout as precedent and anticipated further rescues that benefit creditors first and foremost. If they did, and this forms the main hypothesis of this work, we would expect the market price of default risk to differ across credit and stock markets in the way that the stock-market-implied default risk would exceed its credit default swap (CDS) counterpart. This would imply a structural change in which "default" as measured by a stock price of zero, on the one hand, and "default" as measured by creditors getting less than their promised principal and interest payments, on the other hand, are no longer the same event. Namely, if the government is anticipated to step in to ensure that a company does not go into legal bankruptcy and default on its debt by protecting creditors, but not the equity value, then there is a rational explanation for why these two default assessments can diverge. This realization is the starting point of our research.

This paper analyzes the impact of government guarantees on the market price of credit risk by contrasting CDS premiums to their theoretical counterparts estimated via a Merton-type structural model, in which default occurs when the asset value process reaches an endogenously determined boundary. This class of models allows to model the default propensity of a firm depending on its capital structure, i.e., its share of debt and equity, and is thus naturally suited for the estimation problem at hand aiming to link and compare the default risk component implicitly reflected by stock and CDS prices.

Our findings based on a sample of 498 U.S. companies spanning the period 2002-2010 are the following. Whereas both markets are closely aligned in the pre-crisis period, we find vast evidence of a decoupling as the crisis unfolds and characterize the observed price differential as "the wedge." While this effect is very pronounced for financial institutions and most distinct for banks, it is minor or inexistent for other sectors, consistent with the experience that most interventions pertained to the former. Our analysis indicates that the high equity-implied spreads translate, within the context of the model, into a downward shift of the default boundary and a rise in the distance-to-default that could coincide with a capital injection, a debt guarantee or a purchase of risky assets. When the calibration method explicitly allows for a time-varying default barrier, the magnitude of discrepancies subsides to levels well within the range typically observed during the pre-crisis period. The term structure of the deviations suggests that investors view the effect as transitory.

To corroborate our findings and more directly test the TBTF hypothesis, we attempt to explain price deviations across markets with a set of variables presumably related to TBTF and systemic risk, especially firm size, default correlation, and measures of participation in the Troubled Asset Relief Program (TARP). The results under various regression settings indicate that each of the aforementioned proxies has a positive and significant influence on both deviation levels and changes. Moreover, we note that deviations are counter-cyclical and positively influenced by the rating class, in line with intuition. Counterparty risk, proxied by a beta measure of the joint default correlation between a firm and a constructed primary dealer index, has also a significant impact, but this is no surprise given its sensibility to systemic risk. A graphical analysis and an adjustment of the deviations for counterparty risk support that it plays a minor role in explaining the wedge.

We also explore the time series properties of predicted and observed CDS spreads and find that they are cointegrated for the majority of reference entities, emphasizing the long-term linkage and information efficiency across markets.[1] Further, Gonzalo-Granger and Granger Causality analyses reveal that the prices of stocks and CDSs of financial institutions reflect the same information content as both markets contribute almost equally to price discovery. These additional insights allow us to rule out cross-market information inefficiencies as alternative explanations for the wedge pattern.

Finally, we provide an application to demonstrate how our method can be useful for the assessment of the implicit subsidies that financial firms perceive due to their lower borrowing costs, the TBTF premium. Relying on a comprehensive data set of all public bond issues by U.S. debtors, we revalue the offering price of every bond and arrive at an aggregate estimate of the magnitude of support of \$129.2 billion for the period 2007-2010. Viewed from another angle, firms would have suffered a shortage of \$91.6 billion in debt issuance if they had not adjusted their terms.

Our paper contributes to the existing literature in several ways. First, it integrates a strand of literature that investigates the effect of TBTF on market prices and ratings. Some studies investigate the effect of the designation of banks as TBTF by the Comptroller of Currency in September 1984 on the associated stock prices and bond ratings and report a positive wealth effect and a one-notch elevation of the ratings for these banks compared to non-TBTF organizations (O'Hara and Shaw (1990); Morgan and Stiroh (2001)). Rime (2005) studies a global sample covering the period 1999 to 2003 and confirms prior results of a positive impact of TBTF on credit ratings by approximating the TBTF status of a bank by its size and market share. Another kind of literature contemplates bank merger activity, including Peñas and Unal (2004) who report a decline in bond spreads after mergers. In comparison, our paper differs from the prior literature in that we are the first to measure impact of TBTF and government interventions as the deviation in default estimates between CDS and equity markets.

Second, our work is related to a long literature investigating the default and nondefault drivers of credit spreads (e.g., Collin-Dufresne, Goldstein, and Martin (2001); Zhang, Zhou, and Zhu (2009)) and highlights the importance of a "guarantee component" in addition to the classical factors like standalone default risk, illiquidity, macroeconomic condition, and counterparty risk (in the case of CDSs) discussed in prior research.

Third, our results may prove useful for the current debate on bank regulation and the prevention and handling of future crises. To begin with, we provide evidence of a negative

[1] The corresponding section was removed from this edited version of the paper in order to better comply with the submission guidelines of the British Academy.

side effect of bailouts, namely the funding cost premium that TBTF firms receive and the distortion of prices across markets. Further, our findings emphasize the unreliability of CDS prices to monitor the health of financial institutions. Since these prices may be biased to the downside in the way that they only reflect part of the underlying default risk, i.e., the default probability conditional on the guarantee, they must be weak estimators of the true financial condition. To overcome this issue, Hart and Zingales (2009) propose that, whenever the CDS premium of a monitored firm exceeds a certain threshold, stress tests should precede further regulatory actions like replacing the CEO or recapitalizing the distressed firm. In contrast, our approach of inferring unconditional CDS prices from stock market data could enhance such a framework in that it would provide decisionmakers with more sensible estimates of the standalone credit quality of a firm, alleviating the need for time-consuming stress tests.[2]

More remotely, our paper alludes to the recent literature on the market-based assessment of single-bank contributions to systemic risk. The most popular approaches include the conditional value at risk (CoVaR; Adrian and Brunnermeier (2010)), the marginal expected shortfall (MES; Acharya et al. (2010)), and the distress insurance premium (DIP; Huang, Zhou, and Zhu (2011)). According to our regression results, our price deviations are closely related to each of these measures: The CoVaR is linked to size and market beta, the MES depends on the stock volatility and the correlation between the stock and the market return (Brownlees and Engle (2010)), and the DIP is driven by size and asset correlation. Viewed in this light, these papers further support our conclusion that the structural break was due to the market perception of a surge in systemic risk and associated government actions.

The remainder of this paper is organized as follows. Section I discusses the structural framework used to extract credit information from equity markets and link it to CDS observations. Section II describes our CDS data set as well as the data necessary to generate stock-implied estimates of default. Section III compares estimated and actual CDS spreads under different calibration schemes. In Section V, we use regression analysis to identify the determinants of the model-market deviations on. Section VI presents estimates of the magnitude of the government support by applying our method to the revaluation of new bond issues. To conclude, we summarize and discuss our results in Section VII.

[2]The stress test mechanism has one shortcoming: Conducting stress tests once the market CDS price hits a trigger essentially prevents "type-II" errors of intervening "too early", i.e., when observed CDS spreads are wider than they should. However, under the more likely circumstances of too low premiums due to continuous interventions, the proposed mechanism would draw the regulator's attention too late. In other words, running stress tests when the variable in question understates default risk fails to protect against this form of market price inaccuracy.

I. Linking CDS and Equity Markets

A CDS provides insurance against the risk of default by a particular company. If a credit event occurs during the life of the contract, the buyer of the insurance has the right to sell bonds issued by the company for their face value, the CDS's notional principal, and is therefore compensated for the losses she would otherwise incur. The protection seller receives fixed periodic payments in return whose annual sum, as a percentage of the notional principal and quoted in basis points (bps) per annum, is referred to as the CDS spread. The contract terminates as soon as a credit event, as defined by the restructuring clause, is recorded and no further payments occur afterwards (see, e.g., Hull (2009)).

Relying on CDS rather than corporate bond yield spreads presents several advantages: First, by construction, CDS spreads provide a relatively direct and pure measure of the default risk of the reference entity compared to bond prices that can be heavily affected by short sale restrictions, liquidity, and interest rate risk. This is the reason why structural factors tend to be more successful at explaining CDS than bond spreads (Ericsson, Reneby, and Wang (2007); Blanco, Brennan, and Marsh (2005)). Second, CDSs are traded on more standardized terms while bonds vary on a large array of features, like time to maturity, covenants, and options that complicate the task of obtaining a sample of homogeneous default estimates. Third, individual corporate bonds can be very illiquid and timely prices hard to obtain. Fourth, several studies have demonstrated that the CDS leads the bond market in price discovery and that CDS premiums react more timely to changes in the credit conditions of the underlying firm (see, e.g., Longstaff, Mithal, and Neis (2005); Zhu (2006); Forte and Peña (2009)).

Consequently, the CDS spread is a natural choice in our analysis aiming to compare stock and credit market estimates of default risk. The valuation of a stock-market-implied benchmark price is based on the CreditGrades model (CG) first presented in Finger et al. (2002) and extended in Finger and Stamicar (2006). It belongs to the class of structural credit models, which emanated from the work of Merton (1974) who values equity and debt as contingent claims on the firm value. In this approach, the risk and the return distribution of debt instruments are solely inferred from firm fundamentals, in particular the liability structure, the stock price, and the stock volatility. The Merton model is the origin of a long strand of literature in the asset pricing field and numerous extensions exist today. While in the original framework the asset value is modeled as a diffusion process and default occurs when the asset value falls below the promised payment of a zero coupon bond at the time of maturity, Black and Cox (1976) introduce an exogenous barrier and define default as the event when the asset value process first falls that help predict observed levels reasonably well, its transparency and closed-form solution, and its wide use in both practice and academia (see, e.g., Yu (2006); Duarte, Longstaff, and Yu (2007); Cao, Yu, and Zhong (2011)).[3]

In the CG model, the firm assets V are assumed to evolve by the diffusion

$$\frac{dV_t}{V_t} = \mu_V dt + \sigma_V dW_t, \tag{1}$$

where W_t is a Brownian motion, σ_V denotes the asset volatility, and μ_V the drift. Consistent with the findings of Collin-Dufresne and Goldstein (2001) that on average, even as firms grow, the level of leverage tends to maintain constant over time, Finger et al. (2002) assume a stationary leverage, implying equal debt, equity, and asset drifts. Further, since for pricing credit, it rather comes down to the relation between the drift of the asset and the drift of the default boundary than to the asset drift per se, for simplicity, μ_V is set equal zero.

The default threshold B equals LD, where L is defined as the average recovery rate of firm debt D. This is similar to the Leland (1994) model in which the default boundary is specified as a constant percentage of the debt level. In the spirit of Duffie and Lando (2001) who emphasize the relevance of incomplete accounting information, the barrier is assumed stochastic and the true level of B does not reveal until default occurs. More precisely, the barrier-related uncertainty arises from L following a lognormal distribution with mean $\overline{L}$ and standard deviation λ. A stochastic default barrier increases short-term default probabilities by capturing the possibility of instantaneous default and leads to predictions closer to actual market spreads. Similar results can be achieved by incorporating jumps into the asset process (see, e.g., Zhou (2001)).

In this setting, the risk-neutral survival probability $P(t)$ that the firm value does not hit the default boundary until time t is given by the approximate closed-form solution

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{log(d)}{A_t}\right), \tag{2}$$

with

$$d = \frac{S_0 + \overline{L}D}{\overline{L}D} \exp \lambda^2, \tag{3}$$

[3] Albeit structural models have difficulties to replicate observed corporate bond spreads (Jones, Mason, and Rosenfeld (1984); Eom, Helwege, and Huang (2004)), they do a good job of explaining CDS price variation (Doshi, Ericsson, Jacobs, and Turnbull (2011); Zhang, Zhou, and Zhu (2009); Ericsson, Reneby, and Wang (2007); Arora, Bohn, and Zhu (2005)). Along the lines of Schaefer and Strebulaev (2008) and Leland (2004), structural models are actually successful at predicting default probabilities and the persistent underestimation of bond spreads in empirical applications appears to rather reflect a large nondefault component than a general inadequacy of the model class. This should be less of an issue with CDSs that are primarily a gauge of default risk, as confirmed empirically by the studies cited above. Additionally, the findings of Blanco, Brennan, and Marsh (2005) underline that structural factors are indeed more relevant at predicting CDS than bond spreads.

$$A_t^2 = \sigma_V^2 t + \lambda^2, \tag{4}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function and σ_V denotes the asset volatility.

Contrary to the CG technical document in which equity volatility is estimated as the historical volatility over a rolling window, we rather rely on the implied volatility of stock options as a more accurate estimate of future volatility. Our tests indicate that historical volatility estimators are impractical in turbulent periods since resulting credit spreads distinctly lag behind their forward-looking counterparts (cf. Benkert (2004), and Cao, Yu, and Zhong (2010)).

The asset volatility is then approximated by the linear relation

$$\sigma_V = \sigma_S \frac{S}{S + \overline{L}D}, \tag{5}$$

where S denotes the stock price, σ_S the equity volatility, and D the debt per share.[4]

Deriving and equating the present values of the protection leg and the premium leg of the contract yields the following solution for the premium c of a CDS with maturity T:

$$c = r(1-R)\frac{1 - P(0) + e^{r\xi}(G(t+\xi) - G(\xi))}{P(0) - P(t)e^{-rt} - e^{r\xi}(G(t+\xi) - G(\xi))}, \tag{6}$$

where $\xi = \frac{\lambda^2}{\sigma^2}$, r is the deterministic risk-free interest rate, and R is the expected recovery rate to a specific debt class.[5] The function G is given by Reiner and Rubinstein (1991) as

$$G(u) = d^{z+\frac{1}{2}}\Phi\left(-\frac{log(d)}{\sigma_V\sqrt{u}} - z\sigma_V\sqrt{u}\right) + d^{-z+\frac{1}{2}}\Phi\left(-\frac{log(d)}{\sigma_V\sqrt{u}} + z\sigma_V\sqrt{u}\right), \tag{7}$$

with $z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma_V^2}}$. We refer the interested reader to Finger et al. (2002) for the complete derivations of the above equations.

After presenting the data in the next section, we follow up on the specification of the model in Section III when we turn our attention to the calibration methodology.

[4]Eq. 5 is based on an inspection of boundary conditions in Finger et al. (2002) and implies $\frac{\partial V}{\partial S} = 1$ in the general relation $\sigma_V = \frac{S}{V}\frac{\partial V}{\partial S}\sigma_S$ underlying the Merton model. This assumption is particularly reasonable when the asset value is away from the barrier, while $\frac{\partial V}{\partial S}$ should exceed one near the barrier. However, the loss of precision is of marginal relevance for the purpose of our analysis. Actually, overcoming this inaccuracy would only reinforce our general results as the stock-implied model spreads increase in σ_V.

[5]For simplicity, Eq. 6 implies a continuous cash flow stream in the premium leg instead of the quarterly payment schedule typically encountered in the market, but the impact of this assumption should be negligible for practical purposes as pointed out by Finger et al. (2002).

II. Data Description

A. CDS Data

While CDSs have existed since the 1990s, liquid markets covering a wide array of obligors have only developed in the new millennium. Being over-the-counter derivatives, data providers aggregate quotes from several trading desks to form a composite CDS spread for a given day. In the aggregation process, contributions reflecting stale observations, flat curves, outliers, and inconsistencies are eliminated. We rely on CDS data by the *Markit Group*. All considered CDS contracts are denominated in U.S. dollars and include a modified restructuring clause (MR), the most prevalent in the U.S., under which restructuring agreements count as a credit event and any bond issued by the reference entity with a remaining life of no more than 30 months is deliverable.

For most of our analyses, we focus on five-year CDSs, which is by far the most frequently traded tenor. Starting with a universe of about 1,900 single-name CDSs for the U.S. market, we successively narrow down the sample using a couple of criteria. On the company level, we exclude sovereign entities, companies that defaulted before the financial crisis, and nonlisted firms. On the individual CDS level, we discard the subordinated class of contracts and CDSs suffering from strong illiquidity. More precisely, we require a CDS series to possess a minimum of 150 daily observations in the two years immediately preceding mid-2007, and at least 100 observations thereafter. Finally, the 784 swaps surviving this filtering are matched against firm-level information.

B. Stock, Option, and Other Data

For the estimation of benchmark CDS spreads under the structural framework described in Section I, we first collect daily stock prices and numbers of shares outstanding from the *Center for Research in Security Prices database (CRSP)* and apply the usual adjustments for stock splits, dividends, and other capital measures. Quarterly balance sheet items, monthly Standard & Poor's (S&P) issuer ratings, and Global Industry Classification Standard (GICS) codes are from *Compustat*. Our choice of classifying firms according to the GICS scheme is motivated by Bhojraj, Lee, and Oler (2003) who show that it is equal or superior compared to the SIC and other classification standards in a variety of common applications. We apply a few adjustments at the subsector level in that we reclassify firms like Goldman Sachs and Morgan Stanley that were originally included in "Diversified Financials" as "Banks." The remaining diversified financial companies form a new group labeled "Others."

Concerning the option data, we infer the one-year implied volatility of at-the-money put options from the *IvyDB OptionMetrics* volatility surface file. These parameters are virtually identical to those suggested in Finger and Stamicar (2006). All the raw data from the above mentioned sources are cleaned for missing or invalid observations.

Putting forward liquidity and tax reasons, a number of authors have argued that the Treasury rate is too low of a measure for the true risk-free reference rate and advocate the use of Libor or swap rates (see, e.g., Collin-Dufresne and Solnik (2001); Longstaff (2004); Blanco, Brennan, and Marsh (2005)). However, in the context of the recent crisis, it can be argued that the Libor/swap term structure bear some portion of counterparty risk since Libor rates reflect the default risk of unsecured loans between banks. For robustness, we carry out our main analyses on the basis of both Treasuries and swaps and find our numerical results to be virtually identical. The model calibration results reported in the next section are based on a flat term structure approximated by the five-year rate that we read off the Libor/swap zero-yield curve extracted from observed par rates. In doing so, we rely on a standard bootstrapping algorithm outlined in the following (cf. Longstaff, Mithal, and Neis (2005)): First, we collect three-month, six-month, and 12-month Libor spot rates from *Datastream* and two-year, three-year, four-year, five-year, seven-year, and ten-year swap par rates from the Federal Reserve Bank website, which is also the natural source for the Treasury rate series used in some of the analyses. Second, we interpolate a smooth curve with cubic splines. The underlying discount function is then obtained by bootstrapping the interpolated rates at semiannual intervals, consistent with the coupon schedules of the swaps.

While all four databases share the CUSIP as common identifier, it does not always allow for a direct and stable link across data sets due to its nonpermanent nature. As a result, all records merged via CUSIPs have to be manually checked and adjusted if need be. Due to the insufficient availability of option data for certain firms, the remaining sample narrows down to 498 U.S. reference entities across all sectors and rating classes, as summarized in Table I, and an average of 1,487 daily observations per firm over the considered period from January 2002 to September 2010. The total number of daily observations with complete CDS, stock, balance sheet, and option volatility information amounts to 740,498, which makes this data set one of largest of its kind ever studied in the literature. The names, subsectors, and numbers of observations of all the financial institutions in our sample are further detailed in Appendix A.

[Insert Table I about here]

III. Predicted versus Observed CDS Spreads

The Merton (1974) model predicts that a firm is in default when the value of its assets falls below the value of its debt, or, equivalently, when its financial leverage ratio of debt over assets reaches one. It naturally extends to the whole class of structural frameworks that, all else being equal, the default probability and the credit spread increase monotonically in the leverage ratio. A wide array of empirical studies (see, e.g., Collin-Dufresne, Goldstein, and Martin (2001); Zhang, Zhou, and Zhu (2009)) confirms that leverage is indeed an important driver of observed credit spreads. Therefore, a structural model's ability to generate sensible estimates depends on the use of a reasonable exogenous or endogenously determined assessment of firm leverage. A bias at this stage inevitably affects the predictions given that the unobservable asset volatility is usually backed out of the equity volatility by means of the leverage (Eom, Helwege, and Huang (2004)). One difficulty is that while the equity part can easily be determined from stock market data, the debt is usually approximated using book values. The leverage of financial institutions is particularly hard to assess because large parts of their debt are secured or insured and thus do not contribute to our notion of leverage.

We address this issue by adjusting the leverage using CDS spread observations. In the CG model, we note that the linear relation in Eq. (5) incorporates the mean level of the default barrier, $\bar{L}D$, instead of the plain book value D. Hence, we accommodate the model to market-based firmspecific credit information by allowing $\bar{L}$ to fluctuate while minimizing the sum of squared errors between model and market prices over a number of trading days, thereby adjusting the default barrier and the leverage ratio endogenously, consistent with the theory behind Leland (1994) and Leland and Toft (1996) about the endogeneity of bankruptcy. Yu (2006) and Duarte, Longstaff, and Yu (2007) rely on a similar approach to calibrate the CG model. The other model ingredients are assumed as follows:

- The standard deviation of L, λ, is set to 0.3 (Finger et al. (2002)).
- The debt per share D is calculated as the total liabilities reported by *Compustat* over the number of common shares outstanding. The latter is adjusted for stock splits and other capital measures. When matching quarterly updated book values with daily variables, the former ones are considered available from their reporting date on and apply until new financial statements are published.
- The debt class specific recovery rate R is set to 0.5 (Yu (2006)).
- The risk-free interest rate r is assumed to be the five-year constant maturity zero-coupon swap rate inferred from swap rates as described in Section II.B.
- The equity volatility σ_S is the one-year at-the-money implied volatility from put options.
- Unless stated otherwise, we focus on CDSs with a tenor of five years and apply the Act/360 day counting convention prevalent in the CDS market.

Next we examine alternative calibration schemes that differ with respect to the specified default barrier. For expositional convenience, whenever we mention a constant or time-varying default barrier, we actually refer to the expected level of a barrier with a constant or time-varying $\bar{L}$, respectively, and thereby leave aside the impact of the exogenous debt level D.

A. Calibration with a Constant Default Barrier

In the basic calibration scheme, for each firm i, we determine $\bar{L}_i$ using N observations over the estimation period from January 2003 through July 2007 by minimizing the sum of squared errors between model ($\widehat{CDS}$) and market spreads (CDS),

$$\min_{\bar{L}_i} \sum_{n=1}^{N} (\widehat{CDS}_{i,n}(\bar{L}_i) - CDS_{i,n})^2, \tag{8}$$

where N depends on the density of the calibration grid[6], and $\widehat{CDS}$ is a function of $\bar{L}_i$ and the other model ingredients not reproduced here to lighten the notation. We consider intervals of 50, ten, three, and one among the observations in the estimation window and report corresponding results in Panel A of Table II. The average implied $\bar{L}$ is found to be around 1.07, but the distribution appears skewed as the median is only about 0.85. The bank subsample exhibits the lowest average $\bar{L}$ (0.225), which is not unexpected given their special liability structure. While $\bar{L}$ is defined as the global recovery rate in the CG model, we rather view it as an adjustment factor to a book value that inevitably mismeasures the relevant market value of debt, similar to Leland (1994). Furthermore, a firm replacing a portion of its long-term liabilities with short-term debt should, all else staying equal, have a higher default barrier and credit exposure than before (Yu (2006)).

[Insert Table II about here]

First, we observe that the density of the grid and thus the number of calibration points has hardly any impact on the quality of the calibration as measured by the mean pricing error (ME) and the root mean squared error (RMSE). While there is a slight improvement in reducing the interval from 50 to 10, an even denser grid increases the pricing errors, suggesting an overfitting of the model to the data. Hence, an interval of ten appears reasonable in the light of both performance and computational considerations and is the interval we focus on moving forward.

[6]The density of the calibration grid reflects how many observations were used for calibration within a given time frame. For example, a density of 10 indicates that every 10th observation was used in the calibration.

In the pre-crisis period (before August 2007), the model underpredicts observed spreads by 9 bps on average and this figure is largely statistically significant. The underestimation of credit spreads by structural models seems to be a stylized fact in the literature (see, e.g., Eom, Helwege, and Huang (2004)). A common explanation is that the model price reflects only default, but not nondefault components of spreads, like first of all illiquidity. Actually, this number comes very close to the estimates of Tang and Yan (2007) who calculate a liquidity premium of 13 bps in the CDS market, which is incidentally on par with evidence by Longstaff (2004) regarding the Treasury bond market. Moreover, Longstaff, Mithal, and Neis (2005) report a large nondefault component in corporate bond spreads.

Between August 2007 and September 2009, the assumed crisis period, the mean error rises up to 69 bps before reverting back to an average of 31 bps in the post-crisis period (October 2009 to September 2010).

Next, focusing on the cross-section, we decompose our results by sectors in Panel B of Table II. We note that the leverage adjustment implied by our calibration works especially well in the highly-levered financial sector, where both the mean error (-7 bps) and the standard deviation of the pricing error (27 bps) are smallest in absolute terms. Notwithstanding, the overall impression is that the average deviations vary only modestly between industries.

In the crisis period, the average spread differences climb in general, but not uniformly across industries. Financial companies are clearly most affected with an average pricing error of 183 bps. Among these, the bank subset exhibits an even higher mean of 350 bps, followed by insurance companies with 134 bps. The other (sub)sectors exhibit much lower mean errors, and utilities, industrials, consumer staples, and other financial companies are hardly affected at all. Finally, the deviations diminish in the post-crisis period but do not fade away completely. Again, they remain most persistent in the financial industry with an average of 126 bps.

To gain a better understanding of the dynamics at work in the banking industry, we graphically study the cases of six major banks in Figure 1. In the case of Citigroup, JP-Morgan Chase, and Wells Fargo, the wedge progressively builds up from the onset of the crisis in mid-2007, peaks around the turn of year 2009, and slowly reverts back afterwards. In comparison, the evolution of the discrepancies is less smooth and much more abrupt for Goldman Sachs and Morgan Stanley, where the equity-implied spreads match their market counterparts quite well right until the Lehman collapse, then suddenly jump up and remain at a high level before converging quickly in the first half of 2009.

The aggregated time series in Figure 2 confirm that the discrepancies are much larger in the financial than in the other sectors, and, within the financial sector, clearly more pronounced for banks vs. nonbank financials. Furthermore, unlike the other sectors whose curves converge at the end of the crisis, the wedge persists in the financials and banks graphs.

From Figure 3, our conclusions hold even after considering relative spread (or percentage) deviations defined as $\frac{\widehat{CDS}-CDS}{CDS}$. Three interesting findings emerge from this picture. First, the nonfinancial sectors and the nonbank subsectors appear to move in sympathy throughout the sample period. Second, the deviations jumped up in spring 2008, the period surrounding the Bear Stearns rescue, suggesting that this event significantly bolstered TBTF expectations of the market in that it anticipated further bailouts. Third, the spike to the downside of the bank subsector in September 2008 suggests that TBTF expectations suffered a setback during the uncertain phase culminating in the Lehman Brothers collapse. Afterwards, deviations reached new highs with the initiation of massive support programs by the U.S. and other governments in fall 2008. A peak is reached in January 2009 in the course of the Bank of America rescue.

[Insert Figure 1 about here]

[Insert Figure 2 about here]

[Insert Figure 3 about here]

So far, we have calibrated the model individually for each company using a number of equally-spaced CDS premium observations from the pre-crisis period of our sample. We find that the model performance is hardly affected by the density of the calibration points and unreported tests indicate that the results are robust to shorter estimation windows within the pre-crisis period. For example, calibrating over the period 2004-2005 renders $\bar{L}$ estimates and the out-of-sample performance comparable to the base case. This leads us to conclude that our estimates of $\bar{L}$ are robust and stable throughout that period. As we have seen, during the crisis, the model spread surpasses its market counterpart for some companies in our sample. In the following subsections, we investigate a time-varying $\bar{L}$ parameter as a possibility to cope with the deviations.

B. Calibration with a Time-varying Default Barrier

In this subsection, we move from an expected default boundary $\bar{B} = \bar{L}D$ with a fixed $\bar{L}$ to one that fluctuates beyond the variation already associated with the quarterly reportings of the debt per share D. More precisely, we update $\bar{L}_{i,t}$ daily based on a trailing window of observations. The minimization problem,

$$\min_{\bar{L}_{i,t}} \sum_{n=1}^{N} (\widehat{CDS}_{i,n}(\bar{L}_{i,t}) - CDS_{i,n})^2, \tag{9}$$

is virtually identical to the one in Eq. (8), except for the additional t subscripts that stand for the time dependence of the $\bar{L}$. The specification of a dynamic default barrier is in line with Chen, Collin-Dufresne, and Goldstein (2009) who argue that such a boundary is consistent with prior empirical evidence indicating that historical credit spreads are driven by macroeconomic variables beside the standard set of structural factors (see, e.g., Collin-Dufresne, Goldstein, and Martin (2001); Schaefer and Strebulaev (2008); Zhang, Zhou, and Zhu (2009)).[7]

To limit serial correlation and avoid overfitting, but still obtain estimates based on a sufficient number of observations, we choose $N = 5$ and set the interval between calibration points equal to two. Using the example of JPMorgan Chase, Figure 4 illustrates the variations of $\bar{L}$ under the applied calibration scheme. We can see that $\bar{L}$ fluctuates between 0.08 and 0.10 before the crisis and then declines, gets close to zero, so as to accommodate observed market levels. In the last quarter of 2009, $\bar{L}$ rises but still remains slightly below 0.05 throughout the post-crisis period. Comparing the mean $\bar{L}$ across firms and periods in Panel A of Table III confirms that, all else being equal, the default boundary generally lowers during the crisis and slopes upwards in economic recovery without necessarily closing up to pre-crisis levels. Notice that the percentage decrease is steeper for financials.

Further, we report results from a trend regression of daily percentage changes of $\bar{L}$ against time points t in Panel A of Table III. We find a negative and significant trend for financial institutions, indicating that the JPMorgan Chase case is exemplary for the whole sector. At the same time, the coefficients for the whole company sample and the nonfinancial subsample are also negative but smaller in magnitude and first of all insignificant. All reported p-values are based on t-statistics that are robust to heteroskedasticity and cross-sectional correlation of the residuals.

[Insert Figure 4 about here]

[Insert Table III about here]

The model performance clearly improves tremendously in every considered subperiod. At -4 bps, the sample-wide mean error is slightly negative, consistent with the empirical literature. Contrary to the basic calibration scheme, across the different sectors, Panel B of Table III shows that the mean deviations are now mostly close to zero with a negative sign during the crisis, and the financial sector accounts for the highest error of +3 bps. Thereof, the deviation is especially pronounced for banks and insurance companies and amounts

[7]Papers addressing the difficulties of specifying a time-varying barrier include Hackbarth, Miaob, and Morellec (2006) and Davydenko (2010).

to about +11 bps for each of the two categories, suggesting that a mild overprediction prevails even after accounting for adjustments of the default barrier to changing market circumstances.

The above analysis leads to three conclusions. First, the structural model at hand is capable of generating CDS spreads in agreement with observed prices provided that the default barrier adjusts to changing market conditions. Second, the evolution of $\bar{L}$ suggests two regime shifts in the pricing of credit for a large number of reference entities, one at the beginning of crisis period and one at the end. These shifts are directly associated with the discrepancies established under the basic calibration scheme for the crisis period. Third, the financial industry exhibits a statistically significant procyclical decrease of $\bar{L}$. Again, this is just the flipside of our previous finding that model prices exceed market observables.

Thus, the anomaly at hand can either be described by too low market spreads compared to a calibration based on the pre-crisis regime, or by a widening of the distance-to-default due to a decrease of the implied barrier. The latter perspective allows three mutually nonexclusive interpretations in favor of the TBTF hypothesis, namely that of a capital injection or a purchase of risky assets, both directly boosting the asset value process, or that of a debt guarantee, entailing a reduction in the amount of unsecured debt, each eventually driving down market spreads. At this point, we postpone the validation of this argument until Section V and pursue the examination of regime switch properties.

C. Calibration with a Regime Switch

So far, our analysis suggests that, for a large number of firms, the structural model cannot generate estimates in accordance with market prices throughout the sample period when $\bar{L}$ is held fixed. Unreported calibration attempts with a constant $\bar{L}$ fitted to observations scattered over the whole sample period reveal that such a scheme performs poorly both within and outside the crisis, thus supporting that conclusion. However, the graphical analysis in Figure 4 suggests that $\bar{L}$ remains relatively constant over long periods and that significant moves are rare. In this subsection, we allow the level of $\bar{L}$ to change exactly once from $\bar{L}_1$ to $\bar{L}_2$ at the split date t_2. Since we focus on the presumed regime shift around the onset of the crisis and do not consider a possible second shift at the beginning of the economic recovery, we choose the estimation window to range from January 2004 through December 2009. For each firm i, the minimization problem assuming such a step function for $\bar{L}$ is

$$\min_{\bar{L}_{i,1},\bar{L}_{i,2},t_{i,2}} \sum_{n=1}^{N} (\widehat{CDS}_{i,n}(\bar{L}_{i,1}) - CDS_{i,n})^2 \ I_{\{\tau_{i,n}<t_{i,2}\}} + (\widehat{CDS}_{i,n}(\bar{L}_{i,2}) - CDS_{i,n})^2 \ I_{\{\tau_{i,n}\geq t_{i,2}\}}, \tag{10}$$

where $\tau_{i,n}$ gives the date of observation n of firm i and $t_{i,2}$ is the individual split date. We choose a grid interval of ten in line with the result of our comparison in Section III.A. Taking again the example of JPMorgan Chase, Figure 5 shows how the two-step calibration vastly improves the model fit compared to the constant $\bar{L}$ calibration. As described in Panel A of Table IV, the full cross-sectional average of $\bar{L}$ falls from 1.06 to 0.92, and from 0.47 to 0.25 for the financial subsample. These evolutions are comparable to the ones reported for a trailing $\bar{L}$. The median split date t_2 is November 4, 2008 for the financial firms, and September 30, 2008 for all the others, both falling well within the tumultuous period following the bankruptcy of Lehman Brothers on September 15, 2008. The results in Panel B of Table IV indicate negative mean errors for most of the sectors during both the pre-crisis and the crisis period. Not surprisingly, the model performance is weaker than under the time-varying calibration scheme, but the errors are overall still smaller in absolute terms compared to the basic calibration with $\bar{L}$ optimized over the pre-crisis period. The post-crisis period is poorly fitted with negative mean errors ranging between -18 bps and -108 bps, suggesting another upward regime shift that could be accounted for by including an additional step in the objective function specified in Eq. (10).

In summary, the hypothesized anticipation of government support in the cross-market pricing of default risk translates, within the context of the model, into a lowering of the default boundary and a rise in the distance-to-default, both effectively reducing the default risk of financial institutions. As our calibrations have shown, a lower barrier is directly associated with higher model estimates under a pre-crisis regime. In fact, both perspectives are two sides of the same coin and given the better tangibility of price relations, we focus on the price deviations yielded by the basic calibration scheme in the upcoming analyses.

[Insert Figure 5 about here]

[Insert Table IV about here]

[Insert Figure 6 about here]

D. Term Structure of Deviations

Finally, we examine the effect of CDS maturity on the deviations reported in the financial sector. For this purpose, relying on the basic calibration approach, we estimate one- and ten-year CDS spreads and then plot the average differences as well as average relative deviations for the one-, five-, and ten-year maturities in Figure 6. While the five- and ten-year CDSs exhibit very similar patterns, the curve for the one-year CDSs largely surpasses the other maturities and indicates that the anticipation of bailouts is most pronounced among short-term investors. The term structure of deviations thus has an inverse shape. Moreover, while the mid- and long-term deviations slope down as the crisis passes by, the short-term deviations converge only to some extent and remain quite high level until September 2010, indicating that market participants continue to anticipate government interventions in the short run. However, the low deviations of five- and ten-year CDS at the end of the sample period suggest that investors view the distortions as a temporary rather than a permanent phenomenon.

IV. Information Efficiency across Markets

In this section, we use methods of time series analysis to investigate the long-term relation between our credit and stock market measures of default risk. First, we start by a test of the stationarity assumption underlying many econometric principles, including the ordinary least squares (OLS) estimator. Second, we verify the existence of a cointegration relation, that is, whether two related variables move together in the long run regardless of temporary departures from their equilibrium. Third, by examining the mutual adjustment processes, we are able to conclude which market leads in price discovery and thus reflects more timely information. Taken together, the results of these analyses may help us rule out information inefficiencies across CDS and stock markets as a possible cause for the discrepancies.

A. Stationarity

A time series is considered stationary if the mean and the autocovariance of its underlying process are time independent. For a variable Y_t, the augmented Dickey-Fuller (ADF) test performs a regression of the contemporaneous first difference ΔY_t against the lagged value Y_{t-1} as well as lag terms ΔY_{t-1},...,ΔY_{t-p} to cope with higher-order serial correlation in the residuals, where the optimum lag length p is determined by the minimum of the Schwarz information criterion (SIC).

Panel A of Table V reports for both the market and the model price the number of firms for which the null of a unit root is rejected at the 5% level. Over the entire period of September 2004 through August 2010, the market and model price levels are stationary for 51 and 45 of 498 companies, respectively. We note that the nonstationarity disappears completely when performing the ADF test with first differences instead of levels, indicating that the remaining series are first-order integrated (I(1)). In other words, a large majority of about 90% of the series is nonstationary, which confirms what seems to be a stylized fact of credit spreads in the literature (see, e.g., Zhu (2006); Norden and Weber (2007)).

B. Cointegration

To analyze the cointegration and the lead-lag relation of market (CDS) and model ($\widehat{CDS}$) prices, we first estimate the vector error correction model (VECM)

$$\Delta CDS_t = \lambda_1 Z_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta CDS_{t-j} + \sum_{j=1}^{p} \delta_{1j} \Delta \widehat{CDS}_{t-j} + \epsilon_{1t}, \tag{11}$$

$$\Delta \widehat{CDS}_t = \lambda_2 Z_{t-1} + \sum_{j=1}^{p} \beta_{2j} \Delta CDS_{t-j} + \sum_{j=1}^{p} \delta_{2j} \Delta \widehat{CDS}_{t-j} + \epsilon_{2t}, \tag{12}$$

$$Z_{t-1} = CDS_{t-1} - \alpha_0 - \alpha_1 \widehat{CDS}_{t-1}, \tag{13}$$

where ϵ_{1t} and ϵ_{2t} are i.i.d. innovations.

The first two equations model the respective price dynamics and Eq. (13) is the error correction function that reflects deviations between both risk measures.

From our results in Panel B of Table V, over the entire period, we count 359 of 498 firms' series as cointegrated, and the subsample of financials presents an even higher share (60 of 74).[8] In other words, over the long run, the deviations between both default risk measures can be considered transitory effects for a large majority of the sample. However, at the subperiod level, financials are relatively more affected considering the evolution from period one to period two as the decrease in the number of cointegrated firms is even steeper (-27%) than in the case of nonfinancials (-11%). This is reminiscent of our analysis in the previous section showing that price divergences are most striking within the financial sector during the crisis. Not surprisingly, the longer the considered time period, the larger the number of companies for which cointegration is accepted. Summing up, the high share of cointegrated firms suggests that both markets communicate well with each other and are in this sense informationally efficient.

[8]Two variables are considered cointegrated if there exists a linear combination that is stationary, or, equivalently, if the VECM representation above is valid (Engle and Granger (1987)). The employed test is by Johansen (1995) and returns the number of cointegrating equations, mostly either zero or one, where an outcome of zero indicates no cointegration at all.

C. Price Discovery

Beside the analysis of cointegration relations, the VECM framework affords us an opportunity to revisit the question of price discovery. Assuming there is an implicit common factor driving default risk in both the CDS and the stock market, the analysis reveals which marketplace contributes more timely information to the evaluation of that common factor.

Relying on structural model estimates rather than stock returns presents the advantage of incorporating more information relevant to the pricing of credit, like option-implied volatility and the level of debt. As pointed out by Forte and Peña (2009), the contrary approach of merely using stock returns omits these important factors, a shortcoming that cannot be remedied by the application of linear corrections given the highly nonlinear nature of credit spreads.

The information share of each variable is deduced from the relative magnitudes of the coefficients of the error correction term in Eq. (11) and (12), λ_1 and λ_2. Following the approach of Gonzalo and Granger (1995), the CDS and the stock market's contributions to price discovery are defined by the ratios

$$GG_{Market} = \frac{\lambda_2}{\lambda_2 - \lambda_1} \quad \text{and} \quad GG_{Model} = \frac{\lambda_1}{\lambda_1 - \lambda_2}, \tag{14}$$

respectively. Superior price discovery is attributed to the market reacting least to price movements in the other market, or, put differently, to the market with the higher GG ratio.[9]

First conclusions can be drawn from the coefficients themselves: For the market (model) price to play a role in price discovery, we expect λ_2 (λ_1) to be significantly positive (negative), which is the case for 179 (288) of the 359 cointegrated companies, over the entire period. This divergence between market and model spreads obviously develops in period two (102 vs. 221), as the relation is almost balanced before the crisis (178 vs. 171).

With a value 0.573, the mean of the Gonzalo-Granger ratio for the market price suggests that the CDS market plays the predominant role. For the subsample of financial institutions, the respective influence of each market seems almost equal (0.493). Comparing values across subperiods, the leadership of the CDS is much more pronounced in period one (almost 70%) but almost evens out in period two, suggesting that the stock market has gained in importance as a forum for price discovery in recent years.[10]

In addition to the GG measure, previous studies have often relied on the Granger causality

[9]For $GG_{Market} = 0.5$, both markets contribute equally to price discovery and for the extreme cases $GG_{Market} = 1$ and $GG_{Market} = 0$, only the CDS market and the stock market contribute, respectively.

[10]We remind the reader that the model prices used for the tabulated results in this section were generated using our baseline calibration scheme. When model prices are instead calibrated assuming a time-varying default barrier, not surprisingly, GG_{Market} turns out even higher as this calibration scheme implies continuous adjustments to market levels.

test, which consists of two reciprocal regressions of one variable (e.g., the market price) against its past (lagged) values and the lags of another variable of interest (e.g., the model price). The null hypothesis of no Granger causality is accepted if the lags of the other variable are jointly significant as verified by the Wald test. While some view Granger causality as a weaker concept than the GG measure (e.g., Blanco, Brennan, and Marsh (2005)), it has the advantage of being applicable to the full sample of 498 companies irrespective of their cointegration properties. For completeness, we report outcomes of Granger causality testing in Panel C of Table V.

Considering the whole period and all companies, causality goes both ways in the case of 296 firms, while the market price "causes" the model price unilaterally in only 31 cases and the converse holds in 100 cases. Put another way, the CDS market's history reveals significant in improving the prediction of stock-market-implied default risk in 327 (=296+31) cases, whereas the stock market contributes to CDS prices in 396 (=296+100) cases, thereby slightly reversing the outcome of the VECM analysis. However, for the financials subsample, the conclusions between both methods are virtually identical since participants in both markets seem almost equally informed (60 vs. 65). Another finding common to both methods is that of a growing relative importance of the stock market over time. On another note, the number of firms where no causality in either direction is found decreases by 47% between periods one and two, indicating that communication and efficiency across markets greatly improve.

In summary, the case of nonfinancial companies seems inconclusive as the Gonzalo-Granger measure indicates a price leadership of the CDS market, while Granger Causality attributes more importance to the stock market. These conflicting results are reminiscent of the literature: The findings of Forte and Peña (2009) and Norden and Weber (2007) suggest that the stock market more often leads the CDS market, whereas Acharya and Johnson (2007) provide evidence that information flows from the CDS to the stock market due to the prevalence of informed traders in the CDS market. However, and more importantly, the picture is much clearer with respect to financial companies, for which both methods agree that information circulates equally well from one market to the other. This is a relevant insight for the main analysis and goal of this paper, as it rules out the possibility of miscommunication across markets as an explanation for our finding of a wedge pattern for financials that emerged from the previous section.

[Insert Table V about here]

V. Determinants of Relative Price Deviations

Our previous analyses have established that the CDS and the stock market, although being informationally efficient, have developed diverging views about the value of risky debt for a subset of our sample during the recent financial crisis. The next logical step is to investigate determinants of this wedge pattern. The set of considered explanatory variables covers both well-known credit risk drivers usually suspected in the literature, like liquidity, ratings, macroeconomic factors, and variables potentially related to the systemic relevance of a company. The rationale is that, by design, structural credit frameworks do not account for nondefault components of actual credit spreads and could possibly be augmented by such factors. Actually, Collin-Dufresne, Goldstein, and Martin (2001) show that macrofinancial variables reflecting the current state of the economy impact on credit spreads. They also point to the existence of a common factor in the unexplained variation. Some authors suspect this common factor to be related to illiquidity, whose effect is the subject of previous work by Davydenko (2010), Chen, Lesmond, and Wie (2007), and, in the case of CDS spreads, in Tang and Yan (2007). Another determinant of CDS prices that has drawn attention in the recent crisis is counterparty risk. Bai and Collin-Dufresne (2011) find that it accounts for a significant portion of the negative CDS-bond basis observed during the crisis, which is the difference between CDS and corresponding bond yield spreads. The influence of rating changes on CDS spreads is explored in Hull, Predescu, and White (2004) as well as in Norden and Weber (2004), and their evidence indicates that rating reviews for downgrade, as well as negative rating announcements, have a significant positive effect on market values. Furthermore, the evidence by Morgan and Stiroh (2001) and Rime (2005) indicates that, all else being equal, TBTF companies have higher ratings. Therefore, we explicitly control for factors not captured by the structural model at hand and find that they actually account for part of the deviations in line with the previous literature. The results also support the TBTF hypothesis in that indicators related to systemic risk are found to be highly relevant.

A. Basic Regression Setup

The benchmark regression is an OLS test that pools together all valid observations. The generic equation is

$$\frac{\widehat{CDS}_{i,t} - CDS_{i,t}}{CDS_{i,t}} = c + \beta_m Macro_{i,t} + \beta_f Firm_{i,t} + \epsilon_{i,t}, \tag{15}$$

where the explanatory variables $Firm_{i,t}$ and $Macro_{i,t}$ are the variable vectors whose elements we discuss below. We choose relative over absolute deviations to control for the fact that higher market spread levels often entail higher absolute deviations and thus to allow for greater comparability across firms and periods. Incidentally, unreported tests with the price difference as the regressand lead to very comparable results and significance levels are often surpassed. Therefore, we consider the present choice as conservative. First, the *Macro* vector comprises the following elements:

1. *Business climate.* Default probabilities jump up and expected recovery rates decline in times of economic downturn, both contributing to higher credit spreads according to finance theory. This is confirmed empirically by Collin-Dufresne, Goldstein, and Martin (2001) for bonds and by Zhang, Zhou, and Zhu (2009) in the case of CDSs, among others, who find that indicators linked to the overall business climate and the economic outlook have a significant impact on credit spreads. Similarly to them, we use the average daily return of the S&P 500 index over the past six months as a proxy and the level of the VIX, which is a model-free volatility forecast for the next 30-day period implied from index options. The VIX is referred to as an indicator of market fear and uncertainty. Further, TBTF guarantees should become particularly valuable in times of crisis. On these grounds, we expect deviations to be negatively correlated with S&P 500 returns and positively correlated with the VIX. Note that all the index series used for the analyses in this section are retrieved from *Datastream.*

2. *Interest rate term structure.* We approximate the shape of the yield curve by the three-month Treasury rate and the slope between the ten-year and the three-month Treasury rates. The rationale is that, on the one hand, a rise in the spot rate lowers a firm's probability of default (PD) by increasing the risk-neutral drift of its asset value process (Longstaff and Schwartz (1995)); on the other hand, it can be associated with a tightened monetary policy and higher PDs. The slope of the yield curve is similarly ambiguous with respect to PD: While a steeper slope may be associated with the expectation of a recovering economy, it can accompany rising inflation and corresponding monetary countermeasures. We find that these variables have additional explanatory power in line with prior studies.

3. *Illiquidity.* It is beyond debate that illiquidity plays a role in the pricing of bonds and CDSs. Therefore, we expect the relevant coefficients to be highly significant. Since illiquidity drives up market prices while model estimates remain unaffected, it should reduce price deviations. We proxy illiquidity by the yield difference between five-year bonds issued by the Resolution Funding Corporation (Refcorp) and Treasury bonds, as well as by the on-the-run/off-the-run spread of five-year Treasury yields. Refcorp is a U.S. government agency whose bonds are guaranteed by the Treasury. Longstaff (2004) shows that Refcorp and Treasury bonds are identical with respect to the default risk component implied in their prices, but that Treasuries benefit from a flight-to-liquidity premium resulting in lower yields. The Refcorp yields are obtained from the *Bloomberg* system. The second measure

follows the same reasoning, except that the Treasury yield is compared to its less frequently traded off-the-run counterpart. Longstaff, Mithal, and Neis (2005) provide evidence that such macroeconomic liquidity measures are strongly related to the nondefault component of corporate bond spreads. We also looked into CDS bid-ask spreads as a more direct liquidity measure, but it turns out that these spreads actually narrow during the crisis, which might be due to an increased demand for CDSs as hedging instruments, and thus do not adequately reflect illiquidity issues therein. Therefore, we deem Treasury-related spreads that proxy the illiquidity in the underlying bond market to be a more meaningful measure. As a side note, we also looked into the spread between Libor and Overnight Indexed Swap (OIS) rates, a measure that has become increasingly popular in recent studies (e.g., Brunnermeier (2009); Schwarz (2009)) as a proxy reflecting both illiquidity and counterparty risk components. Especially the latter could be another alternative explanation for the model-market discrepancies. It turns out that using the Libor-OIS spread over the Refcorp or the on-the-run/off-the-run spread does not alter our results qualitatively and that the three variables are largely positively correlated with each other. Therefore, we omit to report regression results for the Libor-OIS spread explicitly.

Second, the analysis considers the following firmspecific factors as drivers of relative price deviations:

1. *Ratings.* Due to the large evidence of the influence of rating changes on credit spreads in the literature, dummies for S&P 500 issuer credit rating classes are included to account for the additional information possibly contained therein. Rating records on a monthly basis are obtained from *Compustat*.

2. *Firm condition.* Stock price returns and the corresponding implied volatilities of one-year at-the-money put options are included in the regressions to reflect the firm's financial health beyond what is already incorporated in the structural model price.

3. *Firm size.* In line with the TBTF hypothesis, we expect government interventions to aim at very large firms and corresponding market expectations to be strongly related to firm size, which we measure both by the value of total assets and by a more market-oriented metric, the sum of total liabilities and market capitalization. Total assets and liabilities are book values collected from *Compustat*, while the market capitalization stems from our *CRSP* data set. Firm size has already been considered as a TBTF proxy in prior analyses (see, e.g., Rime (2005)) and is also reported to covary with the measures of systemic risk presented in the recent literature (Adrian and Brunnermeier (2010); Huang, Zhou, and Zhu (2011)).

4. *TARP.* A great number of companies, mostly financial institutions, benefited from TARP, which was officially announced in October 2008 and further revised later on and that comprised the purchase of impaired assets and equity of distressed firms, among other

measures. For our purposes, we interpret the admission of a firm under TARP as an explicit support commitment by the government and create corresponding time-invariant dummies. The financial companies in our sample that received support under the TARP program are flagged in Appendix A. All TARP-related information is collected from the U.S. Treasury's website.

5. *Default correlation.* Firms whose default could spark a chain reaction leading to the collapse of other firms through a systemic shock are more likely to receive government support. A contagion effect is generally observed among financial institutions whose balance sheets are heavily interlinked through market-priced assets and liabilities. On the contrary, in most other industries, a competition effect prevails, i.e., the failure of one company actually strengthens rivals as demand and market shares shift from the bankrupt firm. Therefore, we consider systemic relevance within the financial sector only and proxy default correlation using a CAPM-like beta measure based on individual stock returns and the return of the S&P 500 Diversified Financials index whose composition resembles our subsample of financial institutions. β_{rs}^{DF} is estimated daily over a rolling window covering the previous 50 trading days. Similar correlation measures have been employed in Brownlees and Engle (2010) and Huang, Zhou, and Zhu (2011).

6. *Counterparty risk.* Counterparty risk is the credit risk arising from the possibility that the protection seller in a CDS contract is unable to meet his obligation in a credit event. In a calm environment, counterparty risk generally plays a tangential role in CDS trading as the mark-to-market mechanism helps to minimize the losses of the protection buyer in case the counterparty fails prior to the credit event and the extreme case of simultaneous default is rare. Now, in a crisis environment, the protection buyer faces significant risks, for example because marking-to-market may then work imperfectly due to jumps in credit quality and to the costs for new credit protection that may have increased tremendously. Since protection buyers anticipate such a joint event, they discount CDS premiums accordingly. The impact of counterparty risk on CDS spreads clearly depends on the correlation between the default probability of the insurer and the reference entity, or their joint default probability. The issue of counterparty risk may appear relevant for this study as it moves market premiums downwards, in the same direction as government guarantees. Taking a closer look, this is not surprising as interventions are most likely in times of increased systemic risk, implying higher default correlation among multiple large financial institutions and, given that these are the main suppliers of credit insurance, a higher counterparty risk component in all CDS contracts, especially in those written on financial entities.[11] The

[11] An increased level of systemic risk normally goes hand in hand with higher counterparty risk since it implies that most CDS sellers face higher default risks. However, the converse does not always hold. To

question is how to approximate the size of the effect when the aggregate Markit quotes that we observe reflect several anonymous financial institutions as counterparties. Similar to Bai and Collin-Dufresne (2011), we estimate counterparty risk as the beta between a firm's daily CDS return and the corresponding variation in a representative index of primary dealers designated by the Federal Reserve Bank of New York[12]. The list of primary dealers comprises around 20 of the largest international banks like Goldman Sachs and JPMorgan Chase, which is precisely the reason why counterparty risk is most of a concern in the case of CDSs written on financial institutions. The calculation of the index is a two-step process that we outline briefly. First, we construct daily index values as the average of each constituent's CDS spread weighted by their market capitalization. In doing so, we keep track of changes in the composition of the index. In the second step, for each of the 498 companies in our sample, we calculate daily beta values $\beta^{PD}_{r_{CDS}}$ as the historical covariance of the CDS return and the primary dealer index return divided by the variance of the index return.

[Insert Table VI about here]

[Insert Table VII about here]

Table VI summarizes the predicted effects of the aforementioned variables and provides basic statistics, while Table VII presents pairwise correlations of the most relevant ones. The correlation matrices reveal that one must be cautious when combining some of these variables within one regression specification to avoid bias in the OLS estimates. Considering the whole sample in Panel A, we note that size, TARP, and default correlation are positively correlated with each other and with the counterparty risk proxy, indicating that the individual contributions of these explanatory variables are difficult to perfectly disentangle, as expected from our discussion above. Narrowing down the focus to a subsample comprising only financials during the crisis, Panel B shows that relative deviations remain virtually uncorrelated with counterparty risk, while their correlations with size and TARP increase, suggesting that the hypothesized too-big-to-fail effect is more relevant in explaining the wedge than counterparty risk. We will further discuss this point below.

B. Baseline Results

We begin the econometric analysis with an estimation of Eq. (15) relying on different sets of regressors and report results in Table VIII. For the computation of the *t*-statistics, we

see this, think of the idiosyncratic distress of one bank in a calm period leading to a high counterparty risk component in the CDSs it writes although systemic risk is low.

[12]The list of primary dealers is maintained on the website `http://www.newyorkfed.org/markets/pridealers_current.html`.

adopt the approach proposed by Petersen (2009) to address the issue of potential bias in OLS standard errors due to firm or time effects in our panel. A firm effect refers to a time series dependence due to the correlation of residuals across dates for a given firm, whereas a time effect implies a cross-sectional dependence due to the correlation of residuals across different firms for a given date. By comparing the standard errors clustered by the firm dimension to White (1980) standard errors that already correct for heteroskedasticity, we find vast evidence of a firm effect in the residual terms. Clustering residuals across both dimensions does not indicate the need for additional correction of a time effect. Except stated otherwise, we therefore cluster standard errors on the entity level in all our regressions. The correction leads to higher standard errors and more conservative t-statistics, which could otherwise turn out inflated in the presence of bias in the estimator.

In Columns (1) to (3) of Table VIII, we regress relative deviations on macroeconomic variables solely. The results show that the relative price deviations are associated with negative returns of the S&P 500, high market volatility (VIX), illiquidity (according to both measures considered), and low short- and long-term interest rates, the typical characteristics of a crisis period. Contrary to our expectations, the illiquidity coefficients have a positive sign. It turns out that illiquidity is in fact positively related to the CDS market price, in line with our reasoning, but that the rise in the model price overcompensates this effect. We find that the inclusion of the VIX subsumes the S&P 500 returns and illiquidity measures and therefore discard it in the remaining regressions. We note that the comovement of the VIX with illiquidity has also been pointed out by Bao, Pan, and Wang (2011).

The set of variables of the first three regressions explain between 13% to 19% of the variation in the residuals, as measured by adjusted R^2.The Refcorp spread has greater incremental explanatory power than the on-the-run/off-the-run spread, which is why we retain the former for the next regressions.

[Insert Table VIII about here]

In the next step, we alternate the sets of firmspecific variables that we add to the equation. To reduce the risk of bias, we do not mix size, β_{rs}^{DF}, TARP, and counterparty risk proxies within the same regression equations, but rather consider them separately. Several findings emerge from columns (4) to (8). First, all except one rating class dummies have a positive and highly significant impact on the regressand and there is a tendency of higher coefficients the higher the rating class, suggesting that TBTF expectations are more pronounced for top-rated firms. However, the highest coefficient is found in the AA rather than in the AAA class, which might arise from the fact that the major banks in our sample are rated AA. Second, with a negative sign on stock returns and a positive sign on implied volatility, the firm condition variables point in the expected directions. Third, size matters at the 5% significance level, providing direct support for the TBTF hypothesis. Compared to column (4), column (5) additionally introduces an interaction term between size and the three-month average daily S&P 500 return. The negative coefficient is even more significant (1%) than that of size alone and indicates that size and financial instability, as measured by the market return, reinforce each other in explaining price deviations and possess explanatory power above and beyond the sum of the parts. Intuitively, size matters especially in times of economic downturn. Fourth, we question the effect of the default correlation proxy in column (6). Since this variable is only meaningful within the context of financial firms, we let the variable interact with a financial sector dummy. The coefficient is positive and significant at the 1% level. Interestingly, the aforementioned results reveal a link between our model-market deviation and the different approaches to measuring systemic risk proposed by several authors.[13] Fifth, the results reported in column (7) indicate that the mere admission to the TARP program drives the deviations. In an unreported regression using the individual amounts of TARP support instead of the dummy, we arrive at the same conclusion. Sixth, column (8) shows that the counterparty risk proxy $\beta^{PD}_{r_{CDS}}$ positively matters for the wedge. The Treasury, term structure, and illiquidity variables have to be excluded in the last specification because they render the counterparty risk beta insignificant. Overall, the introduction of firm-level variables increases R^2 to up to 22%.

One may wonder which explanation for the wedge – TBTF or counterparty risk – is more relevant in the end. First, we argue that the distinction is not essential and hard to draw because government guarantees are most valuable in periods of high systemic risk, which coincide with increased counterparty risk in the market. Second, revisiting the evolution of relative spread deviations in Figure 3 reveals that the wedge tightened around the Lehman collapse, a time when counterparty risk must have reached a high. Therefore, if counterparty risk was a major factor in the explanation of the deviations, the wedge would have been exceptionally wide during that time and not only after the announcement of TARP. Third, $\beta^{PD}_{r_{CDS}}$ was calculated as the default correlation between a firm and a group of primary dealer banks and could therefore also be interpreted as a TBTF proxy. Fourth, the correlations in Table VII suggest that variables like size and TARP are more correlated with the wedge than the counterparty risk proxy. Fifth, in Section VI, we attempt to isolate the counterparty risk component incorporated in the model-market deviations using a simple, linear correction. The adjusted deviations largely prevail and outweigh the counterparty risk estimate, but

[13]In detail, Brownlees and Engle's (2010) analysis of the econometric properties of the MES proposed by Acharya et al. (2010) shows that this measure depends on stock volatility and correlation between stock and market returns; the CoVaR by Adrian and Brunnermeier (2010) is related to firm size; and finally, the DIP by Huang, Zhou, and Zhu (2011) covaries with both size and asset correlation.

notwithstanding constitute a more conservative estimate of the government guarantee effect.

C. Alternative Subsamples and Changes of Deviations

Here we repeat the previous estimations for different time periods and subsamples. In columns (1) to (3) of Table IX, we maintain an identical company sample but restrict the relevant time period to start on August 1, 2007, the presumed beginning of the crisis, and range until the end of the sample in September 2010. Columns (4) to (6) further constraint the sample to include only the financial group. In essence, the new regressions confirm our previous conclusions. The coefficient estimates on size, default correlation, and the TARP dummy are significant and exhibit the expected signs. The interaction between size and the S&P 500 return is not significant anymore, though. However, untabulated tests reveal that the outcome for the interaction term is sensitive to the upper limit of the timeframe. More precisely, when we set the estimation period to August 2007 through December 2008, we obtain results comparable to those in Table VIII. Throughout the table, with an adjusted R^2 of 15% at most, the explanatory power of the variable sets turns out lower than before. We attribute this to increased noise during that tumultuous time period.

[Insert Table IX about here]

[Insert Table X about here]

Next, returning to the whole sample again, we examine the relation between changes in relative spread deviations and changes or returns of the independent variables, whichever is more appropriate. Since first-differences are noisier than levels, we mitigate this issue by reducing the data frequency from daily to monthly. Changes and returns are measured by retaining the end-of-month observations of the daily data set. The results of a series of OLS regressions are summarized in Table X. Note that since first-differencing eliminates any firm effect in the data, standard errors are not clustered anymore but still robust to heteroskedasticity. The signs and significances of the variables of interest are robust to this modification in the estimation equation. The explanatory power of these regressions is lower than in Table VIII, which is not unusual with first-differences that generally fluctuate rapidly around zero and a variable like size that changes only quarterly. On top of that, studies considering regressions on both levels and differences typically experience a similar divergence with respect to R^2 (see, for example, Zhang, Zhou, and Zhu (2009)) and the principal component analysis by Collin-Dufresne, Goldstein, and Martin (2001) points to an undefined latent factor as possible reason for the low explanatory power in regressions of credit spread changes. Unreported regressions involving lags and leads of the independent variables reject the possibility of asynchronicity in the data.

D. Alternative Specifications and Dynamics of Deviations

In this subsection, we replace the OLS estimator with more advanced panel data techniques that allow for the inclusion of lags of the dependent variable on the right-hand side of the equation. Thereby, we attempt to model the dynamics of the relative price deviations and to capture their degree of persistence. To confirm the conjecture of a transitory CDS-equity wedge, the estimated coefficient of the lagged dependent variable should be statistically significant and lie within the interval]0;1[, implying that while default estimates in credit and equity markets do still differ even after controlling for other possible explanations, they eventually converge.

The linear Generalized Method of Moments (GMM) estimator by Arellano and Bover (1995) explicitly suits our needs by removing the associated autocorrelation and allowing for time-invariant, firmspecific variables like a TARP dummy (see, e.g., Baltagi (2008)). We use the two-step estimation procedure so as to obtain standard errors that are robust to heteroskedasticity and arbitrary patterns of correlation within firms. Moreover, the applied Windmeijer (2005) correction mitigates the problem of downward bias in the standard errors typically encountered in two-step estimation. While such a dynamic panel model estimator is unbiased in the presence of a lagged dependent variable, it is designed for panels with few time periods and a large number of individuals ("small T, large N") as the size of the system of equations increases quadratically in T (see Roodman (2009) for a detailed discussion). To reduce the computational burden, we limit the analysis to quarterly data in that we select the first available data point at the beginning of every quarter. In this manner, we preserve the variability of the data compared to the alternative of computing quarterly averages.

The main result from columns (1) through (4) of Table XI is that the parameter of the lagged relative deviation is significant at the 1% level and lies well within the range of]0;1[, arguing that the discrepancy between default estimates from credit and equity markets is persistent, in the sense that it cannot be fully explained by the control variables, but mean reverts over time. These dynamics confirm the impression in the charts of Section III of a rather temporary TBTF effect. The coefficient estimates of the various TBTF-related variables confirm our previous findings. Conversely, the rating and term structure variables lose their significance. Concerning the panel model specification, we consider the relative deviation as endogenous to the model and include lags two to 25 into the instrument matrix. The other regressors are considered exogenous and, hence, each accounts for one column in the matrix. The tests at the bottom of the table indicate that the model is correctly specified: The Arellano-Bond (1991) test rejects the null hypothesis of second- or higher-order serial correlation in levels and the Hansen (1982) test of overidentifying restrictions verifies that the set of selected instruments is jointly valid.

An alternative to GMM is to apply the fixed effects (FE) estimator in a dynamic setup, provided the panel is also large in the time dimension. As Hsiao (2003) points out, the dynamic panel bias resulting from the lagged dependent variable becomes insignificant for large T and large N. Results from daily data are summarized in column (5). The coefficient of the lagged deviation is higher (0.95) than before, but this is expected given the higher sampling frequency. Company size maintains its positive sign and significance. For brevity, we do not reproduce the outcomes for the remaining set of TBTF variables that are qualitatively comparable to the results obtained in the previous settings.

In summary, the regression results suggest that although the addition of macroeconomic, liquidity, and other factors enhances the explanatory power of the structural model alone, a large portion of the deviations still persists as observed by the significance of the lagged dependent variable and the moderate R^2. Nevertheless, the significant influence of proxy variables related to TBTF and systemic risk clearly argue in favor of the TBTF hypothesis as an explanation for the observed wedge pattern. In other words, the explanatory analysis lends support to the intuition that the implicit downward shift in the default barrier reflected by the evolution of market prices is connected to support actions like capital injections and debt guarantees, each by their very nature widening the distance-to-default.

[Insert Table XI about here]

VI. Capitalized Subsidies in the Primary Bond Market

The previous section corroborated the TBTF hypothesis that model-market deviations are mainly driven by factors typically associated with government support actions. In this section, we apply the concepts developed in this paper to assess the cash value of the government support that TBTF institutions perceive from their access to cheaper funding. Interpreting the model price as the price of credit in the absence of guarantees, it is straightforward to determine how much more a TBTF firm would have had to spend for refinancing, had it not benefited from implicit guarantees. An important assumption is that the price differential for credit insurance also applies to the underlying cash market, i.e. that a difference in CDS spreads reflects equally in bond yield spreads. This assumption appears reasonable in light of the theoretical equivalence between same-maturity bond and CDS spreads. The remaining question is whether the negative CDS-bond basis reported by several authors (e.g., Bai and Collin-Dufresne (2011)) for financial firms during the crisis affects such a translation. Since the basis arises from both bond illiquidity and CDS counterparty risk, but not default risk divergences, the CDS price deviation appears as a reasonable approximation of the funding cost advantage, or the TBTF premium, in the primary bond market.

Relying on this borrowing cost differential as well as on the detailed characteristics of each bond sold by the 74 financial firms in our sample between 2007 and 2010, we are able to reprice every debt offering as if there was no support. Taking the sum of the price differences for every single bond, we arrive at a conservative estimate of the aggregate value of the government support extended to the financial sector, which excludes private, bilateral debt agreements.

We retrieve information on individual bond offerings from the *Mergent Fixed Income Securities Database (FISD)*, a comprehensive data set covering all public debt offerings by U.S. companies. In doing so, we include the issues of subsidiaries as we assume the parent company would step in in case of distress, for reputational reasons alone, and honor the subsidiary's debt. We retain most bond types, including fixed and floating-rate bonds, zero-coupon bonds, perpetuities, foreign issues, callable and putable bonds, and exclude convertible and secured debt. While most of the offerings are for unsecured senior debt tranches that match the security level of the CDSs in our sample, for simplicity, we extend their results to subordinated debt tranches as these must benefit even more from the guarantees than their senior counterparts, which leads to a rather conservative approximation. Panel A of Table XII decomposes the total offering amounts across issue years and financial subsectors. One can see that public debt issuances decreased substantially over the years and that our analysis covers a total volume of $1.89 trillion, of which 90% accrue from the banking sector.

Drawing on the term structure of deviations calibrated in Subsection D, we are able to accommodate the maturity of a given bond through interpolation. As previously discussed, counterparty risk in the CDS market is likely to go hand in hand with increased systemic risk since the major dealers happen to be large, systemically relevant institutions. We found that the counterparty risk proxy was statistically significant in explaining the wedge, although it also lends itself to a systemic risk interpretation. To be on the safe side, we adjust the model-market deviations in a simple, linear way: In a pooled regression of the basis point deviations on $\beta^{PD}_{r_{CDS}}$, $L_{Refcorp}$, TARP, rating dummies, and $r_{S\&P500}$ for the 2007-2010 financials subsample alone, we arrive at coefficient estimates for $\beta^{PD}_{r_{CDS}}$ of 367, 58, and 27 bps for one, five, and ten-year CDSs, respectively. Multiplying these coefficients with the $\beta^{PD}_{r_{CDS}}$, we obtain the counterparty risk adjustment for a given firm, maturity, and date. Figure 7 illustrates the evolution of the daily averaged adjustments for the five-year maturity CDS. The average adjustment across time and firms amounts to 25 bps.

[Insert Figure 7 about here]

[Insert Table XII about here]

Focusing on the most simple and prevalent case, the fixed-rate bond, we can simulate the counterfactual case of no government support by adjusting the terms of the bond either through its yield-to-maturity (YTM) or its coupon rate.[14] In the first method, holding all other bond determinants constant, we increase the YTM by the maturity-matched and (counterparty-risk-adjusted) model-market deviation. The bond tenors up to ten years are aligned by linear interpolation of the model-market spreads, and higher maturities are extrapolated, but capped to not exceed the ten-year value.[15] Subtracting the issue price calculated under the adjusted YTM from the price under the original terms and multiplying the difference with the offering amount reflects how much less capital the firm would have been able to raise given the yield expected by the market in the absence of guarantees. The discounting of cash flows implied in the bond valuation ensures that all the benefits of the guarantees throughout the life of the bond are capitalized and locked in at the time of issuance. The aggregate results reported in Panel B of Table XII show that, without the guarantees, banks' total offering amounts would have fallen short of $91.6 billion, corresponding to a shortage of 5.6% of the actual total volume. The other subsectors experience a shortage of only $6.49 billion. 92.5% of the subsidies for the whole financial industry occurred in the period 2008-2009.

In the second method, we proceed similarly, but manipulate the coupon rate instead of the YTM. Contrasting the original to the adjusted bond price shows how much more costly it would have been to raise the original amount of debt without the prevailing funding advantage. The results in Panel C of Table XII exhibit a similar pattern than those for method 1, with the exception that the total (bank) subsidies amount to $129.17 billion ($121.29 billion) or 7.1% (7.5%) of the total issuance.

While the estimated magnitudes of the subsidies are quite remarkable, it should be noted that they are conservative because they disregard other forms of financing like interbank liabilities. To provide an approximate figure of their importance, one may look at the aggregate balance sheet for U.S. commercial banks released weekly by the Fed, according to which the ratio between borrowings from banks and borrowings from other sources amounts to 22% on average, over the period 2008-2009.

We also looked into an alternative methodology that relies on the latest book level of debt outstanding instead of issue-specific data. The debt level is then multiplied by the funding cost advantage, yielding the difference in interest expenses as if today's credit terms extended

[14]While the valuation of zero-coupon bonds and perpetuities is straightforward, floating-rate bonds trading at par were priced using the well-known backward induction scheme that entails discounting the cum-coupon value of the bond at the first refixation date.

[15]Unreported results using a cubic spline instead of a linear interpolation/extrapolation scheme turn out to be very similar.

to all existing liabilities. One shortcoming of this method is the implicit assumption that debt raised before the crisis is refinanced under today's and not under conditions actually prevailing when it was sold. It is also clear from Panel A that the volume of debt issuance decreased significantly in the course of the crisis, therefore the book levels in later years may not reflect the proportion of the new debt issued under recent terms adequately. Another obvious weakness is that it is impossible to properly account for different debt maturities and bond-specific properties from balance sheet information alone. For the sake of brevity, we only mention that the results under this "subsidy flow" method are roughly comparable to the ones under the "capitalized subsidy" methodology at hand.

VII. Concluding Remarks

The 2007-2009 financial crisis prompted governments of major economies to massively intervene in markets, notably via capital injections, debt guarantees, and purchases or insurance of toxic assets. This paper analyses the repercussions of these interventions on the valuation of default risk as reflected in the prices of credit and equity. Relying on a structural credit model that is calibrated to pre-crisis data, we find a disconnection between both markets in the case of financial institutions during the crisis, which manifests in higher stock-implied default risk compared to CDS observations. The economic intuition is that shareholders have a sentiment of higher risk exposure compared to creditors because interventions generally focus on the avoidance of default, while shareholders' benefit is of secondary order. In such a context, default may not be perceived as the same event across both markets anymore. We find that market and model observations can be reconciled when the calibration allows for a significant downward shift of the default boundary, which can be interpreted as the anticipation of intervention within the mechanics of the model.

The wedge should not be understood as a consequence of direct intervention in a given firm, but rather as the market anticipation that this firm would be rescued if it came to the worst. Being a forward-looking measure, we refer to the wedge as the TBTF expectation of the market, and its evolution suggests that it is highly driven by the experience of actual interventions in the industry. In fact, the structural break develops gradually from the beginning of the crisis in 2007, but the Bear Stearns rescue in spring 2008 and the launch of TARP in fall 2008 clearly account for a major part of the momentum.

Albeit counterfactual, the model estimates calibrated under the pre-crisis regime give a sense of the CDS price evolution had policymakers not intervened, and at the same time reflect the price distortion due to the sustained bailout practice. From a policy perspective, our results suggest that interventions were actually successful in that they prevented a further escalation of the distrust prevailing in markets at the peak of the crisis. On another note, we do not view the wedge as evidence of a mispricing giving rise to capital structure arbitrage opportunities — CDS market participants were indeed rational by lowering their default risk forecasts in light of the probability of bailouts.

The results of regressions of relative price deviations on proxy variables of systemic risk and TBTF like size, default correlation, ratings, and TARP participation show that these significantly and positively covary with the deviations after controlling for a set of usual suspects like proxies of illiquidity and macroeconomic conditions.

An analysis of the information efficiency across CDS and stock markets suggests that they move closely together in the long term and that they contribute equally to price discovery as none leads the other in the timely incorporation of credit-sensitive information.[16] These insights rule out miscommunication among traders and analysts in different markets as a possible cause for the wedge.

Finally, we present an application that demonstrates how the pricing differential can be used to value the subsidies that financial institutions enjoyed from their access to cheaper funding. Such a procedure could serve as the basis for a taxation scheme ensuring that banks internalize the costs from systemic risk. In a similar fashion, one could also estimate the losses existing debtholders avoided one their implicitly guaranteed positions, thereby valuing the wealth transferred from taxpayers to creditors, which is difficult to account for properly otherwise. Besides, our findings may be useful in extending capital regulation approaches being discussed at the moment (e.g., Hart and Zingales (2009)) that rely on the CDS price as a gauge of financial health and trigger of regulatory actions.

[16]The corresponding section has been removed from this edited submission. The full version is available via the link referred to on the title page.

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Table I: Sample Composition

This table breaks down the number of remaining daily firm-level observations across GICS sectors, S&P rating classes, and years after merging CDS, stock, balance sheet, and implied volatility data sets. The "Banks" subsector is augmented by companies like Goldman Sachs and Morgan Stanley originally included in the "Diversified Financials" group, whereby the latter is relabeled "Others." The data covers the period from January 2002 to September 2010. Subtotals across the time and the cross-sectional dimensions are provided.

	Firms	**Observations**									
		2002	2003	2004	2005	2006	2007	2008	2009	2010	*Total*
Sectors											
Consumer Disc	96	5,861	10,597	15,342	19,256	20,656	22,230	20,830	18,682	13,416	146,870
Consumer Staples	37	2,258	4,340	5,977	7,981	8,055	8,662	8,774	7,907	5,691	59,645
Energy	41	1,474	3,123	5,134	6,774	7,832	9,352	9,717	9,696	6,955	60,057
Financials	74	4,297	7,935	11,412	14,602	15,333	16,218	15,511	13,146	9,994	108,448
Banks	27	2,530	4,004	4,953	5,503	6,075	6,088	5,489	4,123	3,026	41,791
Insurance	24	1,571	2,885	4,088	5,179	4,986	5,389	5,274	4,534	3,406	37,312
Real Estate	18	143	737	1,725	2,851	3,279	3,801	3,848	3,596	2,886	22,866
Others	5	53	309	646	1,069	993	940	900	893	676	6,479
Health Care	42	1,672	3,814	6,099	8,107	8,631	9,562	9,111	8,699	5,796	61,491
Industrials	68	4,194	7,513	10,907	12,802	13,575	14,383	14,591	13,984	10,475	102,424
IT	34	2,001	3,308	4,844	6,128	6,533	7,222	7,158	6,583	5,138	48,915
Materials	52	2,258	4,805	7,273	9,471	10,059	11,317	11,165	9,940	7,695	73,983
Telecom Svcs	13	533	1,038	1,605	1,972	2,583	3,122	2,926	2,486	1,532	17,797
Utilities	41	1,833	4,411	6,055	8,270	8,504	8,962	9,125	8,131	6,057	61,348
Total	498	26,381	50,884	74,648	95,363	101,761	111,030	108,908	99,254	72,749	740,978
Ratings											
AAA	6	237	599	928	1,205	1,294	1,461	1,491	1,390	1,041	9,646
AA	24	1,807	3,122	4,001	5,183	5,583	5,743	5,823	4,986	3,446	39,694
A	128	9,185	16,559	22,225	27,121	27,771	29,082	28,754	26,580	19,341	206,618
BBB	210	10,527	21,230	31,033	40,027	42,806	46,889	47,134	45,304	32,965	317,915
BB	86	2,791	6,344	11,224	14,145	16,066	18,451	16,730	14,631	11,013	111,395
B	35	1,832	2,908	4,852	6,862	7,197	8,175	7,544	5,386	4,379	49,135
Non-Inv Grade	1	0	0	0	27	78	158	145	0	0	408
Nonrated	8	2	122	385	793	966	1,071	1,287	977	564	6,167
Total	498	26,381	50,884	74,648	95,363	101,761	111,030	108,908	99,254	72,749	740,978

Table II: Predicted vs. Observed CDS Spreads under a Constant Default Barrier

This table summarizes calibration results under the basic scheme with a constant adjustment factor $\bar{L}$ related to the default barrier $B = LD$ of the CG model, where the face value of the debt per share D is exogenous. For each firm i, we determine $\bar{L}_i$ by minimizing the sum of squared errors between N model and market CDS spreads over the estimation period from January 2003 through July 2007. The number of observations N depends on the density of the calibration grid, as defined by the interval between grid points, and we consider intervals (Ival) of 50, ten, three, and one. Panel A reports the cross-sectional mean of $\bar{L}_{i,t}$ ($\bar{\bar{L}}$), the mean over all pricing errors defined as the model minus the market spread (ME) as well as the average of the individual root mean squared errors (RMSE) for different (sub)periods. The sample period ranges from January 2002 to September 2010 with the crisis period covering August 2007 through September 2009. cRMSE denotes the firm average of the root mean squared errors obtained in the calibrations. Panel B reports summary statistics, including means and standard deviations (Std) for CDS market and model spreads as well as their pricing errors (Dev). All CDS spreads are denoted in basis points.

Panel A

	Whole Sample Period					Pre-Crisis Period		Crisis Period		Post-Crisis Period	
Ival	N	$\bar{\bar{L}}$	cRMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE
50	16	1.053	40.97	20.14	159.70	-9.17	46.92	68.38	246.92	30.48	141.67
10	76	1.070	39.80	20.60	158.14	-8.90	44.79	69.16	246.30	31.05	138.96
3	253	1.076	39.35	20.47	158.40	-8.84	44.71	68.85	246.89	30.54	138.76
1	757	1.077	38.93	19.94	158.77	-8.93	44.72	67.84	247.60	29.27	138.75

Panel B

	Pre-Crisis Period						Crisis Period						Post-Crisis Period					
	Mean			Std			Mean			Std			Mean			Std		
	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev
Consumer Disc	133.96	126.22	-7.74	161.59	163.78	65.52	509.81	574.32	64.50	1,040.45	581.96	798.43	295.59	369.33	73.74	291.91	364.16	182.74
Consumer Staples	65.60	58.58	-7.02	106.36	106.18	37.74	138.33	170.56	32.23	269.54	251.30	131.46	107.18	89.72	-17.45	137.06	127.52	56.34
Energy	101.70	92.74	-8.96	167.60	169.44	54.27	199.62	253.23	53.61	185.78	263.60	155.27	180.11	146.76	-33.35	153.06	136.72	88.69
Financials	45.42	38.53	-6.89	48.51	51.10	27.17	400.16	583.48	183.32	615.62	685.32	426.12	321.69	447.52	125.83	572.43	611.75	483.53
Banks	41.61	35.91	-5.70	49.58	52.79	24.92	393.27	743.73	350.46	528.47	749.96	456.17	341.73	579.20	237.47	466.62	660.69	333.18
Insurance	47.20	40.07	-7.12	52.35	52.09	25.58	308.88	442.53	133.65	510.58	606.30	332.40	333.15	370.25	37.10	802.46	583.39	695.26
Real Estate	54.22	46.72	-7.50	42.13	48.01	34.50	549.43	613.18	63.75	804.93	695.49	414.18	301.58	473.70	172.12	371.40	622.55	281.46
Others	35.96	23.53	-12.44	23.05	33.63	26.41	332.30	347.96	15.66	587.96	381.91	462.66	259.84	139.11	-120.73	196.64	96.37	164.85
Health Care	66.29	54.56	-11.73	91.21	91.94	38.43	153.64	238.92	85.28	193.18	313.09	174.24	138.16	160.61	22.45	134.96	179.27	104.91
Industrials	133.97	126.36	-7.61	297.71	294.99	85.75	316.70	329.67	12.97	704.21	433.37	410.90	206.36	223.43	17.07	334.18	285.85	143.66
IT	135.06	122.21	-12.85	180.71	192.71	60.83	219.78	283.44	63.66	389.90	350.34	217.47	172.81	200.43	27.62	205.75	220.91	102.84
Materials	108.41	98.95	-9.46	130.95	137.32	59.82	226.91	311.41	84.51	286.92	362.60	209.43	168.89	174.98	6.09	140.11	145.76	118.89
Telcom Svcs	298.00	275.97	-22.03	506.28	459.11	183.47	256.03	330.89	74.86	290.36	358.00	186.32	191.61	197.87	6.26	147.69	220.20	134.76
Utilities	113.98	104.77	-9.20	207.65	202.15	88.93	167.77	166.01	-1.76	178.12	227.98	137.97	159.31	133.62	-25.69	177.25	228.04	136.02

Table III: Predicted vs. Observed CDS Spreads under a Time-varying Default Barrier

This table summarizes calibration results under a time-varying adjustment factor $\bar{L}$ related to the default barrier $B = LD$ of the CG model, where the face value of the debt per share D is exogenous. For each firm i and date t, we determine $\bar{L}_{i,t}$ by minimizing the sum of squared errors within a trailing window of five model and market CDS spreads. We choose an interval of two between calibration points. Panel A reports the coefficient (β) and associated p-value of a trend regression of the daily percentage changes of $\bar{L}_{i,t}$, and the cross-sectional mean of $\bar{L}_{i,t}$ ($\bar{\bar{L}}$), the mean over all pricing errors (ME), defined as the model minus the market spread, as well as the average of the individual root mean squared errors (RMSE) for different (sub)periods. The sample period ranges from January 2002 to September 2010 with the crisis period covering August 2007 through September 2009. The previous results are further broken down cross-sectionally into financial and nonfinancial companies. Panel B reports summary statistics, including means and standard deviations (Std) for CDS market and model spreads as well as their pricing errors (Dev). All CDS spreads are denoted in basis points.

Panel A

	Whole Sample Period					Pre-Crisis Period			Crisis Period			Post-Crisis Period		
	β	p-value	$\bar{\bar{L}}$	ME	RMSE	$\bar{\bar{L}}$	ME	RMSE	$\bar{\bar{L}}$	ME	RMSE	$\bar{\bar{L}}$	ME	RMSE
All	-7.95E+07	0.97	1.133	-4.10	48.84	1.284	-0.87	11.35	0.935	-9.11	74.07	1.081	-3.36	37.48
Fin	-0.0004991	0.01	0.549	-1.92	76.67	0.616	-1.75	7.46	0.455	2.80	111.89	0.524	-14.02	129.38
Nonfin	-1.57E+08	0.95	1.232	-4.47	43.98	1.402	-0.71	12.03	1.013	-11.05	67.47	1.168	-1.68	22.08

Panel B

	Pre-Crisis Period						Crisis Period						Post-Crisis Period					
	Mean			Std			Mean			Std			Mean			Std		
	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev
Consumer Disc	126.83	126.13	-0.70	155.90	156.12	19.70	509.82	470.97	-38.86	1,040.61	666.38	600.18	295.59	293.35	-2.24	291.91	294.19	39.92
Consumer Staples	61.17	60.67	-0.49	97.52	97.84	11.19	138.33	137.58	-0.76	269.55	268.80	29.67	107.18	105.89	-1.28	137.06	136.83	10.91
Energy	81.48	80.79	-0.69	92.38	92.21	12.08	199.62	198.13	-1.49	185.78	186.15	35.43	180.11	178.55	-1.56	153.06	153.99	20.23
Financials	35.75	34.00	-1.75	26.80	27.98	8.71	400.16	402.96	2.80	615.62	580.26	175.29	321.69	307.67	-14.02	572.43	424.71	261.29
Banks	29.87	28.42	-1.45	18.28	19.28	7.45	393.27	403.73	10.46	528.47	534.13	148.08	341.73	337.62	-4.11	466.62	450.94	68.42
Insurance	33.51	30.66	-2.85	20.72	23.24	9.03	308.88	320.50	11.62	510.58	526.75	140.71	333.15	300.14	-33.01	802.46	472.13	440.86
Real Estate	52.03	51.23	-0.80	41.60	41.81	10.75	549.43	531.92	-17.51	804.93	678.43	247.30	301.58	296.95	-4.63	371.40	371.40	48.12
Others	33.84	33.17	-0.67	21.24	21.74	6.17	332.30	326.58	-5.72	587.96	577.63	113.52	259.84	256.39	-3.45	196.64	196.37	29.66
Health Care	61.52	61.00	-0.52	84.47	84.58	10.23	153.64	152.95	-0.69	193.18	195.35	31.63	138.16	136.84	-1.32	134.96	135.33	14.30
Industrials	122.14	121.50	-0.64	276.08	275.05	19.60	316.70	304.55	-12.15	704.21	615.02	189.50	206.36	205.33	-1.04	334.18	333.46	47.56
IT	109.09	108.34	-0.75	139.52	138.98	14.21	219.89	219.29	-0.60	389.99	389.38	48.10	172.81	171.36	-1.45	205.75	206.26	24.17
Materials	97.62	96.77	-0.85	107.60	107.83	18.01	226.89	225.88	-1.01	286.92	284.19	66.89	168.89	166.10	-2.79	140.11	143.43	30.04
Telcom Svcs	246.32	244.92	-1.40	442.62	439.92	56.95	256.03	256.15	0.12	290.36	293.19	48.35	191.61	189.03	-2.58	147.69	147.29	18.98
Utilities	77.82	76.95	-0.87	93.93	94.14	17.71	167.77	167.50	-0.27	178.12	182.12	39.78	159.31	158.33	-0.98	177.25	176.90	24.55

Table IV: Predicted vs. Observed CDS Spreads under a Regime Shift

This table summarizes results of a calibration scheme in which the adjustment factor $\bar{L}$ is allowed to change at the split date t_2 from $\bar{L}_1$ to $\bar{L}_2$ over the estimation period of January 2004 to December 2009. The default barrier is defined as $B = LD$ in the CG model, where the face value of the debt per share D is exogenous. For each firm i, we determine $\bar{L}_{i,1}$, $\bar{L}_{i,2}$, and $t_{i,2}$ by minimizing the sum of squared errors over the number of observations resulting from a grid interval of 10. Panel A reports the cross-sectional means of $\bar{L}_{i,1}$ ($\bar{\bar{L}}_1$) and $\bar{L}_{i,2}$ ($\bar{\bar{L}}_2$), the median of $t_{i,2}$, and the mean over all pricing errors (ME), defined as the model minus the market spread, as well as the average of the individual root mean squared errors (RMSE) for different (sub)periods. The sample period ranges from January 2002 to September 2010 with the crisis period covering August 2007 through September 2009. The previous results are further broken down cross-sectionally into financial and nonfinancial companies. Panel B reports summary statistics, including means and standard deviations (Std) for CDS market and model spreads as well as their pricing errors (Dev). All CDS spreads are denoted in basis points.

Panel A

	Whole Sample Period					Pre-Crisis Period		Crisis Period		Post-Crisis Period	
	$\bar{\bar{L}}_1$	$\bar{\bar{L}}_2$	Median t_2	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE
All	1.056	0.920	09/30/2008	-14.84	91.96	-6.68	53.74	-10.01	110.24	-60.63	125.71
Fin	0.465	0.246	11/04/2008	-26.16	124.73	-16.86	39.84	-21.41	171.21	-81.82	258.29
Nonfin	1.159	1.038	09/30/2008	-12.90	86.24	-4.84	56.17	-8.14	99.60	-57.30	103.43

Panel B

	Pre-Crisis Period						Crisis Period						Post-Crisis Period					
	Mean			Std			Mean			Std			Mean			Std		
	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev	Market	Model	Dev
Consumer Disc	128.60	117.11	-11.48	154.46	166.78	74.77	450.00	440.29	-9.71	684.85	583.54	293.22	295.59	222.27	-73.32	291.91	373.44	179.73
Consumer Staples	65.60	63.33	-2.27	106.36	108.63	41.24	138.33	136.35	-1.98	269.54	274.25	63.72	107.18	50.25	-56.93	137.06	114.51	56.64
Energy	101.70	94.45	-7.25	167.60	186.10	61.00	199.62	190.09	-9.53	185.78	228.36	90.31	180.11	116.20	-63.91	153.06	140.47	83.54
Financials	45.42	28.56	-16.86	48.51	54.21	45.64	400.16	378.75	-21.41	615.62	574.25	257.56	321.69	239.87	-81.82	572.43	440.52	354.09
Banks	41.61	17.95	-23.67	49.58	43.17	41.60	393.27	368.00	-25.27	528.47	559.60	225.69	341.73	230.73	-110.99	466.62	427.16	163.74
Insurance	54.22	60.09	5.87	42.13	75.80	66.08	549.43	554.61	5.19	804.93	675.08	359.96	301.58	245.24	-56.34	371.40	474.14	164.90
Real Estate	47.20	27.07	-20.13	52.35	48.69	34.24	308.88	277.06	-31.82	510.58	490.06	183.48	333.15	232.40	-100.75	802.46	437.75	557.40
Others	35.96	20.15	-15.81	23.05	42.93	35.66	332.30	280.76	-51.54	587.96	455.36	264.19	259.84	294.20	34.36	196.64	358.48	189.63
Health Care	66.29	57.43	-8.86	91.21	101.56	45.53	153.64	149.57	-4.07	193.18	221.50	71.63	138.16	77.84	-60.32	134.96	105.91	66.21
Industrials	133.97	134.85	0.88	297.71	295.62	92.18	280.22	270.78	-9.44	541.59	512.61	140.39	199.54	182.00	-17.54	291.12	452.13	208.05
IT	135.06	135.32	0.26	180.71	199.11	75.39	219.78	214.29	-5.49	389.90	368.17	106.89	172.81	114.10	-58.71	205.75	231.27	106.22
Materials	108.41	103.61	-4.80	130.95	139.07	65.20	225.99	214.13	-11.85	281.03	304.37	114.45	168.89	89.41	-79.49	140.11	141.16	86.53
Telcom Svcs	298.00	305.59	7.59	506.28	477.24	190.81	256.03	252.31	-3.73	290.36	299.98	99.99	191.61	83.31	-108.30	147.69	111.38	87.42
Utilities	113.98	111.78	-2.19	207.65	206.66	93.42	167.77	157.73	-10.04	178.12	193.85	86.06	159.31	121.89	-37.42	177.25	175.24	119.09

Table V: Time Series Characteristics

For both CDS market (CDS) and model prices ($\widehat{CDS}$), Panel A presents the number of companies for which the null of a unit root is rejected at the 5% level in the augmented Dickey-Fuller test. Panel B first reports the number of firms for which cointegration between market and model prices is indicated by the Johansen rank test. Cointegration is assumed if the hypothesis of no cointegrating vectors is rejected at the 10% level. Further, two restriction tests on the cointegrating space are conducted: First, we explore whether $\alpha_0 = 0$ and $\alpha_1 = 1$ hold in the error correction term, and second, whether at least $\alpha_1 = 1$ is satisfied. Subsequently, these results flow into a new VECM estimation used for the computation of the Granger-Gonzalo (GG) measures at the firm level. Panel B reports cross-sectional averages of GG, whereas individual values below zero are set to zero and values exceeding one are set to one beforehand. The columns related to λ report the number of companies for which the market (model) contributes to price discovery, i.e., for which λ_2 (λ_1) is positive (negative) and statistically significant at the 10% level. Finally, Panel C reports the number of firms for each possible case of Granger causality at the 5% rejection level. Throughout these analyses, the number of lags is determined by minimizing the SIC at the firm-level. n is the total number of firms in a given subset. Period I ranges from August 2004 to July 2007 and period II is from August 2007 until July 2010.

Panel A – Augmented Dickey-Fuller Unit-Root Tests

	Period I			**Period II**			**Whole Period**		
	All	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**
n	498	74	424	498	74	424	498	74	424
CDS	93	17	76	28	7	21	51	6	45
$\widehat{CDS}$	175	27	148	25	5	20	45	6	39

Panel B – VECM / Johansen Test of Cointegration and Granger-Gonzalo Measure

	Period I			**Period II**			**Whole Period**		
	All	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**
n	498	74	424	498	74	424	498	74	424
Cointegrated	312	56	256	268	41	227	359	60	299
$\lambda_2 > 0$	178	26	152	102	16	86	179	26	153
$\lambda_1 < 0$	171	31	140	221	28	193	288	44	244
$\overline{GG}_{Market}$	0.685	0.713	0.679	0.527	0.509	0.530	0.573	0.493	0.589

Panel C – VAR / Granger Causality Tests

	Period I			**Period II**			**Whole Period**		
	All	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**	**All**	**Fin**	**Nonfin**
n	498	74	424	498	74	424	498	74	424
CDS causes $\widehat{CDS}$	68	7	61	60	8	52	31	4	27
$\widehat{CDS}$ causes CDS	108	8	100	156	19	137	100	9	91
Bidirectional Causality	100	36	64	165	32	133	296	56	240
No Causality	222	23	199	117	15	102	71	5	66

Table VI: Summary Statistics of Determinants

This table breaks down the mean, standard deviation (Std), minimum (Min) and maximum (Max) statistics for each possible quantitative determinant of price deviations into the three main subperiods of the sample. The pre-crisis period is defined to range from January 2002 to July 2007, the crisis period follows and lasts until September 2009, and the post-crisis period ends in September 2010. The S&P 500 return is a contemporaneous three-month average of daily log returns. The Treasury rate is the three-month spot rate and the term spread is the difference between the ten-year and three-month spot rates. The on/off spread is the off-the-run minus the on-the-run five-year Treasury yield and the Refcorp spread is calculated as the Refcorp minus the Treasury bond yield, both at five-year maturities. The stock return is the daily log return and the stock volatility is the one-year at-the-money implied volatility. $\beta^{DF}_{r_S}$ is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return. $\beta^{PD}_{r_{CDS}}$ is a measure of counterparty risk that reflects the correlation between individual CDS returns and the corresponding variation of a constructed index of primary dealers. All β measures are calculated over a 50-day rolling window. The plus and minus signs represent theoretical predictions of the effects of each variable on price deviations.

		Pre-Crisis				**Crisis**				**Post-Crisis**			
		Mean	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**
Macrofinancial Variables													
Business Climate													
S&P 500 Return $r_{\text{S\&P500}}$ (%)	$-$	0.02	0.12	-0.56	0.33	-0.08	0.22	-0.89	0.52	0.04	0.11	-0.23	0.31
VIX	$+$	17.54	6.83	9.89	45.08	31.25	12.99	16.12	80.86	23.53	5.11	15.58	45.79
Interest Rate Term Structure													
Treasury Rate	$\pm$	2.71	1.60	0.81	5.19	1.43	1.40	0.00	4.95	0.12	0.05	0.02	0.18
Term Spread	$\pm$	1.73	1.42	-0.64	3.85	2.21	0.99	-0.17	3.82	3.27	0.40	2.33	3.83
Illiquidity													
On/Off Spread $L_{\text{On/Off}}$	$-$	-0.01	0.06	-0.11	0.19	0.03	0.06	-0.08	0.17	0.04	0.02	-0.01	0.08
Refcorp Spread L_{Ref}	$-$	0.09	0.08	-0.14	0.34	0.58	0.39	0.03	1.54	0.59	0.14	0.29	0.80
Firmspecific Variables													
Ratings													
S&P Issuer Ratings	$+$												
Firm Condition													
Stock Return r_S (%)	$-$	0.03	1.87	-85.05	48.84	0.00	4.07	-73.17	97.42	-0.07	2.36	-31.02	48.83
Stock Volatility σ_S	$+$	0.27	0.10	0.03	1.99	0.45	0.22	0.03	2.97	0.36	0.14	0.06	2.59
Size													
Total Assets (bn)	$+$	0.05	0.15	0.00	2.22	0.06	0.20	0.00	2.36	0.05	0.21	0.00	2.36
Total Liab. + Market Cap. (bn)	$+$	0.06	0.16	0.00	2.35	0.07	0.20	0.00	2.47	0.06	0.21	0.00	2.30
Default Correlation													
$\beta^{DF}_{r_S}$	$+$	0.79	0.32	-0.20	3.04	0.94	0.44	-0.11	3.70	1.00	0.40	0.02	3.20
Counterparty Risk													
$\beta^{PD}_{r_{CDS}}$	$+$	0.23	0.44	-16.33	12.75	0.28	0.25	-3.58	3.35	0.33	0.26	-1.37	3.88

Table VII: Correlation Matrices of Determinants

Pooling all observations together, we report correlation matrices of variables used in the subsequent linear regressions, both for the whole sample (Panel A) and for the subsample of financial companies over the period August 2007 to September 2009 (Panel B). Dev is the relative deviation between model and market CDS premiums, Size is measured by total assets, and TARP is a dummy variable reflecting whether a company was admitted under that program. $\beta_{r_S}^{DF}$ applies to the financial sector only and is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return, thereby reflecting the default correlation between one company and the whole financial sector. $\beta_{r_{CDS}}^{PD}$ is a measure of counterparty risk that reflects the correlation between individual CDS returns and the corresponding variation of a constructed index of primary dealers. All β measures are calculated over a 50-day rolling window. L_{Ref} and $L_{\text{On/Off}}$ are measures of illiquidity based on the Refcorp spread and the on-the-run/off-the-run treasury bond spread, respectively. $r_{\text{S\&P500}}$ is the S&P 500 return computed as the contemporaneous three-month average of daily log returns.

	Dev	Size	TARP	$\beta_{r_S}^{DF}$	$\beta_{r_{CDS}}^{PD}$	L_{Ref}	$L_{\text{On/Off}}$	$r_{\text{S\&P500}}$
Panel A − All companies from January 2002 to September 2010								
Dev	1							
Size	0.073	1						
TARP	0.071	0.600	1					
$\beta_{r_S}^{DF}$	0.158	0.208	0.162	1				
$\beta_{r_{CDS}}^{PD}$	0.030	0.236	0.150	0.281	1			
L_{Ref}	0.375	0.013	-0.009	0.167	0.075	1		
$L_{\text{On/Off}}$	0.309	0.009	0.008	0.102	0.029	0.601	1	
$r_{\text{S\&P500}}$	-0.152	-0.007	-0.006	-0.011	-0.012	-0.168	-0.196	1
Panel B − Financial companies from August 2007 to September 2009								
Dev	1							
Size	0.191	1						
TARP	0.224	0.561	1					
$\beta_{r_S}^{DF}$	0.133	0.197	0.170	1				
$\beta_{r_{CDS}}^{PD}$	0.030	0.566	0.366	0.371	1			
L_{Ref}	0.168	0.005	0.038	0.035	0.080	1		
$L_{\text{On/Off}}$	0.160	0.003	0.027	0.010	-0.009	0.6671	1	
$r_{\text{S\&P500}}$	-0.084	0.007	-0.007	0.027	-0.003	-0.1489	-0.125	1

Table VIII: Determinants of Relative Price Deviations

This table summarizes the results of a series of pooled ordinary least squares regressions of the relative deviations between stock-implied model and market CDS premiums for 498 U.S. reference entities. The underlying daily observations cover the whole sample period from January 2002 through September 2010. The S&P 500 return $r_{\mathrm{S\&P500}}$ is a contemporaneous three-month average of daily log returns. The Treasury rate is the three-month spot rate and the term spread is the difference between the ten-year and three-month spot rates. $L_{\mathrm{On/Off}}$ is the off-the-run minus the on-the-run five-year Treasury yield and the Refcorp spread L_{Ref} is calculated as the Refcorp minus the Treasury bond yield, both at five-year maturities. The stock return r_S is a daily log return and the stock volatility σ_S is a one-year at-the-money implied volatility. Size is measured by the book value of total assets. $\beta^{DF}_{r_S}$ is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return, and $\mathrm{I_{Fin}}$ is a dummy variable equaling one for financial companies. $\beta^{PD}_{r_{CDS}}$ is a measure of counterparty risk that reflects the correlation between individual CDS returns and the corresponding variation of a constructed index of primary dealers. All β measures are calculated over a 50-day rolling window and applies only to financial companies. The TARP dummy reflects participation of a company in that program. Next to average coefficients, we indicate t-statistics based on clustered standard errors that adjust for firm effects (CL-F) as proposed by Petersen (2009). Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
$r_{\mathrm{S\&P500}}$	-26.7657	-7.91 ***	-26.2531	-7.70 ***	1.6687	0.70	-24.1100	-5.42 ***	-21.1758	-4.55 ***	-46.2296	-9.54 ***	-23.9967	-5.35 ***	-91.9176	-12.67 ***
VIX					0.0360	23.46 ***										
Treasury Rate	-0.0843	-6.54 ***	-0.2991	-14.68 ***	-0.0943	-6.15 ***	-0.0104	-0.87	-0.0104	-0.87	-0.0544	-4.36 ***	-0.0109	-0.89		
Term Spread	-0.0531	-3.60 ***	-0.3238	-14.39 ***	-0.0855	-4.93 ***	0.0118	0.89	0.0120	0.90	-0.0190	-1.36	0.0108	0.79		
L_{Ref}	0.8986	17.29 ***					0.5724	10.82 ***	0.5733	10.83 ***	0.8851	17.45 ***	0.5787	10.97 ***		
$L_{\mathrm{On/Off}}$			3.0401	16.12 ***												
Rating (AAA)							2.1533	10.46 ***	2.1374	10.36 ***	1.2663	6.71 ***	2.4805	10.65 ***	0.1785	1.24
Rating (AA)							2.3024	14.10 ***	2.2836	13.90 ***	1.4236	8.75 ***	2.6013	12.94 ***	0.3750	4.50 ***
Rating (A)							2.1064	14.17 ***	2.0929	14.08 ***	1.2184	7.95 ***	2.3805	11.47 ***	0.1521	3.36 ***
Rating (BBB)							2.2419	16.00 ***	2.2279	15.89 ***	1.3870	9.16 ***	2.5128	12.49 ***	0.3281	9.08 ***
Rating (BB)							1.9983	15.57 ***	1.9852	15.47 ***	1.3206	8.49 ***	2.2683	11.74 ***	0.2563	5.88 ***
Rating (B)							1.7528	14.98 ***	1.7408	14.87 ***	1.3037	8.37 ***	2.0221	10.91 ***	0.2415	5.63 ***
Rating (CCC)							1.2664	7.87 ***	1.2555	7.81 ***	1.1579	6.54 ***	1.5392	7.35 ***	0.4660	3.86 ***
Rating (CC)							0.3744	1.24	0.3597	1.20	0.5881	1.52	0.5667	1.51	0.2434	0.74
r_S							-1.2602	-18.36 ***	-1.2555	-18.27 ***	-1.4871	-20.15 ***	-1.2653	-18.25 ***	-1.1669	-16.72 ***
σ_S							1.6813	10.36 ***	1.6709	10.32 ***			1.6776	10.33 ***		
Size							0.3420	2.46 **	0.3372	2.43 **						
Size $\times$ $r_{\mathrm{S\&P500}}$									-70.4856	-2.72 ***						
$\beta^{DF}_{r_S} \times \mathrm{I_{Fin}}$											0.2362	3.61 ***				
TARP													0.3054	2.00 **		
$\beta^{PD}_{r_{CDS}}$															0.1108	2.74 ***
Constant	0.1190	1.93 *	1.3671	14.02 ***	-0.2985	-4.03 ***	-2.8048	-14.57 ***	-2.7878	-14.49 ***	-1.3789	-8.91 ***	-3.0702	-13.00 ***	-0.2019	-6.02 ***
$Adj.R^2$	0.1530		0.1254		0.1935		0.2162		0.2167		0.1724		0.2164		0.0465	
Observations	730,017		730,017		730,017		524,868		524,868		524,868		524,868		520,632	
Coef. Estimates	OLS		OLS		OLS		OLS		OLS		OLS		OLS		OLS	
Standard Errors	CL-F		CL-F		CL-F		CL-F		CL-F		CL-F		CL-F		CL-F	

Table IX: Determinants of Relative Price Deviations - Alternative Subsamples

This table summarizes the results of a series of pooled ordinary least squares regressions of the relative deviations between stock-implied model and market CDS premiums on a daily basis. In columns (1) to (3), we maintain the whole company sample of 498 U.S. reference entities but restrict the relevant time period to range from August 2007 until September 2010. In columns (4) to (6), we further constraint the sample to include only the financial group. The S&P 500 return $r_{\mathrm{S\&P500}}$ is a contemporaneous three-month average of daily log returns. The Treasury rate is the three-month spot rate and the term spread is the difference between the ten-year and three-month spot rates. The Refcorp spread L_{Ref} is calculated as the Refcorp minus the Treasury bond yield, both at five-year maturities. The stock return r_S is a daily log return and the stock volatility σ_S is a one-year at-the-money implied volatility. Size is measured by the book value of total assets. $\beta^{DF}_{r_S}$ is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return, and $\mathrm{I}_{\mathrm{Fin}}$ is a dummy variable equaling one for financial companies. The measure is calculated over a 50-day rolling window and applies only to financial companies. The TARP dummy reflects participation of a company in that program. Next to average coefficients, we indicate t-statistics based on clustered standard errors that adjust for firm effects (CL-F) as proposed by Petersen (2009). Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)			(2)			(3)			(4)			(5)			(6)		
	Coef.	t		Coef.	t		Coef.	t		Coef.	t		Coef.	t		Coef.	t	
$r_{\mathrm{S\&P500}}$	-22.2557	-3.23	***	-43.1111	-6.44	***	-23.1295	-3.53	***	-25.5557	-0.99		-34.9430	-1.69	*	-39.6285	-1.89	*
Treasury Rate	0.0991	5.69	***	0.0875	5.06	***	0.0986	5.65	***	-0.0550	-0.78		-0.0438	-0.60		-0.0556	-0.92	
Term Spread	0.0721	3.67	***	0.0211	1.11		0.0704	3.55	***	-0.1043	-1.42		-0.0897	-1.19		-0.1591	-2.28	**
L_{Ref}	0.6268	8.03	***	1.0786	16.00	***	0.6430	8.84	***	0.4670	1.62		0.7685	2.43	**	0.9046	3.32	***
Rating (AAA)	2.2655	6.87	***	1.6966	5.01	***	2.9417	7.44	***									
Rating (AA)	2.4579	10.72	***	1.9445	7.58	***	3.0589	10.76	***	2.0350	5.70	***	2.7908	6.64	***	2.0512	7.93	***
Rating (A)	2.1857	11.83	***	1.6332	6.99	***	2.7664	8.93	***	1.7829	5.92	***	2.2773	6.28	***	1.7808	4.85	***
Rating (BBB)	2.2790	13.38	***	1.7425	8.01	***	2.8601	9.57	***	1.5205	6.47	***	1.8839	5.81	***	1.5474	4.59	***
Rating (BB)	1.8592	12.25	***	1.5508	6.79	***	2.4535	8.28	***	0.9608	3.82	***	1.2604	4.07	***	1.2312	3.10	***
Rating (B)	1.5025	10.97	***	1.4706	6.42	***	2.0994	7.17	***	1.3609	11.98	***	1.5844	7.50	***	1.9506	5.46	***
Rating (CCC)	1.1217	7.24		1.3468	6.13	***	1.7424	5.58	***	1.4992	6.31	***	1.6945	5.66	***	2.0441	4.98	***
Rating (CC)	0.2772	0.87	***	0.8134	1.78	*	0.7074	1.38		0.0508	0.22		0.3475	1.71	*	0.8075	1.67	*
r_S	-1.1873	-15.22	***	-1.4406	-16.42	***	-1.2035	-14.95	***	-1.0899	-6.34	***	-1.2615	-6.84	***	-1.3517	-6.64	***
σ_S	1.6925	8.41	***				1.6282	8.13	***	0.9385	3.23	***	0.3685	1.10				
Size	0.5130	3.52	***							0.5211	2.92	***						
Size $\times\ r_{\mathrm{S\&P500}}$	-11.9110	-0.40								-27.4761	-0.58							
$\beta^{DF}_{r_S} \times \mathrm{I}_{\mathrm{Fin}}$				0.4063	4.12	***							0.5026	2.56	**			
TARP							0.6985	2.33	**							0.8072	2.25	**
Constant	-3.0780	-12.66	***	-2.0582	-9.13	***	-3.6396	-11.06	***	-1.4653	-3.17	***	-2.1809	-3.45	***	-1.2177	-3.51	***
Adj. R^2	0.1426			0.0991			0.1471			0.1096			0.1021			0.1135		
Observations	247,189			247,189			247,189			34,218			34,218			34,218		
Coef. Estimates	OLS			OLS			OLS			OLS			OLS			OLS		
Standard Errors	CL-F			CL-F			CL-F			CL-F			CL-F			CL-F		

Table X: Determinants of Changes in Relative Price Deviations

This table summarizes the results of a series of pooled ordinary least squares regressions of changes in relative deviations between stock-implied model and market CDS premiums for 498 U.S. reference entities. The underlying observations cover the whole sample period from January 2002 through September 2010 and are on a monthly basis by retaining the end-of-month observations from the daily data set. We examine the relation between changes in relative spread deviations and changes (Δ) or returns of the independent variables, whichever is more appropriate. The S&P 500 return $r_{\text{S\&P500}}$ is a contemporaneous three-month average of daily log returns. The Treasury rate is the three-month spot rate and the term spread is the difference between the ten-year and three-month spot rates. The Refcorp spread L_{Ref} is calculated as the Refcorp minus the Treasury bond yield, both at five-year maturities. The stock return r_S is a daily log return and the stock volatility σ_S is a one-year at-the-money implied volatility. Size_{t-1} is the one-month lagged sum of the total liabilities and the market capitalization. $\beta_{r_S}^{DF}$ is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return, and I_{Fin} is a dummy variable equaling one for financial companies. The measure is calculated over a 50-day rolling window and applies only to financial companies. Next to average coefficients, we indicate t-statistics based on robust standard errors. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)			(2)			(3)			(4)			(5)		
	Coef.	t		Coef.	t		Coef.	t		Coef.	t		Coef.	t	
$r_{\text{S\&P500}}$	-21.5784	-8.33	***	-20.9954	-7.86	***	-10.4251	-4.1	***	-20.9872	-7.85	***	-17.0695	-7.94	***
Δ Treasury Rate	-0.0935	-5.43	***	-0.0896	-5.15	***	0.0722	4.16	***	-0.089	-5.11	***	-0.1074	-6.39	***
Δ Term Spread	0.0588	4.49	***	0.0616	4.65	***	0.1079	8.54	***	0.0622	4.68	***	0.0476	3.72	***
Δ L_{Ref}	-0.0428	-1.4		-0.0446	-1.45		-0.072	-2.53	**	-0.0447	-1.45		-0.0316	-1.03	
r_S							-0.004	-5.02	***						
Δ σ_S							3.415	11.33	***						
Δ Size_{t-1}	1.9412	4.23	***	1.8389	4.39	***	1.757	5.08	***	1.83	4.38	***			
Δ $\text{Size}_{t-1} \times r_{\text{S\&P500}}$				-0.0001	-4.09	***				-0.0001	-4.09	***			
Δ $(\beta_{r_S}^{DF} \times \text{I}_{\text{Fin}})$										0.1149	2.08	**			
TARP													0.0333	1.71	*
Constant	0.0023	0.93		0.0026	1.02		0.0034	1.49		0.0025	1.00		0.001	0.4	
Adj. R^2	0.025			0.0266			0.1838			0.0269			0.0215		
Observations	40,964			40,569			40,964			40,569			41,353		
Coefficient Estimates	OLS			OLS			OLS			OLS			OLS		
Standard Errors	White			White			White			White			White		

Table XI: Dynamics of Relative Price Deviations

This table summarizes the results of a series of dynamic panel regressions of the relative deviations between stock-implied model and market CDS premiums for 498 U.S. reference entities. The underlying observations cover the whole sample period from January 2002 through September 2010. All regressions include an additional lagged dependent variable to account for the persistence of deviations over time, as well as time dummies. The coefficients presented in columns (1) to (4) are based on the Arellano and Bover (1995) GMM estimator. The sample consists of the first available record at the beginning of every quarter. Standard errors are estimated in two steps and corrected according to Windmeijer (2005). We report p-values of the Arellano-Bond (1991) test of serial correlation and the Hansen (1982) test of overidentifying restrictions. The coefficients in column (5) are fixed effects (FE) estimates based on daily observations. The associated t-statistics based on robust standard errors. The S&P 500 return $r_{\mathrm{S\&P500}}$ is a contemporaneous three-month average of daily log returns. The Treasury rate is the three-month spot rate and the term spread is the difference between the ten-year and three-month spot rates. The on/off spread $L_{\mathrm{On/Off}}$ is the off-the-run minus the on-the-run five-year Treasury yield. The stock return is a daily log return and the stock volatility is a one-year at-the-money implied volatility. Size is measured by the book value of total assets. Beta is the contemporaneous covariance between the daily stock return and the daily return of the S&P 500 Diversified Financials index, divided by the variance of the index return. The measure is calculated over a 50-day rolling window and applies only to financial companies. The TARP dummy reflects participation of a company in that program. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)			(2)			(3)			(4)			(5)		
	Coef.	z		Coef.	z		Coef.	z		Coef.	z		Coef.	t	
Lagged Dep. Variable	0.6612	8.36	***	0.6634	8.36	***	0.6612	8.40	***	0.6599	8.45	***	0.9499	60.68	***
$r_{\mathrm{S\&P500}}$	-291.0800	-3.67	***	-284.3867	-3.64	***	-292.9566	-3.68	***	-289.6206	-3.66	***	-3.4609	-3.03	***
Treasury Rate	0.3041	1.59		0.3137	1.63	*	0.3049	1.60		0.3007	1.58		0.0222	11.87	***
Term Spread	-0.0321	-0.20		-0.0302	-0.19		-0.0326	-0.20		-0.0339	-0.21		0.0072	3.78	***
$L_{\mathrm{On/Off}}$	11.5784	2.80	***	11.7749	2.83	***	11.5357	2.80	***	11.5654	2.81	***	-0.0639	-3.06	***
Rating (AAA)	0.3558	1.15		0.3173	0.95		0.5714	1.34		0.4677	1.38		0.0100	0.64	
Rating (AA)	0.3629	1.16		0.3307	0.98		0.5519	1.29		0.4362	1.26		0.0283	1.61	*
Rating (A)	0.3404	1.12		0.2997	0.91		0.5055	1.20		0.4138	1.24		0.0373	2.62	***
Rating (BBB)	0.3616	1.16		0.3191	0.95		0.5316	1.25		0.4402	1.30		0.0415	2.66	***
Rating (BB)	0.3155	1.03		0.2738	0.82		0.4947	1.17		0.3950	1.17		0.0390	2.59	*
Rating (B)	0.3353	1.09		0.2955	0.89		0.5173	1.22		0.4125	1.22		0.0416	2.45	
Rating (CCC)	0.3364	1.02		0.2818	0.79		0.4870	1.08		0.4155	1.14		0.0313	2.35	
Rating (CC)	0.1713	0.47		0.1542	0.39		0.3289	0.69		0.2121	0.52		0.0178	1.03	
Size	0.1674	2.72	***	0.1156	2.13	**							0.1056	2.94	***
Size × $r_{\mathrm{S\&P500}}$				-207.3666	-7.04	***									
$\beta_{r_S}^{DF}$ × $\mathrm{I_{Fin}}$							0.1389	4.08	***						
TARP										0.2247	2.53	**			
Constant	-1.0282	-1.46		-1.0085	-1.41		-1.2127	-1.61		-1.0957	-1.55		-0.0679	-3.86	***
Observations	9,604			9,604			9,604			9,604			404,132		
Coefficient Estimates	GMM			GMM			GMM			GMM			FE		
Standard Errors															
	p-value			p-value			p-value			p-value					
Arellano-Bond Test AR(1)	0.00			0.00			0.00			0.00					
Arellano-Bond Test AR(2)	0.13			0.14			0.13			0.14					
Hansen Test	0.27			0.25			0.27			0.26					

Table XII: Capitalized Subsidies in the Primary Bond Market

Panel A decomposes the total offering amounts across issue years and financial subsectors. Panel B reflects, ceteris paribus, the aggregate shortage in raised debt under the adjusted (guarantee-free) yield-to-maturity. Panel C reflects, ceteris paribus, the higher funding costs under the adjusted (guarantee-free) coupon rates. The underlying sample ends in September 2010. All values are in billion USD.

Panel A – Offering amounts

	2007	2008	2009	2010	*Total*
Banks	877.40	459.38	205.68	83.79	1626.25
Insurance	58.78	32.23	24.38	18.40	133.79
Real Estate	16.68	4.90	6.45	9.75	37.78
Others	2.25	2.97	5.07	1.25	11.54
Total	955.11	499.48	241.58	113.19	1809.36

Panel B – Subsidies calc. by increasing YTMs

	2007	2008	2009	2010	*Total*
Banks	3.06	31.28	54.72	2.49	91.55
Insurance	0.14	1.56	1.28	1.32	4.30
Real Estate	0.14	0.10	0.74	0.23	1.21
Others	0.00	0.21	0.76	0.01	0.98
Total	3.34	33.15	57.50	4.05	98.04

Panel C – Subsidies calc. by increasing coupon rates

	2007	2008	2009	2010	*Total*
Banks	3.31	38.25	77.15	2.58	121.29
Insurance	0.17	1.76	1.44	2.05	5.42
Real Estate	0.14	0.11	0.83	0.24	1.32
Others	0.00	0.27	0.86	0.01	1.14
Total	3.62	40.39	80.28	4.88	129.17

Figure 1: Predicted versus Observed CDS Spreads – Individual Banks

These charts depict the evolution of stock-implied model (dashed line) and CDS market spreads (solid line) in basis points for six major U.S. banks during the period 2004 to 2010. Model predictions are based on the basic calibration scheme outlined in Section III.A.

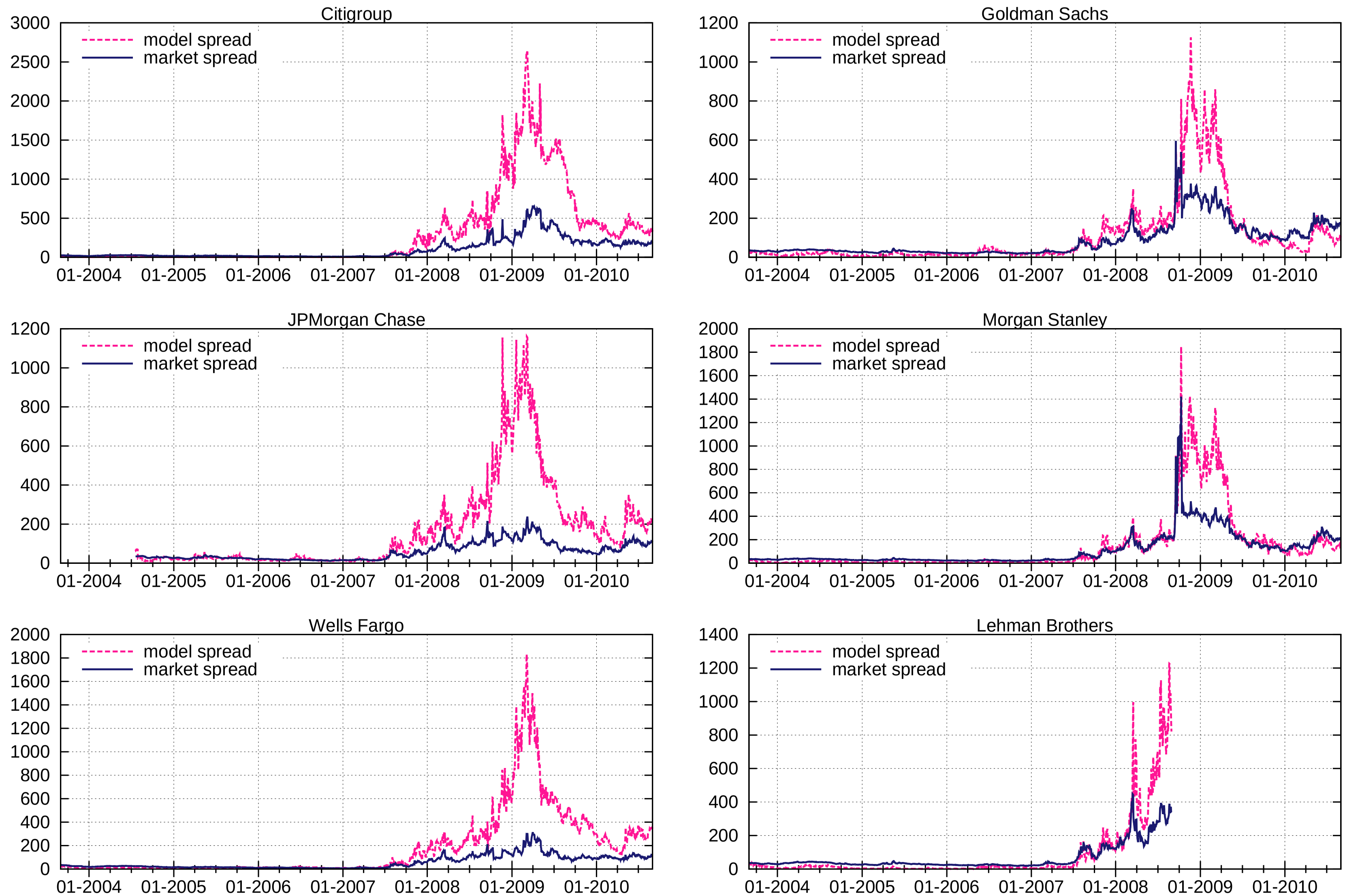


Figure 2: Predicted versus Observed CDS Spreads – Sector Aggregates

These charts depict the evolution of weekly averages of stock-implied model (dashed line) and CDS market spreads (solid line) in basis points for sector aggregates during the period 2004 to 2010. Model predictions are based on the basic calibration scheme outlined in Section III.A.

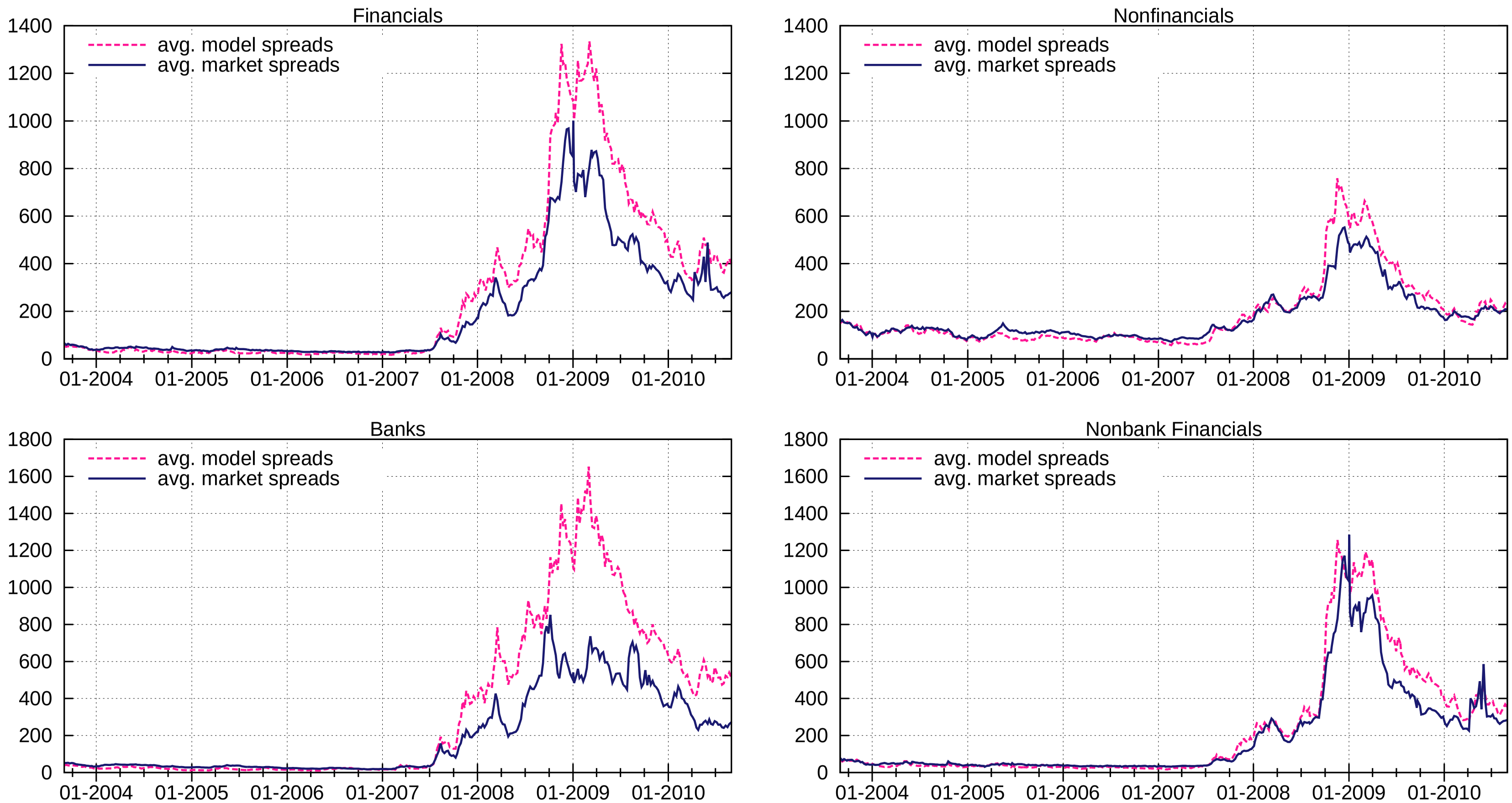


Figure 3: Relative CDS Price Deviations

This plot demonstrates the evolution of weekly averages of percentage deviations between CDS model and market spreads for several sector aggregates during the period 2004 to 2010. Model predictions are based on the basic calibration scheme outlined in Section III.A.

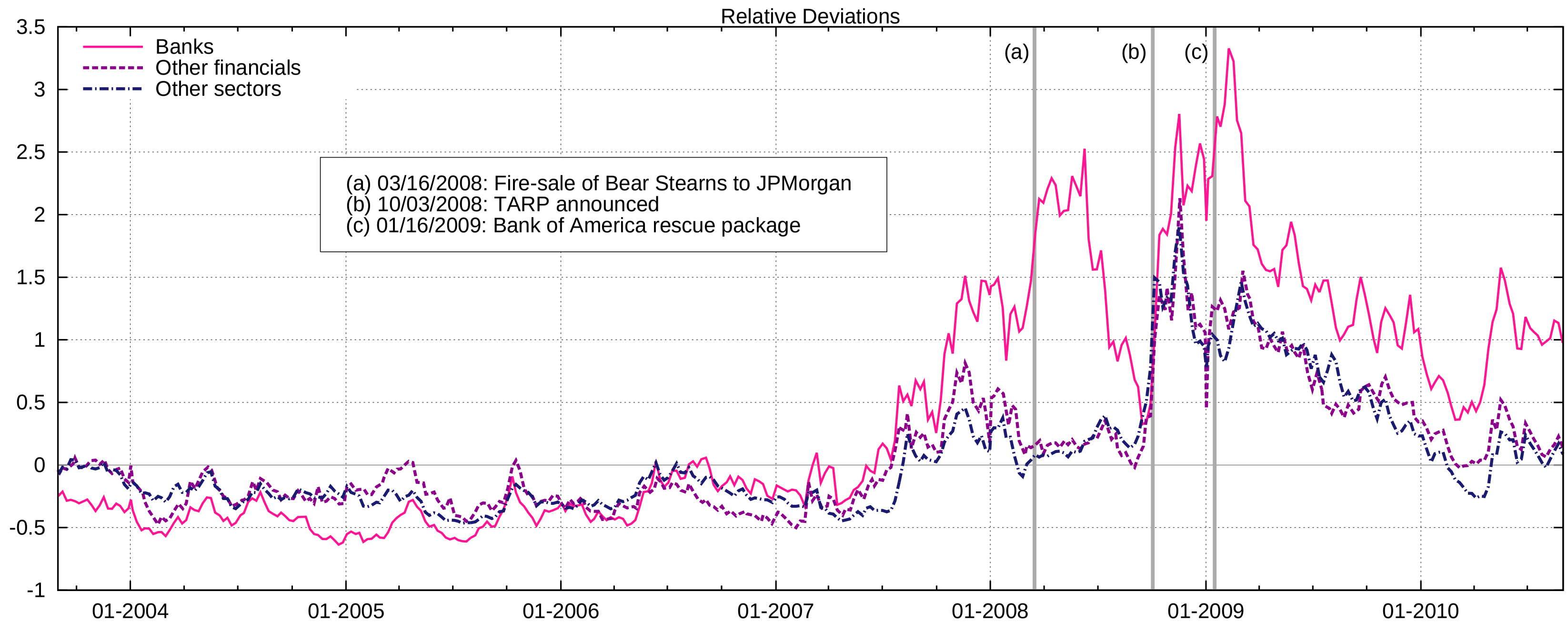


Figure 4: Time-varying Default Barrier

Using the example of JPMorgan Chase, this chart depicts the evolution of weekly averages of the default barrier determinant $\bar{L}$, the CDS model spreads under a constant and under a time-varying $\bar{L}$, and the CDS market spreads during the period 2004 to 2010. Model predictions are based on the calibration schemes outlined in Sections III.A and III.B. CDS spreads are denoted in basis points.

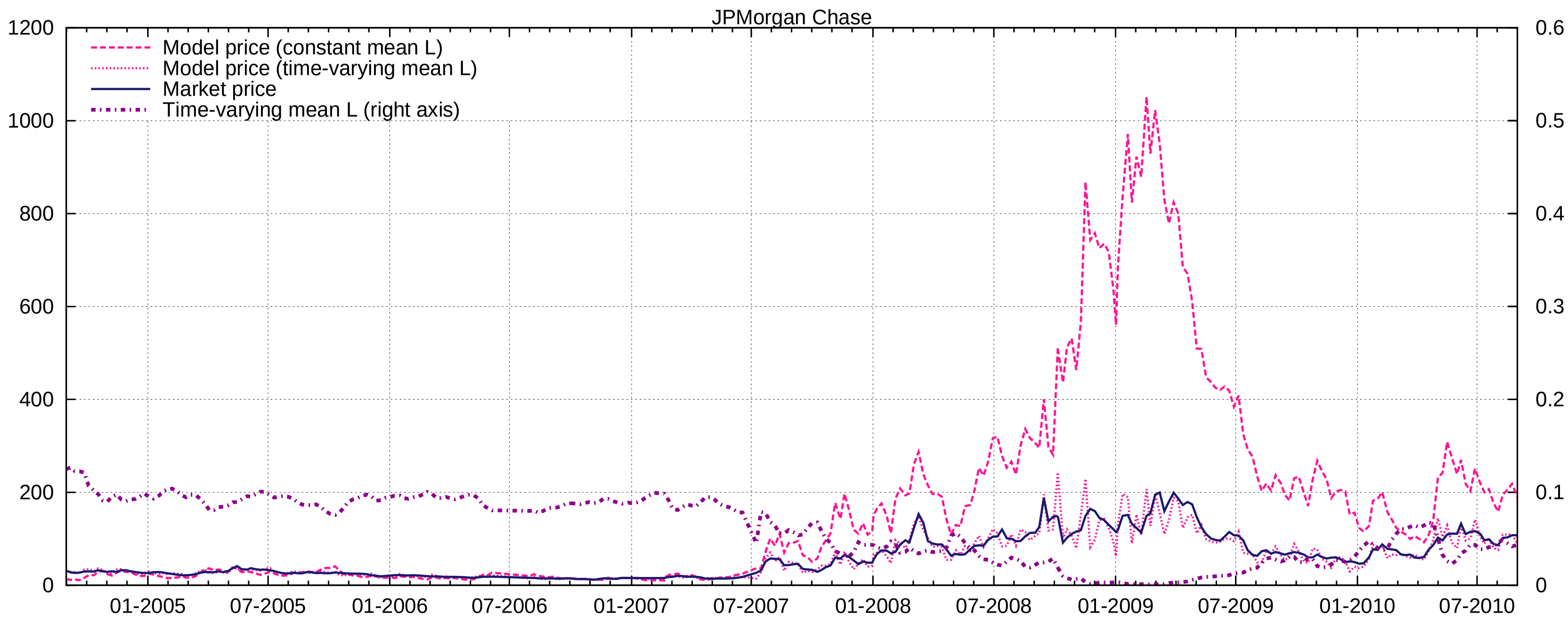


Figure 5: Default Barrier with a Regime Shift

Using the example of JPMorgan Chase, this chart depicts the evolution of weekly averages of the default barrier determinant $\bar{L}$, the CDS model spreads under a constant and under a regime-shifting $\bar{L}$, and the CDS market spreads during the period 2004 to 2010. Model predictions are based on the calibration schemes outlined in Sections III.A and III.C. CDS spreads are denoted in basis points.

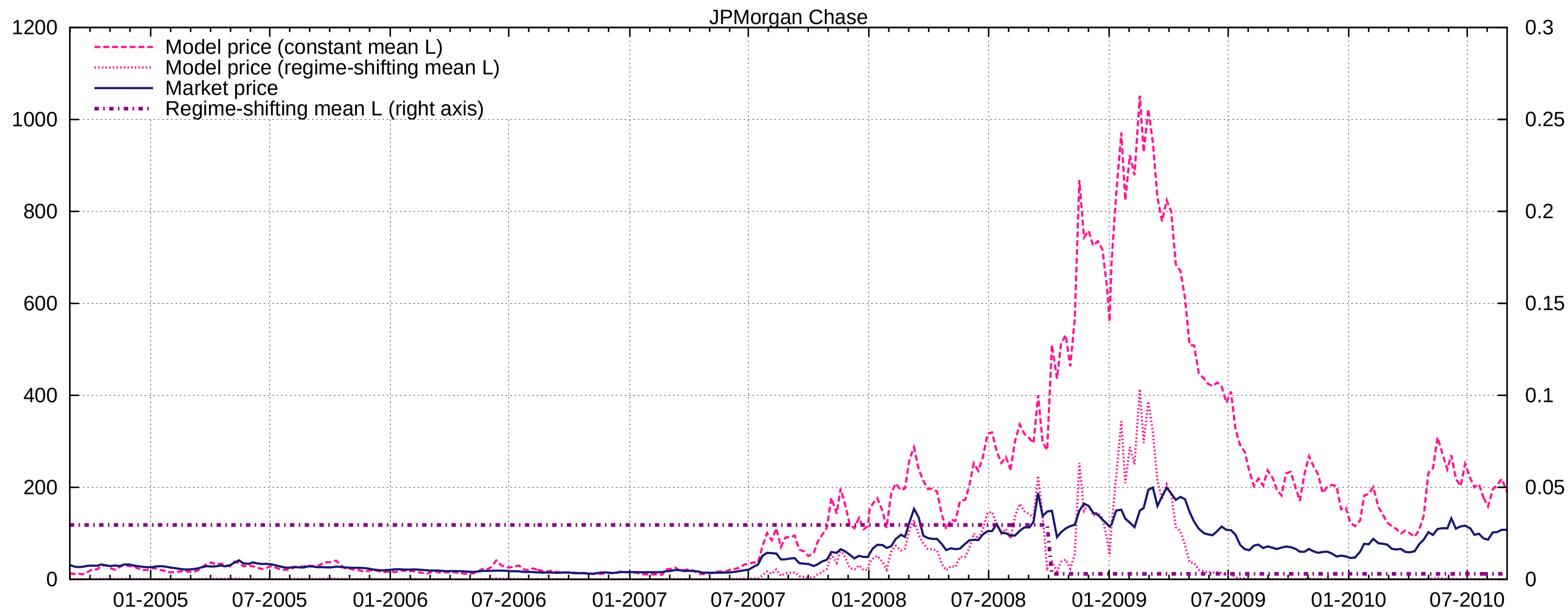
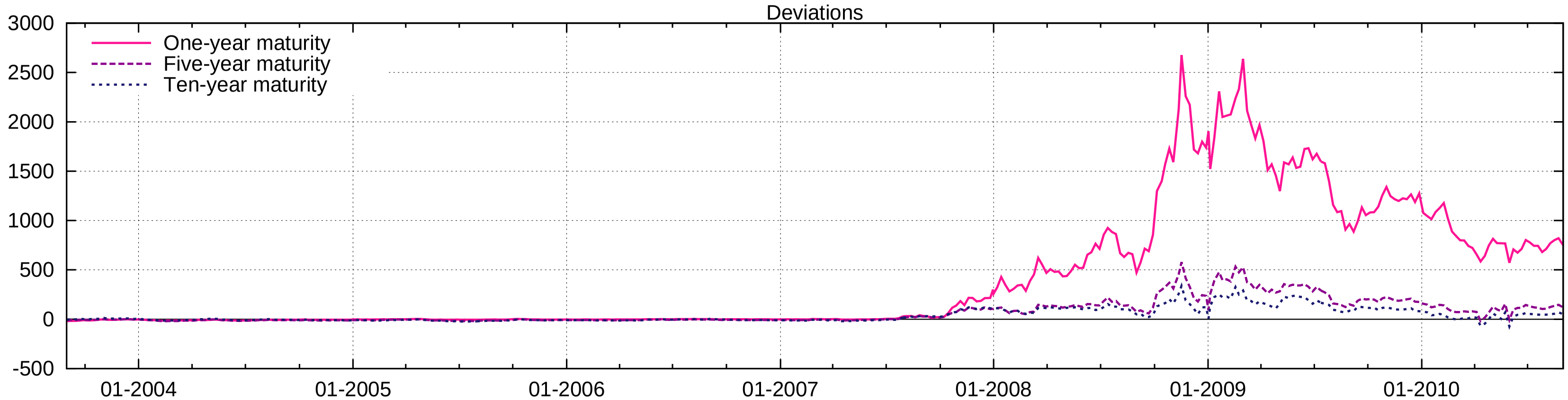


Figure 6: Term Structure of Deviations

Aggregating over all financial firms in the sample, these graphs show the evolution of weekly averages of differences and percentage deviations between CDS model and market spreads for several maturities during the period 2004 to 2010. Model predictions are based on the basic calibration scheme outlined in Section III.A. CDS spreads are denoted in basis points.



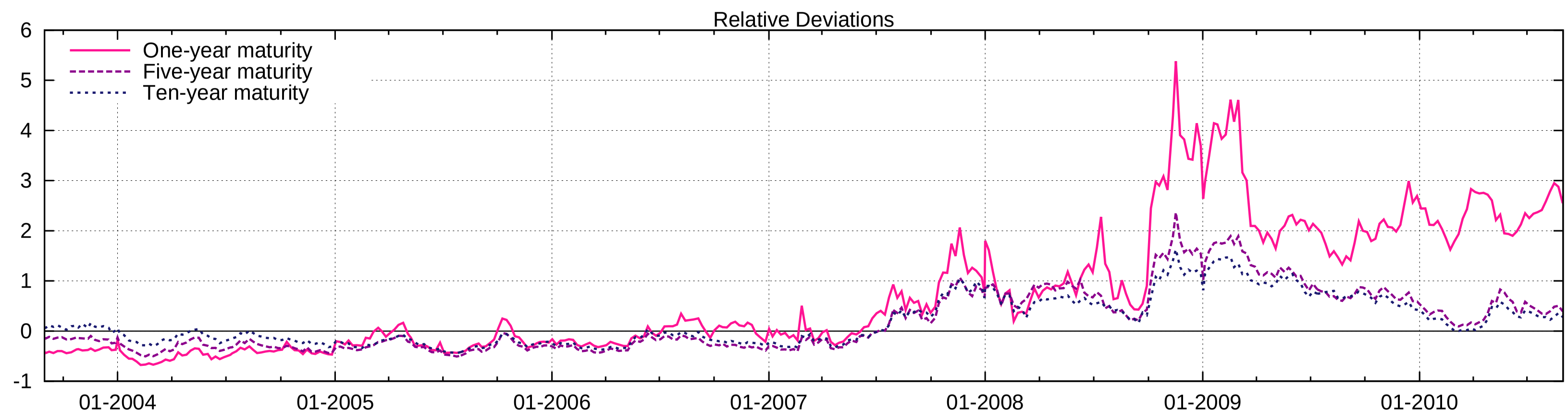


Figure 7: Counterparty Risk Adjustment

Focusing on the financial sector, we plot evolution of average absolute CDS price deviations in basis points before and after adjusting for counterparty risk. The firmspecific and time-varying adjustment is estimated within the financial subsample by the linear regression of basis point deviations on the primary dealer index beta $\beta^{PD}_{r_{CDS}}$ and a number of controlling variables over the period January 2007 to September 2010.