Implied Equity and Firm Asset Volatility in Credit Default Swap Premia

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Abstract

We investigate the informational content of credit default swap (CDS) spreads for future volatility of firm assets and equity, and compare our results with information provided by historical volatilities. CDS implied asset (*equity*) volatilities explain as much as 68.40% (*only 18.56%*) of the cross-sectional variation in future realized asset (*equity*) volatilities. This informational content is clearly superior, and almost subsumes (*is similar, and complements*), the informational content of historical asset (*equity*) volatilities. We show that these results are explained by the leverage effect component in equity volatility, and the interconnection between leverage and asset volatility documented earlier in the literature.

Keywords: Credit Default Swap; Implied Firm Asset Volatility; Implied Equity Volatility; Leverage Effect.

JEL classification: G12; G13; G14; G17

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1. Introduction

Structural credit risk models, first developed by Merton (1974), describe corporate bonds as contingent claims on firm asset value. A regular outcome of these models is a closed-form solution for the bond's yield spread that incorporates (firm) asset volatility as a key parameter. Following the vast literature on the implied/realized volatility relationship[1], a natural question to investigate is what informational content corporate bonds have about future realized asset volatility. There are two main reasons why this question has not been formally addressed in the literature. The first has to do with estimating the underlying firm asset value. This is an unobservable variable, and, thus, any closed-form solution for the bond yield spread will be a function of (at least) two unknowns: firm asset value and asset volatility. Accordingly, any estimate of implied (or realized) asset volatility will depend on how firm asset value is estimated in the first place. The second has to do with the characteristics of the bond market itself. While the equity options market provides periodic quotes for standardized instruments with a given maturity, this is not the case in the corporate bond market. Corporate bonds are in most cases infrequently traded, can include specific covenants (e.g., convertible bonds), and can differ significantly in their maturity.

The development of the credit default swap (CDS) market offers a unique opportunity to address most of the bond market limitations to collect a homogenous sample of implied asset volatilities. Like corporate bonds, CDS contracts can be thought of as contingent claims on firm asset value. However, contrary to corporate bonds, CDS contracts represent standardized, liquid credit instruments that are quoted on a daily basis, and always with the same maturity.

The first question we address in this study is precisely what informational content CDS spreads have about future realized asset volatility. Our database consists of 52 European companies with highly liquid 5-year CDS spreads for the period 2004–2017. We consider two

[1] See Poon and Granger (2003) for a review of this literature.

different approaches to deal with the problem of estimating firm asset value. The base case approach consists of using a structural credit risk model to derive the time series of firm asset values from the time series of equity values and a limited number of accounting figures. The alternative approach is a naïve one, in which firm asset value is simply the equity value plus the book value of total liabilities. Estimated firm asset values are used in each case to derive a sample of CDS implied asset volatilities and a sample of realized asset volatilities. It is worth stressing that, in both cases, the database used to estimate firm asset values in the first step (equity values), is independent of the database used to estimate implied asset volatilities in the second step (CDS spreads). In other words, once we have estimated the time series of firm asset values from the equity market *alone*, our procedure of comparing CDS implied asset volatilities and future realized asset volatilities is identical to the procedure regularly used to compare option implied equity volatilities and future realized equity volatilities. It is also important to note that in the case of the naïve approach, we not only differentiate the databases used in each step (equity values vs. CDS spreads) but also the underlying model (naïve vs. structural). These precautions are taken to prevent any sort of endogeneity problem in our conclusions.

Another important aspect of our analysis relates to the specific dimension of the implied/realized volatility relationship that we explore. One possibility would be to focus on the time-series dimension of the problem, in other words, on the following research question: is the CDS implied asset volatility of a given company informative about the future realized asset volatility of that same company? A different possibility, and the one we consider in this study, consists of analyzing the cross-sectional dimension of the implied/realized volatility relationship: are cross-sectional differences in CDS implied asset volatilities informative about future cross-sectional differences in realized asset volatilities? While it is clear that the time-series dimension of the problem would also be worth investigating, the very long maturity of

CDS contracts rules out the possibility of generating a large enough sample of non-overlapping data for implied and realized asset volatilities and, therefore, the possibility of a time-series analysis.[2] These data restrictions are comparable to those borne by early research on the implied/realized volatility relationship in the context of equity options, that is, studies that investigated this relationship even when the available time series of option prices was rather short (e.g., Latané and Rendleman, 1976).

Our results indicate that the answer to the first question we address in this study is yes: (cross-sectional differences in CDS) implied asset volatilities are informative about future (cross-sectional differences in) realized asset volatilities. Implied asset volatilities explain as much as 68.40% of the variation in future realized asset volatilities, compared to 54.89% explained by historical asset volatilities. Moreover, while implied asset volatility does not subsume all the information contained in historical asset volatility, incorporating historical data increases the explanatory power of the model by only 1.86% (a total of 70.26%).

The second question we address here is whether CDS spreads are equally informative about future realized *equity* volatility as they are about future realized *asset* volatility. This question seems particularly relevant. If CDS spreads are informative about future realized equity volatility, then (long-run) CDS spreads represent a perfect complement to (short-run) equity options when it comes to obtaining forward-looking measures of equity volatility. However, the significant difference between the notion of implied equity volatility in an equity option (where the input parameter is precisely equity volatility), and the notion of implied equity volatility in a CDS spread should be stressed. The relationship between CDS spreads and equity prices is an indirect one, because they both represent contingent claims on *firm asset value*, and their value also depends on *asset volatility*. Therefore, investigating the implied

[2] We notice that the problem is particularly severe for the most liquid 5-year contracts; however, choosing a shorter maturity (e.g., one year) would not be a solution (14 observations at the most). A detailed description of the problems associated with the use of overlapping data for this type of time-series analysis can be found in Christensen and Prabhala (1998).

equity volatility in a CDS spread could be considered analogous to investigating the implied call option volatility embedded in a put option on the same stock. A more formal discussion of the estimation and potential limitations of implied equity volatility in a CDS spread is provided in this paper.

Our evidence suggests that the answer to the second question we address in this study is, in any case, no: when compared to their asset volatility counterparts, (cross-sectional differences in CDS) implied equity volatilities are significantly less informative about future (cross-sectional differences in) realized equity volatilities. Moreover, implied and historical equity volatilities are roughly equally informative about future realized equity volatility and contain complementary information. In numbers, the explanatory power of implied equity volatility, historical equity volatility, and the comprehensive model is 18.56%, 19.35%, and 23.55%, respectively. We show that these results are closely related to the leverage effect component in equity volatility, and the interconnection between leverage and asset volatility documented recently by Choi and Richardson (2016).

Our study is not the first to explore the relationship between credit spreads and equity volatility. For example, Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Avramov et al. (2007), and Cremers et al. (2008) use a model-free (regression-based) setting to confirm the positive relationship between corporate bonds' yield spreads and equity volatility. In these regressions, either an option implied or a historical measure of equity volatility is used as a proxy for equity volatility.[3] In a similar vein, Ericsson et al. (2009) and Zhang et al. (2009) document a positive relationship between CDS spreads and historical measures of equity volatility. Another stream of literature explores the relationship between CDS spreads and forward-looking measures of equity volatility. Within this stream of literature, we find studies that investigate whether the implied equity volatility in equity options could help explain

[3] Cremers et al. (2008) use both of them.

observed CDS spreads using the aforementioned model-free setting (Benkert, 2004; Cao, et al., 2010); explore whether the implied equity volatility in equity options could help improve the performance of structural credit risk models in terms of CDS spread prediction (Hull et al., 2005; Stamicar and Finger, 2006; Cao, et al., 2011); and investigate whether the implied equity volatility in CDS spreads—derived using a structural credit risk model—contains information on future realized equity volatility (Byström, 2015; Guo, 2016). The overall conclusion of this stream of literature is the forward-looking nature of the equity volatility embedded in CDS spreads. Our study is unique in that it is the first to investigate the informational content of CDS spreads about the future volatility of *firm asset value*, which, according to structural credit risk models, is the actual underlying financial variable in CDS spreads. Our study is also the first to analyze whether CDS spreads are significantly more/less informative about future realized asset volatility than about future realized equity volatility, and why.

The remainder of the paper is organized as follows. Section 2 describes our base case approach for the estimation of implied and realized volatilities. Section 3 describes the sample. Section 4 presents the analysis of implied vs. realized asset volatilities. Section 5 is devoted to the subsequent analysis of implied vs. realized equity volatilities. Section 6 explores the reasons behind the different results for asset and equity volatilities. Section 7 presents the results based on the naïve approach and confirms the robustness of our conclusions. Section 8 summarizes our main findings and concludes the paper.

2. Estimation Method

2.1. CDS Spreads

We consider a standard structural credit risk model setting in which the market value of total assets at any time t, V_t, evolves according to the following continuous diffusion process:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dZ_t, \tag{1}$$

where μ is the expected rate of return on the asset value, δ is the fraction of the asset value paid out to investors, σ is asset volatility, and Z_t is a standard Brownian motion. Default occurs whenever V_t reaches a specific critical point, V_b, which can always be expressed as a fraction β of the nominal value of total debt P:

$$V_b = \beta P. \tag{2}$$

Following Ericsson et al. (2015), this general setting implies a closed-form solution for the spread of a CDS contract:

$$CDS_t = v(V_t, \beta, \sigma) = \frac{r(1-\theta)G_t(\tau)}{[1 - H_t(\tau) - G_t(\tau)]}, \tag{3}$$

where r represents the risk-free interest rate, θ the recovery rate, and τ the maturity of the contract. Specific expressions for $G_t(\tau)$ and $H_t(\tau)$ are provided in Appendix A.

Expression (3) can be inverted to derive, at any time t, the implied asset volatility in an observed CDS spread. We return to this point in subsection 2.4. Subsections 2.2 and 2.3 deal with the fundamental problem of determining the underlying firm asset value and the parameter β.

2.2. Structural Credit Risk Model

So far, we have omitted any reference to a particular structural credit risk model. This is important to stress because it implies that expression (3) should not be associated with any specific model, but with the general setting described above. That said, implied asset volatility will still depend on how firm asset value and the parameter β are defined, that is, on the particular model and estimation method selected.[4]

In this study, we consider the model proposed by Forte (2011). This is a relatively simple model which has already been shown to produce sensible CDS spread predictions.

[4] Ericsson et al. (2015) make a specific reference to how model assumptions affect the default barrier.

According to this model, the value of an individual bond d_n with maturity τ_n, principal p_n, and constant coupon flow c_n is given by [5]

$$d_n(V_t, \beta, \sigma, \lambda) = \frac{c_n}{r} + \left[p_n - \frac{c_n}{r}\right] H_t(\tau_n) + \left[(1-\lambda)\beta p_n - \frac{c_n}{r}\right] G_t(\tau_n), \tag{4}$$

where λ represents bankruptcy costs and $(1-\lambda)\beta$ is the recovery rate on the bond's face value in case of default.[6] The total debt value is represented by the sum of all outstanding bonds,

$$D(V_t, \beta, \sigma, \lambda) = \sum_{n=1}^{N} d_n(V_t, \beta, \sigma, \lambda), \tag{5}$$

and the equity value is given by

$$S_t = g(V_t, \beta, \sigma) = V_t - D(V_t, \beta, \sigma, 0), \tag{6}$$

where $D(V_t, \beta, \sigma, 0)$ is the market value of total debt when bankruptcy costs equal zero.[7]

2.3. Model Estimation

We use expression (6) to derive the time series of firm asset values, $\boldsymbol{V} = (V_1, \dots, V_T)$, and the default barrier parameter, β, using the information available on the time series of equity values, $\boldsymbol{S} = (S_1, \dots, S_T)$. While our interest at this point is only for $\boldsymbol{V}$ and β, expression (6) is also dependent on σ; therefore, we need to specify a value for this parameter as well. We estimate the full set of values $\{\boldsymbol{V}, \beta, \sigma\}$ by applying a recursive scheme in the spirit of Forte and Lovreta (2012). The procedure we employ can be described as an inversion-correction-maximization (*ICM*) algorithm. In subsections 2.3.1 and 2.3.2, we provide a detailed description of the algorithm and the properties of the final outcome, respectively.

[5] Forte (2011) adopts this expression from Leland and Toft (1996).

[6] The interested reader can easily verify that the yield spread of a par bond with maturity τ will reproduce the CDS spread for that maturity. The only requirement is that the recovery rates are the same: $(1-\lambda)\beta = \theta$. Theoretical CDS spreads in Forte (2011) are based precisely on this equivalence.

[7] Expressions (5) and (6) imply that, *provided a given debt structure*, bankruptcy costs affect the debt value but not the equity value. While this may seem a counterintuitive result, it also applies in other models like Leland (1994). Please refer to the original papers for details.

2.3.1. Description

Let $\{\beta_0, \sigma_0\}$ *denote some initial values for* $\{\beta, \sigma\}$*, and let* $\{\boldsymbol{V}_{k-1}, \beta_{k-1}, \sigma_{k-1}\}$ *denote the* $\{\boldsymbol{V}, \beta, \sigma\}$ *values resulting from iteration* $k-1$*. Iteration* k *implies the following steps:*

Inversion (I). *Fix* $\{\beta, \sigma\} = \{\beta_{k-1}, \sigma_{k-1}\}$ *and find the value of* $\boldsymbol{V}$ *that satisfies the equity pricing equation for all* t*:*

$$V_{Inv,t} = g^{-1}(S_t|\beta_{k-1}, \sigma_{k-1}). \tag{7}$$

Correction (C). *Estimate the volatility of the* $\boldsymbol{V}_{Inv}$ *series,* σ_{Inv}*, and proceed as follows:*

- *If* $\sigma_{Inv} \neq \sigma_{k-1}$*, assume* $\sigma_{k-1} = \sigma_{Inv}$ *and return to Step I.*
- *If* $\sigma_{Inv} = \sigma_{k-1}$*, define* $\{\boldsymbol{V}_k, \sigma_k\} = \{\boldsymbol{V}_{Inv}, \sigma_{Inv}\}$ *and move to Step M.*

At the time of the move to Step M, the combination of Steps I and C will have generated an updated value for $\{\boldsymbol{V}, \sigma\}$*,* $\{\boldsymbol{V}_k, \sigma_k\}$*.*

Maximization (M). *Fix* $\{\boldsymbol{V}, \sigma\} = \{\boldsymbol{V}_k, \sigma_k\}$ *and find the value of* β *that maximizes the average equity holder's participation in the firm asset value during the sample period,*

$$Max_{\{\beta\}} \ \frac{1}{T}\sum_{t=1}^{T}\frac{g\left(\beta|V_{k,t}, \sigma_k\right)}{V_{k,t}}. \tag{8}$$

This last step will provide an updated value for β*,* β_k*. The algorithm is recursively repeated until convergence is achieved, that is, until* β_k*=*β_{k-1}*.*

2.3.2. Properties

The final outcome of the algorithm is given by the set of values $\{\boldsymbol{V}^*, \beta^*, \sigma^*\}$ that satisfies the following conditions:

a) $\{\boldsymbol{V}^*, \beta^*, \sigma^*\}$ fulfill the equity pricing equation for all t, given $\boldsymbol{S}$ (Step *I*).

b) σ^* equals the volatility of the estimated time series of firm assets values, $\boldsymbol{V}^*$ (Step *C*).

c) β^* is consistent with the assumption of an optimal default policy reflected in equity prices, given $\{\boldsymbol{V}^*, \sigma^*\}$ (Step *M*).

Condition a) implies that the set of values $\{\boldsymbol{V}^*, \beta^*, \sigma^*\}$ is consistent with the underlying structural credit risk model. By ensuring condition b), we actually assume that the "equity implied asset volatility" is a constant value that fits the realized asset volatility during the whole sample period. This is clearly a convenient assumption, but not necessarily an unrealistic one. Equity represents a perpetual claim on the firm's assets; thus, it makes sense that the implied asset volatility in equity prices is long-run asset volatility. Condition c) is the main element we adopt from Forte and Lovreta (2012). It implies incorporating the assumption of an optimal default in a model that is flexible enough to accommodate the actual debt structure of any company but, precisely for this reason, does not lead to a closed-form solution for the optimal default barrier. Considering all these properties, it can be argued that $\{\boldsymbol{V}^*, \beta^*, \sigma^*\}$ represents a coherent assessment of $\{\boldsymbol{V}, \beta, \sigma\}$.

2.4. Estimation of Implied and Realized Asset Volatilities

The standard implementation of a structural credit risk model consists of using $\{\boldsymbol{V}^*, \beta^*, \sigma^*\}$ values and expression (3) to derive predictions of CDS spreads. Our objective, however, is to test whether implied asset volatilities in actual CDS spreads contain information about future realized asset volatilities. As our empirical analysis is conducted on the log of the volatility series, we first estimate implied asset volatility at time *t*,

$$\sigma_{i,t} = v^{-1}\,(CDS_t | V_t^*, \beta^*), \tag{9}$$

and then compute the corresponding log implied asset volatility, $i_t = log(\sigma_{i,t})$.[8]

The realized asset volatility at time *t*, $\sigma_{h,t}$, is estimated as the annualized standard deviation of the continuously compounded returns of the last 1,260 trading days (1,259 return observations). If we define $R_{t,m} = log(V_{t-1,259+m}^* / V_{t-1,260+m}^*)$ and $\bar{R}_t = (1{,}259)^{-1} \sum_{m=1}^{1,259} R_{t,m}$, then:

[8] The log transformation is standard in the literature on equity volatility due to its better normality properties and lower impact of potential outliers. See Christensen and Prabhala (1998) and Poteshman (2000) among others.

$$\sigma_{h,t} = \sqrt{\frac{252}{1{,}258}\sum_{m=1}^{1{,}259}\left(R_{t,m} - \bar{R}_t\right)}. \tag{10}$$

The log realized asset volatility will be $h_t = log\left(\sigma_{h,t}\right)$.

2.5. Estimation of Implied and Realized Equity Volatilities

Again according to structural credit risk models, equity volatility at time t, $\sigma_{S,t}$, is related to asset volatility as follows:

$$\sigma_{S,t} = \left(\frac{\partial S_t}{\partial V_t}\cdot\frac{V_t}{S_t}\right)\cdot\sigma, \tag{11}$$

or

$$log\left(\sigma_{S,t}\right) = log\left(\frac{\partial S_t}{\partial V_t}\cdot\frac{V_t}{S_t}\right) + log(\sigma). \tag{12}$$

The first term on the right hand side of expression (12) accounts for the leverage effect component in equity volatility, where $\partial S_t/\partial V_t$ is a function of the particular model at hand. The specific expression for $\partial S_t/\partial V_t$ in Forte's (2011) model is provided in Forte and Lovreta (2012) and reproduced in Appendix B.

The implications of expression (12) are straightforward. First, because CDS spreads are related to asset volatility, not to equity volatility, an implied equity volatility measure from a CDS spread can only be the result of adjusting implied asset volatility to account for the leverage effect. Second, CDS spreads can hardly provide any "implied" leverage effect other than the current leverage effect. Finally, and to sum up, CDS implied equity volatility will be the result of adding the *current* leverage effect to the *forward-looking* CDS implied asset volatility. More formally, let $le_{c,t}$ denote the current leverage effect at time t:

$$le_{c,t} = \left[\frac{\partial g(V_t^*, \beta^*, \sigma^*)}{\partial V_t^*}\cdot\frac{V_t^*}{g(V_t^*, \beta^*, \sigma^*)}\right]. \tag{13}$$

The log current leverage effect will be $c_{le,t} = log\left(le_{c,t}\right)$.

Expression (13) can be used to derive implied equity volatility at time t:

$$\sigma_{S,i,t} = le_{c,t} \cdot \sigma_{i,t}. \tag{14}$$

The log implied equity volatility, $i_{S,t} = log(\sigma_{S,i,t})$, can always be expressed as the result of adding the log current leverage effect to log implied asset volatility:

$$i_{S,t} = c_{le,t} + i_t. \tag{15}$$

Realized equity volatility at time t, $\sigma_{S,h,t}$, is estimated using the information available on equity values in the same way we estimate realized asset volatility. If we define $R_{S,t,m} = log(S_{t-1,259+m}/S_{t-1,260+m})$ and $\bar{R}_{S,t} = (1{,}259)^{-1} \sum_{m=1}^{1,259} R_{S,t,m}$, then:

$$\sigma_{S,h,t} = \sqrt{\frac{252}{1{,}258} \sum_{m=1}^{1,259} (R_{S,t,m} - \bar{R}_{S,t})}. \tag{16}$$

The log realized equity volatility will be $h_{S,t} = log(\sigma_{S,h,t})$.

For reasons that will become clear later on, we also define the realized leverage effect at time *t* as the ratio between realized equity volatility and realized asset volatility:

$$le_{h,t} = \frac{\sigma_{S,h,t}}{\sigma_{h,t}}. \tag{17}$$

The log realized leverage effect will be $h_{le,t} = log(le_{h,t})$.

Expression (17) implies decomposition of log realized equity volatility into a leverage effect component and an asset volatility component; in particular,

$$h_{S,t} = h_{le,t} + h_t. \tag{18}$$

This decomposition can be naturally interpreted as the historical counterpart of the log implied equity volatility decomposition in expression (15).

In what follows, and to simplify the exposition, it will be understood that volatility and leverage effect refer to log volatility and log leverage effect, respectively. This simplification will be made unless an explicit differentiation between original variables and log variables becomes relevant.

3. Data

Our initial database is composed of the 100 non-financial companies included in the Dow Jones iTraxx Europe Industrials Series 1, published on June 24, 2004. We restrict our initial sample to companies included in the iTraxx index because their CDS have higher liquidity. For those companies, we use Datastream (Thomson Reuters) to collect the following information for the period 1999–2017:

- *Market Capitalization.* Daily data in local currency.
- *Current Liabilities*. Yearly data in local currency.
- *Total Liabilities*. Yearly data in local currency.
- *Interest Expenses*. Yearly data in local currency.
- *Cash Dividends*. Yearly data in local currency.
- *1 to 10-Year Swap Rates*. Daily data in local currency.
- *5-Year Euro-Denominated CDS Spread*s. Daily data for the period 2004–2017.

The collection of data on market capitalization, accounting numbers, and swap rates starts five years before the first CDS spread is available. Using this data makes it possible to compare, starting January 2004, the informational content of implied and historical volatilities for future realized volatilities.

We delete private companies and those with missing data from the sample. We also delete companies that were acquired during the sample period, and companies involved in other corporate operations that resulted in a significant modification of their corporate structure. These initial filters lead to a provisional sample of 55 companies. Of these, three additional companies are eliminated because of the illiquidity of their stock (EnBW Energie Baden Wuerttemberg AG), the presence of suspicious data (Portugal Telecom SGPS SA), or the presence of outliers in the time series of equity values (Volkswagen AG). Table 1 contains the final sample of 52 companies to be considered in further analyses. The main descriptive statistics are provided in Table 2, Panel A.

[Table 1 about here]

[Table 2 about here]

Using the previous data for the period 1999–2017, we define the model inputs that are treated as known or observable at any time t in the *ICM* algorithm:

a) Equity value: Daily data on equity values correspond to daily data on market capitalization.

b) Principal value of debt: Daily data on the principal value of debt is obtained using a linear interpolation of yearly total liability data.[9]

c) Debt structure: Expressions (4)–(6) imply that we need to define the debt structure, that is, the number of individual bonds and their corresponding characteristics: time to maturity, coupon, and principal. Following Forte (2011) and Forte and Lovreta (2012), we assume that at each instant t the company has ten bonds—one with a maturity of one year and principal equal to short-term liabilities, and nine with maturities ranging from two to ten years, each with principal equal to 1/9 of long-term liabilities. Each bond's coupon is measured as 1/10 of interest expenses. As before, we perform a linear interpolation of annual data to derive the daily data.

d) Payout rate: For each year, we compute the ratio of interest expenses plus cash dividends to the proxy value of the firm, calculated as the sum of the market value of equity (yearly average) and book value of total liabilities. A constant payout rate is finally determined by computing the average of these annual values during the sample period.

[9] Collin-Drufesne et al. (2001) and Ericsson et al. (2009) use a similar linear interpolation.

e) Risk-free interest rate: The risk-free rate for each individual bond at time t is determined according to the swap rate for the corresponding maturity.[10]

Table 2, Panel B, provides results from applying the *ICM* algorithm to the previous data: the time series of firm asset values, $\boldsymbol{V}^{*}$; default-to-debt ratio, β^{*}; and realized asset volatility, σ^{*}.

4. Implied vs. Realized Asset Volatilities

We use the previous results to estimate implied and realized asset volatilities as described in subsection 2.4. We compute these values on a monthly basis (constant time interval of 21 trading days) starting January 2004. This leads to a total of 114 months with available cross-sectional information on implied, historical, and future realized asset volatilities. The main descriptive statistics for implied and realized asset volatilities are provided in Table 3. The reported numbers correspond to the mean of the cross-sectional statistics estimated for each of the 114 monthly observations.[11] Implied asset volatility is on average higher, more disperse, less asymmetric, and less leptokurtic than realized asset volatility. Using logs actually makes implied asset volatility slightly more asymmetric and leptokurtic; however, the realized asset volatility distribution is now more like the implied asset volatility distribution, and significantly closer to a normal distribution.

[Table 3 about here]

Before we proceed with our empirical analysis, note that time t will be a constant in each of the 114 consecutive cross-sectional regressions that we perform. As a result, it is possible (and convenient) to simplify notation. In particular, we omit the time subscripts and denote i_j as the implied asset volatility of company j ($i_j \equiv i_{j,t}$), h_j its historical asset volatility

[10] Zero and negative values are sometimes observed starting October 2015. To avoid potential problems associated with non-positive risk-free interest rates, we impose a minimum value of 0.01%.
[11] We must stress the difference with the time-series statistics usually provided by studies that perform a time-series analysis (e.g., Christensen and Prahabala, 1998).

($h_j \equiv h_{j,t}$), and f_j its future realized asset volatility ($f_j \equiv h_{j,t+1,260}$). With this notation, the three models we estimate at any particular time t can be expressed as follows:

Model 1: $$f_j = \alpha_0 + \alpha_i i_j + \varepsilon_j, \tag{19}$$

Model 2: $$f_j = \alpha_0 + \alpha_h h_j + \varepsilon_j, \tag{20}$$

Model 3: $$f_j = \alpha_0 + \alpha_i i_j + \alpha_h h_j + \varepsilon_j, \tag{21}$$

where $j = 1, \dots, 52$. In these three models, the future realized asset volatility of company j is related to its implied asset volatility (Model 1), its historical asset volatility (Model 2), and the two explanatory variables (Model 3), respectively. These and all following models will be estimated using ordinary least squares (OLS) with White standard errors.

The overall results are provided in Table 4. When considered alone, the coefficients of implied asset volatility and historical asset volatility are both significant at the 5% level in each of the 114 regressions. The mean values for these coefficients are also similar: 0.767 and 0.734, respectively. However, the mean explanatory power of Model 1 is 68.40%, clearly above that of Model 2 at 54.89%. When the comprehensive Model 3 is considered, the mean of the coefficient of implied asset volatility and the number of times this coefficient is significant are both higher than their historical asset volatility counterparts: 0.636 vs 0.176, and 99% vs 28%, respectively. Moreover, the explanatory power of Model 3 is 70.26%, a modest difference of 1.86% from Model 1 (68.40%). In other words, the additional informational content of historical asset volatility is not zero, but rather small. The overall conclusion is that implied asset volatility has very significant informational content regarding future realized asset volatility. This informational content is clearly superior, and almost subsumes, the informational content of historical asset volatility.

[Table 4 about here]

5. Implied vs. Realized Equity Volatilities

Does the informational content of CDS spreads about future realized asset volatility translate into equivalent informational content for future realized equity volatility? To answer this question, we estimate implied and realized equity volatilities as described in subsection 2.5. The main descriptive statistics for implied and realized equity volatilities are presented in Table 5. Implied equity volatility is on average higher, equally disperse, more asymmetric, and more leptokurtic than realized equity volatility. Using logs reduces the asymmetry and leptokurtosis of both distributions.

[Table 5 about here]

Consistent with our previous analysis of asset volatility, we avoid time subscripts and denote $i_{S,j}$ as the implied equity volatility of company j ($i_{S,j} \equiv i_{S,j,t}$), $h_{S,j}$ its historical equity volatility ($h_{S,j} \equiv h_{S,j,t}$), and $f_{S,j}$ its future realized equity volatility ($f_{S,j} \equiv h_{S,j,t+1,260}$). The three models to be tested are the following:

Model 4: $$f_{S,j} = \gamma_0 + \gamma_{S,i} i_{S,j} + \varepsilon_{S,j}, \tag{22}$$

Model 5: $$f_{S,j} = \gamma_0 + \gamma_{S,h} h_{S,j} + \varepsilon_{S,j}, \tag{23}$$

Model 6: $$f_{S,j} = \gamma_0 + \gamma_{S,i} i_{S,j} + \gamma_{S,h} h_{S,j} + \varepsilon_{S,j}. \tag{24}$$

In these three models, the future realized equity volatility of company j is related to its implied equity volatility (Model 4), its historical equity volatility (Model 5), and the two explanatory variables (Model 6), respectively.

According to results in Table 6, the mean explanatory power of implied equity volatility in Model 4 is “only” 18.56%, quite far from the mean explanatory power of 68.40% for implied asset volatility in Model 1. Moreover, implied equity volatility does not seem to contain more information than historical equity volatility either. While the coefficient of implied equity volatility in Model 4 is on average higher and more often significant than the coefficient of historical equity volatility in Model 5, these differences are not sizable: 0.579 vs. 0.499, and

67% vs. 63%, respectively. The mean explanatory power of Model 5 is 19.35%, also slightly higher than the mean explanatory power of Model 4. Additional results from the comprehensive Model 6 only confirm the perception that the two explanatory variables have very similar informational content. Roughly speaking, implied and historical equity volatility exhibit the same mean coefficient and same number of regressions where those coefficients are significant: 0.385 vs. 0.328, and 36% vs. 39%, respectively. It seems, however, that implied and historical equity volatility provide different information. The mean explanatory power of Model 6 is 23.55%, an increase of 4.99% with respect to that of Model 5. Finally, and despite the fact that our main interest is in the informational content of implied volatility measures, it is worth repeating that the mean explanatory power of historical equity volatility in Model 5 (19.35%) is also significantly lower than the mean explanatory power of historical asset volatility in Model 2 (54.89%).

[Table 6 about here]

The marked disagreement in our results for asset volatility and equity volatility leads to two main questions. First, why does implied (and historical) equity volatility have such small explanatory power regarding future realized equity volatility? Second, why is implied equity volatility not more informative than historical equity volatility? In Section 6, we explore three possible explanations.

6. Implied Asset and Equity Volatility: Exploring the Differences

6.1. Current Leverage Effect is a Poor Predictor of Future Realized Leverage Effect

According to expression (15), implied equity volatility is the result of adding the current leverage effect and implied asset volatility. If the current leverage effect is not really informative about the future realized leverage effect, then the explanatory power of implied equity volatility in Model 4 will be affected. Similarly, expression (18) states that historical equity volatility can be decomposed into a historical leverage effect component and a historical asset volatility component. If the historical leverage effect is again a poor predictor of the future realized leverage effect, then the explanatory power of historical equity volatility in Model 5 will be affected as well. Finally, the current leverage effect represents a point in time estimate, which depends on the equity value at that specific moment. Suppose we also consider the hypothesis that, following this argument, the (long-run) historical leverage effect contains more information on the (long-run) future realized leverage effect than the (potentially noisy) current leverage effect. This situation could explain why, despite the higher informational content of implied asset volatility vis-à-vis historical asset volatility, implied equity volatility is not more informative than historical equity volatility.

To test these hypotheses, we estimate current and realized leverage effects as described in subsection 2.5. The main descriptive statistics in Table 7 indicate that the current and realized leverage effects have, on average, very similar distributions. They also indicate that taking logs makes those distributions closer to a normal distribution.

[Table 7 about here]

Following the simplified notation already used in previous analyses, we denote $c_{le,j}$ as the current leverage effect of company j ($c_{le,j} \equiv c_{le,j,t}$), $h_{le,j}$ its historical leverage effect ($h_{le,j} \equiv h_{le,j,t}$), and $f_{le,j}$ its future realized leverage effect ($f_{le,j} \equiv h_{le,j,t+1,260}$). With this notation, the three models to be estimated are:

Model 7: $$f_{le,j} = \omega_0 + \omega_{le,c} c_{le,j} + \varepsilon_{le,j}, \tag{25}$$

Model 8: $$f_{le,j} = \omega_0 + \omega_{le,h} h_{le,j} + \varepsilon_{le,j}, \tag{26}$$

Model 9: $$f_{le,j} = \omega_0 + \omega_{le,c} c_{le,j} + \omega_{le,h} h_{le,j} + \varepsilon_{le,j}. \tag{27}$$

In these three models, the future realized leverage effect of company j is related to its current leverage effect (Model 7), its historical leverage effect (Model 8), and the two explanatory variables (Model 9), respectively.

The results, summarized in Table 8, do not support any of our previous hypotheses. To begin, the current leverage effect has considerable informational content regarding the future realized leverage effect. The coefficient of this variable in Model 7 is significant in all regressions, with a mean value of 0.959. Moreover, its mean explanatory power of 77.95% is actually higher than the mean explanatory power of implied asset volatility in Model 1. Similar results apply when we consider the historical leverage effect. The coefficient of this variable in Model 8 is again significant in all regressions, with a mean value of 0.904. Moreover, its mean explanatory power of 63.00% is higher than the mean explanatory power of historical asset volatility in Model 4. Our last hypothesis—i.e., lower explanatory power for the current leverage effect than the historical leverage effect—is also not supported. As already noted, the mean explanatory power of the current leverage effect in Model 7 is higher than the mean explanatory power of the historical leverage effect in Model 8. Complementary results from Model 9, where the two explanatory variables are considered together, indicate that the additional informational content of the historical leverage effect is actually very small. On one hand, its coefficient is significant in only 12% of the regressions, with a mean value that drops to 0.058. This is a clear contrast with the corresponding values for the current leverage effect: 95% and 0.911, respectively. On the other hand, incorporating the historical leverage effect only increases the mean explanatory power of Model 7 by a negligible 0.58%. All things considered, our different results for asset and equity volatility cannot be explained by the explanatory power of the current and/or historical leverage effect for the future realized leverage effect.

[Table 8 about here]

6.2. Different Coefficients for Current Leverage Effect and Implied Asset Volatility

At the individual level, our estimates of the current leverage effect and implied asset volatility have very significant explanatory power regarding the future realized leverage effect and future realized asset volatility, respectively. This, however, does not imply that they are both unbiased estimates. By regressing the future realized equity volatility on the sum of the current leverage effect and implied asset volatility, we are actually imposing the same coefficient on the two explanatory variables. Because their potential bias can be different, it makes sense to evaluate the explanatory power of a more flexible model that allows their respective coefficients to be different. At the same time, to establish a fair comparison with the information provided by historical data, we consider an equally flexible competing model. In particular, historical equity volatility will be replaced by its two constituents—historical leverage effect and historical asset volatility—also allowing their coefficients to be different. The three models to be estimated are, therefore:

Model 10: $$f_{S,j} = \gamma_0 + \gamma_{le,c} c_{le,j} + \gamma_i i_j + \varepsilon_{S,j}, \tag{28}$$

Model 11: $$f_{S,j} = \gamma_0 + \gamma_{le,h} h_{le,j} + \gamma_h h_j + \varepsilon_{S,j}, \tag{29}$$

Model 12: $$f_{S,j} = \gamma_0 + \gamma_{le,c} c_{le,j} + \gamma_i i_j + \gamma_{le,h} h_{le,j} + \gamma_h h_j + \varepsilon_{S,j}. \tag{30}$$

In these three models, the future realized equity volatility of company j is related to the current leverage effect and implied asset volatility (Model 10), the historical leverage effect and historical asset volatility (Model 11), and the four explanatory variables (Model 12), respectively.

Overall results in Table 9 provide mixed evidence. Comparing Models 10 and 11, the coefficient of the current leverage effect in Model 10 (0.809, 90%) is, on average, higher and more often significant than the coefficient of the historical leverage effect in Model 11 (0.597, 63%). Likewise, the coefficient of implied asset volatility in Model 10 (0.579, 85%) is, on average, higher and more often significant than the coefficient of historical asset volatility in Model 11 (0.423, 61%). Finally, the mean explanatory power of Model 10 is 27.59%, higher than Model 11's mean explanatory power of 24.11%. These results support the idea that the current leverage effect and implied asset volatility together contain more information about future realized equity volatility than historical equity volatility, particularly if we compare the explanatory power of Model 10 with that of Model 5. However, additional results from the comprehensive Model 12 are more difficult to interpret. On one hand, consistent with the evidence provided by Model 9, the historical leverage effect has marginal contribution once the current leverage effect is accounted for. To be precise, the coefficient of the current leverage effect is significant in 74% of the regressions with a mean value of 0.655, while the corresponding numbers for the historical leverage effect are 4% and 0.247, respectively. On the other hand, contrary to the evidence provided by Model 3, implied and historical asset volatility have a similar contribution in Model 12. This is reflected in the mean of their coefficients and the number of times those coefficients are significant: 0.392 vs 0.319, and 44% vs 48%, respectively. In other words, despite the fact that implied asset volatility is clearly more informative about future realized asset volatility than historical asset volatility, it does not seem to be more informative about future realized equity volatility once we control for the leverage effect. Moreover, the inclusion of historical data increases the explanatory power of Model 10 by a non-negligible 5.66%. This is clearly higher than the additional explanatory power of the historical leverage effect in Model 9 (0.58%), and the additional explanatory power of historical asset volatility in Model 3 (1.86%).

While previous considerations about Model 12 are certainly important, the explanatory power of Models 10 and 11 is probably the aspect that deserves the most attention. The mean explanatory power of the decomposed implied equity volatility in Model 10 is still much lower than both the mean explanatory power of the current leverage effect in Model 7 and the mean explanatory power of implied asset volatility in Model 1. Likewise, the mean explanatory power of the decomposed historical equity volatility in Model 11 is still much lower than the mean explanatory power of the historical leverage effect in Model 8, and also lower than the mean explanatory power of historical asset volatility in Model 2. In conclusion, most of our puzzling results from Models 1 to 9 are so far unexplained.

[Table 9 about here]

6.3. The Interconnection between Leverage and Asset Volatility

6.3.1. Motivation

According to results in Choi and Richardson (2016), there is a very significant negative correlation between asset volatility and leverage. The explanation can be found in the trade-off theory of capital structure. Companies with lower asset volatility can obtain higher tax benefits by increasing their leverage ratio, and still control for their risk of default. As reflected in expression (12), this negative relationship between asset volatility and leverage—defined as the ratio (V_t/S_t)—makes it possible that companies with quite different leverage ratios exhibit very similar equity volatilities. The empirical evidence in Choi and Richardson (2016) leads to the following two questions. First, are our data on realized leverage, realized asset volatility, and realized equity volatility consistent with that empirical evidence? Second, could the described interconnection between leverage and asset volatility explain our results?

Figure 1 provides evidence for the first question. It depicts realized asset and equity volatility as a function of the mean realized leverage for each of the 52 companies along the whole sample period of 1999–2017. It seems, in fact, that our estimations are fully consistent with those in Choi and Richardson (2016). Thus, higher leverage is associated with lower asset volatility in such a way that the resulting equity volatility has no apparent connection with leverage.[12]

[Figure 1 about here]

As an initial step toward answering the second question, Figure 2 plots the correlation between the future realized leverage effect and future realized asset volatility for each of our

[12] Our Figure 1 can be directly compared with Figure 1 in Choi and Richardson (2016).

114 regressions, as well as the standard deviation of the future realized leverage effect, future realized asset volatility, and future realized equity volatility. The figure confirms two important characteristics of our dependent variables in Models 7, 1, and 4, respectively. First, there is a very significant negative correlation between the future realized leverage effect and future realized asset volatility. Second, this negative correlation makes the cross-sectional variation in future realized equity volatility lower than the cross-sectional variation in both the future realized leverage effect and future realized asset volatility.

[Figure 2 about here]

The information in Figures 1 and 2, along with the evidence from Models 1 to 12, leads us to propose a simple model of the dynamic relationship between the leverage effect, asset volatility, and equity volatility. It should be stressed that it is not our intention to provide a sound representation of said relationship. On the contrary, the main objective is to offer the simplest representation that helps explain our empirical results.

6.3.2. Theoretical Model and Empirical Implications

We first assume that the future realized asset volatility and future realized leverage effect of company j are given, respectively, by

$$f_j = i_j + \eta_j \tag{31}$$

and

$$f_{le,j} = c_{le,j} + \eta_{le,j}, \tag{32}$$

where η_j and $\eta_{le,j}$ represent white noise, uncorrelated with each other or with either i_j or $c_{le,j}$. Expressions (31) and (32) imply that the future realized equity volatility is

$$f_{S,j} = i_{S,j} + \eta_{S,j}, \tag{33}$$

where $i_{S,j} = c_{le,j} + i_j$ and $\eta_{S,j} = \eta_{le,j} + \eta_j$.

We next assume that, following the trade-off theory of capital structure, all companies aim to maximize their tax benefits while controlling for their risk of default. In particular, we make the assumption that they will choose the highest possible debt level under the restriction that their expected default probability not exceed a maximum threshold q^*. This identical default probability target for all companies will translate, in turn, into an identical equity volatility target, f_S^*. The argument would be as follows. Because default can be associated with the value of equity falling to zero, the distance-to-default in terms of equity value and equity volatility will be:

$$DD_S = \frac{S-0}{\sigma_S S} = \frac{1}{\sigma_S}. \tag{34}$$

Accordingly, two companies will have the same default probability whenever they have the same equity volatility.[13]

Consider now that, while all companies have the same equity volatility target, their asset volatility is not the same, neither in the cross-section nor in the time-series. The prediction that company j makes about its future realized asset volatility is i_j, and, hence, its optimal current leverage effect will be:

$$c_{le,j}^* = f_S^* - i_j. \tag{35}$$

Following this expression and previous results, if companies can select their debt level so that $c_{le,j} = c_{le,j}^*$, then the explanatory variable in Model 4 will be

$$i_{S,j} = f_S^*. \tag{36}$$

In other words, both the cross-sectional variation in the explanatory variable and the explanatory power of Model 4 will be equal to zero. The basic idea is simple. Because the debt policy of all companies leads to the same expected equity volatility, any cross-sectional variation in future realized equity volatility is, by construction, an unpredictable random variable. Finally, it is worth noting that this will happen no matter what the explanatory power

[13] We could relate this assumption with the empirical results in Campbell and Taksler (2003), who find that equity volatility explains as much variation in corporate bonds' yield spreads as do credit ratings.

of Models 1 and 7 is. On the contrary, the higher the explanatory power of Models 1 and 7 (i.e., the higher the variance of i_j and $c_{le,j}$ relative to the variance of η_j and $\eta_{le,j}$ in expressions (31) and (32)), the higher the alignment of the proposed model with the evidence provided in Figure 2 (higher variance for future realized leverage effect and future realized asset volatility than for future realized equity volatility).

As already noted, our simple model is consistent with our finding of high explanatory power for the current leverage effect and implied asset volatility, which is not reflected in high explanatory power for implied equity volatility (actual results from Models 7, 1, and 4, respectively). The model is also consistent with a higher standard deviation for the realized leverage effect and realized asset volatility than for realized equity volatility (as reflected in Figure 2). The model, however, is not consistent with our finding of strictly positive explanatory power for implied equity volatility in Model 4.

We now assume that, in reality, companies do not have the capacity to select their optimal current leverage effect. On the contrary, its actual value is

$$c_{le,j} = c_{le,j}^{*} + dc_{le,j}, \tag{37}$$

where $dc_{le,j}$ stands for the deviation of the current leverage effect of company j from its optimal value. This deviation would be the result of the slow adjustment of debt levels to changes in both firm asset value and expected asset volatility.[14] This new assumption leads to a new value for the explanatory variable in Model 4:

$$i_{S,j} = f_S^{*} + dc_{le,j}. \tag{38}$$

Following this expression, a relatively small cross-sectional variation in $dc_{le,j}$ would be enough to generate strictly positive explanatory power for Model 4, but still lower than the explanatory power of Models 1 and 7. The introduction of this new factor does not necessarily make the

[14] See Choi and Richardson (2016).

model inconsistent with the evidence provided in Figure 2. The question, of course, is whether our data on the current leverage effect, implied asset volatility, and implied equity volatility, are consistent with all those assumptions.

Figure 3 plots the correlation between the current leverage effect and implied asset volatility, along with the standard deviation of the current leverage effect, implied asset volatility, and implied equity volatility. In line with our previous assumptions, the figure reveals a very significant negative correlation between the current leverage effect and implied asset volatility and, as a result, a much higher standard deviation for those two variables than for implied equity volatility. There is also a noteworthy evolution in the time series of those statistics. During the calm period preceding the sub-prime crisis, the correlation between the current leverage effect and implied asset volatility, as well as the standard deviation of implied equity volatility, were both at their minimum levels. This fits with the idea of a period with relatively stable firm asset values and asset volatilities, that is, a period where companies had the highest capacity to adjust their debt levels to their optimal values. On the opposite side, the sub-prime crisis (2008–2009) and the sovereign debt crisis (2011–2012) are the two periods with the highest (i.e., least negative) correlation between the current leverage effect and implied asset volatility, and the highest standard deviation of implied equity volatility. It is also reasonable to presume that those were the two periods where, due to particularly unstable firm asset values and asset volatilities, debt levels deviate most from their optimal values.

[Figure 3 about here]

Figure 4 represents the evolution of the explanatory power of Model 7 (current leverage effect), Model 1 (implied asset volatility), and Model 4 (implied equity volatility). Again consistent with the implications of our simple model, the explanatory power of Models 7 and 1 is always higher than that of Model 4. Also consistent with the model’s predictions, the higher the cross-sectional variation in implied equity volatility (Figure 3), the higher the explanatory power of this variable in Model 4 (Figure 4). More precisely, the explanatory power of implied equity volatility is essentially zero during the calm period preceding the sub-prime crisis, starts to grow mid-2006/mid-2007, and has settled in the range of 25–45% since mid-2008.

[Figure 4 about here]

We have just argued that it is the interconnection between leverage and asset volatility that produces the low explanatory power of implied equity volatility in Model 4. We next show that the low explanatory power of historical equity volatility in Model 5 can also be explained by this interconnection.

Following previous assumptions, future realized equity volatility is

$$f_{S,j} = f_S^* + dc_{le,j} + \eta_{S,j}, \tag{39}$$

while historical equity volatility could be expressed as

$$h_{S,j} = f_S^* + dc_{le,j}^h + \eta_{S,j}^h, \tag{40}$$

where $dc_{le,j}^h$ stands for the deviation of the historical (current) leverage effect from its optimal value, and $\eta_{S,j}^h$ represents white noise, uncorrelated with $\eta_{S,j}$. Expression (40) is simply the historical counterpart to expression (39).

We first consider the simplest version of our model, where companies have the capacity to select their optimal debt levels. If this is the case, then $dc_{le,j}^h = dc_{le,j} = 0$ and the explanatory power of historical equity volatility in Model 5 will be equal to zero, that is, equal to the explanatory power of $\eta_{S,j}^h$ as regards $\eta_{S,j}$. It is worth noting that this is the same prediction we made about the explanatory power of implied equity volatility in Model 4.

We now assume that companies have restrictions in choosing their optimal debt levels. In this instance, to the extent that $dc_{le,j}$ is correlated with $dc_{le,j}^h$, the explanatory power of historical equity volatility in Model 5 will be strictly positive. Such correlation would again be the result of the slow adjustment of debt levels to changes in both the firm asset value and expected asset volatility and, again, our prediction will be the same as the one we made for the explanatory power of implied equity volatility in Model 4. In short, because the underlying explanatory variable in Models 4 and 5 is the deviation of actual debt levels from their optimal values, the explanatory power of these models will be closely related to the presence (or not) of such deviations.

Figure 5 provides evidence on the evolution of the explanatory power of Model 8 (historical leverage effect), Model 2 (historical asset volatility), and Model 5 (historical equity volatility). While the explanatory power of implied equity volatility (Figure 4; Model 4) and the explanatory power of historical equity volatility (Figure 5; Model 5) are not exactly the same, they exhibit a very similar pattern: essentially zero in the pre-crisis period with sudden growth afterwards. We can again presume that the arrival of the sub-prime crisis and the later sovereign debt crisis affected the capacity of companies to select their optimal debt levels. The persistence in the deviation of actual debt levels from their optimal values would explain why Model 5 becomes significant in mid-2006. From 2007–2008, the explanatory power of implied and historical equity volatility move in the same range but, as expected, there is not a perfect fit. In conclusion, Figures 4 and 5 provide a detailed representation of the similar but complementary informational content of implied and historical equity volatility documented in Section 5.

[Figure 5 about here]

We complete our analysis by offering a possible explanation for Model 12's results. As already noted, implied asset volatility has higher explanatory power than historical asset volatility as regards future realized asset volatility (Models 1 to 3); however, this is not clearly translated into a higher contribution to the explanatory power of Model 12. We explore in Table 10 the correlation between the explanatory variables included in this model. The table confirms a very significant correlation in absolute value between those variables, which would explain the problematic interpretation of some of their coefficients. The main conclusion would be the following: when it comes to comparing the joint informational content of the current leverage effect and implied equity volatility with that of historical equity volatility, the comparison is better done based on the explanatory power of Models 10 and 5, or even Model 11. The results of such a comparison will have a meaningful interpretation, fully consistent with the informational content of the current leverage effect and implied asset volatility at the individual level.

[Table 10 about here]

6.3.3. Discussion

As previously stated, we think of our model as the simplest representation of the dynamic relationship between the leverage effect, asset volatility, and equity volatility, which helps explain our empirical results. Accordingly, a discussion of whether the main predictions of the model could be driven by its simplifying assumptions follows.

The underlying assumption in expression (31) is that implied asset volatility represents an unbiased estimate of future realized asset volatility. Results from Model 1 suggest, on the contrary, that implied asset volatility is a powerful but biased estimate of future realized asset volatility. It does not seem, however, that the main predictions of the model rely on the assumption that the constant term in that expression is equal to 0, and the slope is equal to 1.

Expression (32) reflects a more delicate assumption: that the future evolution of the leverage effect is white noise. In other words, it is assumed that the company will have no control over how its leverage evolves after the current time t. As also reflected in expressions (39) and (40), the actual implicit assumption is that decisions about debt levels are made once every five years. It is, in fact, the combination of a stochastic firm asset value and a stepwise debt level that would translate into a white noise term in the future and historical realized leverage effect and, by extension, into a white noise term in the future and historical realized equity volatility. However, recognizing that companies could adjust their debt levels at any point in time would only reinforce the predictions of the model. The higher the capacity of companies to modify their debt levels, the lower the deviation of their realized equity volatilities from the common target, and the lower the explanatory power of Models 4 and 5.

Another simplifying assumption of the model is that the trade-off between tax benefits and bankruptcy costs leads to an identical optimal default probability for all companies. It is further assumed that there is a one-to-one relationship between default probability and (equity based) distance-to-default. These assumptions could also be relaxed without changing the main predictions of the model. In particular, we could consider the possibility that such a trade-off leads to a much lower cross-sectional variation in optimal equity volatility than in expected asset volatility, but not to the point where all companies have the same precise equity volatility target. In this instance, the strictly positive explanatory power of Models 4 and 5 would not rely only on deviations of actual debt levels from their optimal values, but also on that new factor. It would actually be reasonable to presume that, in fact, both elements play a role in explaining the cross-sectional variation in future realized equity volatilities. That said, our results provide little support for the possibility that differences in the optimal equity volatility represent the main driving force. If this were the case, we would expect the explanatory power of historical equity volatility to be significant even when deviations of actual debt levels from their optimal values are relatively small. The evidence in Figure 5 indicates, indeed, the opposite: zero explanatory power for historical equity volatility during the pre-crisis period. All things considered, we have no reason to conclude that the actual fit between our empirical results and the predictions of the model is the product of its simplifying assumptions.

7. Robustness Test: Naïve Approach

Our empirical analysis has been made on the basis of one particular structural credit risk model and estimation method. One possible way to ensure the robustness of our results would be to consider a large set of alternative models and methods. However, a more definite robustness test can be achieved by considering a completely different, naïve approach. In particular, we repeat all previous estimations in a model-free setting, where $V_t = S_t + P_t, \beta = 1$ and $\partial S_t / \partial V_t = 1$.[15] The corresponding new versions of Tables 1–10 and Figures 1–5 are reported in Appendix C. Two main conclusions arise. First, the results provide some support for the structural credit risk model and the estimation method applied. For instance, the mean explanatory power of implied asset volatility in Model 1 falls from 68.40% to 63.20% when the naïve approach is used. Likewise, the mean explanatory power of implied equity volatility in Model 4 falls from 18.56% to 14.09%. Second, apart from those differences, the overall conclusions remain the same. In other words, there is no evidence that our main findings are related to the particular model and estimation method selected.

8. Conclusions

We investigate the informational content of CDS spreads for future realized asset volatility and future realized equity volatility. Our cross-sectional analysis reveals that CDS implied asset volatilities have a very significant informational content for future realized asset volatilities. This informational content is clearly superior, and almost subsumes, the informational content of historical asset volatilities. Results change considerably when we focus our attention on equity volatilities. Compared to their asset volatility counterparts, CDS implied equity volatilities have a much lower informational content for future realized equity volatilities. Moreover, this informational content is similar and complementary to the informational content of historical equity volatilities. After considering other possible explanations, we show that a simple model reflecting the interconnection between leverage and asset volatility can explain these findings. Following the trade-off theory of capital structure,

[15] It is straightforward to verify that, under this simple setting, there is no difference between the traditional distance-to-default in terms of firm asset value and asset volatility, and the distance-to-default in terms of equity value and equity volatility: $DD_V = (V - V_B)/\sigma V = 1/\sigma_S$.

companies with lower asset volatility choose a higher leverage ratio, such that their expected equity volatility is always the same. In this context, the cross-sectional variation in equity volatilities is mainly driven by deviation of debt levels from their optimal values. The final implication of the model is that the more successful companies are in achieving their optimal debt policy, the lower the predictability of future cross-sectional variations in equity volatility. Our empirical results prove to be fully consistent with this prediction. The explanatory power of implied equity volatility is essentially zero during the calm period preceding the sub-prime crisis, but has become clearly positive since that time. We also test whether our results are an artifact of the particular credit risk model and estimation method employed to estimate implied volatilities, and we find that they are not. The same temporal pattern is observed when we analyze the explanatory power of implied equity volatilities estimated in a model-free setting, and the explanatory power of historical equity volatilities. It is worth noting that, in the latter case, our results depend only on fairly observable equity values.

While the focus of this study is the informational content of CDS spreads, it is clear that our findings go above and beyond the information embedded in this particular credit risk instrument. The main conclusion is that there is a very significant difference between forecasting asset volatility and forecasting equity volatility, and that this difference is explained by the interaction between leverage and asset volatility. Another important but unexplored implication of our simple model is that the explanatory power of implied asset and equity volatilities should be different in the time-series than in the cross-section. Because testing this hypothesis requires a long enough non-overlapping database of implied and realized volatilities, the shorter maturity of equity options represents a clear advantage over the very long maturity of the CDS contracts used in the present study. This and other potential extensions are left for further research.

Appendix A

Let us denote $N[\cdot]$ the standard normal cumulative distribution function. The specific expressions for $G_t(\tau)$ and $H_t(\tau)$ are:

$$H_t(\tau) = e^{-r\tau}[1 - F_t(\tau)],$$

with

$$F_t(\tau) = N[x_{1t}] + \left(\frac{V_t}{V_b}\right)^{-2a} N[x_{2t}];$$

and

$$G_t(\tau) = \left(\frac{V_t}{V_b}\right)^{-a+z} N[y_{1t}] + \left(\frac{V_t}{V_b}\right)^{-a-z} N[y_{2t}];$$

where

$$x_{1t} = \frac{-b_t - a\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad x_{2t} = \frac{-b_t + a\sigma^2\tau}{\sigma\sqrt{\tau}};$$

$$y_{1t} = \frac{-b_t - z\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad y_{2t} = \frac{-b_t + z\sigma^2\tau}{\sigma\sqrt{\tau}};$$

$$a = \frac{r - \delta - \frac{\sigma^2}{2}}{\sigma^2}; \qquad b_t = \ln\left(\frac{V_t}{V_b}\right); \qquad z = \frac{\sqrt{(a\sigma^2)^2 + 2r\sigma^2}}{\sigma^2}.$$

Appendix B

We provide here the specific expression for $\partial S_t/\partial V_t$ in Forte's (2011) model. The equity value is given by

$$S_t = V_t - D(V_t, \beta, \sigma, 0)$$

and, therefore,

$$\frac{\partial S_t}{\partial V_t} = 1 - \frac{\partial D(V_t, \beta, \sigma, 0)}{\partial V_t} = 1 - \sum_{n=1}^{N} \frac{\partial d_n(V_t, \beta, \sigma, 0)}{\partial V_t},$$

where

$$\frac{\partial d_n(V_t, \beta, \sigma, 0)}{\partial V_t} = -e^{-r\tau_n}\left[p_n - \frac{c_n}{r}\right]\frac{\partial F_t(\tau_n)}{\partial V_t} + \left[\beta p_n - \frac{c_n}{r}\right]\frac{\partial G_t(\tau_n)}{\partial V_t},$$

and

$$\frac{\partial F_t(\tau_n)}{\partial V_t} = f(x_{1t})\frac{\partial x_{1t}}{\partial V_t} - \left[\frac{2a}{V_b}\left(\frac{V_t}{V_b}\right)^{-2a-1}\right]N[x_{2t}] + \left(\frac{V_t}{V_b}\right)^{-2a} f(x_{2t})\frac{\partial x_{2t}}{\partial V_t};$$

$$\frac{\partial G_t(\tau_n)}{\partial V_t} = \left[\frac{-a+z}{V_b}\left(\frac{V_t}{V_b}\right)^{-a+z-1}\right]N[y_{1t}] + \left(\frac{V_t}{V_b}\right)^{-a+z} f(y_{1t})\frac{\partial y_{1t}}{\partial V_t}$$

$$+\left[\frac{-a-z}{V_b}\left(\frac{V_t}{V_b}\right)^{-a-z-1}\right]N[y_{2t}] + \left(\frac{V_t}{V_b}\right)^{-a-z} f(y_{2t})\frac{\partial y_{2t}}{\partial V_t};$$

with $f(\cdot)$ denoting the standard normal density function, and

$$\frac{\partial x_{1t}}{\partial V_t} = \frac{\partial x_{2t}}{\partial V_t} = \frac{\partial y_{1t}}{\partial V_t} = \frac{\partial y_{2t}}{\partial V_t} = -\frac{1}{V_t\sigma\sqrt{\tau_n}}.$$

Appendix C

We next reproduce all the tables and figures in the core of the paper, this time using the naïve approach to define firm asset value and the parameter β.

Table C.1. Same as Table 1 in the core of the paper.

Table C.2. Main Descriptive Statistics of the Final Sample (Panel A) and Results for $\boldsymbol{V}$, β and σ (Panel B).

	A			B		
	MC	*Eq. Vol.*	*CDS*	$\boldsymbol{V}$	β	σ
Mean	25,601.84	0.32	101.81	54,331.91	1.00	0.15
Median	16,570.36	0.33	81.93	37,088.10	1.00	0.15
SD	23,666.58	0.05	62.25	48,510.24	0.00	0.05
Min.	4,739.57	0.23	30.78	10,660.19	1.00	0.06
Max.	138,695.00	0.46	378.07	244,837.16	1.00	0.33

This table reports, on a cross-sectional basis, the main descriptive statistics for the overall sample of 52 non-financial companies (Panel A), along with the results for $\boldsymbol{V}$, β, and σ (Panel B). *MC* is the average market capitalization in millions of euros. Equity volatility is defined as the unconditional historical volatility calculated as the annualized standard deviation of the continuously compounded return on equity. *CDS* is the average mid bid-ask quote in basis points for the period 2004–2017. $\boldsymbol{V}$ refers to the average of the estimated firm asset values in millions of euros. β and σ are the default-to-debt ratio and asset volatility, respectively.

Table C.3. Main Descriptive Statistics for Implied and Realized Asset Volatilities.

	Implied Asset Volatility	*Realized Asset Volatility*	*Log Implied Asset Volatility*	*Log Realized Asset Volatility*
Mean	0.15	0.13	-1.97	-2.09
SD	0.05	0.04	0.39	0.34
Skewness	0.50	0.97	-0.40	-0.41
Kurtosis	2.85	5.56	2.98	3.81

This table reports the main descriptive statistics for implied and (future) realized asset volatilities at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table C.4. Future Realized Asset Volatility as a Function of Implied and Historical Asset Volatility.

Dependent Variable: Future Realized Asset Volatility, f_j					
Model, Independent Variables, and Explanatory Power					
		Intercept	i_j	h_j	$Adj.R^2$
Model 1	Mean	-0.699	0.710		63.20%
	(Signif. 5%)	*(95%)*	*(100%)*		
Model 2	Mean	-0.606		0.734	53.78%
	(Signif. 5%)	*(74%)*		*(100%)*	
Model 3	Mean	-0.502	0.501	0.291	66.42%
	(Signif. 5%)	*(75%)*	*(94%)*	*(47%)*	

This table summarizes the results of estimating Models 1, 2, and 3 using OLS with White standard errors. In these three models, the future realized asset volatility of company j is related to its implied asset volatility (Model 1), its historical asset volatility (Model 2), and the two explanatory variables (Model 3), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table C.5. Main Descriptive Statistics for Implied and Realized Equity Volatilities.

	Implied Equity Volatility	*Realized Equity Volatility*	*Log Implied Equity Volatility*	*Log Realized Equity Volatility*
Mean	0.33	0.31	-1.14	-1.21
SD	0.06	0.08	0.16	0.23
Skewness	1.20	1.11	0.50	0.51
Kurtosis	7.01	4.23	4.45	2.94

This table reports the main descriptive statistics for implied and (future) realized equity volatilities at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table C.6. Future Realized Equity Volatility as a Function of Implied and Historical Equity Volatility.

Dependent Variable: Future Realized Equity Volatility, $f_{S,j}$					
Model, Independent Variables, and Explanatory Power					
		Intercept	$i_{S,j}$	$h_{S,j}$	$Adj.R^2$
Model 4	Mean	-0.558	0.582		14.09%
	(Signif. 5%)	*(64%)*	*(82%)*		
Model 5	Mean	-0.608		0.499	19.35%
	(Signif. 5%)	*(80%)*		*(63%)*	
Model 6	Mean	-0.317	0.357	0.403	22.60%
	(Signif. 5%)	*(52%)*	*(32%)*	*(63%)*	

This table summarizes the results of estimating Models 4, 5, and 6 using OLS with White standard errors. In these three models, the future realized equity volatility of company j is related to its implied equity volatility (Model 4), its historical equity volatility (Model 5), and the two explanatory variables (Model 6), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table C.7. Main Descriptive Statistics for Current and Realized Leverage Effects.

	Current Leverage Effect	*Realized Leverage Effect*	*Log Current Leverage Effect*	*Log Realized Leverage Effect*
Mean	2.53	2.62	0.83	0.88
SD	1.43	1.38	0.38	0.39
Skewness	2.91	3.00	1.13	1.10
Kurtosis	14.76	15.35	4.86	4.66

This table reports the main descriptive statistics for the current and (future) realized leverage effect at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table C.8. Future Realized Leverage Effect as a Function of Current and Historical Leverage Effects.

Dependent Variable: Future Realized Leverage Effect, $f_{le,j}$					
Model, Independent Variables, and Explanatory Power					
		Intercept	$c_{le,j}$	$h_{le,j}$	$Adj.R^2$
Model 7	Mean	0.121	0.931		75.57%
	(Signif. 5%)	*(38%)*	*(100%)*		
Model 8	Mean	0.138		0.892	60.34%
	(Signif. 5%)	*(28%)*		*(100%)*	
Model 9	Mean	0.115	0.875	0.074	76.13%
	(Signif. 5%)	*(36%)*	*(93%)*	*(13%)*	

This table summarizes the results of estimating Models 7, 8, and 9 using OLS with White standard errors. In these three models, the future realized leverage effect of company j is related to its current leverage effect (Model 7), its historical leverage effect (Model 8), and the two explanatory variables (Model 9), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table C.9. Future Realized Equity Volatility as a Function of Current Leverage Effect, Implied Asset Volatility, Historical Leverage Effect, and Historical Asset Volatility.

Dependent Variable: Future Realized Equity Volatility, $f_{S,j}$							
Model, Independent Variables, and Explanatory Power							
		Intercept	$c_{le,j}$	i_j	$h_{le,j}$	h_j	$Adj.R^2$
Model 10	Mean	-0.758	0.813	0.570			26.88%
	(Signif. 5%)	*(72%)*	*(100%)*	*(98%)*			
Model 11	Mean	-0.851			0.590	0.415	24.41%
	(Signif. 5%)	*(82%)*			*(63%)*	*(59%)*	
Model 12	Mean	-0.467	0.642	0.363	0.290	0.387	34.43%
	(Signif. 5%)	*(59%)*	*(77%)*	*(43%)*	*(15%)*	*(61%)*	

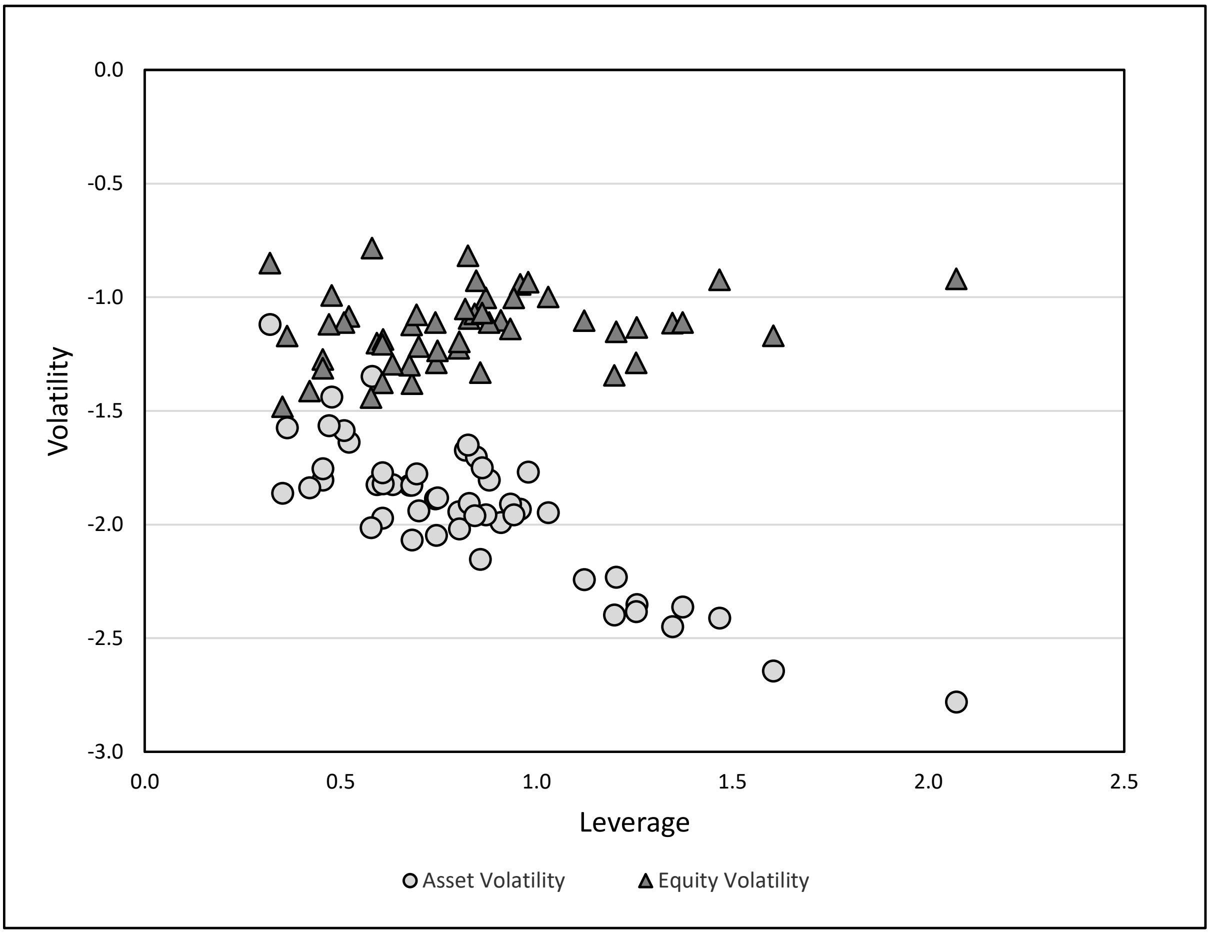
This table summarizes the results of estimating Models 10, 11, and 12 using OLS with White standard errors. In these three models the future realized equity volatility of company j is related to its current leverage effect and its implied asset volatility (Model 10), its historical leverage effect and its historical asset volatility (Model 11), and the four explanatory variables (Model 12), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table C.10. Correlation between Explanatory Variables, Model 12: Current Leverage Effect, Implied Asset Volatility, Historical Leverage Effect, and Historical Asset Volatility.

Correlation Matrix. Explanatory Variables, Model 12.				
	$c_{le,j}$	i_j	$h_{le,j}$	h_j
$c_{le,j}$	1.00	-0.92	0.88	-0.78
i_j		1.00	-0.82	0.82
$h_{le,j}$			1.00	-0.83
h_j				1.00

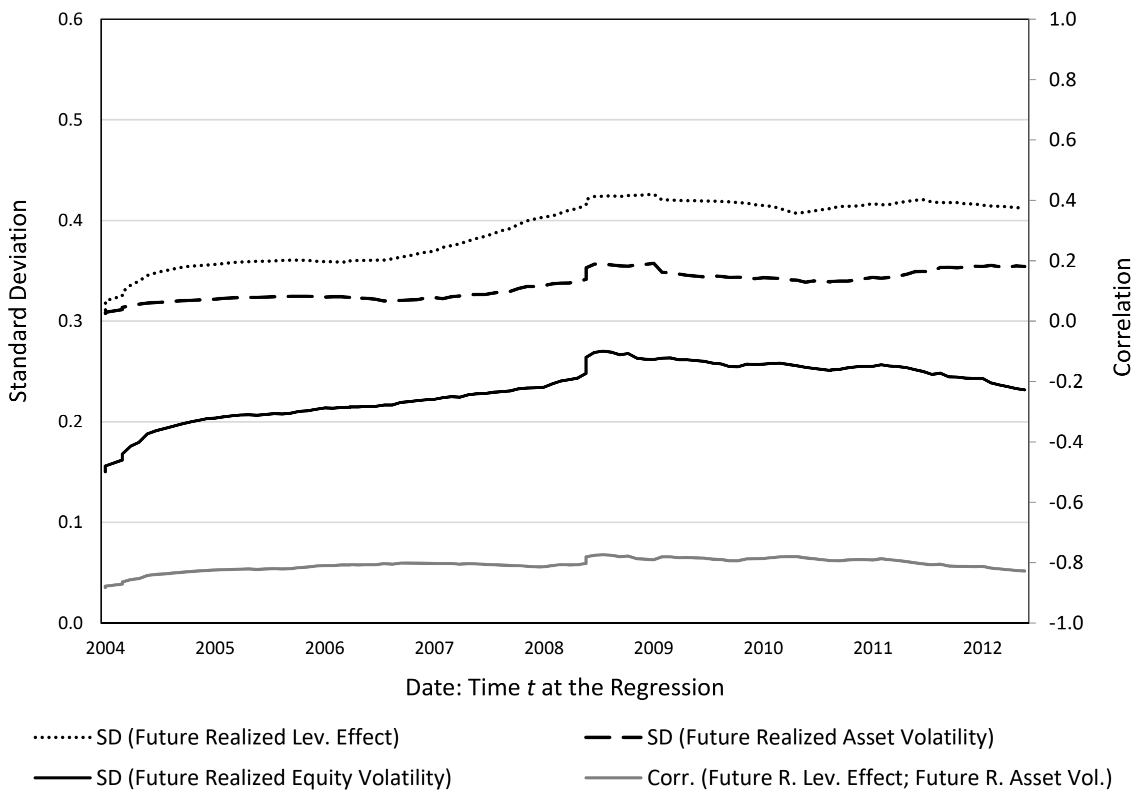
This table shows the correlation matrix of the explanatory variables included in Model 12: current leverage effect, implied asset volatility, historical leverage effect, and historical asset volatility. Reported numbers represent the average across the 114 monthly observations.

Figure C.1. Asset and Equity Volatility as a Function of Leverage.



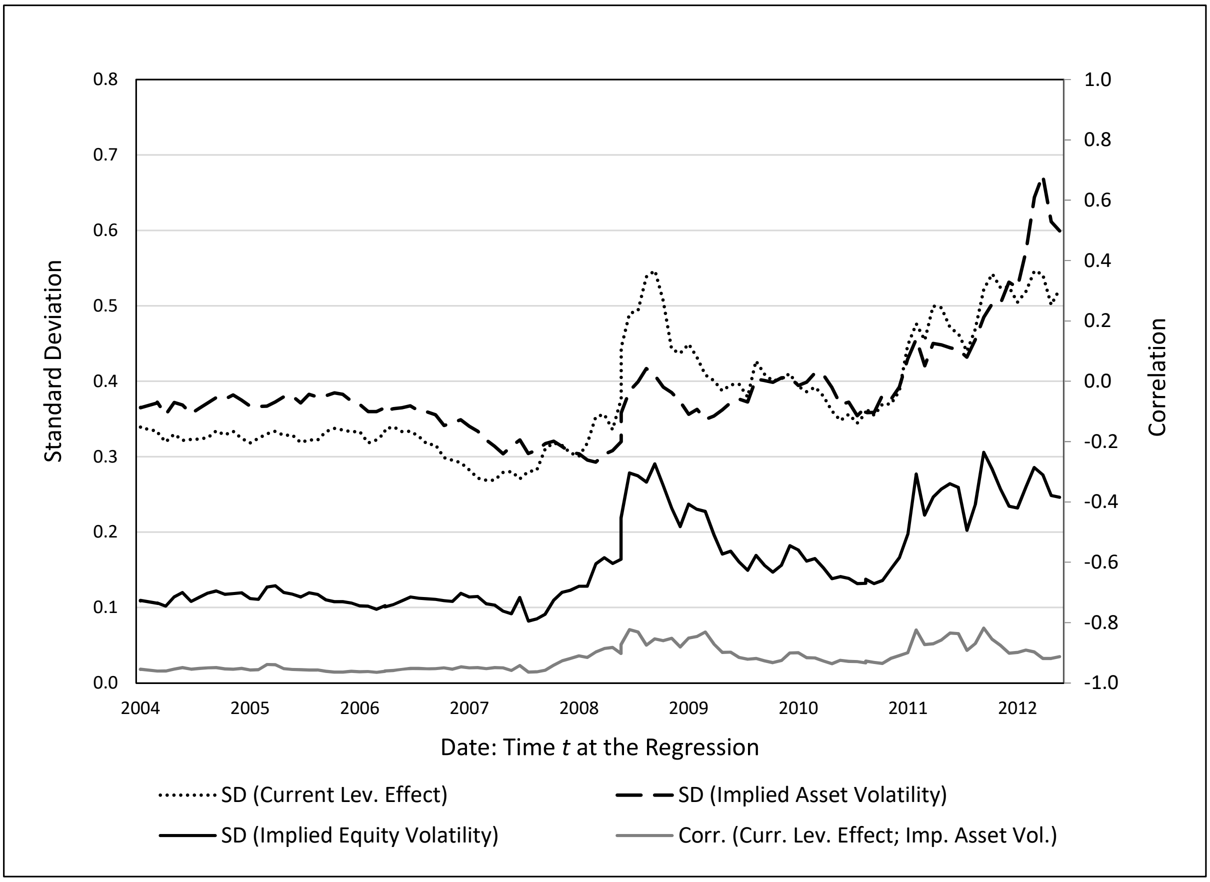
This figure depicts, for each of the 52 companies, asset and equity volatility as a function of leverage. Leverage is defined as the log of the mean value of (V_t/S_t) over the full sample period 1999–2017. Asset and equity volatility refer to the log of the realized volatilities for the same sample period.

Figure C.2. Correlation between Future Realized Leverage Effect and Future Realized Asset Volatility, and Standard Deviation of Future Realized Leverage Effect, Future Realized Asset Volatility, and Future Realized Equity Volatility.



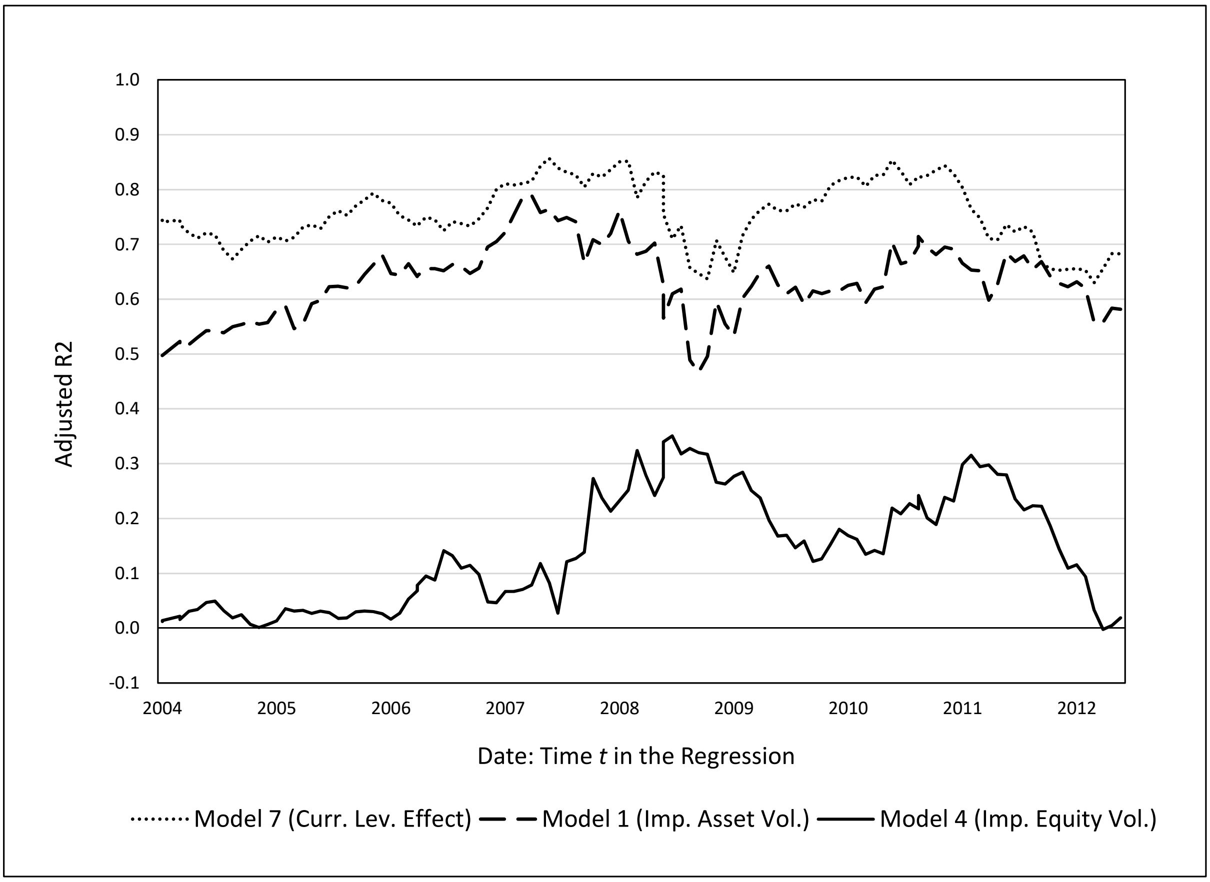
This figure plots the correlation between the future realized leverage effect and future realized asset volatility (grey solid line) for each of the 114 monthly observations. The figure also plots the standard deviation of the future realized leverage effect (black dotted line), future realized asset volatility (black dashed line), and future realized equity volatility (black solid line).

Figure C.3. Correlation between Current Leverage Effect and Implied Asset Volatility, and Standard Deviation of Current Leverage Effect, Implied Asset Volatility, and Implied Equity Volatility.



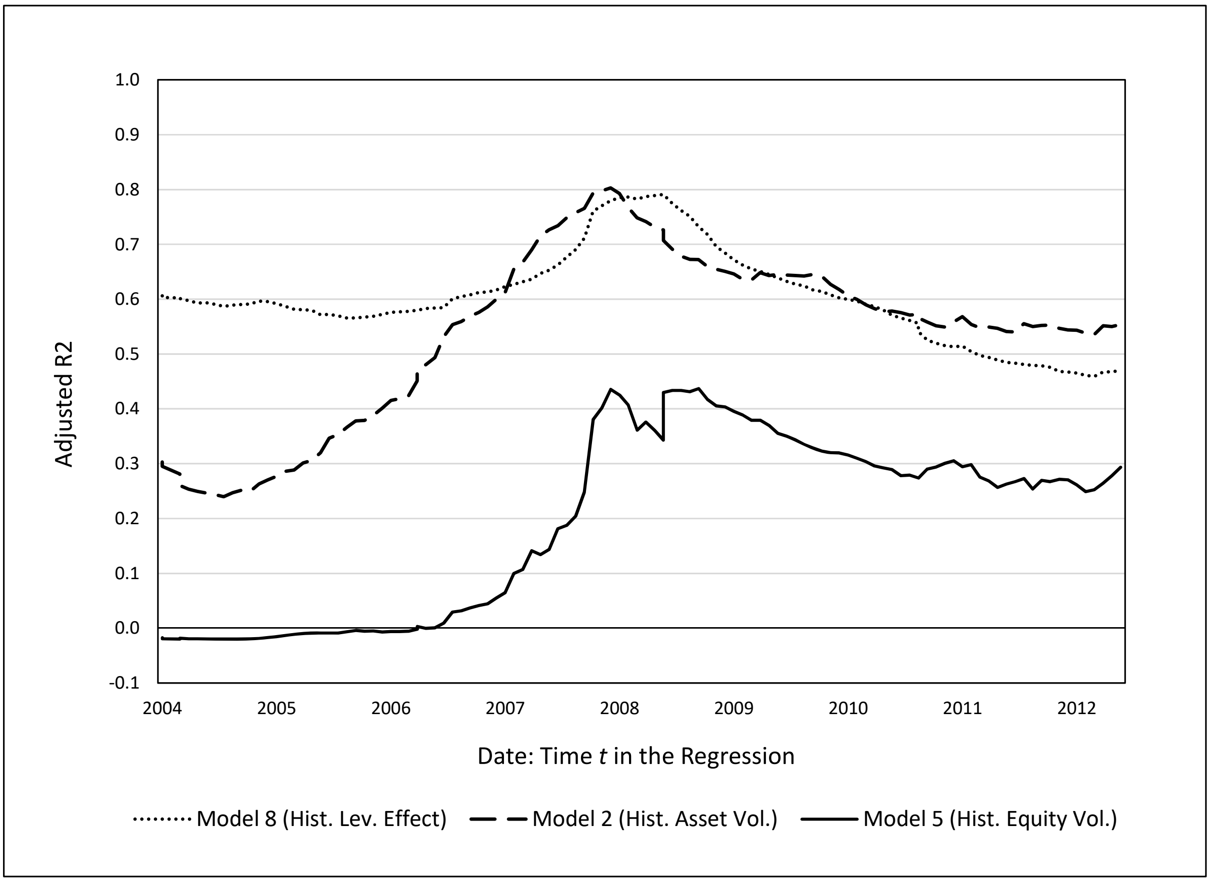
This figure plots the correlation between the current leverage effect and implied asset volatility (grey solid line) for each of the 114 monthly observations. The figure also plots the standard deviation of the current leverage effect (black dotted line), implied asset volatility (black dashed line), and implied equity volatility (black solid line).

Figure C.4. Explanatory Power of Models 7, 1, and 4.



This figure plots the adjusted R^2 of Model 7 (future realized leverage effect as a function of current leverage effect; black dotted line), the adjusted R^2 of Model 1 (future realized asset volatility as a function of implied asset volatility; black dashed line), and the adjusted R^2 of Model 4 (future realized equity volatility as a function of implied equity volatility; black solid line). The figure reflects the results for each of the 114 monthly regressions.

Figure C.5. Explanatory Power of Models 8, 2, and 5.



This figure plots the adjusted R^2 of Model 8 (future realized leverage effect as a function of historical leverage effect; black dotted line), the adjusted R^2 of Model 2 (future realized asset volatility as a function of historical asset volatility; black dashed line), and the adjusted R^2 of Model 5 (future realized equity volatility as a function of historical equity volatility; black solid line). The figure reflects the results for each of the 114 monthly regressions.

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Tables and Figures

Table 1. Final Sample.

AB Volvo	E.ON SE
Bayerische Motoren Werke AG	EDP Energias de Portugal SA
Compagnie Generale des E. Michelin SCA	Iberdrola SA
Continental AG	Repsol SA
Daimler AG	RWE AG
Peugeot SA	Akzo Nobel NV
Renault SA	Anglo American PLC
Valeo SA	BAE Systems PLC
Deutsche Lufthansa AG	Bayer AG
Kingfisher PLC	Compagnie de Saint Gobain SA
Koninklijke Philips NV	Investor AB
LVMH Moet Hennessy Louis Vuitton SE	Linde AG
Marks and Spencer Group PLC	Rolls-Royce Holdings PLC
Kering SA	Siemens AG
Sodexo SA	Stora Enso OYJ
British American Tobacco PLC	UPM Kymmene OYJ
Carrefour SA	BT Group PLC
Casino Guichard Perrachon SA	Deutsche Telekom AG
Diageo PLC	Orange SA
Danone SA	Hellenic Telec. Organization SA
Henkel & Co KGaA AG	Koninklijke KPN NV
Imperial Tobacco Group PLC	Pearson PLC
J Sainsbury PLC	STMicroelectronics NV
Tesco PLC	Telefonica SA
Unilever NV	Wolters Kluwer NV
BP PLC	WPP PLC

Table 2. Main Descriptive Statistics of the Final Sample (Panel A) and Results from the *ICM* Algorithm (Panel B).

	A			B		
	MC	*Eq. Vol.*	*CDS*	$\boldsymbol{V}^*$	β^*	σ^*
Mean	25,601.84	0.32	101.81	54,420.45	0.85	0.15
Median	16,570.36	0.33	81.93	37,585.17	0.86	0.15
SD	23,666.58	0.05	62.25	47,827.25	0.05	0.05
Min.	4,739.57	0.23	30.78	10,665.40	0.67	0.06
Max.	138,695.00	0.46	378.07	238,458.35	0.98	0.33

This table reports, on a cross-sectional basis, the main descriptive statistics for the overall sample of 52 non-financial companies (Panel A), along with the results from the application of the *ICM* algorithm (Panel B). *MC* is the average market capitalization in millions of euros. Equity volatility is defined as the unconditional historical volatility calculated as the annualized standard deviation of the continuously compounded return on equity. *CDS* is the average mid bid-ask quote in basis points for the period 2004–2017. $\boldsymbol{V}^*$ refers to the average of the estimated firm asset values in millions of euros. β^* and σ^* are the estimated default-to-debt ratio and asset volatility, respectively.

Table 3. Main Descriptive Statistics for Implied and Realized Asset Volatilities.

	Implied Asset Volatility	*Realized Asset Volatility*	*Log Implied Asset Volatility*	*Log Realized Asset Volatility*
Mean	0.18	0.13	-1.75	-2.08
SD	0.06	0.04	0.36	0.33
Skewness	0.47	1.09	-0.58	-0.28
Kurtosis	3.21	5.85	3.64	3.72

This table reports the main descriptive statistics for implied and (future) realized asset volatilities at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table 4. Future Realized Asset Volatility as a Function of Implied and Historical Asset Volatility.

Dependent Variable: Future Realized Asset Volatility, f_j					
Model, Independent Variables, and Explanatory Power					
		Intercept	i_j	h_j	$Adj.R^2$
Model 1	Mean	-0.744	0.767		68.40%
	(Signif. 5%)	*(100%)*	*(100%)*		
Model 2	Mean	-0.609		0.734	54.89%
	(Signif. 5%)	*(77%)*		*(100%)*	
Model 3	Mean	-0.591	0.636	0.176	70.26%
	(Signif. 5%)	*(85%)*	*(99%)*	*(28%)*	

This table summarizes the results of estimating Models 1, 2, and 3 using OLS with White standard errors. In these three models, the future realized asset volatility of company j is related to its implied asset volatility (Model 1), its historical asset volatility (Model 2), and the two explanatory variables (Model 3), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table 5. Main Descriptive Statistics for Implied and Realized Equity Volatilities.

	Implied Equity Volatility	*Realized Equity Volatility*	*Log Implied Equity Volatility*	*Log Realized Equity Volatility*
Mean	0.40	0.31	-0.94	-1.21
SD	0.08	0.08	0.16	0.23
Skewness	1.66	1.11	0.90	0.51
Kurtosis	8.94	4.23	5.18	2.94

This table reports the main descriptive statistics for implied and (future) realized equity volatilities at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table 6. Future Realized Equity Volatility as a Function of Implied and Historical Equity Volatility.

Dependent Variable: Future Realized Equity Volatility, $f_{S,j}$					
Model, Independent Variables, and Explanatory Power					
		Intercept	$i_{S,j}$	$h_{S,j}$	$Adj.R^2$
Model 4	Mean	-0.681	0.579		18.56%
	(Signif. 5%)	*(82%)*	*(67%)*		
Model 5	Mean	-0.608		0.499	19.35%
	(Signif. 5%)	*(80%)*		*(63%)*	
Model 6	Mean	-0.445	0.385	0.328	23.55%
	(Signif. 5%)	*(61%)*	*(36%)*	*(39%)*	

This table summarizes the results of estimating Models 4, 5, and 6 using OLS with White standard errors. In these three models, the future realized equity volatility of company j is related to its implied equity volatility (Model 4), its historical equity volatility (Model 5), and the two explanatory variables (Model 6), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table 7. Main Descriptive Statistics for Current and Realized Leverage Effects.

	Current Leverage Effect	*Realized Leverage Effect*	*Log Current Leverage Effect*	*Log Realized Leverage Effect*
Mean	2.45	2.60	0.81	0.87
SD	1.21	1.29	0.36	0.38
Skewness	2.79	2.90	1.07	1.06
Kurtosis	14.01	14.68	4.73	4.58

This table reports the main descriptive statistics for the current and (future) realized leverage effect at the cross-sectional level: mean, standard deviation, skewness, and kurtosis. Reported numbers represent the average across the 114 monthly observations.

Table 8. Future Realized Leverage Effect as a Function of Current and Historical Leverage Effects.

Dependent Variable: Future Realized Leverage Effect, $f_{le,j}$					
Model, Independent Variables, and Explanatory Power					
		Intercept	$c_{le,j}$	$h_{le,j}$	$Adj.R^2$
Model 7	Mean	0.112	0.959		77.95%
	(Signif. 5%)	*(31%)*	*(100%)*		
Model 8	Mean	0.132		0.904	63.00%
	(Signif. 5%)	*(18%)*		*(100%)*	
Model 9	Mean	0.110	0.911	0.058	78.54%
	(Signif. 5%)	*(37%)*	*(95%)*	*(12%)*	

This table summarizes the results of estimating Models 7, 8, and 9 using OLS with White standard errors. In these three models, the future realized leverage effect of company j is related to its current leverage effect (Model 7), its historical leverage effect (Model 8), and the two explanatory variables (Model 9), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

Table 9. Future Realized Equity Volatility as a Function of Current Leverage Effect, Implied Asset Volatility, Historical Leverage Effect, and Historical Asset Volatility.

Dependent Variable: Future Realized Equity Volatility, $f_{S,j}$							
Model, Independent Variables, and Explanatory Power							
		Intercept	$c_{le,j}$	i_j	$h_{le,j}$	h_j	$Adj.R^2$
Model 10	Mean	-0.842	0.809	0.579			27.59%
	(Signif. 5%)	*(84%)*	*(90%)*	*(85%)*			
Model 11	Mean	-0.840			0.597	0.423	24.11%
	(Signif. 5%)	*(82%)*			*(63%)*	*(61%)*	
Model 12	Mean	-0.581	0.655	0.392	0.247	0.319	33.25%
	(Signif. 5%)	*(68%)*	*(74%)*	*(44%)*	*(4%)*	*(48%)*	

This table summarizes the results of estimating Models 10, 11, and 12 using OLS with White standard errors. In these three models, the future realized equity volatility of company j is related to its current leverage effect and its implied asset volatility (Model 10), its historical leverage effect and its historical asset volatility (Model 11), and the four explanatory variables (Model 12), respectively. A total of 114 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of the coefficient of each independent variable, the number of times this coefficient is significant at the 5% confidence level, and the mean $Adj.R^2$ for each model.

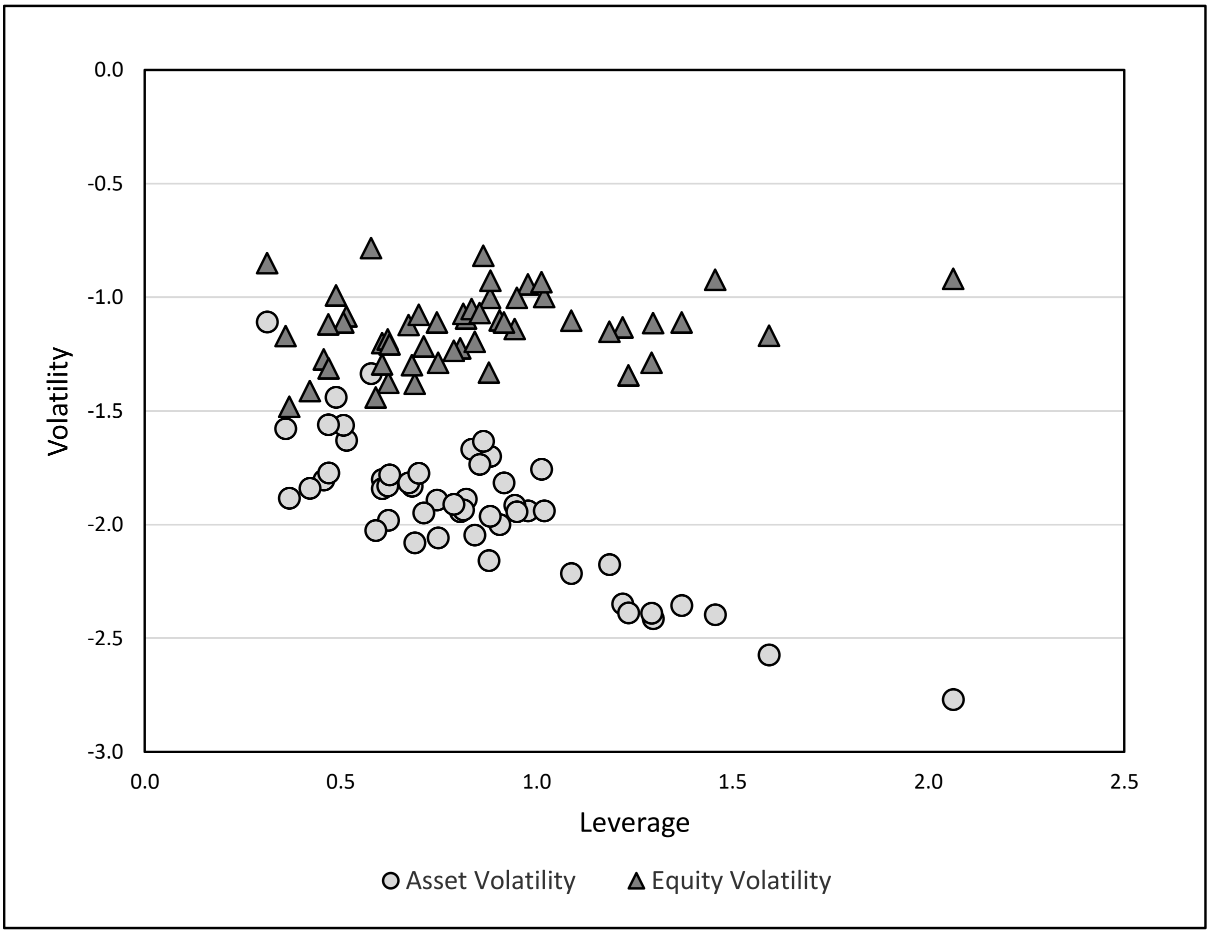
Table 10. Correlation between Explanatory Variables, Model 12: Current Leverage Effect, Implied Asset Volatility, Historical Leverage Effect, and Historical Asset Volatility.

Correlation Matrix. Explanatory Variables, Model 12.

	$c_{le,j}$	i_j	$h_{le,j}$	h_j
$c_{le,j}$	1.00	-0.90	0.89	-0.77
i_j		1.00	-0.83	0.85
$h_{le,j}$			1.00	-0.82
h_j				1.00

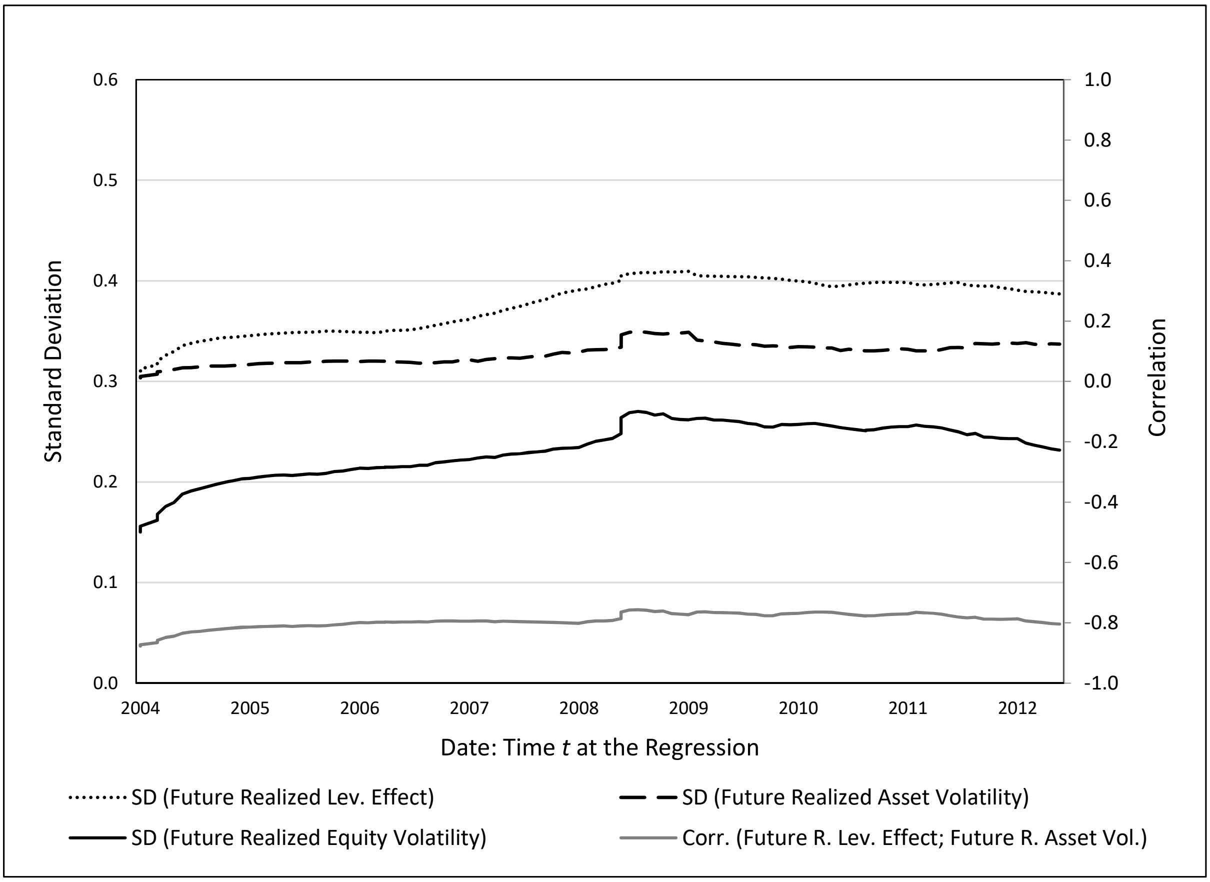
This table shows the correlation matrix between the explanatory variables included in Model 12: current leverage effect, implied asset volatility, historical leverage effect, and historical asset volatility. Reported numbers represent the average across the 114 monthly observations.

Figure 1. Asset and Equity Volatility as a Function of Leverage.



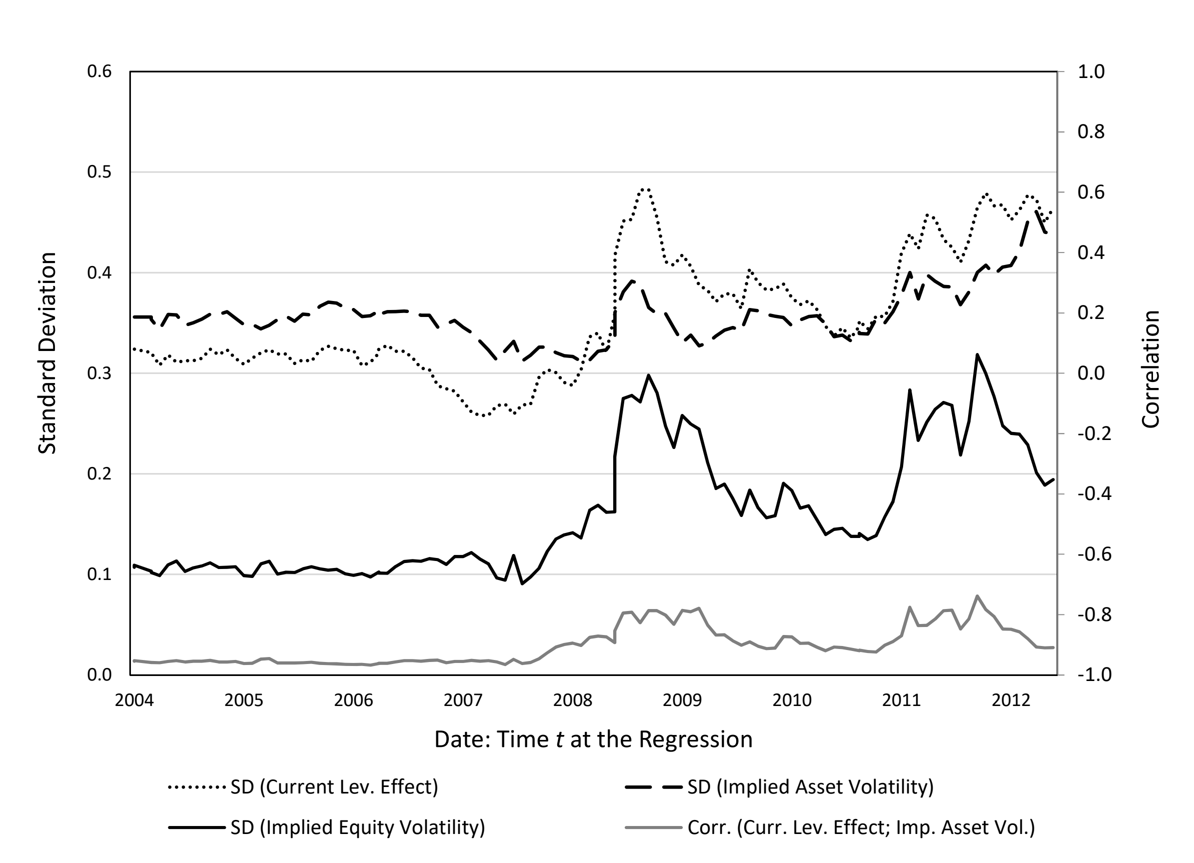
This figure depicts asset and equity volatility as a function of leverage for each of the 52 companies. Leverage is defined as the log of the mean value of (V_t/S_t) over the full sample period 1999–2017. Asset and equity volatility refer to the log of the realized volatilities for the same sample period.

Figure 2. Correlation between Future Realized Leverage Effect and Future Realized Asset Volatility, and Standard Deviation of Future Realized Leverage Effect, Future Realized Asset Volatility, and Future Realized Equity Volatility.



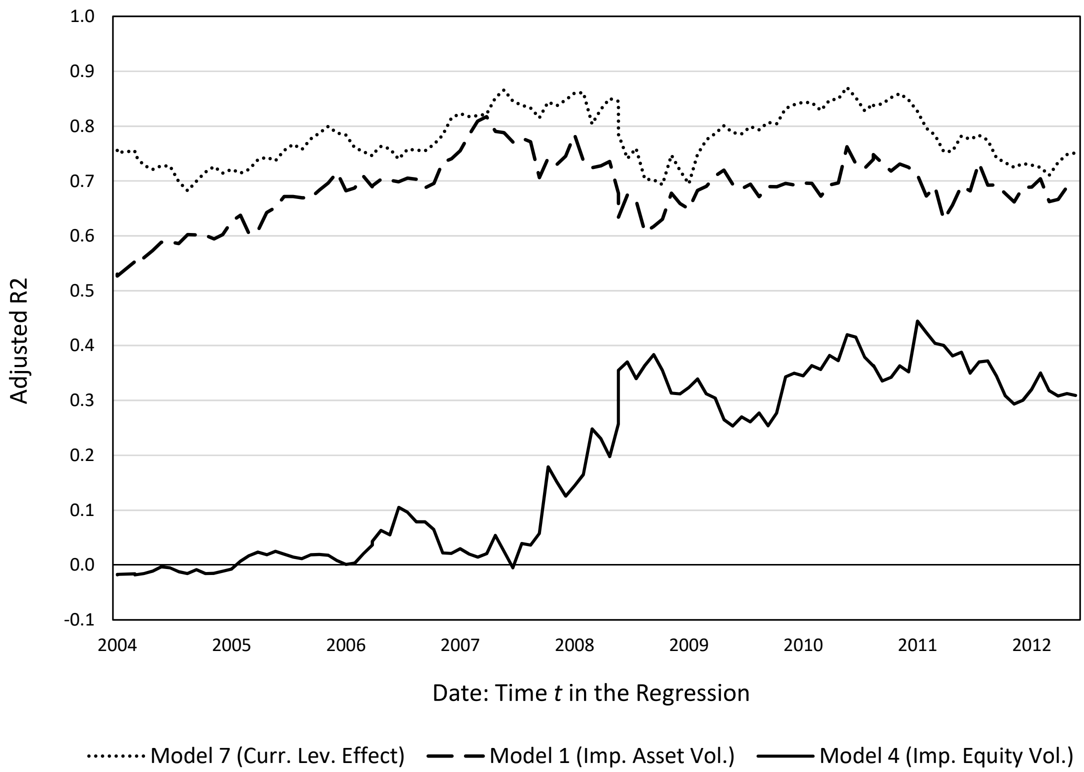
This figure plots the correlation between the future realized leverage effect and future realized asset volatility (grey solid line) for each of the 114 monthly observations. The figure also plots the standard deviation of the future realized leverage effect (black dotted line), future realized asset volatility (black dashed line), and future realized equity volatility (black solid line).

Figure 3. Correlation between Current Leverage Effect and Implied Asset Volatility, and Standard Deviation of Current Leverage Effect, Implied Asset Volatility, and Implied Equity Volatility.



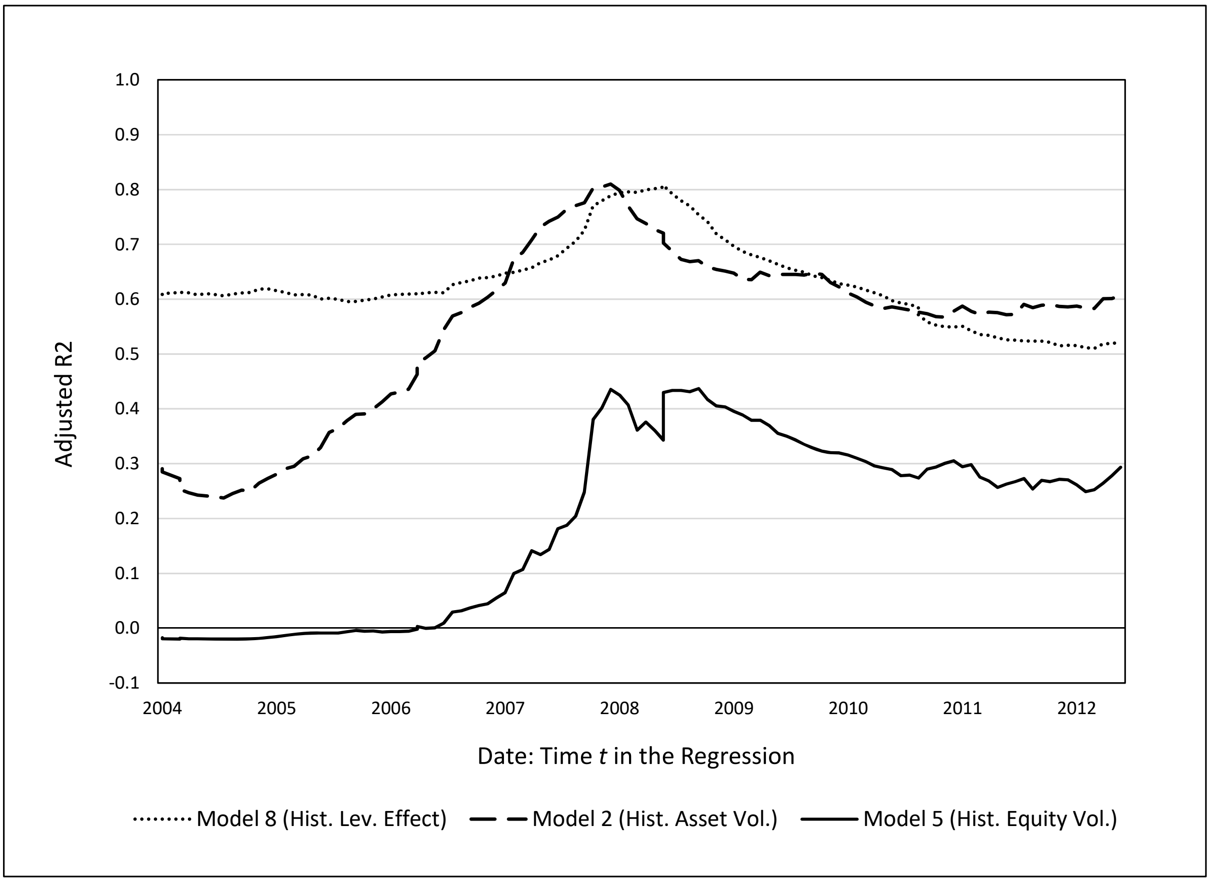
This figure plots the correlation between the current leverage effect and implied asset volatility (grey solid line) for each of the 114 monthly observations. The figure also plots the standard deviation of the current leverage effect (black dotted line), implied asset volatility (black dashed line), and implied equity volatility (black solid line).

Figure 4. Explanatory Power of Models 7, 1 and 4.



This figure plots the adjusted R^2 of Model 7 (future realized leverage effect as a function of current leverage effect; black dotted line), the adjusted R^2 of Model 1 (future realized asset volatility as a function of implied asset volatility; black dashed line), and the adjusted R^2 of Model 4 (future realized equity volatility as a function of implied equity volatility; black solid line). The figure reflects the results for each of the 114 monthly regressions.

Figure 5. Explanatory Power of Models 8, 2, and 5.



This figure plots the adjusted R^2 of Model 8 (future realized leverage effect as a function of historical leverage effect; black dotted line), the adjusted R^2 of Model 2 (future realized asset volatility as a function of historical asset volatility; black dashed line), and the adjusted R^2 of Model 5 (future realized equity volatility as a function of historical equity volatility; black solid line). The figure reflects the results for each of the 114 monthly regressions.